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# TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments

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## Abstract

Tabular data is widely utilized in various machine learning tasks. Current tabular learning research predominantly focuses on closed environments, while in real-world applications, open environments are often encountered, where distribution and feature shifts occur, leading to significant degradation in model performance. Previous research has primarily concentrated on mitigating distribution shifts, whereas feature shifts, a distinctive and unexplored challenge of tabular data, have garnered limited attention. To this end, this paper conducts the first comprehensive study on feature shifts in tabular data and introduces the first **tabular feature-shift benchmark** (TabFSBench). TabFSBench evaluates impacts of four distinct feature-shift scenarios on four tabular model categories across various datasets and assesses the performance of large language models (LLMs) and tabular LLMs in the tabular benchmark for the first time. Our study demonstrates three main observations: (1) most tabular models have the limited applicability in feature-shift scenarios; (2) the shifted feature set importance has a linear relationship with model performance degradation; (3) model performance in closed environments correlates with feature-shift performance. Future research directions and recommendations are also explored for each observation.

Benchmark: [LAMDASZ-ML/TabFSBench](#).

## 1. Introduction

Tabular data ([Altman & Krzywinski, 2017](#)) represents a meticulously structured format of data, systematically arranged in rows and columns, where each row signifies a

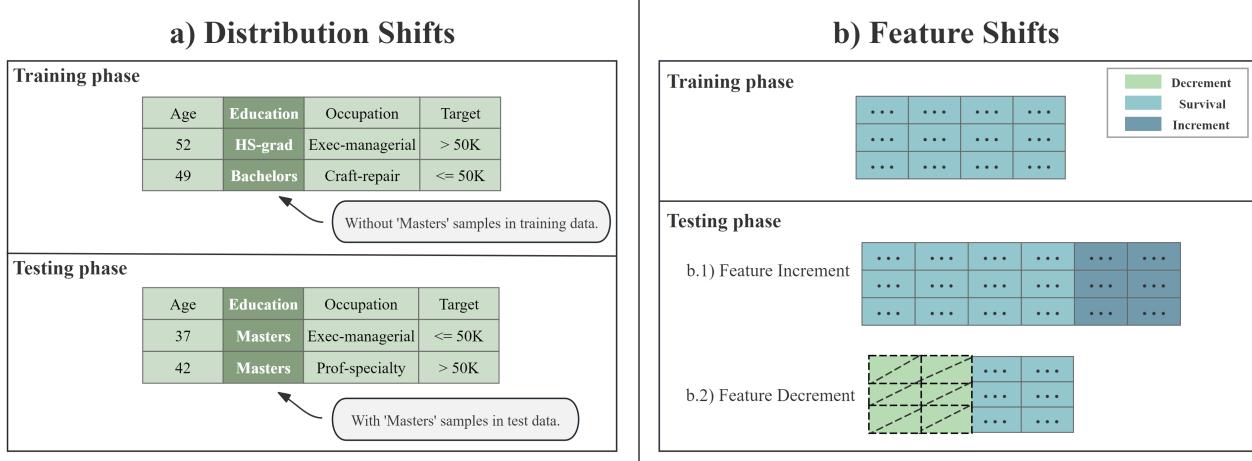
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record and each column corresponds to a feature ([Sahakyan et al., 2021](#)). The applications of tabular data in real-world scenarios are extensive. For instance, tabular data is utilized in financial analyses, including credit scoring ([West, 2000](#)) and stock market predictions ([Zhu et al., 2021](#)). Furthermore, tabular data forms the foundation for various applications in the medical sector, encompassing disease diagnosis ([Yıldız & Kalayci, 2024](#)) and pharmaceutical development ([Meijerink et al., 2020](#)). Existing machine learning models applicable to tabular data can be divided into four categories, containing tree-based models ([Prokhorenkova et al., 2018; Ke et al., 2017](#)), deep-learning models ([Hollmann et al., 2023a; Ye et al., 2024](#)), LLMs ([Touvron et al., 2023; OpenAI, 2024](#)), and specialized LLMs designed for tabular data ([Hegselmann et al., 2023; Wang et al., 2023](#)), namely tabular LLMs. These models have exhibited remarkable effectiveness across diverse tabular tasks.

Most tabular models of the aforementioned four categories are typically trained and tested in closed environments ([Zhou, 2022](#)), where both the distribution of data and the space of features are maintained consistently. However, real-world tabular tasks frequently occur in open environments ([Parmar et al., 2023](#)), where significant challenges such as distribution and feature shift occur. For example, in a traffic management system, alterations in traffic flow due to unforeseen incidents (e.g., extreme meteorological events) illustrate modifications in data distribution. Simultaneously, the failure or substitution of specific traffic monitoring equipment can induce feature shifts. These dynamic alterations underscore the complexity and unpredictability associated with machine learning tasks in open environments, necessitating the development of models characterized by enhanced adaptability and robustness. Therefore, recent research has progressively concentrated on the advancement of tabular machine learning models designed to acclimate effectively in open environments.

Distribution shift ([Zhou et al., 2025](#)) represents a challenge in open environments that has attracted substantial research attention. It refers to the phenomenon where tabular data processed by a model during the training and testing phases exhibit significant differences in distribution ([Wang et al., 2021a](#)). Numerous research have proposed solutions to address distribution shifts, including domain adaptation ([Ajakan et al., 2014; Arjovsky et al., 2019](#)) and domain



*Figure 1.* Open environment challenges: a) Distribution Shifts. Change in data distribution between training and testing while keeping features unchanged. b) Feature Shifts. Change in the feature set between training and testing, either by addition or removal of features.

generalization (Zhou et al., 2022; Zhao et al., 2024). Various benchmarks on distribution shifts in tabular data have been established. For example, TableShift (Gardner et al., 2024b) focuses on distribution shifts in tabular classification tasks, while Wild-Tab (Kolesnikov, 2023) concentrates on distribution shifts in tabular regression tasks.

Feature shift, another prevalent and substantial challenge in open environments, denotes the phenomenon in which the set of features available to a model for the same task dynamically changes due to temporal evolution or spatial variations. For instance, in the weather forecasting task, critical sensors may cease functioning due to malfunctions or aging, or they may be replaced by new sensors due to technological upgrades, leading to significant alterations in accessible features. This shift not only disrupts the consistency of the model’s input features but may also significantly degrade the model performance and robustness. However, research on feature shifts is relatively limited, and there is a lack of high-quality benchmarks for feature-shift scenarios. Therefore, comprehensively investigating the challenge of feature shifts in tabular data is important for enhancing the performance and robustness of models on feature shifts in open environments scenarios.

To this end, this paper presents the first systematic study on the challenge of feature shifts in open environments scenarios and proposes the first feature-shift benchmark for tabular data (TabFSBench). The contributions of this paper are summarized as follows:

- **Tabular Benchmark for Feature Shifts.** We provide publicly available datasets from classification and regression tasks across various domains. We design four feature-shift scenarios: single shift, most/least-relevant

shift, and random shift, to evaluate models.

- **Implementations of Various Models and APIs.** We evaluate four categories of tabular models and conduct the first assessment on LLMs and tabular LLMs in the tabular benchmark. We provide callable APIs to facilitate future research on the feature-shift challenge.
- **Empirical Research and Analysis.** We conduct extensive experiments on feature shifts and identify three observations alongside associated future work:
  - Most models have the limited applicability in feature shifts, where tabular LLMs demonstrate potential. Future work can design multi-level fine-tuning frameworks to enhance tabular LLMs’ reasoning capabilities.
  - Shifted features’ importance has a linear trend with model performance degradation. Future work can propose feature importance-driven optimization algorithms to emphasize and protect strong-correlated features.
  - Model closed environment performance correlates with feature-shift performance. Solid theoretical analysis of the relationship between close and open environments performance should be studied and how to further improve the robustness of these models in open environments is also an important research direction.

## 2. Task and Notation

### 2.1. Task Setting

Formally, the goal of tabular prediction tasks is to train a machine-learning model  $f : \mathcal{X} \rightarrow \mathcal{Y}$ , where  $\mathcal{X}$  is the input

*Table 1.* Datasets in TabFSBench. #Numerical means numerical features. #Categorical means categorical features.

Tasks	Dataset	#Samples	#Numerical	#Categorical	#Labels
Binary Classification	credit	1,000	7	13	2
	electricity	45,312	8	0	2
	heart	918	6	5	2
	MiniBooNE	72,998	50	0	2
Multi-Class Classification	Iris	150	4	0	3
	penguins	345	4	2	3
	eye_movements	10,936	27	0	4
	jannis	83,733	54	0	4
Regression	abalone	4,178	7	1	\
	bike	10,886	6	3	\
	concrete	1,031	8	0	\
	laptop	1,275	8	14	\

space and  $\mathcal{Y}$  is the output space. We define the set of features in  $\mathcal{X}$  as  $C$ .

## 2.2. Feature Shifts Notation

We partition the feature set  $C$  from training and testing phases into  $C^{train}$  and  $C^{test}$ . In closed environments, the feature set from the training phase is identical to that from the testing phase, i.e.,  $C^{train} = C^{test}$ . While in open environments scenarios, although  $C^{train}$  remains invariant,  $C^{test}$  may encounter two challenges, namely, distribution shift and feature shift. We illustrate these challenges by using forest disease monitoring as an example, where a sensor can be regarded as a feature. Figure 1 depicts these challenges of open environments.

**Distribution Shift.** When certain raw sensors fail, new sensors are installed and commence monitoring. The number of features remains unchanged, i.e.,  $C_{train} = C_{test}$ , but the monitoring precision (data distribution) shifts. Therefore, distribution shift refers to the phenomenon where data distribution varies between training and testing phases (see Figure 1(a)). Predictions can be generated without any data processing, although model performance may deteriorate due to covariate shifts or concept shifts (Shao et al., 2024).

**Feature Shift.** Feature shift is another open environments challenge, wherein the feature set previously utilized as inputs is either removed partially or added by new features. It contains two scenarios:

- **Feature Increment.** Additional sensors are deployed and no existing sensor fails, resulting in an expansion of the feature set (see Figure 1(b.1)), i.e.,  $C^{train} \subsetneq C^{test}$ . In this case, to maintain consistency in input dimensions between training and testing phases, the model typically truncates the newly added features in

$C^{test}$  and retains features from  $C^{test}$  corresponding to the features in  $C^{train}$ .

- **Feature Decrement.** Certain existing sensors cease to function and no new sensors are added, leading to a reduction in the feature set (see Figure 1(b.2)), i.e.,  $C^{test} \not\subseteq C^{train}$ . In this case, to maintain consistency in input dimensions between training and testing phases and allow the model to predict properly, shifted features in  $C^{test}$  need to be imputed.

Given the limited research addressing feature shift and the established observation that feature increment generally does not result in model performance degradation, we conduct an empirical experimental analysis focusing on feature-decrement scenarios.

## 3. TabFSBench: A Feature-Shift Benchmark for Tabular Data

TabFSBench is a benchmark for evaluating feature shifts in tabular data, comprising twelve tabular tasks and assessing four categories of tabular models. We compare model performance across four feature-shift scenarios and closed environments. Additionally, we provide callable Python APIs<sup>1</sup> to facilitate future research on the feature-shift challenge in open environments.

### 3.1. Datasets

To effectively reproduce feature-shift scenarios, we select open-source and reliable datasets from OpenML and Kaggle’s extensive dataset library, including three curated tasks of binary classification, multi-class classification, and regression, covering various domains such as finance, healthcare and geology. The primary attributes of the datasets used in

<sup>1</sup><https://github.com/LAMDASZ-ML/TabFSBench>

Table 2. Kendall’s  $\tau$  coefficients for four feature importance metrics consistency.

Metric	$\tau$
Pearson	0.60
Spearman	0.61
SHAP	0.49
Mutual Information	0.53

TabFSBench are presented in Table 1. Detailed information on the datasets can be found in Appendix D.

### 3.2. Feature-shift Scenarios

To evaluate the consistency of feature importance rankings, we compute Kendall’s  $\tau$  correlation coefficients among four metrics: Pearson correlation coefficient, Spearman’s rank correlation, SHAP values, and mutual information. Table 2 reveals high concordance across these measures, with particularly strong agreement between PCC and Spearman ( $\tau = 0.61$ ). While both demonstrate comparable performance, we ultimately select PCC for its widespread adoption and intuitive interpretability. The marginal differences between these metrics’ rankings are found to be statistically insignificant and not affect our analytical conclusions.

Hence, to effectively assess the impact of feature shifts on model performance and analyze whether there is a relationship between the importance of shifted features and model performance degradation, we employ pearson correlation  $\rho$  to rank features of the given dataset, thereby indicating the importance of each feature for the task.  $|\rho|$  greater than 0.7 can be considered as a moderate linear correlation(Iversen & Gergen, 2012). Details regarding experiments on four feature importance metrics and pearson correlation are provided in Appendix G.

**Single Shift.** To evaluate the impact of the absence of features with different importance levels on model performance, we design the single shift experiment. For a given dataset, we first compute correlations of features. Then, we sequentially remove one feature by employing a sampling-with-replacement approach in the ascending order. Finally, we compare the gap in model performance among shifted features with different correlations.

**Most/Least-Relevant Shift.** To evaluate how the model performance changes when the feature set with different importance is shifted, we design the most/least-relevant shift experiment. For a given dataset, we first compute correlations of features. Then, we remove features in the ascending (least relevant) or descending (most relevant) order. Finally, we compare the gap in model performance among shifted feature sets with different importance.

**Random Shift.** To systematically evaluate model robustness under feature shifts, we design a controlled experiment where we randomly sample feature subsets from the training feature space  $\mathcal{C}^{train}$  to create shifted test scenarios. By progressively removing features during testing (where removing one feature represents a shift ratio of  $1/n$ , with  $n$  being the total feature count), we quantify performance degradation across different shift magnitudes. For statistical reliability, we evaluate up to  $\min(10,000, \binom{N}{n})$  distinct feature combinations per shift ratio  $n/N$  and report the mean performance across all combinations.

### 3.3. Impute Strategy.

We compare the performance of various models by using their respective imputation methods, random imputation, and mean imputation. The results (see Appendix F) demonstrate that mean imputation better simulates scenarios with shifted features. Notably, benchmarks such as LAMDA-Talent (Liu et al., 2024) also adopt mean imputation for handling missing values, underscoring its widespread applicability. Hence, we opt for uniform mean-value imputation of shifted features to ensure that predictions intuitively reflect model robustness in feature-shift scenarios. Specifically, for numerical features, we employ the mean value of the feature within the training set as the imputed value. For categorical features, we utilize the value that occurs most frequently as the imputed value. We do not select zero or other arbitrary values for imputation, as this would introduce artificial shifts in the data distribution, which contradicts the objective of evaluating model robustness in the context of feature shifts.

### 3.4. TabFSBench API

To facilitate the use of TabFSBench for experimental setups in feature-shift scenarios, we have designed the TabFSBench APIs. More details are available at <https://github.com/LAMDASZ-ML/TabFSBench>. The APIs are divided into five parameters: dataset, model, task, degree, and export\_dataset.

The dataset parameter specifies the dataset to be used and requires the full name of the dataset. TabFSBench supports datasets from OpenML, Kaggle, and local directories.

The model parameter defines the model to be evaluated and can be selected from tree-based models, deep-learning models, LLMs, and tabular LLMs. New models can be added by following the instructions in the "How to Add New Models" section.

The task parameter determines the type of feature-shift experiment to be conducted. The available options include single, least, most, and random.

The degree parameter indicates the proportion of features

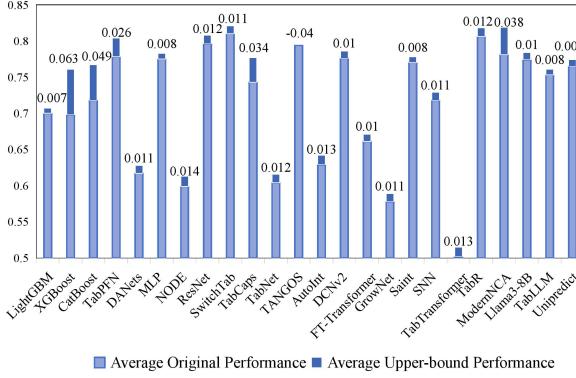


Figure 2. Upper bound and original model performance.

to be shifted. The valid range for this parameter is from 0 to 1, where 0 signifies no features are removed, and 1 signifies all features are removed.

The `export_dataset` parameter controls whether the modified dataset (after removing shifted features) is exported as a CSV file for further use.

An example command for running a feature-shift experiment in TabFSBench is as follows:

#### Example Command

```
python run_experiment.py
--dataset Adult --model LightGBM
--task random --degree 0.3
--export_dataset True
```

## 4. Experiment Setup

### 4.1. Models Benchmarked

We evaluate a suite of models designed for tabular data, drawing from four categories: tree-based models, deep-learning models, LLMs and tabular LLMs. Appendix E provides details of all models and their hyperparameters.

**Tree-Based Models.** Gradient Boosting Decision Tree (GBDT) is a traditional type of tree-based machine learning models that incrementally improve the model by sequentially adding decision trees, optimizes the loss function using gradient descent, and prevents overfitting through regularization and tuning parameters. GBDTs are considered to be state-of-the-art models on tabular tasks (Grinsztajn et al., 2022). Hence, we evaluate LightGBM (Ke et al., 2017), XGBoost (Chen & Guestrin, 2016) and CatBoost (Prokhorenkova et al., 2018) of GBDTs.

**Deep-Learning Models.** Deep-learning models we evaluate consist of MLP, FT-Transformer (Gorishniy et al., 2021),

TabPFN (Hollmann et al., 2023a), and other tabular deep-learning models provided by LAMDA-TALENT<sup>2</sup>, including AutoInt (Song et al., 2019), TabNet (Arik & Pfister, 2021), Tabular ResNet (Gorishniy et al., 2021), DCN2 (Wang et al., 2021b), NODE (Popov et al., 2020), GrowNet (Badirli et al., 2020), DANets (Chen et al., 2022), Saint (Somepalli et al., 2021), Snn (Klambauer et al., 2017), Switchtab (Wu et al., 2024), Tabcaps (Chen et al., 2023), Tabr (Gorishniy et al., 2024), TabTransformer (Huang et al., 2020), Tangos (Jef-fares et al., 2023) and modernNCA (Ye et al., 2024).

**LLMs.** We select Llama3-8B, a LLM released by Meta AI in April 2024, as the representative LLM for our evaluation. To construct the input text for Llama3-8B, we employ the **List Template** format, leveraging the demonstrated proficiency of LLMs in reading and parsing structured list-based inputs, as evidenced by prior research (Hegselmann et al., 2023). A comprehensive explanation of the List Template is provided in Appendix E.3.

**Tabular LLMs.** LLMs have demonstrated remarkable performance in zero-shot and few-shot tabular tasks leading to the development of tabular LLMs which are specifically designed based on LLMs for tabular tasks. We evaluate TabLLM (Hegselmann et al., 2023) and Unipredict (Wang et al., 2023). About Unipredict, we choose the light version instead of the heavy version, because we observe that Unipredict-light can achieve better performance in the original paper and our own evaluations. The rest of model settings follow the original paper.

### 4.2. Pipelines

**Data Set Segmentation.** We begin by partitioning the dataset into a train&validation set and a set of test sets. Appendix D shows the segmentation details of each dataset, including Pearson correlation heat maps of datasets. We uniformly use the same feature segmentation and data pre-processing methods.

**Hyperparameter Optimization.** We use hyperparameter optimization to help models achieve optimal performance in different datasets. In Appendix E, we provide full hyperparameter grids for each model.

**Evaluation Metrics.** For classification tasks, we utilize accuracy and ROC-AUC as model performance, where higher values denote superior model performance. For regression tasks, we utilize Root Mean Square Error (RMSE) as model performance, where lower values denote superior model performance. We also consider the percentage of model performance gap  $\Delta$  as the robustness of model on feature-shift

<sup>2</sup><https://github.com/qile2000/LAMDA-TALENT>

*Table 3.* Average performance gap in different tasks. We attribute the different feature-shift degree for each dataset to 20%, 40%, 60%, 80% and 100%. Then compute the model’s performance gap for each degree of feature shifts, task by task. ‘\’ means this model can’t handle the regression task. For classification tasks, we choose accuracy. For regression tasks, we choose RMSE. The best is in **bold** and second best is underlined. Model abbreviations are in Appendix E.

Task	Shift	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TFI	TABR	NCA	LMA	TLLM	UNI
<b>Binary Classification</b>	20%	-0.065	-0.076	-0.035	-0.048	-0.022	-0.024	<b>-0.009</b>	-0.031	-0.010	-0.020	-0.015	-0.028	-0.026	-0.028	<b>-0.010</b>	<u>-0.016</u>	-0.062	-0.161	-0.045	-0.022	-0.019			
	40%	-0.192	-0.218	-0.105	-0.118	-0.056	-0.062	-0.031	-0.085	<b>-0.031</b>	-0.051	-0.055	-0.069	-0.065	-0.070	-0.077	-0.041	-0.042	-0.048	-0.044	-0.158	-0.271	-0.118	-0.042	-0.038
	60%	-0.249	-0.261	-0.155	-0.165	-0.090	-0.107	-0.061	-0.150	-0.063	-0.090	-0.099	-0.121	-0.115	-0.120	-0.138	-0.077	-0.072	-0.086	-0.078	-0.214	-0.301	-0.176	<b>-0.056</b>	-0.058
	80%	-0.310	-0.328	-0.238	-0.235	-0.154	-0.185	-0.109	-0.233	-0.123	-0.157	-0.161	-0.203	-0.188	-0.201	-0.232	-0.138	-0.142	-0.143	-0.133	-0.263	-0.329	-0.244	<u>-0.066</u>	-0.074
	100%	-0.353	-0.375	-0.332	-0.309	-0.226	-0.271	-0.179	-0.315	-0.235	-0.263	-0.210	-0.286	-0.285	-0.305	-0.198	-0.247	-0.226	-0.203	-0.318	-0.357	-0.351	<b>-0.080</b>	-0.094	
<b>Multi Classification</b>	20%	-0.047	-0.043	-0.043	-0.020	-0.015	-0.023	-0.032	-0.024	-0.019	-0.012	-0.025	-0.030	-0.012	-0.025	-0.017	-0.008	-0.021	-0.017	-0.039	-0.046	-0.087	<b>-0.056</b>	-0.007	-0.135
	40%	-0.144	-0.145	-0.123	-0.069	-0.052	-0.065	-0.023	-0.090	-0.049	-0.044	-0.070	-0.082	-0.071	-0.067	-0.067	-0.026	-0.055	-0.032	-0.016	-0.206	-0.101	<b>-0.017</b>	-0.137	
	60%	-0.274	-0.228	-0.232	-0.132	-0.097	-0.123	<b>-0.045</b>	-0.171	-0.096	-0.084	-0.108	-0.150	-0.145	-0.135	-0.145	-0.045	-0.192	-0.102	-0.056	-0.221	-0.344	-0.217	-0.103	-0.123
	80%	-0.398	-0.342	-0.374	-0.228	-0.178	-0.203	-0.084	-0.279	-0.164	-0.130	-0.165	-0.236	-0.262	-0.216	-0.272	<b>-0.077</b>	-0.320	-0.164	-0.086	-0.355	-0.462	-0.291	-0.314	-0.139
	100%	-0.552	-0.494	-0.516	-0.388	-0.287	-0.360	<u>-0.143</u>	-0.488	-0.347	-0.232	-0.270	-0.423	-0.362	-0.464	<b>-0.105</b>	-0.440	-0.275	-0.150	-0.525	-0.620	-0.429	-0.245	-0.176	
<b>Regression</b>	20%	0.237	0.233	0.250	\	<u>0.001</u>	0.028	0.001	0.054	0.001	\	0.004	0.038	0.012	0.039	0.007	0.003	0.017	0.013	0.001	0.022	0.163	<b>-0.233</b>	\	\
	40%	0.243	0.243	0.647	\	<u>0.004</u>	0.045	0.003	0.136	0.003	\	0.048	0.049	0.012	0.049	0.005	0.005	0.018	0.012	0.002	0.024	0.169	0.454	\	\
	60%	0.793	0.840	0.116	\	<u>0.004</u>	0.128	0.005	0.048	0.005	\	0.140	0.196	0.063	0.180	0.049	0.049	0.087	0.059	<b>0.023</b>	0.119	0.559	0.595	\	\
	80%	1.159	1.197	1.345	\	<u>0.007</u>	0.184	0.007	0.293	<u>0.006</u>	\	0.027	0.294	0.095	0.244	0.078	0.016	0.131	0.066	<b>0.003</b>	0.244	0.795	0.359	\	\
	100%	1.405	1.490	1.669	\	0.011	0.250	<u>0.009</u>	0.380	0.013	\	0.029	0.377	0.163	0.317	0.112	0.018	0.167	0.059	<b>0.006</b>	0.392	1.000	0.669	\	\

scenarios in open environments,

$$\Delta = \frac{(metric_i - metric_0)}{metric_0} \quad (1)$$

$metric_i$  denotes the model performance where  $i$  features shift. In subsequent sections, we use  $metric$  to refer to **performance**, and  $\Delta$  to refer to **robustness**.

## 5. Experiment Results

By conducting four types of experiments to compare the performance and robustness of models in feature shifts, we demonstrate three main observations and corresponding future work below, which are detailed below. Comprehensive experimental details are provided in Appendix H.7.

### Observation 1

**Most models have the limited applicability in feature-shift scenarios.**

To systematically investigate model robustness under varying degrees of distributional shift, we design controlled experiments by simulating four types of feature-shift scenarios. We employ  $\Delta$  as a quantitative metric to assess model performance degradation across different shift magnitudes. Our empirical analysis yields three key observations.

**Feature shift impairs model robustness.** To rigorously assess the theoretical performance limits of the models under feature shift conditions, we conduct an empirical evaluation by training the models directly on the shifted data distribution and subsequently evaluating their generalization capability on a held-out test set. As illustrated in Figure 2, our experimental results reveal a consistent performance gap between tabular models trained on the original dataset versus those trained on the feature-shift dataset. The comparative analysis demonstrates that while training on the original dataset offers the advantage of broader feature rep-

resentation, the inherent distributional shift substantially diminishes model robustness.

**Most models can’t handle feature shifts well.** Table 3 reveals that the majority of models encounter significant difficulties in effectively addressing the challenge posed by feature shifts. As the magnitude of feature shift intensifies, the disparity in performance between models widens correspondingly. Notably, tree-based models are particularly vulnerable to the adverse effects of feature shifts. Within the context of classification tasks, NODE and tabular LLMs demonstrate relatively lower levels of performance degradation. Conversely, in regression tasks, DANets and TabTransformer exhibit greater resilience. Despite the current limitation of tabular LLMs to classification tasks, they exhibit robust adaptability to feature shifts, suggesting their potential for broader application in the future.

**No Model Consistently Outperforms.** Table 4 reveals that no model can consistently outperform in feature-shift scenarios. Although tabular LLMs display notable robustness, their performance in closed environments and low-degree feature-shift scenarios is not superior. CatBoost continues to highlight its effectiveness in solving tabular tasks. Moreover, the limited performance of NODE, DANets, and TabTransformer, which demonstrate outstanding robustness in Table 3, confirm that some models’ robustness is achieved at the expense of closed environment performance.

The potential of tabular LLMs suggests that future work should focus on developing fine-tuning frameworks to enhance semantic parsing capabilities of tabular LLMs for features and improve their reasoning abilities in feature-shift scenarios. Additionally, integrating adaptive prompting mechanisms that dynamically adjust to the presence of feature shifts could further strengthen model robustness. By embedding domain knowledge and causal reasoning into the prompting strategy, LLMs are able to achieve a deeper understanding of feature shifts, thereby generating more accurate and reliable predictions.

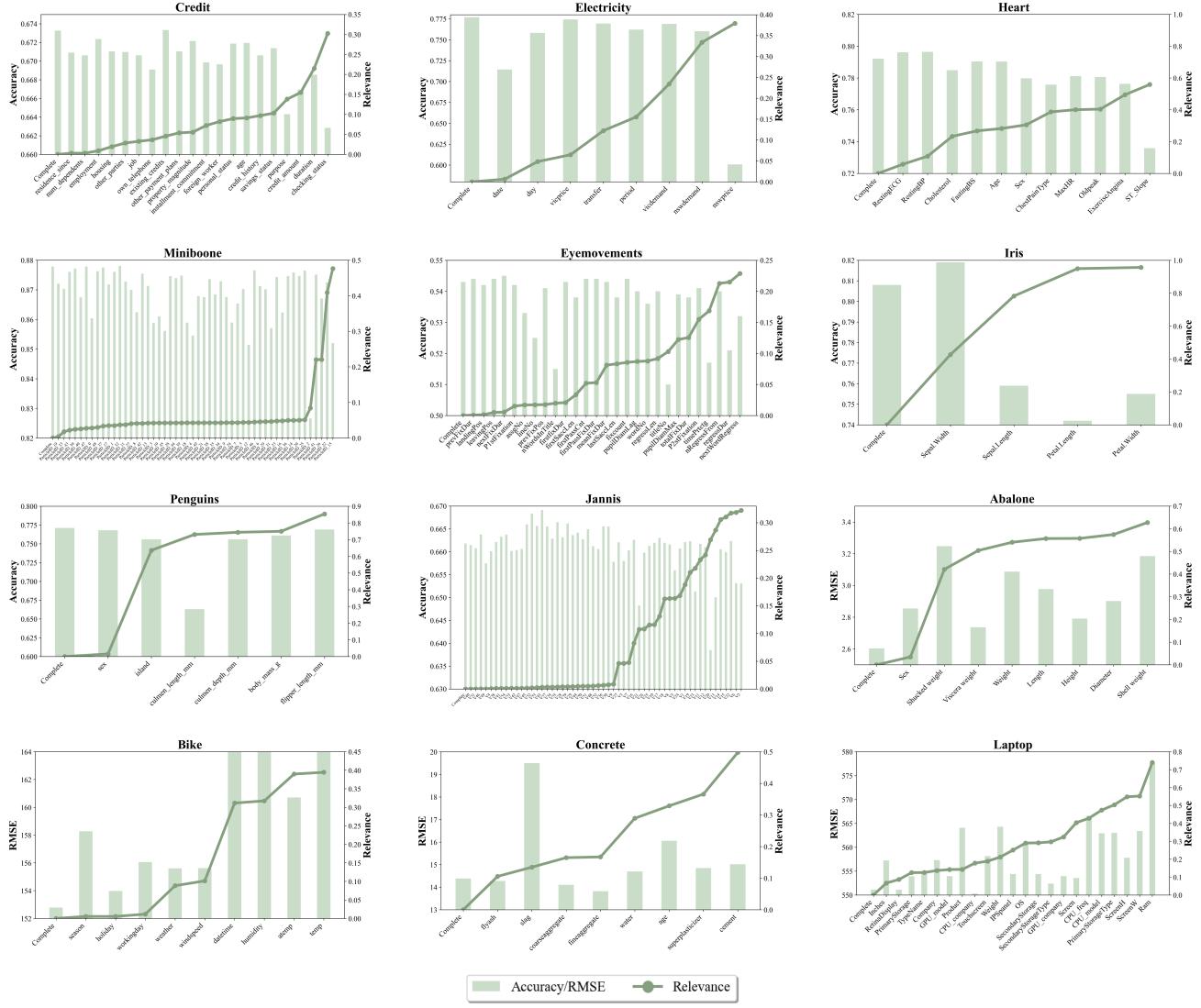


Figure 3. Results for single shift experiments with correlation analysis experiments across 12 datasets. The  $x$ -axis represents features ordered in ascending correlation with the target, the left  $y$ -axis represents the average performance (accuracy or RMSE) of all models and the right  $y$ -axis shows the absolute value of correlation. Features are removed in ascending order of their correlation values to observe the impact on model performance.

*Table 4.* Average rank in different tasks. We attribute the different feature-shift degree for each dataset to 20%, 40%, 60%, and 80%. Then compute the model’s performance rank for each degree of feature shifts, task by task. 0% means the model ID performance. ‘\’ means this model can’t handle the regression task. For classification tasks, we choose accuracy. For regression tasks, we choose RMSE. The best is in **bold** and second best is underlined. Superior accuracy in classification tasks is in *italics*. Model abbreviations are in Appendix E.

Task	Shift	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI
Binary Classification	0%	5	3	2	7	19	13	22	11	14	17	21	10	18	12	16	23	8	20	24	4	1	6	9	15
	20%	10	13	1	5	18	9	23	8	12	17	19	6	16	11	15	20	2	21	24	14	22	4	7	3
	40%	21	23	4	13	15	7	20	9	5	11	17	6	10	8	14	19	1	18	22	16	24	12	3	2
	60%	22	23	5	12	10	6	16	14	4	8	19	7	11	9	15	18	2	17	20	21	24	13	3	1
	80%	22	24	5	12	7	8	14	16	4	6	21	9	10	11	18	17	3	15	20	19	23	13	1	2
	100%	23	24	8	9	5	6	7	18	4	11	17	10	13	12	19	14	3	16	22	15	21	20	1	2
Multi Classification	0%	6	5	2	7	20	15	22	8	12	18	19	14	21	10	16	24	13	17	23	9	1	11	3	4
	20%	10	8	4	16	20	14	23	7	13	19	21	11	18	12	15	24	6	17	22	5	1	9	3	2
	40%	15	13	3	14	20	11	23	9	5	17	21	10	19	6	12	24	7	16	22	8	4	18	2	1
	60%	20	15	6	10	17	7	22	8	3	14	18	5	19	4	13	24	11	9	21	12	16	23	2	1
	80%	24	19	17	9	15	7	12	10	2	6	13	8	21	3	14	23	16	5	11	18	22	20	4	1
	100%	24	18	17	11	13	9	5	19	6	3	10	14	20	8	22	12	15	4	7	21	23	16	2	1
Top 3		4	2	9	0	0	1	0	1	2	1	0	2	0	1	0	0	5	0	0	1	5	1	<u>9</u>	<b>10</b>
Average Rank		13.1	13.6	<b>4.8</b>	10.4	15.5	8.8	16.6	9.6	10.9	12.3	17.0	<u>7.7</u>	15.0	8.4	14.2	18.3	9.2	14.2	18.9	10.6	12.1	12.2	<u>3.3</u>	<b>2.9</b>

## Observation 2

**Shifted features’ importance has a linear trend with model performance degradation.**

Considering that feature shifts exert negative impacts on models from Observation 1, it is necessary to determine whether there is a relationship between the importance of shifted features and model performance degradation. To this end, we conduct single shift experiments by analyzing the average performance of all models for each dataset, and most/least-relevant shift experiments by comparing the correlation sum of shifted feature sets with model performance degradation in feature-shift scenarios. We obtain two observations from these experiments.

**Single strong correlated feature shifted causes greater model performance degradation.** Figure 3 illustrates that model performance decreases more significantly as the shifted single feature becomes more relevant to the target. The extent of model degradation caused by a strongly correlated feature shift is larger than that caused by a weakly correlated feature shift. We also observe that model performance may potentially improve if features that are less relevant to the target are removed, whose detailed analysis can be found in Appendix H.3.

**Shifted feature set’s correlations have a relationship with model performance degradation linearly.** Figure 4 shows that as the correlation sum of the feature set gets larger, the model performance degradation gets larger. We observe a linear trend between the correlations of the shifted feature set and model performance degradation (see the blue line in Figure 4;  $\rho = 0.74$ ).

The linear trend between the correlation sum of shifted features and model performance degradation underscores the

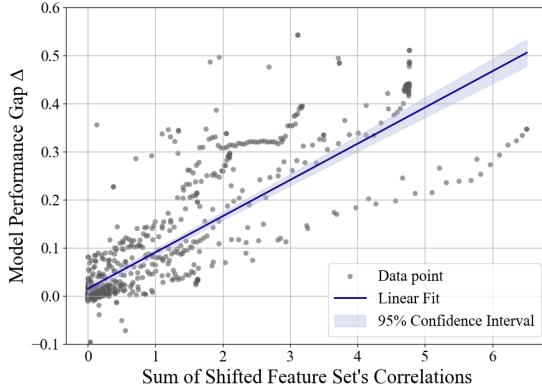
importance of strongly correlated features. Therefore, it is essential to develop feature importance-driven optimization algorithms that incorporate adaptive mechanisms, such as dynamic feature weighting or hierarchical feature selection, to emphasize strong-correlated features. Additionally, this highlights the necessity of mitigating shifts in strong-correlated features in open environments.

## Observation 3

**Model closed environment performance correlates with feature-shift performance.**

In Figure 5, a comparative analysis of model performance is presented, contrasting the outcomes in closed environments with those in feature-shift scenarios within the context of random shift experiments. The analysis reveals a notable trend: models that exhibit superior performance in closed environments tend to demonstrate relatively enhanced performance when subjected to feature-shift scenarios. This observation suggests the existence of a positive correlation between model performance in closed environments and their robustness in feature-shift scenarios. Specifically, the enhanced performance in closed environments appears to confer a degree of resilience to the models when confronted with the challenges posed by feature-shift scenarios, thereby highlighting the potential interdependence between these two distinct operational contexts.

This observation suggests that improving model performance in closed environments may serve as a foundational step to enhance their adaptability and robustness in feature-shift scenarios. A rigorous theoretical investigation into the relationship between closed environment performance and open environments adaptability is warranted, with particular emphasis on elucidating the underlying mechanisms that govern model robustness. Further exploration into method-



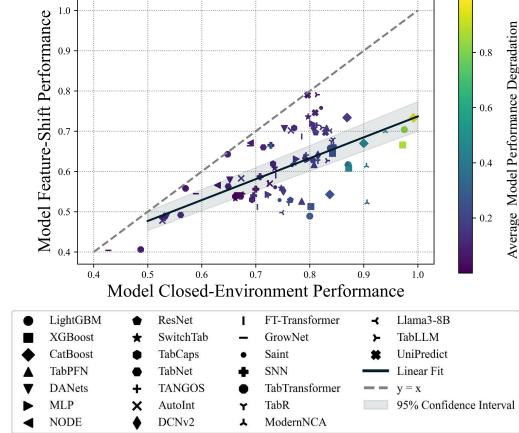
**Figure 4.** We use  $\Delta$  (described in equation 1) to measure the performance decrease. Sum of shifted feature set's correlations refers to the sum of Pearson correlation coefficients of shifted features. Notably, performance decrease and sum of shifted feature set's correlations demonstrate a strong correlation, with a Pearson correlation coefficient of  $\rho = 0.7405$ .

ologies for enhancing model resilience in open environments, such as through domain adaptation, transfer learning, or robustness-aware training paradigms.

## 6. Conclusion

We introduce TabFSBench, a comprehensive and rigorously designed benchmark specifically tailored to systematically investigate feature shifts in tabular data. TabFSBench encompasses diverse tasks, enabling the evaluation of model performance and robustness, and benchmarking of tabular models in feature-shift scenarios. To enhance accessibility and ensure reproducibility, we provide intuitive and user-friendly Python APIs, facilitating seamless dataset retrieval and integration into experimental workflows. Additionally, we conduct extensive empirical evaluations across four distinct feature-shift scenarios. Our three observations not only underscore the significant challenges posed by feature shifts but also offer insights for the future development of feature-shift research.

While this paper provides comprehensive evaluation of feature shift impacts on tabular models, several limitations warrant discussion. First, the current framework focuses primarily on feature decrement scenarios, as conventional tabular models inherently require fixed input dimensions and thus automatically ignore newly added features in increment scenarios. Second, our evaluation excludes specialized architectures designed for feature-increment issues. Third, the analysis does not examine how models respond to shifted features with identical correlation structures. Additionally, while we have evaluated diverse tabular tasks, the scope



**Figure 5.** Model performance in closed environments vs. model feature-shift performance. **Closed environment** means that the dataset does not have any degree of feature shift. **Feature-shift** means average model performance in all degrees of feature shifts.

remains limited by the current absence of large-scale tabular LLM evaluations and comparative studies with other shift types. These aspects represent important directions for future empirical validation and benchmark expansion on feature-shift challenges in open environments.

## Benchmark Availability Statement

The benchmark code for this paper is available at <https://github.com/LAMDASZ-ML/TabFSBench>. The project page of TabFSBench which contains the leaderboard is available at [Home-TabFSBench](#).

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## Impact Statement

The paper introduces a novel contribution aimed at advancing the burgeoning field of open environments. The observations elucidated within this work possess broad and multifaceted societal implications. However, due to the limitations of this paper, a detailed elaboration of these implications is reserved for future discourse. These discussions are expected to center on best practices and the development of regulatory frameworks that can effectively harness the benefits of open environments machine learning.

## References

- Ajakan, H., Germain, P., Larochelle, H., Laviolette, F., and Marchand, M. Domain-adversarial neural networks. *arXiv preprint arXiv:1412.4446*, 2014.
- Altman, N. and Krzywinski, M. Tabular data. *Nature Methods*, 14(4):329–331, 2017.
- Arik, S. Ö. and Pfister, T. Tabnet: Attentive interpretable tabular learning. In *Proceedings of the 35th AAAI Conference on Artificial Intelligence*, pp. 6679–6687, 2021.
- Arjovsky, M., Bottou, L., Gulrajani, I., and Lopez-Paz, D. Invariant risk minimization. *arXiv preprint arXiv:1907.02893*, 2019.
- Badirli, S., Liu, X., Xing, Z., Bhowmik, A., Doan, K., and Keerthi, S. K. Gradient boosting neural networks: Grownet. *arXiv preprint arXiv:2002.07971*, 2020.
- Bao, M., Zhou, A., Zottola, S., Brubach, B., Desmarais, S., Horowitz, A., Lum, K., and Venkatasubramanian, S. It’s COMPASlicated: The Messy Relationship between RAI Datasets and Algorithmic Fairness Benchmarks. *arXiv preprint arXiv:2106.05498*, 2021.
- Borisov, V., Leemann, T., Seßler, K., Haug, J., Pawelczyk, M., and Kasneci, G. Deep neural networks and tabular data: A survey. *IEEE Transactions on Neural Networks and Learning Systems*, 35(6):7499–7519, 2022.
- Chen, J., Liao, K., Wan, Y., Chen, D. Z., and Wu, J. Danets: Deep abstract networks for tabular data classification and regression. In *Proceedings of the 36th AAAI Conference on Artificial Intelligence*, pp. 3930–3938, 2022.
- Chen, J., Liao, K., Fang, Y., Chen, D., and Wu, J. Tabcaps: A capsule neural network for tabular data classification with bow routing. In *Proceedings of the 11th International Conference on Learning Representations*, 2023.
- Chen, T. and Guestrin, C. XGBoost: A Scalable Tree Boosting System. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 785–794, 2016.
- Chizat, L., Roussillon, P., Léger, F., Vialard, F.-X., and Peyré, G. Faster Wasserstein distance estimation with the Sinkhorn divergence. *Advances in Neural Information Processing Systems*, pp. 2257–2269, 2020.
- Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., and Fei-Fei, L. ImageNet: A large-scale hierarchical image database. In *Proceedings of the IEEE/CVF conference on Computer Vision and Pattern Recognition*, pp. 248–255, 2009.
- Fang, X., Xu, W., Tan, F. A., Zhang, J., Hu, Z., Qi, Y. J., Nickleach, S., Socolinsky, D., Sengamedu, S., and Faloutsos, C. Large language models on tabular data: Prediction, generation, and understanding-a survey. *arXiv preprint arXiv:2402.17944*, 2024.
- Gardner, J., Perdomo, J. C., and Schmidt, L. Large Scale Transfer Learning for Tabular Data via Language Modeling. *arXiv preprint arXiv:2406.12031*, 2024a.
- Gardner, J., Popovic, Z., and Schmidt, L. Benchmarking distribution shift in tabular data with tableshift. *Advances in Neural Information Processing Systems*, pp. 53385–53432, 2024b.
- Gemmeke, J. F., Ellis, D. P., Freedman, D., Jansen, A., Lawrence, W., Moore, R. C., Plakal, M., and Ritter, M. Audio set: An ontology and human-labeled dataset for audio events. In *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing*, pp. 776–780, 2017.
- Gorishniy, Y., Rubachev, I., Khrulkov, V., and Babenko, A. Revisiting deep learning models for tabular data. *Advances in Neural Information Processing Systems*, pp. 18932–18943, 2021.
- Gorishniy, Y., Rubachev, I., Kartashev, N., Shlenskii, D., Kotelnikov, A., and Babenko, A. TabR: Tabular Deep Learning Meets Nearest Neighbors. In *Proceedings of the 12th International Conference on Learning Representations*, 2024.
- Grinsztajn, L., Oyallon, E., and Varoquaux, G. Why do tree-based models still outperform deep learning on typical tabular data? *Advances in Neural Information Processing Systems*, pp. 507–520, 2022.
- Guo, L.-Z., Jia, L.-H., Shao, J.-J., and Li, Y.-F. Robust semi-supervised learning in open environments. *Frontiers of Computer Science*, 19(8):198345, 2025.
- He, H., Queen, O., Koker, T., Cuevas, C., Tsiligkaridis, T., and Zitnik, M. Domain adaptation for time series under feature and label shifts. In *Proceedings of the 40th International Conference on Machine Learning*, pp. 12746–12774, 2023.
- Hegselmann, S., Buendia, A., Lang, H., Agrawal, M., Jiang, X., and Sontag, D. TabLLM: Few-shot Classification of Tabular Data with Large Language Models. In *Proceedings of the 26th International Conference on Artificial Intelligence and Statistics*, pp. 5549–5581, 2023.
- Hollmann, N., Müller, S., Eggensperger, K., and Hutter, F. TabPFN: A Transformer That Solves Small Tabular Classification Problems in a Second. In *Proceedings of the 11th International Conference on Learning Representations*, 2023a.

- Hollmann, N., Müller, S., and Hutter, F. Large language models for automated data science: Introducing caafe for context-aware automated feature engineering. *Advances in Neural Information Processing Systems*, pp. 44753–44775, 2023b.
- Huang, X., Khetan, A., Cvitkovic, M., and Karnin, Z. Tab-transformer: Tabular data modeling using contextual embeddings. *arXiv preprint arXiv:2012.06678*, 2020.
- Iversen, G. R. and Gergen, M. *Statistics: The conceptual approach*. Springer Science & Business Media, 2012.
- Jeffares, A., Liu, T., Crabbé, J., Imrie, F., and van der Schaar, M. TANGOS: Regularizing Tabular Neural Networks through Gradient Orthogonalization and Specialization. In *Proceedings of the 11th International Conference on Learning Representations*, 2023.
- Jia, L.-H., Guo, L.-Z., Zhou, Z., and Li, Y.-F. LAMDA-SSL: a comprehensive semi-supervised learning toolkit. *Science China. Information Sciences*, 67(1):117101, 2024a.
- Jia, L.-H., Guo, L.-Z., Zhou, Z., and Li, Y.-F. Realistic evaluation of semi-supervised learning algorithms in open environments. In *Proceedings of the 12th International Conference on Learning Representations*, 2024b.
- Kadra, A., Lindauer, M., Hutter, F., and Grabocka, J. Well-tuned simple nets excel on tabular datasets. *Advances in Neural Information Processing Systems*, pp. 23928–23941, 2021.
- Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., and Liu, T.-Y. LightGBM: A Highly Efficient Gradient Boosting Decision Tree. *Advances in Neural Information Processing Systems*, pp. 3149–3157, 2017.
- Klambauer, G., Unterthiner, T., Mayr, A., and Hochreiter, S. Self-normalizing neural networks. *Advances in Neural Information Processing Systems*, pp. 972—981, 2017.
- Kolesnikov, S. Wild-Tab: A Benchmark For Out-Of-Distribution Generalization In Tabular Regression. *arXiv preprint arXiv:2312.01792*, 2023.
- Liang, J., He, R., and Tan, T. A comprehensive survey on test-time adaptation under distribution shifts. *International Journal of Computer Vision*, pp. 1–34, 2024.
- Liu, J., Wang, T., Cui, P., and Namkoong, H. On the need for a language describing distribution shifts: Illustrations on tabular datasets. *Advances in Neural Information Processing Systems*, pp. 51371–51408, 2023.
- Liu, S.-Y., Cai, H.-R., Zhou, Q.-L., and Ye, H.-J. TALENT: A Tabular Analytics and Learning Toolbox. *arXiv preprint arXiv:2407.04057*, 2024.
- Malinin, A., Band, N., Gal, Y., Gales, M., Ganshin, A., Chesnokov, G., Noskov, A., Ploskonosov, A., Prokhorenkova, L., Prosvirkov, I., Raina, V., Raina, V., Roginskiy, D., Shmatova, M., Tigas, P., and Yangel, B. Shifts: A Dataset of Real Distributional Shift Across Multiple Large-Scale Tasks. *Advances in Neural Information Processing Systems, Datasets and Benchmarks Track*, 2021.
- Malinin, A., Athanasopoulos, A., Barakovic, M., Cuadra, M. B., Gales, M. J. F., Granziera, C., Graziani, M., Kartashov, N., Kyriakopoulos, K., Lu, P.-J., Molchanova, N., Nikitakis, A., Raina, V., Rosa, F. L., Sivena, E., Tsarsitalidis, V., Tsompopoulou, E., and Volf, E. Shifts 2.0: Extending the dataset of real distributional shifts. *arXiv preprint arXiv:2206.15407*, 2022.
- McElfresh, D., Khandagale, S., Valverde, J., Prasad C, V., Ramakrishnan, G., Goldblum, M., and White, C. When do neural nets outperform boosted trees on tabular data? *Advances in Neural Information Processing Systems*, pp. 76336–76369, 2023.
- Meijerink, L., Cinà, G., and Tonutti, M. Uncertainty estimation for classification and risk prediction on medical tabular data. *arXiv preprint arXiv:2004.05824*, 2020.
- Miller, J., Krauth, K., Recht, B., and Schmidt, L. The effect of natural distribution shift on question answering models. In *Proceedings of the 37th International Conference on Machine Learning*, pp. 6905–6916, 2020.
- Nam, J., Kim, K., Oh, S., Tack, J., Kim, J., and Shin, J. Optimized Feature Generation for Tabular Data via LLMs with Decision Tree Reasoning. *Advances in Neural Information Processing Systems*, pp. 92352–92380, 2024.
- OpenAI. GPT-4 Technical Report. *arXiv preprint arXiv:2303.08774*, 2024.
- Parmar, J., Chouhan, S., Raychoudhury, V., and Rathore, S. Open-world machine learning: applications, challenges, and opportunities. *ACM Computing Surveys*, 55(10):1–37, 2023.
- Popov, S., Morozov, S., and Babenko, A. Neural Oblivious Decision Ensembles for Deep Learning on Tabular Data. In *Proceedings of the 8th International Conference on Learning Representations*, 2020.
- Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V., and Gulin, A. CatBoost: unbiased boosting with categorical features. *Advances in Neural Information Processing Systems*, pp. 6639—6649, 2018.
- Ruder, S. An overview of gradient descent optimization algorithms. *arXiv preprint arXiv:1609.04747*, 2016.

- Sahakyan, M., Aung, Z., and Rahwan, T. Explainable artificial intelligence for tabular data: A survey. *IEEE access*, 9:135392–135422, 2021.
- Shao, J.-J., Yang, X.-W., and Guo, L.-Z. Open-set learning under covariate shift. *Machine Learning*, 113(4):1643–1659, 2024.
- Shen, M., Bu, Y., and Wornell, G. W. On balancing bias and variance in unsupervised multi-source-free domain adaptation. In *Proceedings of the 40th International Conference on Machine Learning*, pp. 30976–30991, 2023.
- Somepalli, G., Goldblum, M., Schwarzschild, A., Bruss, C. B., and Goldstein, T. Saint: Improved neural networks for tabular data via row attention and contrastive pre-training. *arXiv preprint arXiv:2106.01342*, 2021.
- Song, W., Shi, C., Xiao, Z., Duan, Z., Xu, Y., Zhang, M., and Tang, J. Autoint: Automatic feature interaction learning via self-attentive neural networks. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, pp. 1161–1170, 2019.
- Touvron, H., Lavril, T., Izacard, G., Martinet, X., Lachaux, M.-A., Lacroix, T., Rozière, B., Goyal, N., Hambro, E., Azhar, F., et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.
- Wang, A., Singh, A., Michael, J., Hill, F., Levy, O., and Bowman, S. GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pp. 353–355, 2018.
- Wang, D., Shelhamer, E., Liu, S., Olshausen, B., and Darrell, T. Tent: Fully Test-Time Adaptation by Entropy Minimization. In *Proceedings of the 9th International Conference on Learning Representations*, 2021a.
- Wang, R., Shivanna, R., Cheng, D., Jain, S., Lin, D., Hong, L., and Chi, E. Dcn v2: Improved deep & cross network and practical lessons for web-scale learning to rank systems. In *Proceedings of the Web Conference 2021*, pp. 1785–1797, 2021b.
- Wang, R., Wang, Z., and Sun, J. Unipredict: Large language models are universal tabular predictors. *arXiv preprint arXiv:2310.03266*, 2023.
- Wang, Y., Chen, H., Fan, Y., Sun, W., Tao, R., Hou, W., Wang, R., Yang, L., Zhou, Z., Guo, L.-Z., et al. Usb: A unified semi-supervised learning benchmark for classification. *Advances in Neural Information Processing Systems*, pp. 3938–3961, 2022.
- West, D. Neural network credit scoring models. *Computers & operations research*, 27(11-12):1131–1152, 2000.
- Wu, J., Chen, S., Zhao, Q., Sergazinov, R., Li, C., Liu, S., Zhao, C., Xie, T., Guo, H., and Ji, C. Switchtab: Switched autoencoders are effective tabular learners. In *Proceedings of the 38th AAAI Conference on Artificial Intelligence*, pp. 15924–15933, 2024.
- Ye, H.-J., Yin, H.-H., and Zhan, D.-C. Modern Neighborhood Components Analysis: A Deep Tabular Baseline Two Decades Later. *arXiv preprint arXiv:2407.03257*, 2024.
- Yıldız, A. Y. and Kalayci, A. Gradient Boosting Decision Trees on Medical Diagnosis over Tabular Data. *arXiv preprint arXiv:2410.03705*, 2024.
- Zhang, T., Zhang, Z. A., Fan, Z., Luo, H., Liu, F., Liu, Q., Cao, W., and Jian, L. OpenFE: automated feature generation with expert-level performance. In *Proceedings of the 40th International Conference on Machine Learning*, pp. 41880–41901, 2023.
- Zhao, C., Zio, E., and Shen, W. Domain generalization for cross-domain fault diagnosis: An application-oriented perspective and a benchmark study. *Reliability Engineering & System Safety*, pp. 109964, 2024.
- Zhou, K., Yang, Y., Qiao, Y., and Xiang, T. Domain Generalization with MixStyle. In *Proceedings of the 9th International Conference on Learning Representations*, 2021.
- Zhou, K., Liu, Z., Qiao, Y., Xiang, T., and Loy, C. C. Domain generalization: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(4):4396–4415, 2022.
- Zhou, Z., Guo, L.-Z., Jia, L.-H., Zhang, D., and Li, Y.-F. Ods: Test-time adaptation in the presence of open-world data shift. In *Proceedings of the 40th International Conference on Machine Learning*, pp. 42574–42588, 2023.
- Zhou, Z., Yang, Y.-K., Guo, L.-Z., and Li, Y.-F. Fully Test-time Adaptation for Tabular Data. In *Proceedings of the 39th AAAI conference on Artificial Intelligence*, 2025.
- Zhou, Z.-H. Open-environment machine learning. *National Science Review*, 9(8):nwac123, 2022.
- Zhu, F., Lei, W., Huang, Y., Wang, C., Zhang, S., Lv, J., Feng, F., and Chua, T.-S. TAT-QA: A question answering benchmark on a hybrid of tabular and textual content in finance. *arXiv preprint arXiv:2105.07624*, 2021.
- Zhu, X., Hu, H., Lin, S., and Dai, J. Deformable convnets v2: More deformable, better results. In *Proceedings of the IEEE/CVF conference on Computer Vision and Pattern Recognition*, pp. 9308–9316, 2019.

## A. Related work

### A.1. Open Environments Challenges

Traditional machine learning research predominantly assumes closed environment scenarios, where key factors in the learning process remain stable and predictable (Guo et al., 2025; Jia et al., 2024b). Although machine learning has achieved remarkable success across various applications, an increasing number of real-world tasks—particularly those situated in open environments—face dynamic changes in critical factors. These challenges have given rise to the field of open environments Machine Learning (Open ML). Zhou (2022) identified four core challenges in Open ML: the emergence of new classes, data distribution shifts, evolving learning objectives, and feature space shifts.

The emergence of new classes refers to the occurrence of previously unseen categories during the testing phase that were entirely absent during training. Data distribution shift pertains to changes in the distribution of test data, violating the traditional assumption that data are independent and identically distributed (i.i.d.). Evolving learning objectives arise as data volume increases and model accuracy improves, prompting a shift in focus from solely maximizing accuracy to addressing additional practical priorities, such as minimizing energy consumption. Feature space shift is characterized by the introduction of new features or the removal of existing ones. Conventional machine learning models, which typically rely on the assumption that training and testing data share the same feature space, often struggle to adapt to such changes, leading to substantial performance degradation in open-environment deployment scenarios. To address these emerging challenges, recent research has primarily centered on domain adaptation and domain generalization. Domain adaptation methods utilize a limited amount of labeled or unlabeled target-domain data to transfer knowledge effectively (Shen et al., 2023). In contrast, domain generalization focuses on training models with robust generalization capabilities to maintain high performance across diverse target-domain distributions. For instance, the MixStyle method (Zhou et al., 2021) improves generalization by blending statistical properties, such as mean and standard deviation, from different domains. More recently, Test-Time Adaptation (TTA) has been proposed as a promising and flexible approach to address data distribution shifts. TTA enables models to adapt dynamically during inference by leveraging test data batches for continual learning (Liang et al., 2024). However, much of the research on these approaches has primarily targeted non-tabular domains, such as computer vision and natural language processing (Miller et al., 2020). Moreover, these methods often fail to surpass the performance of traditional optimization algorithms, such as Stochastic Gradient Descent (SGD) (Ruder, 2016), highlighting the need for further advancements tailored to open-environment challenges in tabular data.

Although existing Heterogeneous Domain Adaptation (HeDA) methods have achieved significant progress on feature shift of images, tabular data presents a fundamentally different pattern. The inherent structure of it presents challenges when attempting to directly implement HeDA on such datasets. Moreover, our review of the literature reveals that what is often referred to as "feature shift" in many papers is essentially a form of distribution shift. For example, He et al. (2023) regards covariate shift as feature shift.

### A.2. Tabular Data in Machine Learning

Tabular data, characterized by its structured and heterogeneous features, is extensively used across various fields, including medical diagnostics, financial analysis, recommendation systems, and social sciences (Borisov et al., 2022; Kadra et al., 2021). Unlike domains such as computer vision or natural language processing, tabular data poses unique challenges to machine learning models due to its high dimensionality, heterogeneity, and the complex interdependencies among features (Fang et al., 2024). Current approaches for modeling tabular data can be broadly classified into two main categories: tree-based ensemble models and deep learning models.

Tree-based ensemble models, such as XGBoost (Chizat et al., 2020), LightGBM (Badirli et al., 2020), and CatBoost (Prokhorenkova et al., 2018), have long been regarded as the state-of-the-art for tabular data modeling. These models excel in handling irregular patterns and non-informative features within the objective function and are well-suited for addressing the non-rotation invariance of tabular data (Grinsztajn et al., 2022). Their robustness and interpretability further contribute to their widespread adoption. In contrast, the rise of deep learning has spurred the development of numerous deep learning-based models tailored for tabular data. Notable examples include DCN V2 (Wang et al., 2021b), which integrates multi-layer perceptron (MLP) modules and feature crossover modules; AutoInt (Song et al., 2019) and FT-Transformer (Gorishniy et al., 2021), both of which leverage Transformer architectures; ResNet-based tabular variants (Gorishniy et al., 2021); and differentiable tree-based heuristics, such as Neural Oblivious Decision Ensembles (NODE) (Popov et al., 2020). These models aim to exploit the complex inter-feature dependencies inherent in tabular data to improve predictive performance. In close-environment scenarios, the performance of deep learning models on tabular data has not yet surpassed

that of tree-based models. Furthermore, the generalization capabilities of both types of models in open environments, particularly when facing feature distribution shifts, have not been assessed.

### A.3. Benchmark in Tabular Data

In machine learning, establishing effective benchmarks is essential for evaluating and comparing the performance of various algorithms. An ideal benchmark provides standardized datasets and evaluation criteria to ensure the effectiveness, reliability, and robustness of algorithms in practical applications (Wang et al., 2022; Jia et al., 2024a). While benchmarks in domains such as computer vision (e.g., ImageNet (Deng et al., 2009)), natural language processing (e.g., GLUE (Wang et al., 2018)), and audio classification (e.g., AudioSet (Gemmeke et al., 2017)) are relatively mature, benchmarks for tabular data remain underdeveloped. Many existing tabular data benchmarks suffer from significant quality issues. For instance, the German Credit dataset is small in scale, and the Adult dataset contains inherent biases and data quality problems (Bao et al., 2021). These limitations constrain their utility for conducting in-depth research and hinder the development of robust machine learning methods for tabular data.

Furthermore, benchmarks capable of systematically evaluating distribution shifts are crucial for assessing the robustness and adaptability of models to real-world data variations. Distribution shifts refer to the discrepancy between the data distribution during inference and that during training, which can severely impact model performance (Zhou et al., 2023). To address this, several benchmarks have been proposed to evaluate the handling of distribution shifts in tabular data. For example, Shifts and Shifts 2.0 (Malinin et al., 2021; 2022) focus on uncertainty estimation and include tasks with temporal and spatio-temporal variations in tabular data. WhyShift (Liu et al., 2023) specializes in evaluating spatio-temporal shifts using five real-world tabular datasets. TableShift (Gardner et al., 2024b) provides a comprehensive evaluation of 19 model types across 15 binary classification tasks, with 10 tasks explicitly related to domain generalization. Similarly, Wild-Tab (Kolesnikov, 2023) emphasizes domain generalization in tabular regression tasks, comparing 10 domain generalization methods against standard Empirical Risk Minimization (ERM) applied to Multilayer Perceptrons (MLPs). However, despite these benchmarks offering comprehensive scenarios for addressing distribution shifts, their focus remains primarily on changes in data distributions, with limited attention to feature space shifts, such as the addition or removal of entire features in a dataset. Although Gardner et al. (2024a) explored feature drop experiments, their evaluation was confined to XGBoost and their proposed model, lacking comprehensiveness. The absence of benchmarks that adequately account for feature space shifts hinders researchers from effectively evaluating and optimizing algorithms to address such challenges, which remains a critical gap in the field of tabular data processing.

## B. TabFSBench Components

To promote systematic evaluation and community collaboration in the context of feature-shifted tabular data learning, we present TabFSBench, a modular benchmark framework. It features reproducible evaluation protocols, an extensible API interface, and a continuously updated public leaderboard.

### B.1. Benchmark Composition and Datasets

TabFSBench currently comprises 12 datasets selected from Grinsztajn et al. (Grinsztajn et al., 2022) and TabZilla (McElfresh et al., 2023). These datasets exhibit significant heterogeneity in terms of scale, domain, and task structure, covering a wide range of potential feature shift scenarios such as covariate shift and missing values. To comprehensively assess model robustness under real-world distributional changes, we design four distinct experimental configurations that systematically evaluate model generalization across various perturbations. All experiments are repeated with multiple random seeds to mitigate stochastic variance. We further aim to construct practically meaningful feature-shift datasets in future versions, thereby encouraging deeper investigation into robustness under feature shift.

### B.2. Public Leaderboard and Community Contribution

We have established and actively maintain a project homepage and a complete ranking system. Evaluation results of newly released models or datasets are updated regularly to ensure that the research community can access the latest benchmark performance. For instance, TabFSBench already includes evaluation results for representative models such as TabPFN v2. We encourage researchers to submit evaluation results for their custom models or datasets. In future updates, we plan to support both public and private leaderboard modes to meet a broader range of user requirements.

### B.3. API Design

To enable reproducibility and flexible evaluation, TabFSBench offers a command-line option `-export_dataset`, which allows users to export dataset variants under different feature-shift settings (e.g., single-column missingness, controlled levels of missingness, and complete enumeration of missing scenarios) by setting the flag to True.

We also provide a `README.md` file, which describes how users can add new datasets and models. Further details on code functionality will be elaborated in the final version.

## C. Real-World Feature-Shift Challenges

### C.1. Real-World Feature-Shift Datasets

There currently exists no dataset specifically designed for feature shift, unlike Tableshift (Gardner et al., 2024b) which was developed for distribution shifts. However, we have preliminarily constructed a feature-shifted dataset based on the Heart dataset. Given that different features in the original dataset require distinct measurement instruments, we categorized the features into three groups: basic features, electrocardiogram (ECG) features, and exercise stress test features.

In the constructed feature-shifted Heart dataset, both the training set and the test set step 0 contain all features. However, patients in the test set step 1 lack ECG measurements, resulting in the absence of RestingECG and ST\_Slope features. Similarly, patients in the test set step 2 did not undergo an exercise stress test, leading to the absence of ExerciseAngina and Oldpeak. A subset of examples is provided at <https://github.com/LAMDASZ-ML/TabFSBench>.

Note that for meaningful evaluation of feature-shifted datasets, models must be assessed under specific partitioning schemes. Applying the four experimental settings proposed in our paper would undermine the unique characteristics and practical relevance of such datasets.

### C.2. Real-World Feature-Shift Issues

Section 2.2 of this paper employs forest disease monitoring as a case study to demonstrate how sensor degradation leads to a reduction in available features. As further evidenced by the designed heart dataset in above, incomplete medical examinations may result in missing diagnostic indicators (features) due to the absence of specific equipment.

The feature shift phenomenon also manifests prominently in financial and transportation domains:

- **Finance:** Stock prediction models trained on comprehensive features (e.g., financial ratios, macroeconomic indicators) may encounter missing features (e.g., sentiment indices) during real-world deployment due to unforeseen events.
- **Transportation:** Accident prediction models relying on features like road conditions and weather data may experience partial feature absence caused by sensor failures or insufficient data collection.

## D. Benchmark Datasets

This section provides background information and the sources of each dataset in TabFSBench. Pearson correlation analyses of the datasets are also provided in Figure 6.

### D.1. Binary Classification

**Credit** The original dataset contains 1,000 entries with 20 categorical/symbolic attributes prepared by Prof. Hofmann. In this dataset, each entry represents a person who takes a credit from a bank. Each person is classified as having good or bad credit risk according to the set of attributes. The target is to determine whether the customer's credit is good or bad. This dataset is available at <https://www.openml.org/search?type=data&sort=runs&id=31&status=active>.

**Electricity** The Electricity dataset, collected from the Australian New South Wales Electricity Market, contains 45,312 instances from May 1996 to December 1998. Each instance represents a 30-minute period and includes fields for the day, timestamp, electricity demand in New South Wales and Victoria, scheduled electricity transfer, and a class label. The target is to predict whether the price in New South Wales is up or down relative to a 24-hour moving average, based on market demand and supply fluctuations. This dataset is available on <https://www.kaggle.com/datasets/vstacknocopyright/electricity>.

**Heart** Cardiovascular diseases (CVDs) are the leading cause of death globally, responsible for 17.9 million deaths annually. Heart failure is a common event caused by CVDs and this dataset contains 11 features that can be used to predict a possible heart disease. The target is to determine whether the patient’s heart disease is present or absent. This dataset is available on <https://www.kaggle.com/datasets/fedesoriano/heart-failure-prediction>.

**Miniboone** This dataset aims to construct a predictive model using various machine learning algorithms and document the end-to-end steps using a template. The MiniBooNE Particle Identification dataset is a binary classification task where we attempt to predict one of two possible outcomes. The target is to determine whether the neutrino is an electron or a muon. This dataset is available at <https://www.kaggle.com/datasets/alexanderliapatis/miniboone>.

## D.2. Multi-class Classification

**Iris** The Iris flower dataset, introduced by Ronald Fisher in 1936, contains 150 samples from three Iris species: Iris setosa, Iris virginica, and Iris versicolor. Each sample has four features: sepal length, sepal width, petal length, and petal width, measured in centimeters. The target is to classify the Iris species as setosa, versicolor, or virginica. This dataset is available on <https://www.kaggle.com/datasets/uciml/iris>.

**Jannis** This dataset is used in the tabular benchmark from (Grinsztajn et al., 2022). It belongs to the ‘classification on numerical features’ benchmark. The dataset is designed to test classification performance using numerical features, and it presents challenges such as varying data distributions, class imbalances, and potential missing values. It serves as a critical evaluation tool for machine learning models in real-world scenarios, including medical diagnosis, credit rating, and object recognition tasks. This dataset is available on <https://www.openml.org/search?type=data&status=active&id=45021>.

**Penguins** Data were collected and made available by Dr. Kristen Gorman and the Palmer Station, Antarctica LTER, a member of the Long Term Ecological Research Network. The goal of the Palmer Penguins dataset is to offer a comprehensive resource for data exploration and visualization, serving as an alternative to the Iris dataset. The target is to classify the penguin species as Adelie, Chinstrap, or Gentoo. This dataset is available at <https://www.kaggle.com/datasets/youssefaboelwafa/clustering-penguins-species>.

**Eye Movements** This dataset is designed to predict the relevance of sentences in relation to a given question based on eye movement data. The target is to classify sentences as irrelevant, relevant, or correct, using 27 features, including landing position (landingPos), first fixation duration (P1stFixation), next fixation duration (nextFixDur), time spent on the predicted region (timePrtctg), and other relevant eye movement metrics. This dataset is available at <https://www.kaggle.com/datasets/vinnyr12/eye-movements>.

## D.3. Regression

**Abalone** The age of abalone is traditionally determined by cutting the shell, staining it, and counting the rings under a microscope, a process that is both tedious and time-consuming. This dataset uses easier-to-obtain physical measurements, such as length, diameter, and weight, to predict the abalone’s age. The target is to predict the age, providing a more efficient approach. This dataset is available on <https://www.kaggle.com/datasets/rodolfomendes/abalone-dataset>.

**Bike** The dataset records the rental of shared bikes in the Washington area from 2011-01-01 to 2012-12-31, containing 11 features such as season, holiday, working day, and weather conditions. The goal is to predict the total count of bikes rented each hour, with the target being to forecast the number of bicycles available for rent today based on historical rental patterns and external factors like temperature, humidity, and seasonal trends. This dataset is available on <https://www.kaggle.com/datasets/abdullapathan/bikesharingdemand>.

**Concrete** Concrete is the most important material in civil engineering, and its compressive strength is influenced by a highly nonlinear relationship with its ingredients and age. The dataset contains 9 attributes, including variables such as cement, water, and age. The target is to predict the concrete compressive strength (measured in MPa) using these input variables. This dataset is available on <https://www.kaggle.com/datasets/maajdl/yeh-concret-data>.

**Laptop** The original dataset was pretty compact with a lot of details in each column. The columns mostly consisted of long strings of data, which was pretty human-readable and concise but for Machine Learning algorithms to work more

Table 5. Hyperparameter Grids of Tree-based Models.

Model	Hyperparameter	Values
<b>LightGBM</b>	Num Leaves	{31, 127}
	Learning Rate	{0.01, 0.1}
	Min Data In Leaf	{20, 50, 100}
	Min Sum Hessian In Leaf	{1e - 3, 1e - 2, 1e - 1}
<b>XGBoost</b>	Learning Rate	{0.01, 0.1}
	Max. Depth	{1, 5, 9}
	N Estimators	{10000, 20000, 30000}
	Subsample	{0.5, 0.8, 1.0}
	Colsample Bytree	{0.5, 0.8, 1.0}
<b>CatBoost</b>	Min Child Weight	{1, 3, 5}
	Learning Rate	{0.01, 0.05, 0.1}
	Depth	{4, 6, 8}
	Iterations	{500, 1000, 2000}

efficiently it's better to separate the different details into their own columns. After doing so, 28 duplicate rows were exposed and removed with this dataset being the final result. The target is to predict the price of this laptop. This dataset is available on <https://www.kaggle.com/datasets/owm4096/laptop-prices>.

## E. Benchmark Models

In this section, we provide introductions to tree-based and deep learning models and hyperparameter grids in Table 5, 6. Among them, TabPFN and tabcaps are only applicable to the classification task, not to the regression task. We implement adaptive hyperparameter optimization based on the Optuna framework and following previous studies (Liu et al., 2024), fixing the batch size at 1024 and conducting 100 independent trials through train-validation splits to prevent test set leakage, with the best-performed hyperparameters fixed during the final 15 seeds. For LLMs, we provide their prompts in Figure 7.

### E.1. Tree-Based Models

**LightGBM** LightGBM(Badirlı et al., 2020) is a machine learning model based on the Boosting algorithm. Its core algorithms are Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). GOSS calculates the importance of each sample through gradients, discards unimportant samples, and selects a subset of important samples for training. EFB is used to reduce the dimensionality of the feature space."

**XGBoost** XGBoost(Chizat et al., 2020) is an efficient and flexible machine learning model that incrementally builds multiple decision trees by optimizing the loss function, with each tree correcting the errors of the previous one to continuously improve the model's predictive performance. XGBoost also incorporates the gradient boosting algorithm, iteratively training decision tree-based models with the goal of minimizing residuals and enhancing predictive accuracy.

**CatBoost** CatBoost (Prokhorenkova et al., 2018) is a powerful boosting-based model designed for efficient handling of categorical features. It uses the "Ordered Boosting" technique, which calculates gradients sequentially to prevent target leakage and maintain the independence of each training instance. At the same time, CatBoost employs "Target-based Categorical Encoding," converting categorical variables into numerical representations based on target statistics, thereby reducing the need for extensive preprocessing and improving model performance.

### E.2. Deep Learning Models

**AutoInt** AutoInt(Song et al., 2019) efficiently handles large-scale data by mapping numerical and categorical features into the same low-dimensional space and leveraging multi-head self-attentive neural networks to model feature interactions.

**DANets** DANets(Chen et al., 2022) enhance the feature representation capacity of tabular data by introducing Abstract Layers and shortcut paths, and employ structure re-parameterization to reduce computational complexity, demonstrating

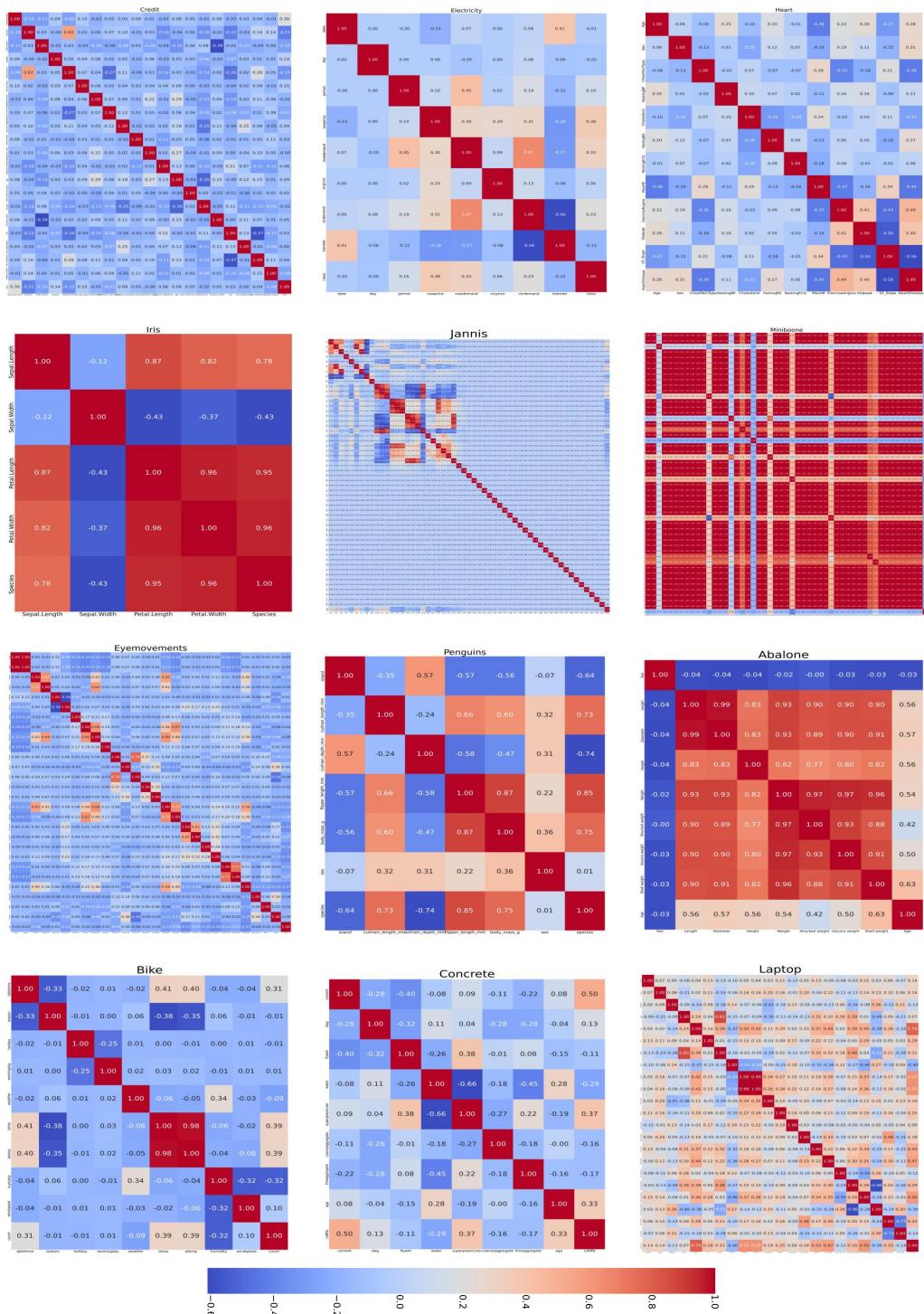


Figure 6. Pearson Correlation Analysis of the Datasets. Images are sorted in binary classification, multi-class classification, and regression order. The last column of each image is chosen as the input column with the target Pearson correlation coefficient.

effectiveness and extensibility in tabular data tasks.

**DCN2** Deformable ConvNets v2 (DCN2) ([Zhu et al., 2019](#)) enhances object detection and instance segmentation by adapting to the geometric variations of objects. Its reformulation improves the network's focus on relevant image regions through advanced modeling and modulation techniques. Additionally, a feature mimicking scheme is introduced to guide network training, leading to significant performance gains on the COCO benchmark.

**FT-Transformer** FT-Transformer ([Gorishniy et al., 2021](#)) is a Transformer-based model specifically designed to handle tabular data. It employs separate feature tokenizers for numerical and categorical data, enabling the Transformer to effectively capture complex relationships between features. This adaptation improves performance in structured data tasks.

**GrowNet** GrowNet ([Badirli et al., 2020](#)) is a gradient boosting model that uses shallow neural networks as weak learners. It incorporates a fully corrective step to address the greedy function approximation issue, enhancing performance in classification, regression, and ranking tasks.

**MLP** A Multi-Layer Perceptron (MLP) comprises multiple layers of fully connected neurons, typically including an input layer, one or more hidden layers, and an output layer. During training, the MLP iteratively updates the connection weights between neurons using optimization techniques such as backpropagation and gradient descent, aiming to minimize the prediction error and improve model generalization.

**ModernNCA** ModernNCA ([Ye et al., 2024](#)) is an enhanced Neighborhood Component Analysis (NCA) model that improves tabular data processing by adjusting learning objectives, integrating deep learning architectures, and using stochastic neighbor sampling for better efficiency and accuracy.

**NODE** Neural Oblivious Decision Ensembles (NODE) ([Popov et al., 2020](#)) is a deep learning method that combines the Oblivious Ensembles algorithm with neural networks, enabling end-to-end gradient-based optimization and multi-layer hierarchical representation learning for tabular data tasks.

**Saint** Based on the Transformer architecture, SAINT ([Somepalli et al., 2021](#)) employs an enhanced embedding method to classify features better while performing attention over both rows and columns to improve the model's focus on relevant data for tabular problems.

**SNN** SNN ([Klambauer et al., 2017](#)) is a neural network designed to improve tabular data processing by using self-normalizing properties and the Scaled Exponential Linear Units (SELUs) activation function, enabling robust training of deep networks with layers and enhancing performance across various tasks.

**SwitchTab** SwitchTab([Wu et al., 2024](#)) is a self-supervised method that uses an asymmetric encoder-decoder framework to separate mutual and salient features in tabular data, generating more representative embeddings for improved prediction and classification performance.

**TabCaps** TabCaps ([Chen et al., 2023](#)) is a capsule-based neural network architecture that encapsulates all feature values of a record into structured vectorial representations, thereby enabling collective feature processing and simplifying the treatment of heterogeneous and high-dimensional tabular data for enhanced classification performance.

**Tabnet** TabNet([Arik & Pfister, 2021](#)) enhances tabular data modeling by using sequential attention to select salient features at each decision step, enabling efficient learning and interpretability. It utilizes sparse attention mechanisms within decision steps to prioritize the most relevant features.

**TabPFN** TabPFN([Hollmann et al., 2023a](#)) is a Transformer-based model that approximates the posterior predictive distribution for tabular data, enabling fast supervised classification with no hyperparameter tuning. It performs in-context learning, making predictions with labeled sequences without further parameter updates, and can be reused for downstream tasks without retraining.

**TabR** TabR(Gorishniy et al., 2024) is a neural network that enhances tabular data processing by integrating a k-Nearest-Neighbors-like component. It uses an attention mechanism to efficiently retrieve neighbors and extract valuable information, boosting predictive performance.

**TabTransformer** TabTransformer(Huang et al., 2020) is a deep learning model that leverages Transformer layers to learn contextual embeddings for categorical features and normalize continuous features, achieving higher prediction accuracy and robust performance against noisy or missing data.

**tabular ResNet** Tabular ResNet(Gorishniy et al., 2021) introduces residual connections by combining the original input  $x$  with its transformed version  $f(x)$ , meaning the output of each block is  $x + f(x)$ , which improves gradient flow and captures complex feature interactions in tabular data.

**TANGOS** A regularization framework that enhances tabular data modeling by encouraging orthogonalization and specialization of neuron attributions. TANGOS(Jeffares et al., 2023) leverages gradient attributions of neurons to input features to promote focus on sparse and non-overlapping features, thereby achieving diverse and specialized latent unit allocation and improving generalization performance.

Table 6: Hyperparameter Grids of Deep Learning Models.

Model	Hyperparameter	Values
<b>AutoInt</b>	N_Layers	Int{1, 6}
	D_Token	{8, 16, 32, 64, 128}
	Residual Dropout	Uniform {0.0, 0.2}
	Attention Dropout	Uniform {0.0, 0.5}
	Learning Rate	Loguniform{ $e^{-5}$ , 0.001}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}
<b>DANets</b>	N_Layers	Int{6, 32}
	Dropout	Uniform {0.0, 0.2}
	Base Outdim	Int{64, 128}
	Learning Rate	Loguniform{ $e^{-5}$ , 0.1}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}
<b>FT-transformer</b>	Num. Blocks	{1, 2, 3, 4}
	Residual Dropout	Uniform {0.0, 0.2}
	Attention Dropout	Uniform {0.0, 0.5}
	FFN Dropout	Uniform {0.0, 0.5}
	FFN Factor	{64, 128, 256, 512}
<b>GrowNet</b>	D_Embdding	Int{32, 512}
	Hidden_D	Int{32, 512}
	Learning Rate	Loguniform{ $e^{-5}$ , 0.1}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}
	Epochs Per Stage	Int{1, 2}
	Correct Epoch	Int{1, 2}
<b>MLP</b>	D_layers	{1, 8, 64, 512}
	Dropout	Uniform {0.0, 0.5}
	Learning Rate	Loguniform{ $e^{-5}$ , 0.01}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}
<b>ModernNCA</b>	Dropout	Uniform {0.0, 0.5}
	D_block	Int{64, 1024}
	N_blocks	Int{0, 2}
	N_frequencies	Int{16, 96}

Continued on next page

Table 6: Hyperparameter Grids of Deep Learning Models.

Model	Hyperparameter	Values
NODE	Frequency Scale	Loguniform{0.005, 10}
	D_embedding	Int{16, 64}
	Sample Rate	Uniform{0.05, 0.6}
	Learning Rate	Loguniform{ $e^{-5}$ , 0.1}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}
Saint	Num Layers	Int{1, 4}
	Depth	Int{4, 6}
	Tree Dim	Int{2, 3}
	Layer Dim	{512, 1024}
	Learning Rate	Loguniform{ $e^{-5}$ , 0.1}
SNN	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}
	Depth	{4, 6}
	Heads	{4, 8}
	Dim	{16, 32, 64}
	Attn_Dropout	Uniform {0.0, 0.5}
SwitchTab	FF_Dropout	Uniform {0.0, 0.5}
	Attentiontype	{"colrow", "row", "col"}
	Learning Rate	Loguniform{ $3e^{-5}$ , 0.001}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.0001}
	D_layers	{2, 16, 1, 512}
TabCaps	Dropout	Uniform {0.0, 0.1}
	D_embedding	Int{64, 512}
	Learning Rate	Loguniform{ $e^{-5}$ , 0.01}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}
	$\alpha$	Loguniform{0.01, 100}
Tabnet	Learning Rate	Loguniform{ $e^{-6}$ , 0.001}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}
	Sub Class	Int{1, 5}
	Init Dim	Int{32, 128}
	Primary Capsule Size	Int{4, 32}
TabR	Digit Capsule Size	Int{4, 32}
	Leaves	Int{16, 64}
	Learning Rate	uniform{0.001, 0.01}
	$\gamma$	uniform{1, 2}
	N Steps	Int{3, 10}
TabR	N Independent	Int{1, 5}
	N Shared	Int{1, 5}
	Momentum	Uniform{0.01, 4}
	D_main	Int{96, 384}
	Context Dropout	uniform{0.0, 0.6}
TabR	Encoder N Blocks	Int{0, 1}
	Predictor N Blocks	Int{1, 2}
	Dropout0	uniform{0.0, 0.6}
	N Frequencies	Int{16, 96}

Continued on next page

Table 6: Hyperparameter Grids of Deep Learning Models.

Model	Hyperparameter	Values
<b>TabTransformer</b>	Frequency Scale	Loguniform{0.01, 100}
	D Embedding	Int{16, 64}
	Learning Rate	Loguniform{ $3e^{-5}$ , 0.001}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}
<b>tabular ResNet</b>	Depth	{1, 2, 3, 6, 12}
	Heads	{2, 4, 8}
	Dim	{32, 64, 128, 256}
	Attn_Dropout	Uniform {0.0, 0.5}
	FF_Dropout	Uniform {0.0, 0.5}
	Learning Rate	Loguniform{ $e^{-5}$ , 0.1}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}
<b>TANGOS</b>	N Layers	Int{1, 8}
	D	Int{64, 512}
	D Hidden Factor	Uniform {1.0, 4.0}
	Hidden Dropout	Uniform {0.0, 0.5}
	Residual Dropout	Uniform {0.0, 0.5}
	Learning Rate	Loguniform{ $e^{-5}$ , 0.01}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}
	D_layers	{1, 8, 64, 512}
	Dropout	uniform{0.0, 0.5}
	$\lambda_1$	Loguniform{0.001, 1}
	$\lambda_2$	Loguniform{0.0001, 1}
	Subsample	Int{30, 100}
	Learning Rate	Loguniform{0.0001, 0.001}
	Weight Decay	Loguniform{ $e^{-6}$ , 0.001}

### E.3. Large Language Models

**Llama3-8B** Llama3-8B, released by Meta AI in April 2024, is a high-performance Transformer-based model. It utilizes open source datasets and multiple optimization techniques for efficient training. The model integrates reinforcement learning from human feedback to address multi-turn consistency, while dynamic position encoding overcomes the limitations of traditional positional encoding in processing long sequences. The development process ensures data legality and fairness.

We convert every row from tabular data into a List Template for input into the LLM. The List Template is a list of column names and feature values, achieving the same outstanding performance as the Text Template according to (Hegselmann et al., 2023). We fix an arbitrary ordering of the columns. Figure 7 uses the Iris Dataset as an example to show how we use the LLM to handle tabular tasks.

### E.4. Tabular LLMs

**TabLLM** TabLLM (Hegselmann et al., 2023) is a framework that leverages LLMs for efficient tabular data classification. It converts tabular data into natural language strings and uses a few labeled examples for fine-tuning. This approach enables high performance in both zero-shot and few-shot settings, demonstrating its ability to exploit the prior knowledge encoded in LLMs on tabular data.

**UniPredict** UniPredict (Wang et al., 2023) is a framework that leverages LLMs for data-efficient tabular classification. Unlike TabLLM, which uses a generic LLM directly for the task, UniPredict is the first model which is trained on multiple datasets to acquire a rich repository of prior knowledge. This approach allows UniPredict to efficiently handle diverse tabular prediction tasks, achieving strong performance in both few-shot and full-data scenarios while offering scalability

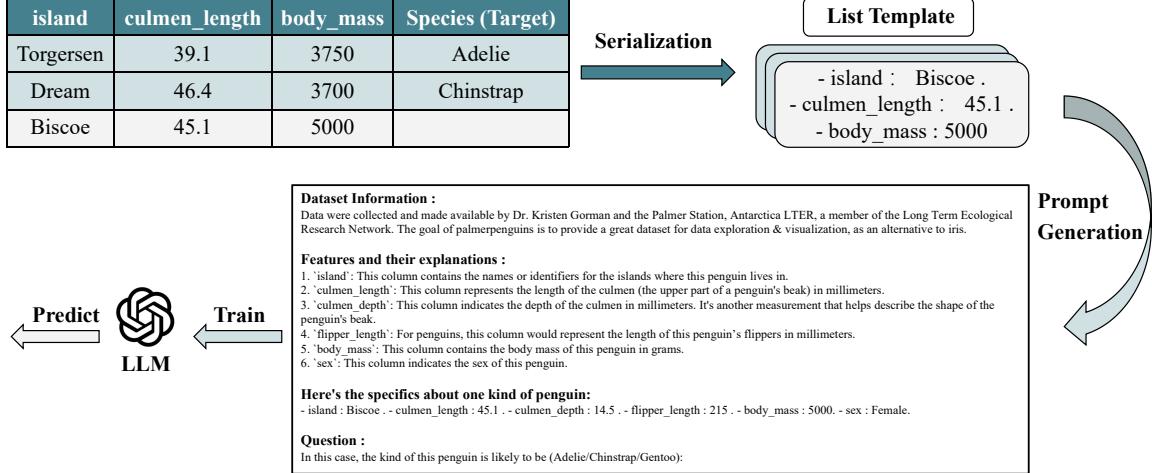


Figure 7. LLM Prompt for the experiments. Take the Penguins dataset as an example.

across a wide range of datasets.

## F. Feature Imputation Methods

We compared the performance of various models using their own imputation methods, random imputation, and mean imputation. Table 7 provides a comparison of representative models employing these three missing-feature imputation methods. We present the average performance of several representative models under different imputation methods. Table 8 shows that the model performs best under mean imputation, and its performance declines under all three types of imputation methods, indicating that the model still faces challenges from feature shift.

## G. Feature Importance Analysis

### G.1. Importance Metrics

To evaluate the consistency of feature importance rankings, we compute Kendall's  $\tau$  correlation coefficients among four metrics: Pearson correlation coefficient (PCC), Spearman's rank correlation, SHAP values, and mutual information. Figure 8 reveal high concordance across these measures, with particularly strong agreement between PCC and Spearman ( $\tau = 0.61$ ). While both demonstrate comparable performance, we ultimately select PCC for its widespread adoption and intuitive interpretability in the research community. The marginal differences between these metrics' rankings were found to be statistically insignificant and did not affect our analytical conclusions.

Notably, the feature importance derived from PCC exhibits a strong negative correlation with model performance degradation upon feature removal ( $\rho = -0.78$ ,  $p < 0.01$ ). This inverse relationship indicates that features assigned higher importance scores by PCC corresponded to greater performance declines when omitted, suggesting consistent feature dependencies across both closed-environment training and feature shift scenarios. This observed stability likely stems from our model's robust feature selection and dynamic weighting mechanisms.

### G.2. Pearson Correlation

To effectively evaluate the impact of feature shifts on model performance, we employ Pearson correlation to rank the features within a given dataset. The Pearson correlation explicitly provides the correlation coefficient between an input feature and the target variable. By applying Pearson correlation analysis to datasets with feature shifts, we can observe how the absence of features with varying degrees of correlation affects model performance. This analysis facilitates the identification of patterns and provides insights into feature shifts from multiple perspectives. Pearson correlation serves as an enhancement

# TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments

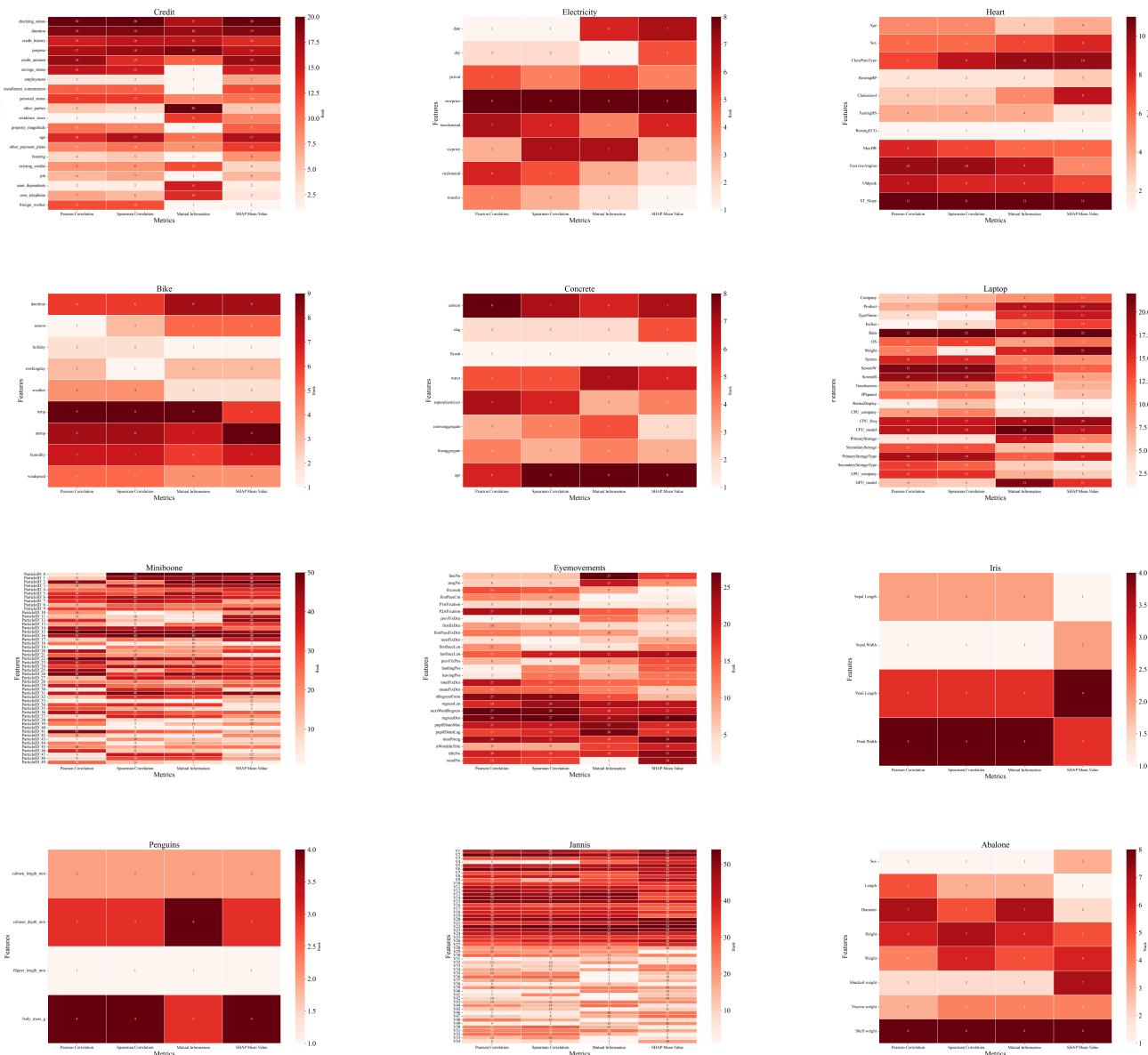


Figure 8. Visual comparison of feature importance rankings across Pearson correlation, Spearman correlation, mutual information, and SHAP values on twelve datasets.

Table 7. Representative self-imputation methods.

Method Type	Method	Representative Models
Has Internal Module	Treat missing-feature values as feature minima	CatBoost
	Left subtree split	XGBoost, LightGBM
	Missing-feature values as a separate category	TabTransformer
	No dimension consistency requirement	Llam3-8B
No Internal Module	Imput missing features by 0	Most deep-learning models

Table 8. Methods performance comparison: model imputation methods vs. mean-value imputation vs. random-value imputation.

Shift	CatBoost			XGBoost			MLP			TabPFN			TabTransformer			Llam3-8B		
	NAN	Mean	Random	NAN	Mean	Random	NAN	Mean	Random	NAN	Mean	Random	NAN	Mean	Random	NAN	Mean	Random
10%	0.845	0.851	0.818	0.823	0.825	0.800	0.747	0.843	0.724	0.858	0.859	0.829	0.497	0.513	0.487	0.765	0.772	0.517
20%	0.820	0.826	0.807	0.784	0.798	0.796	0.704	0.833	0.665	0.828	0.848	0.797	0.480	0.516	0.470	0.750	0.752	0.526
30%	0.792	0.801	0.767	0.746	0.773	0.756	0.686	0.821	0.624	0.798	0.835	0.762	0.486	0.502	0.476	0.736	0.721	0.520
40%	0.763	0.775	0.739	0.709	0.747	0.720	0.656	0.821	0.598	0.769	0.820	0.724	0.480	0.511	0.470	0.724	0.708	0.532
50%	0.733	0.747	0.702	0.673	0.720	0.681	0.639	0.803	0.585	0.741	0.803	0.698	0.469	0.513	0.459	0.720	0.677	0.502
60%	0.702	0.716	0.665	0.639	0.692	0.655	0.616	0.792	0.580	0.694	0.784	0.656	0.482	0.510	0.472	0.704	0.683	0.546
70%	0.670	0.682	0.630	0.606	0.662	0.625	0.584	0.779	0.580	0.657	0.762	0.632	0.477	0.492	0.467	0.685	0.672	0.539
80%	0.637	0.643	0.608	0.577	0.628	0.596	0.572	0.723	0.582	0.640	0.734	0.600	0.467	0.483	0.457	0.659	0.655	0.555
90%	0.600	0.596	0.574	0.559	0.589	0.571	0.546	0.718	0.578	0.593	0.695	0.575	0.467	0.494	0.455	0.625	0.651	0.529
100%	0.538	0.541	0.502	0.561	0.545	0.548	0.559	0.621	0.551	0.557	0.638	0.556	0.467	0.482	0.454	0.575	0.622	0.517

over both Euclidean distance and cosine similarity when handling datasets with missing dimensions. The Pearson correlation coefficient quantifies the linear relationship between two variables by computing the ratio of their covariance to the product of their standard deviations. It is defined within the range  $[-1, 1]$  and is calculated as follows:

$$\rho_{X,Y} = \frac{cov(X, Y)}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \quad (2)$$

Here,  $X$  and  $Y$  represent two variables,  $cov(X, Y)$  denotes their covariance, and  $\sigma_X$  and  $\sigma_Y$  are their respective standard deviations. If the Pearson correlation coefficient ( $PCC$ )  $\rho_{X,Y}$  equals 0, it indicates no linear relationship between  $X$  and  $Y$ . A positive correlation ( $0 < \rho_{X,Y} \leq 1$ ) implies that as  $X$  increases,  $Y$  also increases. Conversely, a negative correlation ( $-1 \leq \rho_{X,Y} < 0$ ) signifies that as  $X$  increases,  $Y$  decreases. The closer  $|\rho_{X,Y}|$  is to 1, the stronger the linear relationship between the two variables.

### G.3. Automated Feature Engineering Analysis

We posit that Automated Feature Engineering (AutoFE) can address feature shift scenarios through two approaches.

- **Imputation:** CAAFE (Hollmann et al., 2023b) and OcTree (Nam et al., 2024) generate rules for imputing specific features, while OpenFE’s generated features do not match the originals (Zhang et al., 2023). We test single shifts using CAAFE and OctTree for imputation. Table 9 shows that LLM-based AutoFE can effectively generate matching features, enhancing model robustness compared to mean imputation.
- **Generation:** We use AutoFE to generate new features to offset the impact of missing original features on model performance. Table 10 shows that LLM-based AutoFE has significant potential in feature shift scenarios.

As the importance of features increases, both model performance declines more significantly, further corroborating Observation 2 of TabFSBench.

## H. Experiment Details of Observations

### H.1. Training Details

The deep learning models, LLMs, and Tabular LLMs were trained on an NVIDIA A800 GPU. Gradient-boosted tree models, where applicable, were trained on a CPU rather than a GPU, using an AMD Ryzen 5 7500F 6-Core Processor. All experimental results are reported as the average of three different random seeds to ensure robustness.

*Table 9.* Results from AutoFE as an imputation strategy. We evaluate CAAFE and OcTree on the downstream model of CatBoost and TabPFN under the Single Shift experiment.

Shift	CatBoost			TabPFN		
	Baseline	CAAFE	OcTree	Baseline	CAAFE	OcTree
1	0.870	0.869	0.870	0.866	0.875	0.873
2	0.871	0.880	0.872	0.862	0.877	0.872
3	0.864	0.874	0.872	0.859	0.876	0.877
4	0.861	0.865	0.864	0.861	0.868	0.874
5	0.875	0.882	0.885	0.866	0.861	0.868
6	0.859	0.859	0.863	0.857	0.883	0.875
7	0.844	0.854	0.853	0.853	0.865	0.868
8	0.866	0.871	0.868	0.873	0.845	0.852
9	0.871	0.875	0.871	0.868	0.871	0.866
10	0.864	0.874	0.864	0.871	0.875	0.874
11	0.663	0.664	0.666	0.817	0.868	0.872
100%	0.464	0.832	0.830	0.518	0.865	0.857

## H.2. Different Types of Feature Shift

We address the analysis that compare model performance on different types of feature shifts by clarifying two distinct analytical perspectives on feature shifts. First, regarding different types of feature shifts, we direct attention to our comprehensive robustness evaluation across multiple shift categories presented in the leaderboard analysis. Second, examining shifts by feature type, Table 11 reveals differential sensitivity patterns: model performance demonstrates greatest vulnerability to categorical feature perturbations, followed by boolean features, with numerical features exhibiting the most stable behavior. This hierarchy of susceptibility persists across all tested datasets, suggesting inherent algorithmic dependencies on feature types.

## H.3. Removing Most/Least Relevant Features

As shown in the experimental results in Figure H.3, under the least relevant feature removal setting, the model’s performance remains largely unchanged when removing  $0 \sim t\%$  of the least relevant columns. Interestingly, we observe that removing a certain number of the most irrelevant columns improves model performance. This observation aligns with the insight from (Grinsztajn et al., 2022) that **uninformative features can negatively impact model performance**.

## H.4. Detailed Explanations of Figure 4

The reason for the presence of multiple trajectories in Figure 4 is that each trajectory comprises points derived from a single dataset. During the fitting process, the results from all datasets were aggregated, leading to the emergence of distinct trajectories corresponding to individual datasets. Notably, these trajectories capture the relationship between feature importance and model performance across different datasets. Specifically, each dataset’s trajectory illustrates how its particular pattern of feature importance influences the resulting model performance.

To better support our conclusions, Figure H.4 provides correlation and accuracy plots for twelve different datasets. It indicates that although levels of feature importance vary across different datasets, they all support our research conclusion, namely, that there is a significant linear correlation between feature importance and model performance. These trajectories further confirm the generality and reliability of Observation 2.

## H.5. Results on High-Dimensional Datasets

Following OcTree (Nam et al., 2024), we conducted random shift experiments on two high-dimensional datasets, *madelon* and *nomao*, and present model performance under 10%, 20%, ..., and 100% feature shift degrees. Table 12 and 13 demonstrate that as the degree of feature shift increases, the model performance decreases significantly.

Table 10. Results from AutoFE as feature generator. We evaluate OpenFE, CAAFE and OcTree on the downstream model of CatBoost and TabPFN under the Random Shift experiment.

Shift	CatBoost				TabPFN Baseline			
	Baseline	OpenFE	CAAFE	OcTree	Baseline	OpenFE	CAAFE	OcTree
0	0.879	0.886	0.887	0.888	0.862	0.853	0.863	0.860
9%	0.851	0.859	0.861	0.859	0.859	0.871	0.874	0.876
18%	0.826	0.857	0.859	0.857	0.848	0.866	0.876	0.872
27%	0.801	0.855	0.862	0.855	0.835	0.866	0.872	0.870
36%	0.775	0.853	0.860	0.853	0.820	0.864	0.874	0.870
45%	0.747	0.841	0.849	0.841	0.803	0.868	0.878	0.862
54%	0.716	0.842	0.845	0.842	0.784	0.851	0.861	0.861
63%	0.682	0.835	0.842	0.835	0.762	0.853	0.860	0.869
72%	0.643	0.842	0.844	0.842	0.734	0.846	0.857	0.857
81%	0.596	0.850	0.853	0.850	0.695	0.857	0.860	0.867
90%	0.541	0.841	0.850	0.841	0.638	0.856	0.860	0.863
100%	0.464	0.830	0.832	0.830	0.518	0.853	0.865	0.857

**Madelon** The *madelon* dataset was originally designed for the NIPS 2003 feature selection challenge. It is an artificial binary classification task in which instances are generated from clusters positioned at the vertices of a five-dimensional hypercube. The dataset contains 500 features, including 20 informative (or redundant) features and 480 noise features, making it a prototypical benchmark for evaluating robustness and feature selection under high-dimensional settings. The dataset is available from the UCI Machine Learning Repository: <https://archive.ics.uci.edu/dataset/171/madelon>.

**Nomao** The *nomao* dataset originates from a real-world deduplication task involving geolocated business entries. Each sample represents a comparison between two records, described by both numerical and categorical similarity features such as name, address, and geocoordinates. The dataset includes 34,465 samples and 118 features (89 numeric and 29 categorical), with a notable proportion of missing values. Its mixed-type, noisy, and partially incomplete nature makes it a valuable resource for studying model robustness in practical high-dimensional scenarios. The dataset is publicly accessible at <https://archive.ics.uci.edu/dataset/227/nomao>.

## H.6. Feature-Shift Performance vs. Runtime

In Figure H.6, we plot feature-shift performance versus runtime for all models, averaged across datasets. LLMs and Tabular LLMs exhibit the longest runtime, whereas tree-based models achieve excellent performance with minimal runtime requirements. However, we observe that models such as NODE and LLMs consume significantly more memory compared to tree-based approaches.

## H.7. Dataset-Specific Experiment Details

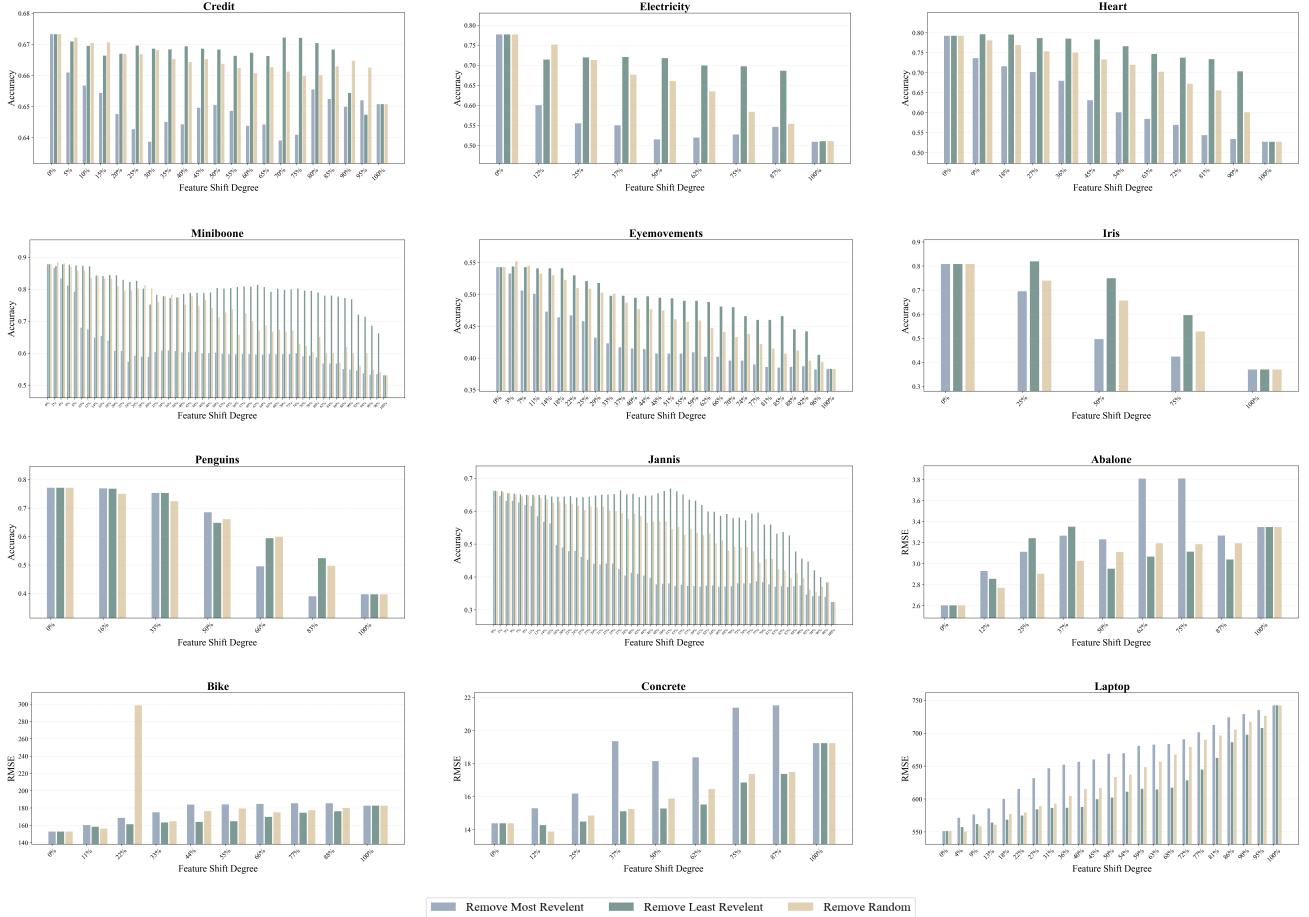
This section provides detailed dataset-specific experimental results. For each dataset, we list all models and their corresponding performance metrics. The experiments are categorized into four scenarios: **SC** (single-column missing), **MC-D** (multi-column missing in Pearson correlation descending order), **MC-A** (multi-column missing in Pearson correlation ascending order), and **MC-R** (multi-column missing randomly). For classification tasks, we report accuracy and ROC-AUC scores, while for regression tasks, we provide RMSE results.

Table 11. Results on different types of features shifted. We divide feature types into Categorical, Numerical and Boolean.

Model	Baseline	Categorical	Numerical	Boolean
LightGBM	0.833	0.786	0.83	0.821
XGBoost	0.855	0.804	0.84	0.81
CatBoost	0.879	0.792	0.868	0.861
TabPFN	0.862	0.845	0.865	0.864
DANets	0.674	0.648	0.667	0.661
MLP	0.848	0.837	0.848	0.838
NODE	0.663	0.651	0.641	0.637
ResNet	0.857	0.845	0.86	0.851
SwitchTab	0.871	0.858	0.867	0.859
TabCaps	0.775	0.76	0.772	0.763
TabNet	0.681	0.659	0.678	0.654
TANGOS	0.859	0.853	0.863	0.86
AutoInt	0.683	0.678	0.673	0.696
DCNv2	0.868	0.854	0.861	0.841
FT-Transformer	0.774	0.734	0.773	0.768
GrowNet	0.589	0.586	0.598	0.591
Saint	0.875	0.861	0.866	0.861
SNN	0.788	0.775	0.78	0.776
TabTransformer	0.522	0.504	0.523	0.508
TabR	0.893	0.877	0.893	0.896
ModernNCA	0.88	0.849	0.881	0.889
Llama3-8B	0.848	0.76	0.805	0.765
TabLLM	0.783	0.786	0.795	0.766
UniPredict	0.853	0.861	0.849	0.84

Table 12. Results on nomao dataset. We don't evaluate TabPFN(due to the limitation of TabPFN on high-dimension datasets which have more than 100 features), Llama3-8B and Unipredict (due to the limitations of input).

ACC	ID	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
LightGBM	0.970	0.969	0.968	0.969	0.967	0.964	0.958	0.961	0.954	0.926	0.890
XGBoost	0.974	0.974	0.973	0.973	0.972	0.967	0.971	0.964	0.933	0.939	0.874
CatBoost	0.970	0.969	0.969	0.969	0.969	0.960	0.960	0.960	0.955	0.945	0.892
TabPFN	\	\	\	\	\	\	\	\	\	\	\
DANets	0.933	0.930	0.921	0.908	0.888	0.872	0.845	0.816	0.808	0.719	0.713
MLP	0.949	0.946	0.938	0.931	0.914	0.894	0.884	0.847	0.874	0.762	0.756
NODE	0.778	0.768	0.760	0.750	0.723	0.716	0.713	0.713	0.713	0.713	0.713
ResNet	0.953	0.946	0.936	0.929	0.882	0.852	0.815	0.777	0.824	0.719	0.714
SwitchTab	0.936	0.941	0.935	0.931	0.911	0.886	0.874	0.847	0.867	0.767	0.753
TabCaps	0.920	0.916	0.905	0.897	0.899	0.882	0.876	0.852	0.864	0.832	0.804
TabNet	0.921	0.899	0.907	0.900	0.822	0.878	0.875	0.806	0.876	0.715	0.756
TANGOS	0.955	0.950	0.937	0.930	0.904	0.874	0.869	0.816	0.881	0.760	0.736
AutoInt	0.939	0.934	0.912	0.901	0.862	0.823	0.759	0.757	0.771	0.718	0.714
DCNv2	0.949	0.946	0.938	0.930	0.916	0.903	0.899	0.859	0.881	0.772	0.806
FT-Transformer	0.934	0.933	0.925	0.909	0.860	0.859	0.801	0.772	0.790	0.714	0.713
GrowNet	0.832	0.818	0.812	0.797	0.779	0.785	0.759	0.741	0.759	0.715	0.729
Saint	0.952	0.943	0.928	0.915	0.852	0.842	0.801	0.762	0.792	0.718	0.713
SNN	0.910	0.909	0.904	0.890	0.889	0.880	0.885	0.859	0.857	0.837	0.798
TabTransformer	0.928	0.925	0.915	0.905	0.884	0.879	0.871	0.852	0.877	0.802	0.779
TabR	0.915	0.913	0.904	0.894	0.894	0.881	0.881	0.855	0.860	0.834	0.801
ModernNCA	0.964	0.952	0.945	0.928	0.842	0.861	0.842	0.768	0.812	0.719	0.713
Llama3-8B	\	\	\	\	\	\	\	\	\	\	\
TabLLM	0.959	0.957	0.938	0.893	0.856	0.842	0.616	0.676	0.506	0.432	0.329
UniPredict	\	\	\	\	\	\	\	\	\	\	\



**Figure 9.** Results for most/least shift experiments with correlation analysis across datasets. The  $x$ -axis represents the percentage of features removed, while the  $y$ -axis indicates the average performance (accuracy or RMSE) of all models. Three feature removal strategies are compared: **Remove Most Relevant** (blue), which removes  $k$  most correlated columns; **Remove Least Relevant** (green), which removes  $k$  least correlated columns; and **Remove Random** (yellow), which removes  $k$  randomly selected features.

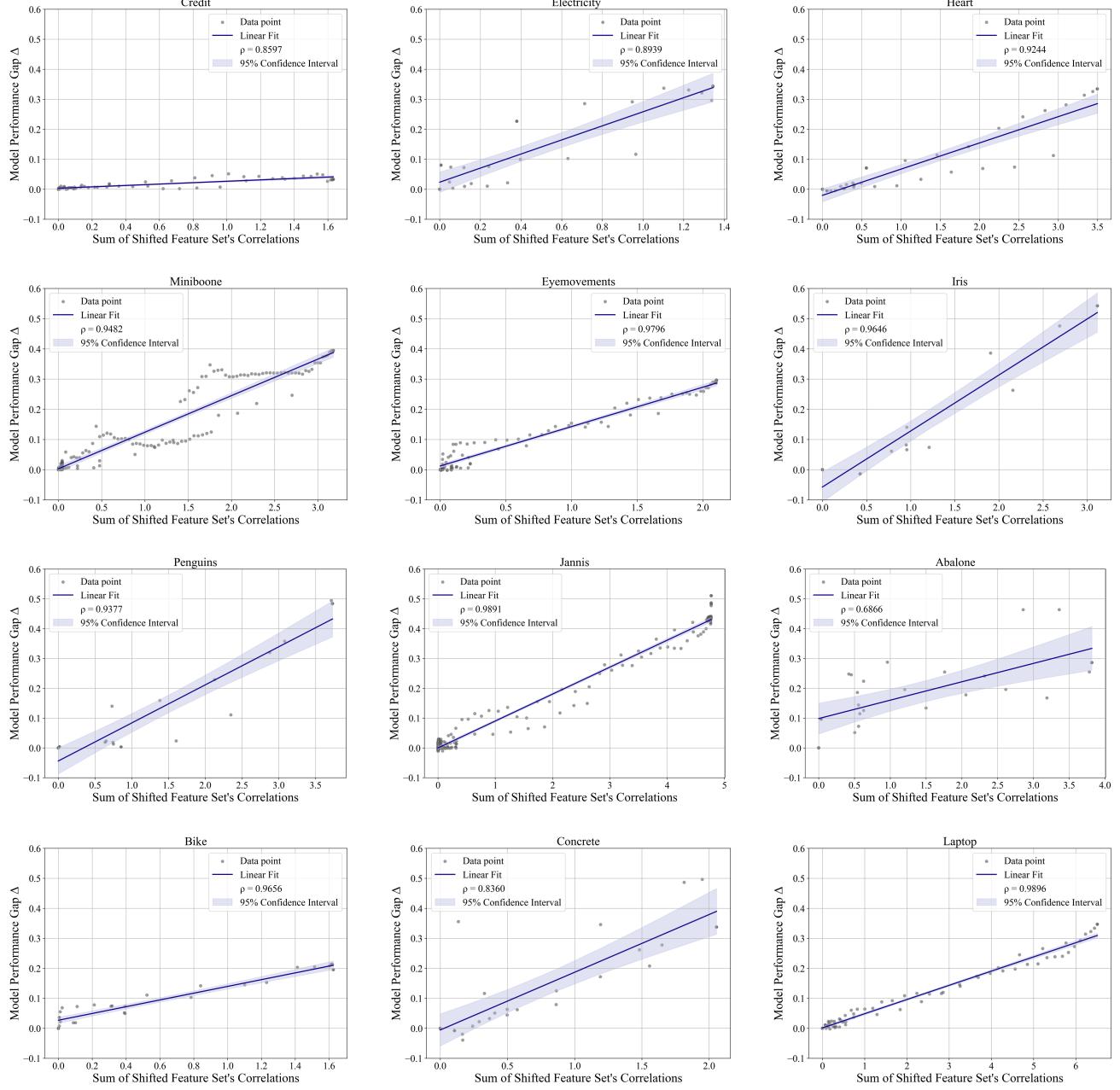


Figure 10. Trajectories between correlation and accuracy for each of twelve datasets.

Table 13. Results on madelon dataset. We don't evaluate TabPFN (due to the limitation of TabPFN on high-dimension datasets which have more than 100 features), Llama3-8B, TabLLM and Unipredict (due to the limitations of input).

ACC	ID	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
LightGBM	0.819	0.813	0.815	0.819	0.825	0.796	0.737	0.723	0.635	0.574	0.562
XGBoost	0.828	0.818	0.827	0.804	0.829	0.769	0.772	0.693	0.614	0.560	0.554
CatBoost	0.865	0.859	0.797	0.862	0.831	0.836	0.770	0.786	0.630	0.547	0.841
DANets	0.523	0.523	0.524	0.514	0.513	0.510	0.509	0.502	0.503	0.496	0.495
MLP	0.518	0.521	0.521	0.515	0.528	0.519	0.511	0.506	0.507	0.503	0.498
NODE	0.507	0.512	0.515	0.500	0.526	0.510	0.505	0.494	0.501	0.499	0.495
ResNet	0.555	0.553	0.553	0.535	0.537	0.547	0.536	0.516	0.529	0.507	0.501
SwitchTab	0.483	0.483	0.483	0.483	0.483	0.483	0.483	0.483	0.483	0.483	0.479
TabCaps	0.516	0.509	0.515	0.508	0.516	0.514	0.490	0.504	0.503	0.502	0.498
TabNet	0.512	0.504	0.504	0.507	0.505	0.502	0.496	0.500	0.497	0.496	0.490
TANGOS	0.571	0.560	0.562	0.551	0.566	0.545	0.550	0.523	0.525	0.511	0.504
AutoInt	0.592	0.558	0.543	0.543	0.532	0.530	0.526	0.519	0.511	0.503	0.501
DCNv2	0.528	0.522	0.523	0.509	0.519	0.512	0.528	0.512	0.508	0.513	0.507
FT-Transformer	0.640	0.579	0.553	0.554	0.546	0.541	0.540	0.536	0.522	0.521	0.517
GrowNet	0.506	0.503	0.494	0.496	0.499	0.508	0.509	0.502	0.517	0.509	0.506
Saint	0.544	0.543	0.541	0.539	0.536	0.528	0.524	0.523	0.506	0.503	0.501
SNN	0.508	0.507	0.503	0.498	0.508	0.506	0.513	0.501	0.493	0.505	0.502
TabTransformer	0.543	0.544	0.534	0.532	0.548	0.540	0.534	0.513	0.523	0.520	0.514
TabR	0.640	0.620	0.556	0.538	0.534	0.525	0.520	0.511	0.505	0.506	0.503
ModernNCA	0.593	0.587	0.573	0.549	0.588	0.553	0.539	0.519	0.516	0.505	0.502
Llama3-8B	\	\	\	\	\	\	\	\	\	\	\
TabLLM	\	\	\	\	\	\	\	\	\	\	\
UniPredict	\	\	\	\	\	\	\	\	\	\	\

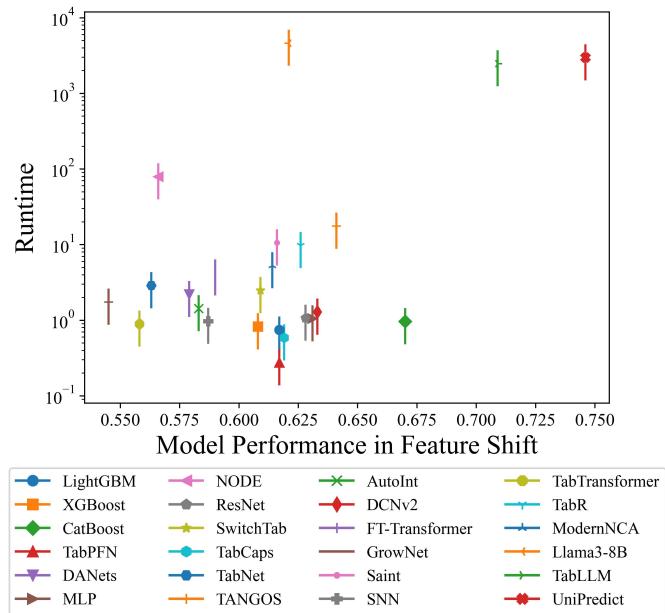


Figure 11. Average feature-shift performance vs. average runtime for each model.

## TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments

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**Table 14.** Model performance on Credit dataset.

(a) Model performance of SC experiment under accuracy on Credit dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.757	0.750	0.775	0.762	0.695	0.693	0.693	0.688	0.695	0.668	0.525	0.695	0.688	0.685	0.695	0.608	0.695	0.537	0.528	0.687	0.717	0.750	0.630	0.620	0.676
1	-0.003	0.755	0.753	0.773	0.753	0.695	0.692	0.693	0.683	0.695	0.678	0.540	0.695	0.682	0.687	0.695	0.607	0.695	0.543	0.537	0.697	0.713	0.645	0.580	0.615	0.671
2	0.003	0.755	0.750	0.772	0.755	0.695	0.695	0.692	0.673	0.695	0.660	0.528	0.695	0.688	0.678	0.695	0.613	0.695	0.540	0.545	0.685	0.715	0.650	0.605	0.620	0.671
3	-0.009	0.733	0.748	0.780	0.763	0.695	0.697	0.695	0.692	0.695	0.677	0.582	0.695	0.682	0.685	0.695	0.607	0.695	0.532	0.528	0.683	0.713	0.645	0.595	0.625	0.672
4	-0.019	0.758	0.757	0.772	0.753	0.695	0.697	0.692	0.680	0.695	0.650	0.542	0.695	0.678	0.682	0.695	0.617	0.695	0.535	0.527	0.693	0.703	0.675	0.590	0.630	0.671
5	0.028	0.750	0.750	0.780	0.737	0.695	0.695	0.693	0.680	0.695	0.668	0.522	0.695	0.680	0.677	0.695	0.615	0.695	0.537	0.537	0.680	0.713	0.700	0.615	0.600	0.671
6	0.033	0.752	0.752	0.778	0.758	0.695	0.692	0.693	0.675	0.695	0.655	0.527	0.695	0.687	0.683	0.695	0.620	0.695	0.515	0.532	0.688	0.723	0.685	0.595	0.610	0.671
7	0.036	0.750	0.743	0.772	0.757	0.695	0.697	0.695	0.692	0.695	0.662	0.527	0.695	0.678	0.682	0.695	0.632	0.695	0.532	0.528	0.685	0.703	0.680	0.575	0.595	0.669
8	0.046	0.762	0.755	0.785	0.757	0.695	0.692	0.695	0.688	0.695	0.658	0.555	0.695	0.680	0.675	0.695	0.617	0.695	0.537	0.538	0.688	0.717	0.690	0.600	0.600	0.673
9	0.054	0.755	0.723	0.777	0.757	0.695	0.697	0.695	0.672	0.695	0.675	0.532	0.695	0.682	0.695	0.617	0.695	0.535	0.548	0.688	0.717	0.685	0.600	0.595	0.671	
10	0.056	0.747	0.742	0.768	0.757	0.695	0.692	0.693	0.682	0.695	0.658	0.528	0.695	0.680	0.675	0.695	0.603	0.695	0.548	0.540	0.683	0.720	0.675	0.625	0.640	0.672
11	-0.072	0.752	0.765	0.790	0.732	0.695	0.693	0.693	0.663	0.695	0.647	0.532	0.695	0.680	0.685	0.695	0.613	0.695	0.532	0.525	0.680	0.715	0.675	0.610	0.620	0.670
12	-0.082	0.753	0.747	0.775	0.742	0.695	0.695	0.693	0.685	0.695	0.672	0.535	0.695	0.682	0.685	0.695	0.617	0.695	0.515	0.528	0.687	0.717	0.680	0.585	0.605	0.670
13	0.090	0.745	0.722	0.775	0.753	0.695	0.693	0.693	0.685	0.695	0.653	0.542	0.695	0.677	0.685	0.695	0.615	0.695	0.542	0.542	0.680	0.718	0.725	0.595	0.610	0.672
14	0.091	0.755	0.753	0.773	0.750	0.695	0.692	0.692	0.685	0.695	0.652	0.525	0.695	0.683	0.690	0.605	0.695	0.550	0.528	0.688	0.723	0.715	0.580	0.600	0.672	
15	-0.097	0.738	0.742	0.777	0.758	0.695	0.697	0.692	0.678	0.695	0.663	0.535	0.695	0.682	0.690	0.695	0.613	0.695	0.520	0.535	0.688	0.712	0.680	0.595	0.625	0.671
16	0.103	0.733	0.732	0.767	0.770	0.695	0.693	0.693	0.683	0.695	0.675	0.553	0.695	0.688	0.682	0.695	0.622	0.695	0.522	0.525	0.688	0.723	0.675	0.595	0.610	0.671
17	0.138	0.738	0.710	0.768	0.753	0.695	0.695	0.693	0.660	0.695	0.677	0.523	0.695	0.683	0.673	0.695	0.627	0.695	0.518	0.542	0.680	0.697	0.685	0.575	0.570	0.664
18	-0.155	0.745	0.743	0.765	0.752	0.695	0.695	0.695	0.688	0.695	0.653	0.513	0.695	0.687	0.677	0.695	0.630	0.695	0.533	0.540	0.690	0.725	0.630	0.580	0.590	0.667
19	-0.215	0.755	0.738	0.753	0.733	0.695	0.697	0.692	0.662	0.695	0.672	0.542	0.695	0.685	0.695	0.628	0.695	0.538	0.547	0.678	0.732	0.595	0.640	0.600	0.669	
20	0.302	0.727	0.645	0.735	0.728	0.695	0.693	0.693	0.678	0.695	0.675	0.552	0.695	0.685	0.695	0.627	0.695	0.503	0.532	0.668	0.693	0.695	0.605	0.615	0.663	

(b) Model performance of SC experiment under ROC-AUC on Credit dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.761	0.755	0.799	0.781	0.486	0.504	0.644	0.697	0.699	0.650	0.496	0.592	0.538	0.591	0.576	0.470	0.732	0.559	0.528	0.691	0.755	0.701	0.580	0.642	0.634
1	-0.003	0.769	0.762	0.804	0.782	0.483	0.504	0.641	0.696	0.698	0.653	0.490	0.595	0.545	0.594	0.576	0.470	0.736	0.563	0.530	0.697	0.750	0.615	0.508	0.631	0.629
2	0.003	0.762	0.755	0.794	0.777	0.487	0.510	0.641	0.688	0.700	0.645	0.484	0.599	0.552	0.611	0.563	0.470	0.738	0.566	0.528	0.692	0.754	0.569	0.548	0.654	0.629
3	-0.009	0.754	0.746	0.805	0.784	0.481	0.493	0.641	0.695	0.693	0.643	0.525	0.617	0.547	0.604	0.556	0.466	0.726	0.580	0.528	0.691	0.757	0.536	0.527	0.607	0.625
4	-0.019	0.763	0.756	0.802	0.781	0.495	0.523	0.641	0.694	0.693	0.643	0.525	0.617	0.547	0.604	0.556	0.466	0.726	0.580	0.509	0.690	0.745	0.538	0.526	0.638	0.627
5	0.028	0.757	0.751	0.780	0.771	0.489	0.519	0.651	0.699	0.700	0.655	0.471	0.603	0.539	0.593	0.580	0.468	0.733	0.559	0.528	0.692	0.751	0.570	0.570	0.598	0.627
6	0.033	0.762	0.756	0.800	0.781	0.485	0.492	0.640	0.698	0.704	0.663	0.483	0.578	0.557	0.585	0.586	0.461	0.733	0.548	0.518	0.705	0.758	0.570	0.542	0.642	0.627
7	0.036	0.760	0.753	0.792	0.775	0.486	0.492	0.654	0.700	0.698	0.650	0.482	0.586	0.547	0.591	0.574	0.484	0.729	0.554	0.547	0.689	0.750	0.561	0.521	0.633	0.625
8	0.046	0.766	0.760	0.803	0.782	0.493	0.538	0.645	0.698	0.703	0.651	0.532	0.601	0.537	0.589	0.615	0.468	0.729	0.563	0.525	0.695	0.761	0.573	0.549	0.621	0.633
9	0.054	0.762	0.756	0.808	0.782	0.487	0.500	0.653	0.699	0.698	0.650	0.501	0.599	0.543	0.586	0.572	0.472	0.729	0.555	0.549	0.687	0.749	0.565	0.515	0.615	0.627
10	0.056	0.758	0.752	0.798	0.778	0.489	0.491	0.642	0.698	0.701	0.647	0.566	0.581	0.578	0.601	0.548	0.473	0.731	0.552	0.528	0.690	0.753	0.561	0.557	0.640	0.625
11	-0.079	0.759	0.754	0.796	0.767	0.479	0.508	0.640	0.695	0.694	0.646	0.511	0.581	0.531	0.581	0.577	0.473	0.722	0.558	0.528	0.686	0.753	0.561	0.527	0.629	0.623
12	-0.082	0.756	0.751	0.799	0.776	0.479	0.508	0.640	0.695	0.694	0.646	0.510	0.584	0.538	0.584	0.574	0.480	0.731	0.552	0.528	0.686	0.753	0.561	0.527	0.632	0.624
13	0.091	0.774	0.763	0.799	0.786	0.478	0.501	0.651	0.697	0.706	0.656	0.499	0.591	0.555	0.575	0.576	0.473	0.746	0.557	0.532	0.717	0.755	0.561	0.518	0.609	0.628
14	-0.097	0.739	0.734	0.784	0.769	0.487	0.498	0.647	0.699	0.707	0.641	0.497	0.587	0.543	0.574	0.586	0.479	0.730	0.554	0.538	0.698	0.762	0.565	0.547	0.663	0.626
15	0.103	0.748	0.740	0.790	0.781	0.483	0.502	0.648	0.701	0.698	0.652	0.528	0.591	0.553	0.585	0.587	0.480	0.732	0.557	0.538	0.707	0.760	0.563	0.547	0.642	0.626
16	0.138	0.749	0.744	0.7																						

**TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments**

(e) Model performance of MC-L experiment under accuracy on Credit dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE	
0	0.757	0.750	0.775	0.762	0.695	0.693	0.693	0.680	0.695	0.668	0.525	0.695	0.688	0.685	0.695	0.608	0.695	0.537	0.528	0.687	0.717	0.750	0.630	0.620	0.676	
5%	0.755	0.753	0.773	0.753	0.695	0.692	0.693	0.683	0.695	0.678	0.540	0.695	0.682	0.687	0.695	0.607	0.695	0.543	0.537	0.697	0.713	0.645	0.580	0.615	0.671	
10%	0.755	0.753	0.775	0.748	0.695	0.692	0.690	0.668	0.695	0.678	0.537	0.695	0.682	0.678	0.695	0.615	0.695	0.553	0.538	0.695	0.710	0.630	0.580	0.615	0.670	
15%	0.743	0.750	0.772	0.760	0.695	0.695	0.695	0.677	0.695	0.672	0.578	0.695	0.680	0.695	0.695	0.607	0.695	0.564	0.543	0.682	0.710	0.535	0.575	0.595	0.666	
20%	0.737	0.755	0.782	0.755	0.695	0.700	0.693	0.675	0.695	0.682	0.563	0.695	0.677	0.700	0.695	0.610	0.695	0.577	0.538	0.692	0.702	0.530	0.585	0.580	0.667	
25%	0.735	0.733	0.783	0.730	0.695	0.698	0.692	0.685	0.695	0.682	0.577	0.695	0.688	0.705	0.695	0.603	0.695	0.564	0.537	0.690	0.708	0.555	0.595	0.630	0.670	
30%	0.735	0.732	0.790	0.735	0.695	0.697	0.693	0.695	0.695	0.689	0.653	0.695	0.688	0.698	0.695	0.605	0.695	0.565	0.535	0.703	0.708	0.545	0.600	0.625	0.669	
35%	0.738	0.737	0.793	0.738	0.695	0.695	0.695	0.695	0.695	0.680	0.600	0.695	0.688	0.687	0.695	0.607	0.695	0.565	0.527	0.690	0.692	0.555	0.595	0.590	0.668	
40%	0.737	0.743	0.788	0.738	0.695	0.697	0.700	0.697	0.695	0.680	0.588	0.695	0.687	0.688	0.695	0.625	0.695	0.577	0.513	0.688	0.703	0.540	0.590	0.610	0.669	
45%	0.737	0.737	0.792	0.735	0.695	0.695	0.700	0.683	0.695	0.677	0.580	0.695	0.687	0.682	0.695	0.630	0.695	0.573	0.520	0.695	0.700	0.565	0.585	0.600	0.669	
50%	0.742	0.742	0.770	0.733	0.695	0.700	0.698	0.680	0.695	0.668	0.618	0.695	0.688	0.682	0.695	0.620	0.695	0.568	0.510	0.682	0.698	0.550	0.600	0.615	0.668	
55%	0.733	0.740	0.775	0.748	0.695	0.697	0.693	0.670	0.695	0.668	0.607	0.695	0.685	0.677	0.695	0.603	0.695	0.557	0.518	0.685	0.705	0.555	0.580	0.620	0.666	
60%	0.733	0.733	0.775	0.743	0.695	0.702	0.695	0.665	0.695	0.670	0.598	0.695	0.685	0.680	0.695	0.618	0.695	0.555	0.515	0.670	0.707	0.575	0.595	0.625	0.667	
65%	0.737	0.730	0.762	0.738	0.695	0.695	0.695	0.660	0.695	0.668	0.620	0.695	0.678	0.687	0.695	0.593	0.695	0.565	0.527	0.675	0.705	0.595	0.610	0.590	0.666	
70%	0.747	0.738	0.770	0.733	0.695	0.695	0.695	0.668	0.695	0.677	0.627	0.695	0.680	0.695	0.695	0.587	0.695	0.590	0.523	0.682	0.700	0.665	0.590	0.600	0.672	
75%	0.733	0.733	0.752	0.732	0.695	0.695	0.695	0.668	0.695	0.688	0.617	0.695	0.683	0.698	0.695	0.600	0.695	0.583	0.535	0.683	0.693	0.665	0.605	0.595	0.672	
80%	0.720	0.730	0.737	0.740	0.695	0.695	0.692	0.662	0.695	0.682	0.618	0.695	0.692	0.695	0.695	0.612	0.695	0.695	0.592	0.538	0.687	0.690	0.645	0.575	0.615	0.670
85%	0.720	0.725	0.717	0.737	0.695	0.695	0.693	0.643	0.695	0.637	0.655	0.695	0.695	0.692	0.695	0.620	0.695	0.585	0.547	0.680	0.680	0.645	0.585	0.615	0.668	
90%	0.715	0.728	0.690	0.735	0.695	0.695	0.695	0.660	0.695	0.613	0.645	0.695	0.695	0.680	0.695	0.645	0.695	0.615	0.578	0.673	0.685	0.450	0.585	0.595	0.654	
95%	0.723	0.723	0.672	0.723	0.695	0.695	0.695	0.607	0.695	0.607	0.695	0.695	0.695	0.695	0.695	0.602	0.695	0.565	0.568	0.667	0.695	0.295	0.600	0.540	0.647	
100%	0.723	0.723	0.723	0.723	0.695	0.695	0.695	0.565	0.695	0.565	0.695	0.695	0.695	0.695	0.695	0.695	0.565	0.565	0.695	0.695	0.295	0.575	0.560	0.651		

(f) Model performance of MC-L experiment under ROC-AUC on Credit dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE	
0	0.761	0.755	0.799	0.781	0.486	0.504	0.644	0.697	0.699	0.650	0.496	0.592	0.538	0.591	0.576	0.470	0.732	0.558	0.528	0.691	0.755	0.701	0.580	0.642	0.634	
5%	0.769	0.762	0.804	0.782	0.483	0.504	0.641	0.696	0.698	0.653	0.490	0.595	0.545	0.594	0.576	0.470	0.736	0.563	0.530	0.697	0.750	0.615	0.508	0.631	0.629	
10%	0.770	0.762	0.799	0.779	0.481	0.511	0.637	0.692	0.700	0.649	0.499	0.603	0.554	0.612	0.562	0.473	0.742	0.573	0.528	0.701	0.749	0.619	0.510	0.627	0.630	
15%	0.762	0.754	0.809	0.782	0.476	0.497	0.639	0.693	0.704	0.657	0.541	0.600	0.542	0.615	0.563	0.487	0.742	0.570	0.520	0.695	0.750	0.586	0.501	0.612	0.629	
20%	0.763	0.756	0.813	0.779	0.489	0.516	0.632	0.695	0.699	0.649	0.544	0.625	0.551	0.627	0.541	0.481	0.738	0.601	0.500	0.692	0.738	0.578	0.512	0.590	0.630	
25%	0.759	0.751	0.813	0.775	0.494	0.538	0.639	0.698	0.697	0.657	0.558	0.644	0.551	0.629	0.543	0.471	0.738	0.603	0.487	0.694	0.736	0.596	0.523	0.619	0.634	
30%	0.762	0.753	0.813	0.770	0.500	0.529	0.634	0.703	0.701	0.670	0.553	0.634	0.577	0.622	0.554	0.463	0.738	0.597	0.485	0.692	0.740	0.589	0.529	0.621	0.635	
35%	0.760	0.750	0.810	0.774	0.501	0.527	0.649	0.714	0.707	0.676	0.666	0.563	0.629	0.583	0.619	0.554	0.473	0.734	0.603	0.495	0.680	0.736	0.590	0.523	0.615	0.637
40%	0.766	0.757	0.812	0.776	0.505	0.552	0.656	0.708	0.700	0.676	0.646	0.563	0.618	0.568	0.595	0.483	0.731	0.612	0.479	0.687	0.742	0.570	0.514	0.634	0.639	
45%	0.769	0.757	0.813	0.776	0.509	0.553	0.663	0.696	0.700	0.664	0.522	0.650	0.567	0.613	0.592	0.488	0.729	0.607	0.503	0.681	0.738	0.588	0.512	0.628	0.639	
50%	0.764	0.755	0.807	0.779	0.510	0.553	0.657	0.696	0.711	0.659	0.543	0.637	0.546	0.599	0.595	0.463	0.727	0.606	0.506	0.681	0.737	0.572	0.524	0.630	0.636	
55%	0.761	0.752	0.808	0.768	0.511	0.549	0.660	0.684	0.706	0.662	0.552	0.638	0.525	0.594	0.595	0.454	0.721	0.610	0.513	0.675	0.732	0.581	0.508	0.652	0.633	
60%	0.757	0.748	0.807	0.765	0.503	0.548	0.662	0.685	0.706	0.657	0.505	0.630	0.527	0.594	0.595	0.456	0.720	0.608	0.504	0.682	0.728	0.580	0.520	0.659	0.662	
65%	0.752	0.744	0.805	0.759	0.508	0.575	0.666	0.684	0.690	0.660	0.531	0.641	0.503	0.607	0.598	0.443	0.704	0.604	0.508	0.661	0.713	0.550	0.537	0.627	0.628	
70%	0.774	0.760	0.807	0.770	0.523	0.580	0.671	0.693	0.677	0.515	0.635	0.514	0.606	0.599	0.446	0.721	0.611	0.498	0.693	0.723	0.550	0.519	0.624	0.634		
75%	0.751	0.736	0.800	0.764	0.537	0.592	0.678	0.705	0.707	0.679	0.516	0.652	0.505	0.584	0.627	0.435	0.719	0.601	0.488	0.707	0.741	0.536	0.533	0.672	0.636	
80%	0.735	0.716	0.795	0.759	0.546	0.598	0.685	0.716	0.712	0.674	0.526	0.678	0.499	0.581	0.644	0.421	0.719	0.604	0.442	0.711	0.749	0.512	0.504	0.692	0.634	
85%	0.716	0.704	0.785	0.736	0.531	0.554	0.654	0.684	0.679	0.522	0.552	0.503	0.571	0.563	0.456	0.703	0.616	0.486</td								

(i) Model performance gap  $\Delta$  of RD experiment under accuracy on Credit dataset. Partial model performance degradation of 0.000 as the table retains three decimal places.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TF	TABR	NCA	LMA	TLLM	UNI	AVE
5%	-0.012	-0.014	-0.006	-0.015	0.000	0.002	0.000	0.001	0.000	-0.010	0.011	0.000	-0.008	0.000	0.000	0.019	0.000	-0.011	0.009	0.000	-0.002	-0.024	-0.053	-0.023	-0.006
10%	-0.020	-0.028	-0.011	-0.020	0.000	0.004	0.000	-0.003	0.000	-0.011	0.022	0.000	-0.011	-0.007	0.000	0.021	0.000	-0.013	0.012	0.005	-0.010	-0.021	-0.064	-0.031	-0.008
15%	-0.027	-0.041	-0.015	-0.024	0.000	0.005	0.002	-0.006	0.000	-0.017	0.068	0.000	-0.012	-0.001	0.000	0.034	0.000	-0.005	0.013	-0.005	-0.008	-0.025	-0.070	-0.034	-0.008
20%	-0.046	-0.099	-0.020	-0.027	0.000	0.003	-0.001	-0.014	0.000	-0.025	0.062	0.000	-0.011	-0.004	0.000	0.030	0.000	-0.004	0.011	-0.006	-0.015	-0.030	-0.059	-0.036	-0.014
25%	-0.033	-0.084	-0.029	-0.031	0.000	0.005	0.001	-0.019	0.000	-0.027	0.071	0.000	-0.010	-0.000	0.000	0.046	0.000	-0.011	0.021	-0.007	-0.018	-0.033	-0.071	-0.053	-0.014
30%	-0.050	-0.092	-0.034	-0.046	0.000	0.004	0.002	-0.003	0.000	-0.024	0.087	0.000	-0.008	0.000	0.000	0.033	0.000	0.007	0.022	0.007	-0.006	-0.043	-0.072	-0.015	-0.012
35%	-0.057	-0.094	-0.040	-0.040	0.000	0.007	0.001	-0.029	0.000	-0.034	0.090	0.000	-0.006	-0.006	0.000	0.049	0.000	0.001	0.008	-0.009	-0.016	-0.049	-0.075	-0.033	-0.016
40%	-0.052	-0.115	-0.044	-0.034	0.000	0.005	0.001	-0.035	0.000	-0.049	0.098	0.000	-0.010	0.003	0.000	0.046	0.000	-0.007	0.015	0.001	-0.019	-0.051	-0.069	-0.050	-0.018
45%	-0.038	-0.065	-0.051	-0.036	0.000	0.002	0.002	-0.037	0.000	-0.048	0.091	0.000	-0.001	-0.007	0.000	0.064	0.000	-0.017	0.013	0.000	-0.020	-0.045	-0.070	-0.081	-0.016
50%	-0.083	-0.097	-0.063	-0.047	0.000	0.002	0.002	-0.017	0.000	-0.050	0.122	0.000	-0.005	-0.004	0.000	0.030	0.000	0.018	0.010	0.002	-0.026	-0.062	-0.067	-0.035	-0.018
55%	-0.058	-0.140	-0.068	-0.046	0.000	0.003	0.002	-0.046	0.000	-0.048	0.139	0.000	-0.008	0.000	0.000	0.071	0.000	0.003	0.012	-0.007	-0.019	-0.058	-0.073	-0.074	-0.020
60%	-0.071	-0.079	-0.074	-0.046	0.000	0.001	0.002	-0.054	0.000	-0.077	0.142	0.000	-0.003	-0.011	0.000	0.051	0.000	-0.020	0.006	-0.012	-0.032	-0.063	-0.067	-0.076	-0.023
65%	-0.075	-0.116	-0.069	-0.050	0.000	0.003	0.001	-0.035	0.000	-0.073	0.173	0.000	-0.008	0.000	0.000	0.067	0.000	-0.002	0.013	-0.016	-0.029	-0.052	-0.063	-0.064	-0.020
70%	-0.049	-0.111	-0.077	-0.047	0.000	-0.001	0.002	-0.057	0.000	-0.088	0.189	0.000	-0.010	0.003	0.000	0.079	0.000	-0.008	0.002	-0.009	-0.033	-0.069	-0.072	-0.094	-0.022
75%	-0.052	-0.153	-0.076	-0.049	0.000	0.002	0.002	-0.051	0.000	-0.111	0.199	0.000	-0.010	-0.003	0.000	0.067	0.000	-0.037	0.014	-0.003	-0.026	-0.067	-0.070	-0.072	-0.024
80%	-0.074	-0.203	-0.085	-0.051	0.000	0.003	0.002	-0.038	0.000	-0.055	0.215	0.000	-0.001	-0.007	0.000	0.072	0.000	-0.017	0.003	-0.005	-0.005	-0.030	-0.074	-0.063	-0.024
85%	-0.046	-0.186	-0.084	-0.050	0.000	0.001	0.002	-0.052	0.000	-0.082	0.266	0.000	-0.008	0.006	0.000	0.098	0.000	-0.033	0.010	-0.004	-0.031	-0.065	-0.068	-0.020	-0.002
90%	-0.052	-0.093	-0.077	-0.050	0.000	0.002	0.002	-0.077	0.000	-0.093	0.246	0.000	-0.002	0.007	0.000	0.118	0.000	0.032	0.009	-0.008	-0.031	-0.062	-0.069	-0.103	-0.017
95%	-0.053	-0.156	-0.074	-0.050	0.000	0.002	0.002	-0.054	0.000	-0.114	0.298	0.000	-0.003	0.014	0.000	0.130	0.000	-0.030	0.003	-0.005	-0.030	-0.066	-0.071	-0.137	-0.020
100%	-0.044	-0.036	-0.067	-0.050	0.000	0.002	0.002	-0.169	0.000	-0.155	0.324	0.000	-0.010	0.015	0.000	0.142	0.000	0.053	0.069	0.012	-0.030	-0.067	-0.087	-0.097	-0.038

(j) Model performance gap  $\Delta$  of RD experiment under ROC-AUC on Credit dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TF	TABR	NCA	LMA	TLLM	UNI	AVE	
5%	-0.008	-0.009	-0.005	-0.012	-0.007	-0.004	-0.006	-0.015	-0.012	-0.012	0.006	-0.011	0.003	-0.008	-0.009	0.004	-0.008	-0.007	0.004	-0.011	-0.014	-0.073	-0.073	-0.014		
10%	-0.017	-0.017	-0.018	-0.022	-0.002	-0.011	-0.007	-0.013	-0.013	-0.011	-0.002	-0.005	0.016	-0.009	-0.020	0.010	-0.013	-0.002	0.003	-0.007	-0.020	-0.083	-0.094	-0.042	-0.018	
15%	-0.026	-0.026	-0.025	-0.032	-0.015	0.005	-0.021	-0.033	-0.032	-0.024	-0.025	-0.056	-0.027	-0.019	-0.022	-0.002	0.011	-0.030	-0.016	-0.015	-0.019	-0.038	-0.092	-0.108	0.020	-0.024
20%	-0.050	-0.049	-0.035	-0.061	-0.007	0.009	-0.032	-0.043	-0.035	-0.042	-0.033	-0.030	0.027	-0.043	-0.030	-0.002	0.002	-0.036	-0.007	-0.017	-0.034	-0.042	-0.127	-0.095	-0.030	-0.035
25%	-0.041	-0.037	-0.047	-0.051	-0.005	-0.001	-0.042	-0.056	-0.059	-0.046	-0.053	-0.036	0.015	-0.033	-0.042	0.023	-0.055	-0.025	-0.008	-0.050	-0.070	-0.141	-0.116	-0.028	-0.041	
30%	-0.055	-0.050	-0.063	-0.064	-0.016	-0.020	-0.014	-0.022	-0.016	-0.024	-0.029	-0.019	0.027	-0.034	-0.019	0.040	-0.023	-0.004	0.001	-0.006	-0.033	-0.161	-0.118	0.031	-0.030	
35%	-0.063	-0.059	-0.070	-0.075	-0.024	-0.005	-0.017	-0.053	-0.045	-0.043	-0.026	-0.040	-0.016	-0.043	0.022	-0.059	-0.014	-0.020	-0.048	-0.053	-0.175	-0.121	-0.010	-0.046		
40%	-0.073	-0.067	-0.063	-0.067	0.006	0.033	-0.052	-0.065	-0.056	-0.029	-0.025	-0.023	-0.044	-0.021	0.034	-0.068	-0.008	-0.034	-0.044	-0.082	-0.166	-0.115	0.007	-0.046		
45%	-0.036	-0.034	-0.101	-0.051	0.003	0.025	-0.048	-0.082	-0.066	-0.068	0.000	-0.056	0.050	-0.077	0.014	-0.066	-0.034	-0.024	-0.052	-0.084	-0.170	-0.115	0.013	-0.049		
50%	-0.089	-0.083	-0.127	-0.106	0.012	0.052	-0.020	-0.037	-0.039	-0.022	-0.061	-0.002	-0.011	-0.035	0.010	-0.045	-0.041	0.000	-0.040	-0.017	-0.049	-0.212	-0.114	0.052	-0.043	
55%	-0.169	-0.167	-0.134	-0.182	-0.001	0.009	-0.064	-0.091	-0.081	-0.096	0.021	-0.046	0.001	-0.061	-0.040	0.055	-0.099	-0.019	-0.027	-0.088	-0.103	-0.211	-0.118	0.042	-0.079	
60%	-0.114	-0.115	-0.153	-0.118	-0.009	-0.026	-0.053	-0.104	-0.096	-0.095	-0.005	-0.085	0.005	-0.105	-0.047	0.008	-0.110	-0.065	-0.007	-0.089	-0.121	-0.247	-0.116	0.033	-0.083	
65%	-0.105	-0.103	-0.149	-0.118	-0.002	-0.008	-0.088	-0.129	-0.120	-0.107	-0.005	-0.088	-0.026	-0.082	-0.050	0.061	-0.146	-0.034	-0.054	-0.137	-0.163	-0.258	-0.111	0.048	-0.090	
70%	-0.103	-0.093	-0.206	-0.143	0.017	0.002	-0.089	-0.135	-0.127	-0.120	0.002	-0.084	-0.031	-0.083	-0.045	0.059	-0.140	-0.056	-0.021	-0.115	-0.143	-0.259	-0.121	0.046	-0.092	
75%	-0.145	-0.139	-0.222	-0.193	-0.005	-0.023	-0.108	-0.178	-0.158	-0.153	-0.015	-0.137	-0.004	-0.124	-0.052	0.041	-0.173	-0.082	-0.037	-0.154	-0.202	-0.271	-0.119	0.070	-0.118	
80%	-0.241	-0.228	-0.241	-0.272	-0.020	-0.003	-0.102	-0.162	-0.156	-0.135	-0.024	-0.097	-0.017	-0.098	-0.067	0.045	-0.172	-0.055	-0.022	-0.160	-0.207	-0.268	-0.123	0.097	-0.127	
85%	-0.175	-0.169	-0.256	-0.250	0.043	0.046	-0.127	-0.184	-0.188	-0.132	0.002	-0.073	-0.109	-0.095	-0.070	0.008	-0.188	-0.057	-0.047	-0.170	-0.222	-0.283	-0.119	0.141	-0.124	
90%	-0.247	-0.239	-0.292	-0.291	0.055	0.041	-0.129	-0.211	-0.191	-0.163	-0.035	-0.055	-0.092	-0.089	-0.064	0.002	-0.215	-0.072	-0.024	-0.204	-0.247	-0.285	-0.118	0.109	-0.143	
95%	-0.288	-0.282	-0.327	-0.319	0.028	0.008	-0.175	-0.243	-0.233	-0.193	-0.041	-0.138	-0.044	-0.124	-0.074	0.065	-0.247	-0.								

Table 15. Model performance on Electricity dataset.

(a) Model performance of SC experiment under accuracy on Electricity dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.913	0.913	0.953	0.861	0.847	0.863	0.729	0.873	0.829	0.843	0.857	0.871	0.861	0.862	0.863	0.794	0.878	0.834	0.720	0.940	0.985	0.804	0.921	0.858	0.861
1	-0.006	0.817	0.818	0.840	0.842	0.832	0.844	0.731	0.847	0.819	0.830	0.834	0.847	0.843	0.843	0.838	0.772	0.845	0.821	0.716	0.839	0.764	0.500	0.887	0.778	0.806
2	-0.048	0.905	0.906	0.925	0.851	0.839	0.852	0.727	0.859	0.828	0.835	0.847	0.857	0.850	0.850	0.853	0.798	0.857	0.828	0.751	0.852	0.881	0.501	0.888	0.864	0.834
3	0.065	0.906	0.905	0.945	0.849	0.848	0.863	0.728	0.873	0.836	0.843	0.856	0.871	0.860	0.862	0.863	0.794	0.876	0.834	0.722	0.937	0.976	0.501	0.920	0.858	0.847
4	-0.122	0.909	0.910	0.946	0.848	0.839	0.857	0.734	0.862	0.827	0.837	0.846	0.862	0.855	0.857	0.859	0.788	0.870	0.825	0.721	0.895	0.972	0.501	0.921	0.857	0.842
5	0.155	0.909	0.909	0.945	0.848	0.842	0.853	0.732	0.858	0.822	0.835	0.843	0.858	0.851	0.853	0.858	0.773	0.856	0.830	0.715	0.869	0.962	0.500	0.916	0.855	0.837
6	0.234	0.908	0.908	0.947	0.853	0.844	0.858	0.740	0.865	0.830	0.841	0.844	0.862	0.855	0.857	0.862	0.781	0.870	0.831	0.716	0.874	0.975	0.503	0.920	0.864	0.842
7	0.334	0.911	0.911	0.947	0.822	0.824	0.834	0.726	0.840	0.817	0.823	0.822	0.842	0.840	0.837	0.854	0.768	0.854	0.814	0.711	0.864	0.982	0.502	0.920	0.861	0.830
8	0.379	0.485	0.480	0.571	0.614	0.697	0.665	0.687	0.678	0.677	0.700	0.667	0.691	0.667	0.658	0.661	0.665	0.648	0.672	0.587	0.552	0.498	0.503	0.835	0.786	0.639

(b) Model performance of SC experiment under ROC-AUC on Electricity dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.913	0.913	0.953	0.861	0.847	0.863	0.729	0.873	0.829	0.843	0.857	0.871	0.861	0.862	0.863	0.794	0.878	0.834	0.720	0.940	0.985	0.804	0.921	0.858	0.861
1	-0.006	0.817	0.818	0.840	0.842	0.832	0.844	0.731	0.847	0.819	0.830	0.834	0.847	0.843	0.843	0.838	0.772	0.845	0.821	0.716	0.839	0.764	0.500	0.887	0.778	0.806
2	-0.048	0.905	0.906	0.925	0.851	0.839	0.852	0.727	0.859	0.828	0.835	0.847	0.857	0.850	0.850	0.853	0.798	0.857	0.828	0.751	0.852	0.881	0.501	0.888	0.864	0.834
3	0.065	0.906	0.905	0.945	0.849	0.848	0.863	0.728	0.873	0.836	0.843	0.856	0.871	0.860	0.862	0.863	0.794	0.876	0.834	0.722	0.937	0.976	0.501	0.920	0.858	0.847
4	-0.122	0.909	0.910	0.946	0.848	0.839	0.857	0.734	0.862	0.827	0.837	0.846	0.862	0.855	0.857	0.859	0.788	0.870	0.825	0.721	0.895	0.972	0.501	0.921	0.857	0.842
5	0.155	0.909	0.909	0.945	0.848	0.842	0.853	0.732	0.858	0.822	0.835	0.843	0.858	0.851	0.853	0.858	0.773	0.856	0.830	0.715	0.869	0.962	0.500	0.916	0.855	0.837
6	0.234	0.908	0.908	0.947	0.853	0.844	0.858	0.740	0.865	0.830	0.841	0.844	0.862	0.855	0.857	0.862	0.781	0.870	0.831	0.716	0.874	0.975	0.503	0.920	0.864	0.842
7	0.334	0.911	0.911	0.947	0.822	0.824	0.834	0.726	0.840	0.817	0.823	0.822	0.842	0.840	0.837	0.854	0.768	0.854	0.814	0.711	0.864	0.982	0.502	0.920	0.861	0.830
8	0.379	0.485	0.480	0.571	0.614	0.697	0.665	0.687	0.678	0.677	0.700	0.667	0.691	0.667	0.658	0.661	0.665	0.648	0.672	0.587	0.552	0.498	0.503	0.835	0.786	0.639

(c) Model performance of MC-M experiment under accuracy on Electricity dataset.

Degree	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	0.838	0.839	0.880	0.784	0.772	0.787	0.633	0.798	0.763	0.771	0.780	0.795	0.785	0.786	0.784	0.729	0.799	0.763	0.660	0.860	0.941	0.833	0.925	0.740	0.794	
12.5%	0.480	0.477	0.532	0.580	0.637	0.630	0.606	0.634	0.614	0.644	0.626	0.639	0.632	0.622	0.625	0.625	0.623	0.623	0.578	0.554	0.506	0.427	0.836	0.669	0.601	
25%	0.482	0.480	0.518	0.492	0.552	0.514	0.580	0.510	0.587	0.621	0.571	0.542	0.562	0.517	0.597	0.581	0.583	0.522	0.555	0.527	0.503	0.427	0.835	0.667	0.555	
37.5%	0.474	0.473	0.518	0.491	0.541	0.530	0.572	0.531	0.567	0.604	0.559	0.559	0.570	0.525	0.576	0.549	0.576	0.519	0.545	0.505	0.499	0.427	0.834	0.668	0.551	
50%	0.454	0.451	0.498	0.465	0.500	0.479	0.572	0.493	0.497	0.490	0.546	0.489	0.491	0.466	0.493	0.509	0.514	0.511	0.540	0.490	0.489	0.427	0.832	0.670	0.515	
62.5%	0.452	0.445	0.496	0.463	0.516	0.516	0.572	0.516	0.465	0.508	0.547	0.513	0.523	0.485	0.508	0.509	0.518	0.526	0.517	0.479	0.491	0.427	0.831	0.668	0.520	
75%	0.479	0.474	0.491	0.518	0.490	0.503	0.572	0.510	0.536	0.485	0.550	0.572	0.542	0.504	0.535	0.533	0.501	0.514	0.532	0.538	0.515	0.491	0.427	0.832	0.680	0.527
87.5%	0.487	0.483	0.501	0.526	0.523	0.572	0.572	0.572	0.549	0.500	0.572	0.572	0.544	0.559	0.535	0.501	0.514	0.532	0.538	0.493	0.496	0.427	0.847	0.706	0.547	
100%	0.426	0.426	0.426	0.475	0.524	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.572	0.476	0.476	0.524	0.572	0.428	0.428	0.428	0.427	0.852	0.618	0.509	

(d) Model performance of MC-M experiment under ROC-AUC on Electricity dataset.

Degree	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	0.838	0.839	0.880	0.784	0.772	0.787	0.633	0.798	0.763	0.771	0.780	0.795	0.785	0.786	0.784	0.729	0.799	0.763	0.660	0.860	0.941	0.833	0.925	0.740	0.794	
12.5%	0.633	0.636	0.655	0.770	0.762	0.766	0.633	0.768	0.754	0.760	0.762	0.769	0.767	0.762	0.761	0.705	0.759	0.651	0.659	0.705	0.427	0.889	0.678	0.639		
25%	0.647	0.653	0.687	0.763	0.762	0.768	0.631	0.768	0.758	0.765	0.760	0.751	0.758	0.752	0.753	0.708	0.764	0.656	0.647	0.765	0.500	0.833	0.782	0.564		
37.5%	0.647	0.644	0.523	0.495	0.547	0.536	0.622	0.543	0.535	0.531	0.558	0.548	0.523	0.573	0.608	0.546	0.508	0.550	0.501	0.499	0.500	0.482	0.832	0.781	0.552	
50%	0.432	0.429	0.498	0.480	0.516	0.500	0.550	0.509	0.413	0.581	0.493	0.517	0.517	0.479	0.501	0.525	0.492	0.522	0.489	0.446	0.487	0.500	0.429	0.779	0.522	
62.5%	0.437	0.434	0.496	0.480	0.549	0.500	0.550	0.509	0.413	0.581	0.493	0.517	0.517	0.479	0.501	0.525	0.492	0.522	0.489	0.446	0.487	0.500	0.429	0.779	0.522	
75%	0.47																									

(g) Model performance of RD experiment under accuracy on Electricity dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	0.838	0.839	0.880	0.784	0.772	0.787	0.633	0.798	0.763	0.771	0.780	0.795	0.785	0.786	0.784	0.729	0.799	0.763	0.660	0.860	0.941	0.833	0.925	0.740	0.794
12.5%	0.761	0.761	0.788	0.747	0.750	0.757	0.621	0.761	0.742	0.751	0.752	0.762	0.756	0.755	0.750	0.707	0.762	0.743	0.650	0.755	0.757	0.817	0.905	0.728	0.752
25%	0.693	0.693	0.716	0.714	0.727	0.726	0.610	0.727	0.721	0.729	0.724	0.731	0.727	0.724	0.715	0.682	0.729	0.721	0.638	0.663	0.664	0.764	0.877	0.704	0.713
37.5%	0.633	0.633	0.651	0.682	0.702	0.694	0.599	0.694	0.697	0.706	0.697	0.701	0.696	0.692	0.676	0.657	0.698	0.697	0.625	0.611	0.564	0.649	0.881	0.703	0.677
50%	0.579	0.579	0.593	0.649	0.706	0.697	0.598	0.694	0.690	0.699	0.695	0.703	0.691	0.688	0.647	0.639	0.687	0.692	0.622	0.579	0.538	0.639	0.867	0.686	0.661
62.5%	0.532	0.532	0.541	0.615	0.683	0.668	0.589	0.667	0.668	0.675	0.672	0.677	0.668	0.664	0.617	0.619	0.660	0.667	0.609	0.573	0.509	0.601	0.863	0.673	0.635
75%	0.491	0.491	0.495	0.578	0.614	0.595	0.577	0.596	0.612	0.602	0.616	0.606	0.591	0.586	0.551	0.573	0.599	0.614	0.575	0.518	0.489	0.538	0.857	0.655	0.584
87.5%	0.456	0.456	0.457	0.541	0.610	0.588	0.575	0.596	0.594	0.563	0.613	0.599	0.577	0.551	0.496	0.543	0.552	0.573	0.492	0.454	0.427	0.479	0.851	0.655	0.554
100%	0.426	0.426	0.426	0.475	0.524	0.572	0.572	0.569	0.476	0.524	0.572	0.476	0.476	0.428	0.476	0.524	0.572	0.428	0.428	0.428	0.427	0.851	0.618	0.511	

(h) Model performance of RD experiment under ROC-AUC on Electricity dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	0.913	0.913	0.953	0.861	0.847	0.863	0.729	0.873	0.829	0.843	0.857	0.871	0.861	0.862	0.863	0.794	0.878	0.834	0.720	0.940	0.985	0.804	0.921	0.858	0.861
12.5%	0.844	0.844	0.876	0.816	0.821	0.828	0.726	0.835	0.807	0.818	0.821	0.836	0.828	0.827	0.831	0.768	0.835	0.807	0.705	0.835	0.807	0.814	0.901	0.843	0.820
25%	0.780	0.779	0.814	0.774	0.791	0.791	0.721	0.795	0.781	0.790	0.782	0.799	0.791	0.789	0.796	0.739	0.793	0.777	0.688	0.720	0.711	0.761	0.873	0.827	0.777
37.5%	0.722	0.720	0.755	0.733	0.758	0.752	0.714	0.754	0.749	0.759	0.742	0.761	0.751	0.749	0.761	0.710	0.752	0.743	0.669	0.665	0.658	0.657	0.876	0.817	0.739
50%	0.670	0.667	0.699	0.692	0.754	0.748	0.713	0.744	0.736	0.752	0.740	0.753	0.744	0.740	0.762	0.698	0.750	0.733	0.667	0.653	0.636	0.647	0.858	0.813	0.724
62.5%	0.623	0.621	0.648	0.649	0.721	0.710	0.704	0.705	0.693	0.723	0.702	0.716	0.704	0.704	0.739	0.677	0.718	0.696	0.641	0.618	0.570	0.616	0.856	0.806	0.690
75%	0.582	0.579	0.599	0.603	0.639	0.619	0.657	0.617	0.609	0.649	0.611	0.630	0.609	0.610	0.649	0.616	0.630	0.624	0.581	0.605	0.530	0.569	0.847	0.810	0.628
87.5%	0.544	0.542	0.558	0.555	0.638	0.582	0.648	0.629	0.567	0.635	0.615	0.633	0.590	0.552	0.655	0.619	0.578	0.558	0.516	0.530	0.835	0.811	0.601		
100%	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.498	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.501	0.500	0.835	0.803	0.527

 (i) Model performance gap  $\Delta$  of RD experiment under accuracy on Electricity dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
12.5%	-0.092	-0.093	-0.105	-0.047	-0.028	-0.038	-0.019	-0.046	-0.027	-0.026	-0.036	-0.042	-0.036	-0.039	-0.043	-0.031	-0.046	-0.026	-0.015	-0.123	-0.195	-0.020	-0.021	-0.017	-0.053
25%	-0.173	-0.174	-0.187	-0.088	-0.058	-0.077	-0.037	-0.089	-0.056	-0.054	-0.073	-0.080	-0.073	-0.079	-0.088	-0.065	-0.088	-0.056	-0.034	-0.229	-0.294	-0.083	-0.052	-0.049	-0.101
37.5%	-0.245	-0.246	-0.261	-0.130	-0.090	-0.117	-0.053	-0.131	-0.086	-0.084	-0.108	-0.118	-0.113	-0.120	-0.137	-0.100	-0.127	-0.087	-0.053	-0.290	-0.401	-0.221	-0.047	-0.050	-0.147
50%	-0.309	-0.309	-0.327	-0.172	-0.085	-0.114	-0.054	-0.131	-0.096	-0.093	-0.110	-0.116	-0.119	-0.124	-0.175	-0.124	-0.141	-0.093	-0.058	-0.326	-0.428	-0.232	-0.062	-0.074	-0.167
62.5%	-0.366	-0.366	-0.385	-0.216	-0.115	-0.150	-0.070	-0.165	-0.125	-0.124	-0.139	-0.149	-0.148	-0.156	-0.213	-0.151	-0.173	-0.126	-0.077	-0.334	-0.459	-0.278	-0.067	-0.091	-0.200
75%	-0.415	-0.415	-0.437	-0.263	-0.205	-0.244	-0.087	-0.254	-0.198	-0.219	-0.210	-0.238	-0.247	-0.254	-0.297	-0.214	-0.250	-0.196	-0.128	-0.398	-0.480	-0.354	-0.073	-0.116	-0.264
87.5%	-0.456	-0.457	-0.480	-0.310	-0.209	-0.253	-0.092	-0.254	-0.222	-0.269	-0.215	-0.247	-0.265	-0.299	-0.367	-0.255	-0.309	-0.249	-0.254	-0.472	-0.546	-0.425	-0.080	-0.115	-0.302
100%	-0.492	-0.492	-0.516	-0.395	-0.321	-0.273	-0.096	-0.284	-0.255	-0.382	-0.329	-0.281	-0.393	-0.394	-0.453	-0.347	-0.344	-0.251	-0.351	-0.502	-0.545	-0.487	-0.079	-0.165	-0.356

 (j) Model performance gap  $\Delta$  of RD experiment under ROC-AUC on Electricity dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
12.5%	-0.075	-0.076	-0.080	-0.052	-0.031	-0.041	-0.005	-0.043	-0.026	-0.029	-0.042	-0.040	-0.038	-0.041	-0.037	-0.034	-0.049	-0.032	-0.021	-0.111	-0.181	0.013	-0.022	-0.018	-0.048
25%	-0.145	-0.147	-0.146	-0.101	-0.066	-0.084	-0.011	-0.089	-0.058	-0.063	-0.088	-0.082	-0.085	-0.078	-0.070	-0.097	-0.069	-0.044	-0.234	-0.278	-0.053	-0.053	-0.037	-0.097	
37.5%	-0.209	-0.211	-0.208	-0.148	-0.105	-0.129	-0.021	-0.136	-0.097	-0.100	-0.134	-0.126	-0.128	-0.131	-0.119	-0.107	-0.143	-0.109	-0.071	-0.292	-0.332	-0.182	-0.048	-0.142	
50%	-0.266	-0.266	-0.266	-0.196	-0.110	-0.133	-0.023	-0.148	-0.112	-0.108	-0.136	-0.136	-0.136	-0.136	-0.117	-0.121	-0.145	-0.121	-0.073	-0.305	-0.354	-0.194	-0.068	-0.052	-0.160
62.5%	-0.317	-0.320	-0.320	-0.246	-0.149	-0.178	-0.034	-0.193	-0.164	-0.142	-0.181	-0.178	-0.183	-0.183	-0.144	-0.147	-0.182	-0.166	-0.110	-0.342	-0.421	-0.234	-0.071	-0.062	-0.199
75%	-0.362	-0.365	-0.371	-0.299	-0.245	-0.282	-0.099	-0.293	-0.265	-0.230	-0.287	-0.276	-0.292	-0.292	-0.248	-0.224	-0.283	-0.252	-0.193	-0.357	-0.461	-0.292	-0.080	-0.057	-0.271
87.5%	-0.404	-0.406	-0.414	-0.355	-0.246	-0.326	-0.111	-0.280	-0.317	-0.246	-0.283	-0.273	-0.315	-0.360	-0.241	-0.220	-0.342	-0.331	-0.283	-0.436	-0.480	-0.341	-0.094	-0.055	-0.302
100%	-0.452	-0.452	-0.475	-0.419	-0.410	-0.421	-0.314	-0.427	-0.399	-0.407	-0.417	-0.428	-0.419	-0.420	-0.421	-0.370	-0.428	-0.400	-0.305	-0.470	-0.491	-0.378	-0.093	-0.064	-0.389</

**Table 16.** Model performance on Heart dataset.

(a) Model performance of SC experiment under accuracy on Heart dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.833	0.855	0.879	0.862	0.674	0.848	0.663	0.857	0.871	0.775	0.681	0.859	0.683	0.868	0.774	0.580	0.875	0.788	0.522	0.893	0.880	0.848	0.783	0.853	0.792
1	0.057	0.837	0.859	0.870	0.866	0.683	0.857	0.667	0.861	0.871	0.788	0.687	0.864	0.685	0.870	0.777	0.594	0.880	0.788	0.522	0.889	0.882	0.853	0.788	0.870	0.796
2	0.108	0.839	0.855	0.871	0.862	0.659	0.855	0.645	0.866	0.879	0.779	0.705	0.866	0.701	0.868	0.784	0.603	0.880	0.784	0.529	0.895	0.879	0.851	0.804	0.853	0.796
3	-0.233	0.817	0.824	0.864	0.859	0.674	0.839	0.649	0.842	0.862	0.781	0.685	0.859	0.654	0.851	0.772	0.592	0.861	0.797	0.516	0.879	0.877	0.843	0.804	0.837	0.785
4	0.267	0.828	0.844	0.861	0.861	0.683	0.864	0.636	0.864	0.853	0.750	0.668	0.871	0.674	0.864	0.797	0.591	0.868	0.775	0.522	0.891	0.895	0.856	0.799	0.853	0.790
5	0.282	0.822	0.833	0.875	0.866	0.676	0.855	0.621	0.870	0.888	0.766	0.656	0.875	0.696	0.875	0.752	0.607	0.866	0.803	0.524	0.895	0.880	0.821	0.783	0.864	0.790
6	0.305	0.821	0.792	0.859	0.857	0.654	0.837	0.643	0.855	0.868	0.784	0.665	0.861	0.692	0.848	0.772	0.585	0.870	0.788	0.487	0.893	0.880	0.807	0.761	0.837	0.780
7	-0.387	0.784	0.803	0.844	0.853	0.679	0.846	0.647	0.851	0.868	0.772	0.634	0.861	0.690	0.861	0.730	0.567	0.870	0.766	0.504	0.888	0.877	0.752	0.810	0.864	0.776
8	-0.400	0.846	0.850	0.866	0.873	0.665	0.839	0.654	0.857	0.855	0.779	0.679	0.859	0.643	0.846	0.761	0.591	0.861	0.755	0.524	0.895	0.877	0.728	0.788	0.859	0.781
9	0.404	0.830	0.833	0.871	0.868	0.647	0.837	0.641	0.859	0.862	0.775	0.674	0.850	0.672	0.859	0.774	0.605	0.861	0.763	0.522	0.900	0.880	0.734	0.793	0.826	0.781
10	0.494	0.821	0.828	0.864	0.871	0.666	0.839	0.630	0.848	0.850	0.741	0.643	0.859	0.699	0.833	0.764	0.596	0.851	0.764	0.529	0.899	0.897	0.723	0.772	0.842	0.776
11	-0.559	0.736	0.750	0.663	0.681	0.582	0.808	0.639	0.824	0.835	0.721	0.656	0.835	0.659	0.832	0.694	0.596	0.832	0.770	0.487	0.853	0.788	0.674	0.761	0.848	0.736

(b) Model performance of SC experiment under ROC-AUC on Heart dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.902	0.909	0.938	0.939	0.727	0.931	0.881	0.937	0.949	0.867	0.706	0.947	0.784	0.938	0.865	0.626	0.955	0.865	0.448	0.961	0.960	0.653	0.773	0.911	0.849
1	0.057	0.903	0.910	0.932	0.934	0.732	0.934	0.880	0.936	0.951	0.874	0.732	0.945	0.793	0.942	0.878	0.623	0.954	0.861	0.465	0.958	0.961	0.629	0.786	0.894	0.850
2	0.108	0.905	0.910	0.936	0.936	0.734	0.940	0.883	0.940	0.950	0.878	0.745	0.949	0.797	0.938	0.872	0.628	0.957	0.871	0.447	0.959	0.958	0.727	0.797	0.894	0.856
3	-0.233	0.889	0.900	0.932	0.937	0.734	0.926	0.871	0.926	0.944	0.872	0.721	0.940	0.749	0.925	0.847	0.623	0.951	0.869	0.457	0.955	0.950	0.739	0.804	0.904	0.849
4	0.267	0.898	0.905	0.929	0.931	0.747	0.929	0.884	0.939	0.947	0.856	0.701	0.942	0.766	0.932	0.879	0.620	0.951	0.861	0.456	0.957	0.958	0.735	0.795	0.900	0.851
5	0.282	0.905	0.912	0.939	0.939	0.734	0.937	0.889	0.940	0.953	0.870	0.689	0.952	0.786	0.938	0.841	0.642	0.955	0.876	0.435	0.963	0.960	0.815	0.771	0.908	0.856
6	0.305	0.888	0.898	0.923	0.929	0.681	0.925	0.890	0.932	0.944	0.874	0.702	0.944	0.712	0.933	0.871	0.607	0.951	0.839	0.422	0.960	0.950	0.653	0.761	0.901	0.837
7	-0.387	0.868	0.876	0.920	0.919	0.735	0.913	0.859	0.922	0.929	0.846	0.670	0.928	0.756	0.932	0.814	0.591	0.936	0.841	0.413	0.939	0.938	0.584	0.796	0.904	0.826
8	-0.400	0.920	0.922	0.934	0.936	0.737	0.919	0.865	0.930	0.943	0.875	0.706	0.937	0.720	0.915	0.845	0.630	0.949	0.833	0.456	0.958	0.958	0.679	0.782	0.906	0.844
9	0.404	0.896	0.905	0.927	0.937	0.743	0.930	0.873	0.935	0.948	0.855	0.714	0.948	0.769	0.924	0.859	0.655	0.953	0.836	0.493	0.964	0.965	0.687	0.790	0.906	0.850
10	0.494	0.891	0.900	0.932	0.938	0.725	0.920	0.862	0.925	0.945	0.810	0.698	0.936	0.808	0.921	0.863	0.623	0.951	0.851	0.431	0.958	0.960	0.672	0.764	0.901	0.841
11	-0.559	0.848	0.861	0.856	0.908	0.651	0.910	0.843	0.918	0.930	0.826	0.691	0.935	0.720	0.920	0.794	0.646	0.936	0.851	0.457	0.942	0.949	0.500	0.750	0.896	0.813

(c) Model performance of MC-M experiment under accuracy on Heart dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	0.833	0.855	0.879	0.862	0.674	0.848	0.663	0.857	0.871	0.775	0.681	0.859	0.683	0.868	0.774	0.589	0.875	0.788	0.522	0.893	0.880	0.848	0.783	0.853	0.792
9%	0.736	0.750	0.663	0.817	0.582	0.808	0.639	0.824	0.835	0.721	0.656	0.835	0.659	0.832	0.694	0.596	0.832	0.770	0.487	0.853	0.788	0.674	0.777	0.842	0.736
18%	0.665	0.737	0.663	0.97	0.571	0.783	0.616	0.781	0.821	0.665	0.616	0.793	0.665	0.797	0.681	0.596	0.792	0.732	0.509	0.842	0.739	0.685	0.783	0.859	0.716
27%	0.634	0.688	0.730	0.779	0.585	0.750	0.603	0.766	0.790	0.645	0.623	0.763	0.629	0.763	0.678	0.596	0.755	0.692	0.529	0.817	0.714	0.707	0.793	0.810	0.702
36%	0.625	0.710	0.779	0.777	0.594	0.701	0.571	0.745	0.752	0.650	0.583	0.717	0.758	0.658	0.625	0.583	0.703	0.638	0.527	0.774	0.712	0.707	0.772	0.784	0.680
45%	0.625	0.592	0.638	0.688	0.591	0.652	0.529	0.696	0.719	0.600	0.527	0.665	0.553	0.661	0.520	0.571	0.634	0.596	0.518	0.725	0.694	0.576	0.772	0.810	0.631
54%	0.562	0.603	0.621	0.76	0.499	0.607	0.543	0.630	0.692	0.641	0.558	0.652	0.505	0.587	0.538	0.522	0.596	0.527	0.491	0.612	0.607	0.560	0.772	0.821	0.601
63%	0.551	0.565	0.643	0.663	0.496	0.533	0.543	0.620	0.645	0.574	0.540	0.609	0.486	0.558	0.505	0.562	0.571	0.529	0.480	0.582	0.616	0.571	0.788	0.799	0.584
72%	0.527	0.556	0.603	0.596	0.525	0.533	0.545	0.645	0.565	0.558	0.493	0.531	0.522	0.543	0.514	0.547	0.565	0.502	0.493	0.572	0.565	0.576	0.799	0.788	0.569
81%	0.518	0.495	0.491	0.536	0.531	0.524	0.524	0.594	0.538	0.529	0.495	0.533	0.525	0.505	0.505	0.553	0.533	0.509	0.493	0.531	0.533	0.554	0.755	0.750	0.544
90%	0.536	0.482	0.464	0.554	0.524	0.533	0.502	0.547	0.520	0.538	0.480	0.533	0.507	0.471	0.501	0.560	0.493	0.524	0.486	0.511	0.511	0.582	0.739	0.723	0.534
100%	0.536	0.482	0.464	0.518	0.533	0.533	0.533	0.467	0.511	0.489	0.511	0.533	0.467	0.533	0.533	0.489	0.489	0.467	0.511	0.511	0.582	0.717	0.712	0.527	

(d) Model performance of MC-M experiment under ROC-AUC on Heart dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	0.902	0.909	0.938	0.939	0.727	0.931	0.881	0.937	0.949	0.867	0.706	0.947	0.784	0.938	0.865	0.626	0.955	0.865	0.448	0.961	0.960	0.653	0.773	0.911	0.849
9%	0.848	0.861	0.856	0.908	0.651	0.910	0.843	0.918	0.930	0.826	0.691	0.935	0.720	0.920	0.794	0.646	0.936	0.851	0.457	0.942	0.919	0.630	0.762	0.888	0.818
18%	0.817	0.832	0.811	0.897	0.613	0.887	0.819	0.892	0.911	0.737	0.651	0.917	0.738	0.887	0.783	0.639	0.923	0.805	0.442	0.928	0.904	0.649	0.771	0.894	0.798
27%	0.789	0.810	0.834	0.862	0.592	0.858	0.781	0.861	0.871	0.685	0.640	0.889	0.715	0.845	0.805	0.641	0.893	0.757	0.496	0.893	0.861	0.680	0.782	0.896	0.781
36%	0.832	0.836	0.841	0.856	0.588	0.826	0.747	0.841	0.839	0.706	0.639	0.860	0.677	0.771	0.766	0.615	0.870	0.711	0.510	0.862	0.861	0.691	0.762	0.895	0.767
45%	0.727	0.727	0.741	0.760	0.618	0.779	0.677	0.786	0.777	0.650	0.552	0.805	0.593	0.756	0.644	0.581	0.798	0.656	0.473	0.794	0.790	0.515	0.753	0.899	0.702
54%	0.679	0.685	0.692	0.731	0.542	0.731	0.708	0.728	0.750	0.673	0.561	0.768	0.530	0.701	0.649	0.531	0.752	0.571	0.493	0.724	0.708	0.492	0.760	0.877	0.668
63%	0.688	0.696	0.723	0.713	0.532	0.677	0.667	0.699	0.712	0.597	0.548	0.719	0.538	0.683	0.537	0.531	0.680	0.539	0.439	0.701	0.698	0.491	0.775	0.888	0.645
72%	0.657	0.665	0.671	0.615	0.548	0.663	0.662	0.696	0.622	0.552	0.477	0.710	0.558	0.635	0.562	0.528	0.645	0.497	0.478	0.696	0.648	0.501	0.791	0.878	0.623
81%	0.523	0.506	0.549	0.563	0.520	0.599	0.554	0.612	0.554	0.536	0.475	0.642	0.535	0.531	0.467	0.507	0.566	0.535	0.496	0.591	0.537	0.493	0.764	0.874	0.564
90%	0.428	0.441	0.511	0.511	0.518	0.588	0.537	0.580	0.526	0.537	0.447	0.611	0.482	0.482	0.518	0.518	0.498	0.553	0.471	0.580	0.482	0.500	0.747	0.874	0.539
100%	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.732	0.856	0.525

(e) Model performance of MC-L experiment under accuracy on Heart dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	0.833	0.855	0.879	0.862	0.674	0.848	0.663	0.857	0.871	0.775	0.681	0.859	0.683	0.868	0.774	0.589	0.875	0.788	0.522	0.893	0.880	0.848	0.783	0.853	0.792
9%	0.837	0.859	0.870	0.866	0.683	0.857	0.667	0.861	0.871	0.788	0.687	0.864	0.685	0.870	0.777	0.594	0.880	0.788	0.522	0.889	0.882	0.853	0.788	0.870	0.796
18%	0.842	0.857	0.871	0.861	0.668	0.862	0.652	0.864	0.875	0.795	0.685	0.871	0.712	0.871	0.793	0.600	0.879	0.783	0.516	0.819	0.879	0.804	0.815	0.837	0.795
27%	0.817	0.830	0.844	0.855	0.690	0.850	0.647	0.850	0.866	0.810	0.690	0.862	0.685	0.861	0.781	0.585	0.861	0.793	0.516	0.875	0.875	0.793	0.788	0.853	0.787
36%	0.824	0.808	0.832	0.855	0.730	0.857	0.634	0.841	0.846	0.790	0.699	0.861	0.685	0.857	0.797	0.603	0.855	0.788	0.513	0.866	0.862	0.810	0.799	0.832	0.785
45%	0.813	0.788	0.830	0.853	0.732	0.871	0.611	0.850	0.861	0.783	0.659	0.862	0.685	0.870	0.779	0.658	0.855	0.793	0.525	0.862	0.866	0.766	0.761	0.859	0.783
54%	0.795	0.674	0.826	0.824	0.721	0.846	0.632	0.866	0.841	0.817	0.634	0.848	0.667	0.851	0.763	0.582	0.846	0.781	0.460	0.873	0.862	0.793	0.739	0.842	0.766
63%	0.716	0.690	0.804	0.808	0.730	0.861	0.630	0.846	0.832	0.806	0.612	0.850	0.710	0.846	0.723	0.504	0.833	0.743	0.438	0.830	0.832	0.793	0.712	0.777	0.747
72%	0.663	0.667	0.797	0.808	0.723	0.817	0.638	0.812	0.790	0.828	0.540	0.810	0.663	0.848	0.618	0.571	0.826	0.743	0.509	0.835	0.832	0.793	0.728	0.842	0.737
81%	0.763	0.663	0.721	0.799	0.746	0.853	0.638	0.793	0.853	0.853	0.457	0.853	0.679	0.853	0.638	0.596	0.826	0.560	0.496	0.948	0.821	0.788	0.723	0.788	0.734
90%	0.790	0.663	0.464	0.799	0.743	0.848	0.638	0.848	0.848	0.848	0.511	0.848	0.594	0.743	0.533	0.406	0.743	0.616	0.467	0.848	0.848	0.761	0.707	0.766	0.703
100%	0.536	0.482	0.464	0.518	0.523	0.532	0.522	0.467	0.511	0.489	0.511	0.532	0.467	0.532	0.523	0.489	0.467	0.511	0.582	0.717	0.714	0.522			

(f) Model performance of MC-L experiment under ROC-AUC on Heart dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	0.902	0.909	0.938	0.939	0.727	0.931	0.881	0.937	0.949	0.867	0.706	0.947	0.784	0.938	0.865	0.626	0.955	0.865	0.448	0.961	0.960	0.653	0.773	0.911	0.849
9%	0.903	0.910	0.932	0.934	0.732	0.934	0.880	0.936	0.951	0.874	0.732	0.945	0.793	0.942	0.878	0.623	0.954	0.861	0.465	0.958	0.961	0.629	0.786	0.896	0.850
18%	0.907	0.910	0.929	0.931	0.732	0.944	0.883	0.939	0.951	0.884	0.748	0.948	0.814	0.944	0.886	0.616	0.956	0.869	0.462	0.957	0.960	0.812	0.817	0.898	0.862
27%	0.899	0.905	0.924	0.930	0.742	0.937	0.876	0.928	0.946	0.889	0.757	0.940	0.777	0.938	0.872	0.613	0.952	0.873	0.461	0.951	0.954	0.804	0.794	0.914	0.857
36%	0.892	0.897	0.916	0.920	0.746	0.934	0.879	0.929	0.944	0.881	0.772	0.933	0.766	0.931	0.888	0.609	0.947	0.873	0.477	0.948	0.950	0.822	0.805	0.905	0.857
45%	0.897	0.902	0.917	0.920	0.751	0.936	0.893	0.932	0.946	0.884	0.733	0.937	0.779	0.935	0.877	0.642	0.948	0.884	0.468	0.947	0.951	0.786	0.767	0.918	0.856
54%	0.877	0.882	0.899	0.906	0.672	0.927	0.906	0.924	0.936	0.897	0.756	0.930	0.700	0.929	0.889	0.609	0.941	0.873	0.428	0.942	0.944	0.815	0.755	0.902	0.843
63%	0.820	0.827	0.875	0.880	0.689	0.910	0.891	0.911	0.909	0.874	0.711	0.909	0.691	0.926	0.858	0.502	0.919	0.841	0.318	0.915	0.914	0.795	0.724	0.888	0.812
72%	0.851	0.846	0.866	0.870	0.718	0.896	0.883	0.898	0.887	0.871	0.664	0.896	0.643	0.891	0.776	0.512	0.906	0.751	0.350	0.905	0.916	0.795	0.744	0.911	0.802
81%	0.844	0.843	0.852	0.847	0.843	0.869	0.883	0.883	0.889	0.894	0.409	0.874	0.740	0.877	0.620	0.621	0.892	0.631	0.564	0.894	0.898	0.796	0.737	0.876	0.795
90%	0.801	0.801	0.801	0.794	0.836	0.836	0.836	0.836	0.836	0.842	0.836	0.836	0.612	0.836	0.612	0.410	0.849	0.612	0.186	0.842	0.842	0.773	0.723	0.887	0.753
100%	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.732	0.856	0.525

(g) Model performance of RD experiment under accuracy on Heart dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	0.833	0.855	0.879	0.862	0.674	0.848	0.663	0.857	0.871	0.775	0.681	0.859	0.683	0.868	0.774	0.589	0.875	0.788	0.522	0.893	0.880	0.848	0.783	0.853	0.792
9%	0.816	0.825	0.851	0.859	0.661	0.843	0.640	0.856	0.864	0.781	0.667	0.859	0.674	0.857	0.760	0.593	0.864	0.779	0.513	0.889	0.872	0.772	0.793	0.847	0.781
18%	0.794	0.798	0.826	0.848	0.649	0.833	0.622	0.849	0.858	0.772	0.661	0.853	0.656	0.846	0.742	0.599	0.849	0.767	0.516	0.886	0.850	0.752	0.793	0.835	0.769
27%	0.772	0.773	0.801	0.835	0.633	0.821	0.603	0.836	0.844	0.767	0.631	0.838	0.656	0.827	0.718	0.585	0.832	0.750	0.502	0.878	0.833	0.721	0.780	0.831	0.753
36%	0.748	0.747	0.775	0.820	0.655	0.821	0.622	0.831	0.848	0.772	0.620	0.842	0.664	0.825	0.708	0.605	0.834	0.755	0.511	0.844	0.842	0.708	0.778	0.831	0.750
45%	0.722	0.720	0.747	0.803	0.633	0.803	0.621	0.820	0.831	0.761	0.617	0.826	0.643	0.809	0.684	0.583	0.811	0.727	0.513	0.829	0.816	0.677	0.777	0.821	0.733
54%	0.693	0.692	0.716	0.784	0.617	0.792	0.603	0.815	0.823	0.758	0.611	0.814	0.629	0.783	0.667	0.572	0.796	0.717	0.510	0.810	0.787	0.683	0.777	0.827	0.720
63%	0.662	0.662	0.682	0.762	0.632	0.779	0.592	0.801	0.813	0.732	0.590	0.795	0.601	0.786	0.633	0.583	0.748	0.699	0.492	0.800	0.756	0.672	0.773	0.804	0.702
72%	0.629	0.628	0.643	0.734	0.557	0.723	0.571	0.762	0.777	0.725	0.572	0.763	0.604	0.693	0.578	0.562	0.721	0.695	0.483	0.753	0.761	0.655	0.754	0.790	0.672
81%	0.597	0.589	0.596	0.695	0.585	0.718	0.591	0.740	0.764	0.718	0.539	0.726	0.595	0.722	0.577	0.561	0.663	0.665	0.494	0.735	0.693	0.651	0.742	0.784	0.656
90%	0.568	0.545	0.541	0.638	0.552	0.621	0.529	0.653	0.674	0.640	0.531	0.627	0.564	0.617	0.540	0.535	0.584	0.617	0.482	0.637	0.596	0.622	0.724	0.782	0.601
100%	0.536	0.482	0.464	0.518	0.533	0.533	0.467	0.511	0.489	0.511	0.533	0.467	0.533	0.489	0.533	0.489	0.533	0.489	0.511	0.511	0.582	0.717	0.712	0.527	

(h) Model performance of RD experiment under ROC-AUC on Heart dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	0.902	0.909	0.938	0.939	0.727	0.931	0.881	0.937	0.949	0.867	0.706	0.947	0.784	0.938	0.865	0.626	0.955	0.865	0.448	0.961	0.960	0.653	0.773	0.911	0.849
9%	0.892	0.900	0.930	0.931	0.723	0.927	0.874	0.933	0.945	0.868	0.708	0.942	0.755	0.930	0.850	0.625	0.949	0.855	0.450	0.955	0.951	0.773	0.787	0.903	0.848
18%	0.881	0.889	0.917	0.922	0.712	0.921	0.872	0.926	0.939	0.858	0.706	0.937	0.728	0.918	0.837	0.633	0.944	0.837	0.456	0.947	0.943	0.753	0.792	0.897	0.840
27%	0.868	0.877	0.903	0.911	0.683	0.913	0.839	0.917	0.930	0.851	0.679	0.927	0.699	0.911	0.821	0.620	0.934	0.828	0.443	0.949	0.931	0.721	0.776	0.896	0.826
36%	0.853	0.862	0.887	0.898	0.701	0.914	0.870	0.910	0.930	0.856	0.679	0.925	0.717	0.903	0.822	0.614	0.934	0.823	0.436	0.925	0.936	0.703	0.775	0.898	0.825
45%	0.835	0.843	0.867	0.882	0.713	0.909	0.844	0.899	0.915	0.841	0.678	0.908	0.704	0.886	0.784	0.617	0.919	0.796	0.460	0.910	0.917	0.668	0.776	0.888	0.810
54%	0.814	0.820	0.844	0.862	0.664	0.890	0.832	0.888	0.901	0.835	0.676	0.899	0.667	0.856	0.789	0.617	0.908	0.774	0.478	0.889	0.906	0.667	0.772	0.892	0.798
63%	0.786	0.792	0.815	0.834	0.686	0.872	0.762	0.866	0.880	0.810	0.636	0.883	0.639	0.863	0.775	0.610	0.889	0.752	0.459	0.874	0.861	0.650	0.769	0.881	0.777
72%	0.750	0.754	0.776	0.796	0.596	0.834	0.767	0.828	0.847	0.787	0.634	0.845	0.623	0.784	0.712	0.606	0.855	0.743	0.475	0.834	0.838	0.623	0.755	0.885	0.748
81%	0.698	0.700	0.721	0.739	0.642	0.818	0.711	0.789	0.808	0.703	0.600	0.824	0.619	0.795	0.738	0.586	0.829	0.688	0.459	0.796	0.774	0.612	0.749	0.872	0.722
90%	0.618	0.620	0.638	0.651	0.537	0.708	0.603	0.686	0.682	0.678	0.577	0.704	0.540	0.663	0.618	0.559	0.695	0.622	0.458	0.695	0.680	0.565	0.734	0.879	0.642
100%	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.732	0.856	0.525

 (j) Model performance gap  $\Delta$  of RD experiment under ROC-AUC on Heart dataset.

Degree	LGB</th

## TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments

**Table 17.** Model performance on MiniBooNE dataset.

(a) Model performance of SC experiment under accuracy on MiniBooNE dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.925	0.925	0.943	0.917	0.873	0.893	0.772	0.907	0.858	0.870	0.902	0.904	0.888	0.888	0.832	0.914	0.824	0.862	0.920	0.940	0.922	0.914	0.946	0.892	
1	-0.004	0.925	0.925	0.942	0.792	0.873	0.893	0.772	0.906	0.873	0.869	0.870	0.902	0.904	0.888	0.888	0.830	0.914	0.824	0.862	0.918	0.934	0.567	0.915	0.947	0.872
2	-0.018	0.925	0.925	0.942	0.907	0.853	0.880	0.768	0.890	0.863	0.856	0.867	0.890	0.895	0.877	0.881	0.821	0.909	0.811	0.846	0.916	0.938	0.571	0.914	0.944	0.870
3	0.022	0.925	0.925	0.943	0.917	0.868	0.891	0.772	0.904	0.857	0.867	0.868	0.898	0.902	0.886	0.884	0.828	0.913	0.823	0.858	0.919	0.939	0.578	0.914	0.947	0.876
4	0.024	0.923	0.922	0.942	0.917	0.871	0.891	0.772	0.906	0.855	0.869	0.870	0.899	0.900	0.887	0.886	0.830	0.909	0.824	0.861	0.917	0.938	0.600	0.915	0.946	0.877
5	0.026	0.924	0.924	0.943	0.915	0.859	0.879	0.770	0.902	0.853	0.851	0.868	0.890	0.893	0.875	0.877	0.826	0.911	0.798	0.847	0.920	0.937	0.579	0.915	0.872	0.867
6	0.027	0.918	0.919	0.940	0.914	0.873	0.893	0.772	0.907	0.858	0.870	0.869	0.902	0.902	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.604	0.915	0.947	0.878
7	0.028	0.860	0.861	0.925	0.893	0.869	0.891	0.772	0.904	0.856	0.869	0.855	0.899	0.897	0.887	0.887	0.831	0.903	0.824	0.861	0.767	0.910	0.597	0.894	0.936	0.860
8	0.030	0.925	0.925	0.943	0.916	0.870	0.892	0.772	0.904	0.856	0.869	0.871	0.901	0.903	0.887	0.887	0.830	0.914	0.825	0.861	0.920	0.940	0.559	0.914	0.945	0.876
9	0.032	0.920	0.920	0.943	0.915	0.872	0.893	0.772	0.907	0.858	0.870	0.869	0.902	0.903	0.888	0.888	0.830	0.914	0.825	0.862	0.920	0.940	0.592	0.914	0.946	0.878
10	-0.035	0.921	0.920	0.939	0.913	0.865	0.883	0.770	0.892	0.852	0.864	0.862	0.890	0.888	0.878	0.868	0.829	0.907	0.822	0.858	0.910	0.939	0.594	0.913	0.946	0.872
11	0.033	0.917	0.917	0.935	0.915	0.872	0.893	0.772	0.907	0.858	0.870	0.870	0.901	0.904	0.888	0.888	0.831	0.914	0.824	0.862	0.918	0.916	0.632	0.895	0.926	0.876
12	0.037	0.923	0.924	0.943	0.914	0.872	0.893	0.772	0.907	0.858	0.870	0.870	0.902	0.903	0.888	0.888	0.830	0.914	0.824	0.862	0.918	0.936	0.608	0.913	0.944	0.878
13	-0.037	0.924	0.923	0.943	0.909	0.872	0.893	0.772	0.907	0.858	0.870	0.870	0.902	0.903	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.597	0.913	0.945	0.873
14	0.040	0.919	0.919	0.940	0.904	0.872	0.893	0.772	0.906	0.857	0.870	0.869	0.902	0.904	0.888	0.888	0.830	0.914	0.824	0.862	0.910	0.945	0.569	0.913	0.945	0.871
15	0.042	0.906	0.906	0.938	0.913	0.872	0.893	0.772	0.906	0.858	0.870	0.870	0.902	0.903	0.888	0.888	0.831	0.914	0.824	0.862	0.919	0.936	0.584	0.914	0.944	0.875
16	0.044	0.906	0.906	0.938	0.913	0.872	0.893	0.772	0.907	0.858	0.870	0.870	0.902	0.903	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.595	0.913	0.946	0.876
17	0.046	0.922	0.920	0.943	0.911	0.872	0.893	0.772	0.907	0.858	0.870	0.869	0.902	0.904	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.593	0.915	0.944	0.874
18	0.048	0.924	0.924	0.943	0.904	0.873	0.893	0.772	0.906	0.857	0.870	0.869	0.902	0.902	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.597	0.912	0.947	0.875
19	0.042	0.919	0.919	0.941	0.904	0.872	0.893	0.772	0.906	0.857	0.870	0.870	0.902	0.903	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.595	0.913	0.944	0.876
20	0.042	0.879	0.878	0.938	0.906	0.873	0.893	0.772	0.907	0.857	0.870	0.869	0.902	0.903	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.552	0.913	0.946	0.856
21	0.042	0.910	0.910	0.938	0.895	0.872	0.893	0.772	0.907	0.858	0.870	0.870	0.902	0.902	0.888	0.888	0.830	0.914	0.824	0.862	0.918	0.936	0.564	0.913	0.945	0.870
22	0.040	0.910	0.910	0.938	0.895	0.872	0.893	0.772	0.907	0.858	0.870	0.870	0.902	0.902	0.888	0.888	0.830	0.914	0.824	0.862	0.917	0.936	0.573	0.914	0.947	0.862
23	0.041	0.906	0.906	0.938	0.913	0.872	0.893	0.772	0.906	0.857	0.870	0.869	0.902	0.902	0.888	0.888	0.830	0.914	0.824	0.862	0.919	0.935	0.582	0.914	0.944	0.875
24	0.042	0.919	0.919	0.941	0.906	0.872	0.893	0.772	0.906	0.857	0.870	0.869	0.902	0.905	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.597	0.912	0.947	0.875
25	0.043	0.919	0.919	0.941	0.906	0.872	0.893	0.772	0.906	0.857	0.870	0.869	0.902	0.904	0.888	0.888	0.831	0.914	0.824	0.862	0.920	0.940	0.501	0.912	0.942	0.859
26	0.043	0.847	0.913	0.941	0.900	0.873	0.893	0.772	0.906	0.857	0.870	0.870	0.902	0.904	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.497	0.912	0.943	0.855
27	0.043	0.925	0.925	0.942	0.900	0.873	0.893	0.772	0.906	0.857	0.870	0.870	0.902	0.903	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.573	0.913	0.945	0.868
28	0.043	0.922	0.921	0.943	0.902	0.873	0.893	0.772	0.906	0.857	0.870	0.870	0.902	0.904	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.576	0.913	0.945	0.868
29	0.043	0.924	0.924	0.942	0.901	0.873	0.893	0.772	0.906	0.857	0.870	0.870	0.902	0.904	0.888	0.888	0.830	0.914	0.824	0.862	0.920	0.940	0.576	0.913	0.945	0.874
30	0.043	0.922	0.922	0.943	0.901	0.873	0.893	0.772	0.906	0.857	0.870	0.870	0.902	0.904	0.888	0.888	0.831	0.914	0.824	0.862	0.920	0.940	0.575	0.913	0.945	0.873
31	0.043	0.924	0.924	0.943	0.901	0.873	0.893	0.772	0.906	0.857	0.870	0.870	0.902	0.904	0.888	0.888	0.831	0.914	0.824	0.862	0.920	0.940	0.574	0.914	0.945	0.872
32	0.043	0.925	0.925	0.943	0.901	0.873	0.893	0.772	0.906	0.857	0.870	0.870	0.902	0.904	0.888	0.888	0.831	0.914	0.824	0.862	0.920	0.940	0.573	0.914	0.945	0.871
33	0.043	0.925	0.925	0.943	0.901	0.873	0.893	0.772	0.906	0.857	0.870	0.870	0.902	0.904	0.888	0.888	0.831	0.914	0.824	0.862	0.920	0.940	0.572	0.914	0.945	0.870
34	0.043	0.924	0.924	0.943	0.901	0.873	0.893	0.772	0.906	0.857	0.870	0.870	0.902	0.904	0.888	0.888	0.831	0.914	0.824	0.862	0.920	0.940	0.571	0.914	0.945	0.869
35	0.044	0.974	0.974	0.984	0.969	0.943	0.957	0.875	0.965	0.935	0.944	0.945	0.955	0.955	0.955	0.955	0.908	0.970	0.910	0.934	0.973	0.983	0.939	0.944	0.977	0.934
36	0.045	0.975	0.975	0.985	0.969	0.943	0.957	0.875	0.965	0.935	0.944	0.945	0.955	0.955	0.955	0.955	0.910	0.970	0.910	0.934	0.973	0.983	0.940	0.945	0.977	0.935
37	0.046	0.975	0.974	0.984	0.968	0.943	0.957	0.875	0.965	0.934	0.945	0.946	0.956	0.956	0.956	0.956	0.911	0.970	0.910	0.934	0.973	0.983	0.941	0.946	0.977	0.935
38	0.046	0.974	0.974	0.984	0.969	0.943	0.957	0.875	0.966	0.935	0.945	0.946	0.956	0.956	0.956	0.956	0.908	0.970	0.910	0.934	0.972	0.981	0.945	0.946	0.975	0.935
39	0.046	0.974	0.974	0.983	0.965	0.943	0.957	0.875	0.965																	

**TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments**

(c) Model performance of MC-M experiment under accuracy on MiniBooNE dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.925	0.925	0.943	0.917	0.873	0.893	0.772	0.907	0.858	0.870	0.870	0.902	0.904	0.888	0.832	0.914	0.824	0.862	0.920	0.940	0.922	0.914	0.946	0.892	
2%	0.917	0.917	0.941	0.908	0.836	0.851	0.765	0.861	0.842	0.835	0.846	0.850	0.876	0.836	0.840	0.773	0.896	0.784	0.813	0.904	0.926	0.914	0.914	0.945	0.866
4%	0.900	0.900	0.939	0.892	0.776	0.805	0.721	0.832	0.790	0.775	0.811	0.816	0.830	0.794	0.796	0.733	0.864	0.712	0.741	0.888	0.924	0.902	0.914	0.944	0.834
6%	0.886	0.885	0.934	0.883	0.759	0.781	0.654	0.797	0.793	0.762	0.776	0.781	0.802	0.767	0.769	0.664	0.841	0.671	0.722	0.864	0.919	0.899	0.909	0.943	0.811
8%	0.887	0.887	0.933	0.878	0.738	0.763	0.568	0.779	0.778	0.735	0.773	0.763	0.790	0.749	0.748	0.590	0.838	0.580	0.682	0.864	0.916	0.902	0.908	0.942	0.792
10%	0.758	0.756	0.839	0.822	0.691	0.572	0.560	0.562	0.719	0.653	0.496	0.550	0.561	0.541	0.530	0.529	0.809	0.594	0.643	0.712	0.833	0.772	0.889	0.920	0.680
12%	0.737	0.747	0.810	0.778	0.678	0.562	0.560	0.557	0.711	0.644	0.496	0.547	0.550	0.538	0.527	0.531	0.809	0.597	0.637	0.725	0.820	0.817	0.893	0.910	0.674
14%	0.641	0.651	0.777	0.702	0.655	0.549	0.560	0.544	0.699	0.633	0.496	0.543	0.530	0.534	0.522	0.532	0.808	0.594	0.632	0.622	0.728	0.821	0.884	0.904	0.648
16%	0.761	0.776	0.766	0.632	0.652	0.550	0.560	0.542	0.690	0.632	0.496	0.543	0.533	0.533	0.521	0.532	0.808	0.593	0.627	0.645	0.658	0.840	0.891	0.899	0.653
18%	0.759	0.764	0.741	0.568	0.637	0.543	0.561	0.537	0.679	0.623	0.496	0.541	0.526	0.531	0.519	0.530	0.796	0.592	0.624	0.550	0.610	0.835	0.883	0.900	0.639
20%	0.510	0.505	0.569	0.548	0.631	0.543	0.561	0.534	0.671	0.622	0.496	0.541	0.525	0.531	0.519	0.531	0.795	0.591	0.619	0.549	0.571	0.824	0.884	0.901	0.607
22%	0.502	0.501	0.571	0.564	0.624	0.542	0.562	0.536	0.668	0.641	0.496	0.542	0.526	0.531	0.518	0.530	0.792	0.591	0.617	0.584	0.550	0.822	0.878	0.897	0.607
24%	0.501	0.500	0.526	0.509	0.000	0.609	0.538	0.562	0.532	0.655	0.611	0.496	0.541	0.523	0.530	0.517	0.589	0.612	0.502	0.825	0.871	0.896	0.573		
26%	0.500	0.500	0.507	0.506	0.497	0.599	0.536	0.563	0.532	0.648	0.608	0.496	0.546	0.522	0.530	0.517	0.785	0.526	0.588	0.609	0.499	0.831	0.870	0.892	0.592
28%	0.500	0.500	0.501	0.504	0.497	0.590	0.535	0.563	0.528	0.643	0.602	0.497	0.540	0.516	0.529	0.516	0.777	0.526	0.588	0.604	0.497	0.820	0.866	0.893	0.589
30%	0.500	0.500	0.500	0.502	0.497	0.581	0.533	0.563	0.526	0.639	0.599	0.497	0.539	0.515	0.528	0.514	0.779	0.524	0.588	0.601	0.497	0.818	0.866	0.893	0.588
32%	0.502	0.501	0.655	0.523	0.497	0.596	0.538	0.564	0.532	0.644	0.605	0.496	0.541	0.531	0.530	0.515	0.818	0.526	0.588	0.604	0.567	0.806	0.885	0.911	0.603
34%	0.504	0.502	0.746	0.507	0.516	0.594	0.539	0.564	0.532	0.641	0.604	0.496	0.542	0.530	0.529	0.515	0.818	0.527	0.588	0.603	0.571	0.825	0.886	0.907	0.608
36%	0.500	0.500	0.752	0.506	0.533	0.595	0.539	0.564	0.531	0.640	0.605	0.496	0.541	0.534	0.529	0.515	0.817	0.527	0.588	0.602	0.570	0.811	0.886	0.906	0.608
38%	0.500	0.500	0.717	0.502	0.547	0.595	0.539	0.564	0.530	0.638	0.605	0.496	0.541	0.530	0.529	0.514	0.818	0.523	0.588	0.601	0.567	0.816	0.887	0.904	0.606
40%	0.500	0.500	0.714	0.501	0.497	0.595	0.539	0.564	0.529	0.637	0.606	0.496	0.541	0.531	0.528	0.514	0.818	0.522	0.587	0.599	0.566	0.782	0.887	0.907	0.603
42%	0.500	0.500	0.714	0.501	0.497	0.596	0.539	0.564	0.527	0.635	0.606	0.496	0.540	0.535	0.528	0.513	0.818	0.520	0.587	0.597	0.568	0.788	0.887	0.906	0.603
44%	0.500	0.500	0.702	0.501	0.546	0.594	0.539	0.564	0.524	0.634	0.607	0.496	0.539	0.537	0.528	0.513	0.818	0.522	0.587	0.595	0.566	0.791	0.888	0.907	0.604
46%	0.500	0.500	0.651	0.501	0.497	0.599	0.539	0.565	0.525	0.634	0.610	0.496	0.540	0.537	0.528	0.513	0.818	0.518	0.587	0.596	0.560	0.776	0.887	0.903	0.599
48%	0.500	0.500	0.645	0.501	0.497	0.600	0.541	0.565	0.524	0.633	0.609	0.496	0.540	0.538	0.528	0.512	0.818	0.517	0.587	0.598	0.561	0.802	0.887	0.903	0.600
50%	0.500	0.500	0.648	0.501	0.497	0.602	0.541	0.565	0.523	0.632	0.608	0.496	0.539	0.544	0.528	0.512	0.818	0.519	0.587	0.597	0.562	0.808	0.887	0.907	0.601
52%	0.500	0.500	0.575	0.501	0.497	0.603	0.540	0.566	0.522	0.631	0.609	0.496	0.539	0.545	0.529	0.512	0.819	0.523	0.588	0.597	0.561	0.816	0.886	0.896	0.598
54%	0.500	0.500	0.551	0.501	0.497	0.606	0.542	0.566	0.521	0.629	0.609	0.496	0.540	0.544	0.529	0.512	0.819	0.524	0.588	0.596	0.565	0.799	0.886	0.896	0.596
56%	0.500	0.500	0.543	0.501	0.497	0.608	0.542	0.566	0.523	0.628	0.609	0.496	0.540	0.554	0.529	0.511	0.819	0.525	0.588	0.596	0.566	0.790	0.886	0.895	0.596
58%	0.500	0.500	0.543	0.501	0.497	0.610	0.542	0.566	0.521	0.626	0.609	0.496	0.539	0.555	0.529	0.511	0.819	0.526	0.588	0.595	0.568	0.802	0.887	0.895	0.597
60%	0.500	0.500	0.544	0.501	0.497	0.613	0.542	0.566	0.520	0.625	0.610	0.496	0.539	0.559	0.529	0.511	0.819	0.525	0.587	0.595	0.567	0.802	0.886	0.894	0.597
62%	0.500	0.500	0.512	0.501	0.497	0.616	0.543	0.566	0.519	0.623	0.609	0.496	0.539	0.559	0.529	0.511	0.819	0.526	0.588	0.594	0.569	0.795	0.885	0.894	0.596
64%	0.500	0.500	0.506	0.501	0.497	0.620	0.544	0.567	0.518	0.623	0.611	0.496	0.539	0.560	0.529	0.511	0.819	0.530	0.587	0.593	0.570	0.781	0.886	0.895	0.595
66%	0.500	0.500	0.545	0.502	0.497	0.624	0.544	0.567	0.517	0.624	0.613	0.496	0.539	0.571	0.529	0.511	0.819	0.529	0.587	0.592	0.577	0.770	0.885	0.888	0.597
68%	0.500	0.500	0.505	0.502	0.497	0.631	0.546	0.567	0.519	0.624	0.613	0.496	0.539	0.573	0.530	0.511	0.819	0.529	0.587	0.593	0.583	0.780	0.886	0.890	0.597
70%	0.500	0.500	0.514	0.502	0.497	0.630	0.547	0.567	0.519	0.624	0.613	0.496	0.539	0.572	0.530	0.511	0.819	0.531	0.588	0.592	0.589	0.769	0.886	0.888	0.597
72%	0.500	0.500	0.511	0.502	0.497	0.630	0.547	0.567	0.519	0.624	0.613	0.496	0.539	0.573	0.530	0.511	0.819	0.531	0.588	0.592	0.589	0.767	0.886	0.888	0.597
74%	0.500	0.500	0.504	0.500	0.497	0.642	0.549	0.566	0.518	0.624	0.614	0.496	0.539	0.576	0.530	0.511	0.819	0.530	0.587	0.593	0.591	0.768	0.885	0.888	0.600
76%	0.500	0.500	0.509	0.500	0.497	0.629	0.549	0.567	0.511	0.611	0.617	0.495	0.539	0.575	0.530	0.511	0.819	0.529	0.587	0.593	0.591	0.768	0.885	0.888	0.597
78%	0.500	0.500	0.503	0.501	0.497	0.629	0.549	0.567	0.503	0.611	0.617	0.495	0.539	0.575	0.530	0.511	0.819	0.529	0.587	0.593	0.591	0.768	0.885	0.888	0.597
80%	0.500	0.500	0.517	0.501	0.497	0.630	0.551	0.567	0.504	0.611	0.617	0.495	0.541	0.575	0.530	0.511	0.819	0.529	0.587	0.597	0.591	0.768	0.885	0.888	0.597
82%	0.500	0.500	0.504	0.501	0.49																				

**TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments**

(e) Model performance of MC-L experiment under accuracy on MiniBooNE dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.925	0.925	0.943	0.917	0.873	0.893	0.772	0.907	0.858	0.870	0.870	0.902	0.904	0.888	0.888	0.832	0.914	0.824	0.862	0.920	0.940	0.922	0.914	0.946	0.892
2%	0.925	0.925	0.942	0.792	0.873	0.893	0.772	0.906	0.873	0.869	0.870	0.902	0.904	0.888	0.888	0.830	0.914	0.824	0.862	0.918	0.934	0.567	0.915	0.947	0.872
4%	0.924	0.924	0.941	0.740	0.853	0.881	0.768	0.888	0.880	0.856	0.867	0.890	0.895	0.877	0.881	0.820	0.909	0.811	0.847	0.914	0.927	0.909	0.914	0.947	0.878
6%	0.924	0.924	0.941	0.729	0.847	0.878	0.768	0.887	0.879	0.853	0.864	0.887	0.894	0.875	0.877	0.816	0.909	0.810	0.843	0.914	0.927	0.915	0.914	0.948	0.876
8%	0.922	0.922	0.941	0.722	0.843	0.875	0.768	0.888	0.875	0.852	0.864	0.884	0.889	0.873	0.875	0.816	0.906	0.810	0.842	0.914	0.922	0.912	0.913	0.946	0.874
10%	0.921	0.921	0.940	0.719	0.858	0.874	0.766	0.883	0.873	0.853	0.863	0.878	0.884	0.871	0.876	0.819	0.905	0.794	0.845	0.913	0.919	0.908	0.913	0.946	0.873
12%	0.905	0.905	0.938	0.719	0.857	0.873	0.766	0.883	0.871	0.854	0.863	0.878	0.880	0.872	0.876	0.819	0.905	0.794	0.845	0.913	0.914	0.914	0.913	0.946	0.871
14%	0.771	0.774	0.926	0.674	0.849	0.866	0.766	0.876	0.863	0.853	0.849	0.872	0.864	0.870	0.874	0.819	0.886	0.794	0.844	0.731	0.924	0.855	0.891	0.932	0.843
16%	0.767	0.771	0.925	0.670	0.841	0.860	0.766	0.871	0.858	0.851	0.850	0.868	0.867	0.874	0.818	0.884	0.795	0.843	0.726	0.924	0.861	0.889	0.933	0.840	
18%	0.814	0.818	0.926	0.671	0.836	0.858	0.766	0.869	0.856	0.850	0.849	0.868	0.873	0.819	0.795	0.842	0.734	0.922	0.830	0.867	0.919	0.932	0.843		
20%	0.832	0.835	0.927	0.652	0.861	0.764	0.874	0.856	0.839	0.845	0.871	0.860	0.861	0.854	0.816	0.791	0.870	0.832	0.755	0.923	0.828	0.861	0.933	0.843	
22%	0.757	0.764	0.907	0.642	0.860	0.764	0.874	0.854	0.839	0.845	0.871	0.855	0.861	0.854	0.816	0.791	0.869	0.832	0.716	0.894	0.824	0.809	0.878	0.925	0.829
24%	0.719	0.726	0.905	0.625	0.859	0.764	0.873	0.853	0.838	0.846	0.870	0.846	0.854	0.817	0.791	0.868	0.832	0.669	0.886	0.837	0.801	0.876	0.924	0.822	
26%	0.719	0.725	0.909	0.611	0.861	0.768	0.873	0.857	0.848	0.845	0.871	0.853	0.863	0.856	0.818	0.794	0.876	0.838	0.672	0.878	0.835	0.848	0.874	0.926	0.826
28%	0.609	0.616	0.852	0.568	0.861	0.768	0.873	0.856	0.848	0.845	0.871	0.848	0.862	0.856	0.818	0.794	0.875	0.838	0.620	0.700	0.832	0.839	0.876	0.918	0.802
30%	0.563	0.566	0.821	0.554	0.860	0.768	0.871	0.856	0.845	0.844	0.871	0.844	0.862	0.856	0.818	0.794	0.875	0.830	0.576	0.550	0.000	0.809	0.874	0.916	0.752
32%	0.518	0.521	0.807	0.554	0.833	0.860	0.768	0.871	0.857	0.845	0.844	0.871	0.842	0.863	0.856	0.818	0.795	0.838	0.566	0.550	0.818	0.874	0.919	0.782	
34%	0.522	0.527	0.847	0.538	0.830	0.859	0.768	0.871	0.857	0.845	0.844	0.871	0.842	0.864	0.856	0.818	0.794	0.838	0.552	0.505	0.754	0.864	0.918	0.777	
36%	0.503	0.504	0.731	0.520	0.828	0.859	0.768	0.872	0.857	0.844	0.843	0.871	0.837	0.864	0.856	0.817	0.795	0.838	0.533	0.506	0.833	0.854	0.915	0.772	
38%	0.520	0.525	0.754	0.524	0.827	0.859	0.768	0.872	0.857	0.844	0.843	0.871	0.834	0.863	0.856	0.817	0.794	0.838	0.532	0.505	0.833	0.854	0.914	0.774	
40%	0.612	0.630	0.799	0.532	0.826	0.858	0.768	0.872	0.857	0.844	0.842	0.872	0.831	0.863	0.856	0.818	0.794	0.839	0.533	0.505	0.839	0.855	0.912	0.785	
42%	0.657	0.682	0.800	0.528	0.825	0.858	0.768	0.873	0.857	0.845	0.843	0.871	0.827	0.863	0.856	0.819	0.795	0.839	0.532	0.505	0.841	0.854	0.912	0.789	
44%	0.654	0.680	0.796	0.529	0.824	0.859	0.768	0.874	0.857	0.844	0.843	0.871	0.830	0.863	0.856	0.818	0.795	0.839	0.531	0.505	0.838	0.855	0.912	0.788	
46%	0.630	0.667	0.808	0.542	0.823	0.859	0.768	0.875	0.857	0.844	0.842	0.871	0.834	0.863	0.856	0.819	0.795	0.839	0.531	0.505	0.835	0.856	0.912	0.787	
48%	0.669	0.719	0.806	0.539	0.821	0.858	0.768	0.875	0.857	0.844	0.841	0.871	0.835	0.863	0.855	0.818	0.795	0.839	0.529	0.505	0.823	0.853	0.903	0.790	
50%	0.850	0.796	0.835	0.550	0.821	0.858	0.768	0.875	0.857	0.844	0.843	0.871	0.832	0.863	0.855	0.816	0.795	0.839	0.529	0.547	0.823	0.859	0.908	0.794	
52%	0.851	0.802	0.822	0.547	0.820	0.859	0.768	0.875	0.857	0.844	0.842	0.871	0.831	0.863	0.855	0.816	0.795	0.839	0.528	0.508	0.823	0.866	0.906	0.802	
54%	0.860	0.829	0.825	0.549	0.819	0.858	0.768	0.875	0.857	0.844	0.843	0.872	0.832	0.863	0.855	0.816	0.795	0.838	0.529	0.523	0.819	0.858	0.903	0.803	
56%	0.867	0.848	0.833	0.545	0.817	0.858	0.768	0.876	0.857	0.842	0.843	0.872	0.832	0.863	0.855	0.816	0.795	0.838	0.531	0.584	0.817	0.861	0.892	0.807	
58%	0.866	0.867	0.838	0.556	0.817	0.858	0.768	0.875	0.857	0.846	0.843	0.872	0.830	0.863	0.856	0.818	0.795	0.838	0.533	0.589	0.816	0.859	0.893	0.808	
60%	0.874	0.868	0.834	0.565	0.816	0.858	0.768	0.875	0.857	0.846	0.842	0.872	0.830	0.864	0.854	0.817	0.795	0.838	0.532	0.589	0.797	0.857	0.891	0.808	
62%	0.868	0.869	0.850	0.559	0.816	0.858	0.768	0.875	0.857	0.844	0.841	0.872	0.830	0.863	0.855	0.817	0.795	0.838	0.534	0.656	0.838	0.855	0.893	0.813	
64%	0.817	0.853	0.861	0.623	0.816	0.858	0.768	0.874	0.855	0.840	0.841	0.869	0.832	0.863	0.855	0.817	0.795	0.839	0.537	0.511	0.847	0.846	0.887	0.806	
66%	0.662	0.647	0.862	0.624	0.815	0.858	0.768	0.874	0.857	0.841	0.840	0.869	0.832	0.863	0.855	0.812	0.794	0.838	0.536	0.561	0.815	0.846	0.889	0.792	
68%	0.709	0.671	0.852	0.644	0.816	0.858	0.768	0.874	0.857	0.841	0.840	0.871	0.832	0.863	0.855	0.812	0.794	0.838	0.534	0.684	0.843	0.846	0.889	0.801	
70%	0.864	0.858	0.748	0.595	0.804	0.852	0.768	0.874	0.859	0.839	0.840	0.871	0.830	0.864	0.854	0.813	0.792	0.838	0.530	0.510	0.850	0.856	0.897	0.905	
72%	0.870	0.881	0.744	0.606	0.810	0.853	0.768	0.874	0.859	0.840	0.841	0.871	0.830	0.863	0.853	0.813	0.791	0.837	0.530	0.505	0.806	0.855	0.910	0.799	
74%	0.865	0.872	0.758	0.629	0.814	0.854	0.768	0.873	0.860	0.841	0.842	0.871	0.830	0.864	0.853	0.814	0.791	0.837	0.530	0.528	0.835	0.838	0.903	0.802	
76%	0.754	0.742	0.793	0.649	0.818	0.855	0.767	0.873	0.860	0.842	0.841	0.871	0.830	0.863	0.852	0.813	0.793	0.837	0.530	0.564	0.818	0.838	0.905	0.795	
78%	0.700	0.686	0.795	0.706	0.823	0.858	0.768	0.871	0.860	0.842	0.840	0.871	0.830	0.862	0.851	0.811	0.786	0.837	0.517	0.600	0.788	0.841	0.904	0.795	
80%	0.636	0.620	0.797	0.704	0.826	0.857	0.767	0.870	0.859	0.842	0.840	0.871	0.831	0.863	0.850	0.809	0.870	0.836	0.507	0.647	0.745	0.841	0.907	0.789	
82%	0.504	0.501	0.794	0.723	0.827	0.857	0.767	0.870	0.859	0.849	0.840	0.871	0.831	0.861	0.850	0.811	0.870	0.835	0.507	0.617	0.777	0.836	0.903	0.779	
84%	0.504	0.501	0.788	0.740	0.821	0.858	0.7																		

**TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments**

(g) Model performance of RD experiment under accuracy on MiniBooNE dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.925	0.925	0.943	0.917	0.873	0.893	0.772	0.907	0.858	0.870	0.870	0.902	0.904	0.888	0.888	0.832	0.914	0.824	0.862	0.920	0.940	0.922	0.914	0.946	0.892
2%	0.918	0.918	0.937	0.908	0.872	0.892	0.772	0.904	0.856	0.869	0.869	0.901	0.902	0.888	0.887	0.829	0.914	0.824	0.861	0.918	0.794	0.912	0.914	0.945	0.884
4%	0.904	0.903	0.930	0.856	0.869	0.889	0.771	0.901	0.856	0.865	0.869	0.898	0.899	0.885	0.885	0.829	0.907	0.818	0.858	0.891	0.887	0.899	0.912	0.944	0.880
6%	0.890	0.901	0.928	0.829	0.863	0.882	0.770	0.892	0.853	0.859	0.863	0.888	0.894	0.875	0.875	0.817	0.908	0.811	0.849	0.914	0.771	0.904	0.907	0.937	0.870
8%	0.850	0.848	0.925	0.815	0.859	0.869	0.768	0.881	0.852	0.856	0.838	0.877	0.885	0.862	0.862	0.823	0.909	0.818	0.849	0.912	0.692	0.908	0.897	0.929	0.858
10%	0.817	0.808	0.911	0.878	0.859	0.879	0.770	0.886	0.857	0.858	0.861	0.884	0.894	0.872	0.873	0.813	0.889	0.811	0.847	0.822	0.768	0.869	0.911	0.940	0.857
12%	0.885	0.872	0.912	0.883	0.825	0.831	0.772	0.825	0.836	0.828	0.807	0.830	0.840	0.825	0.819	0.810	0.898	0.799	0.823	0.867	0.571	0.845	0.899	0.924	0.834
14%	0.848	0.835	0.904	0.869	0.847	0.870	0.772	0.877	0.850	0.850	0.852	0.876	0.877	0.870	0.871	0.810	0.897	0.805	0.844	0.630	0.651	0.875	0.899	0.927	0.842
16%	0.802	0.767	0.891	0.812	0.839	0.849	0.769	0.848	0.841	0.842	0.823	0.850	0.856	0.844	0.839	0.806	0.881	0.805	0.835	0.881	0.613	0.863	0.899	0.931	0.833
18%	0.803	0.805	0.889	0.872	0.819	0.834	0.767	0.835	0.844	0.849	0.829	0.830	0.846	0.829	0.826	0.791	0.875	0.814	0.895	0.792	0.768	0.868	0.912	0.832	
20%	0.758	0.749	0.873	0.839	0.820	0.821	0.753	0.820	0.825	0.817	0.808	0.824	0.824	0.818	0.809	0.772	0.891	0.785	0.803	0.739	0.577	0.867	0.895	0.928	0.809
22%	0.672	0.690	0.856	0.766	0.820	0.818	0.761	0.796	0.835	0.826	0.769	0.830	0.799	0.795	0.776	0.889	0.789	0.813	0.772	0.500	0.867	0.904	0.934	0.795	
24%	0.777	0.727	0.876	0.754	0.791	0.810	0.740	0.801	0.820	0.806	0.786	0.812	0.826	0.799	0.802	0.759	0.705	0.777	0.766	0.612	0.801	0.887	0.905	0.795	
26%	0.695	0.636	0.872	0.815	0.825	0.835	0.752	0.816	0.841	0.833	0.796	0.827	0.843	0.818	0.817	0.771	0.881	0.784	0.818	0.753	0.573	0.840	0.900	0.924	0.802
28%	0.752	0.763	0.869	0.808	0.832	0.846	0.765	0.834	0.843	0.841	0.826	0.848	0.860	0.838	0.838	0.790	0.891	0.797	0.826	0.713	0.532	0.808	0.870	0.914	0.813
30%	0.624	0.622	0.824	0.780	0.829	0.843	0.766	0.836	0.849	0.836	0.829	0.844	0.851	0.834	0.836	0.803	0.869	0.793	0.823	0.730	0.588	0.815	0.896	0.924	0.802
32%	0.634	0.618	0.832	0.746	0.766	0.790	0.679	0.789	0.804	0.774	0.793	0.799	0.782	0.775	0.713	0.744	0.704	0.726	0.584	0.734	0.871	0.917	0.759		
34%	0.679	0.643	0.850	0.767	0.811	0.802	0.766	0.775	0.815	0.816	0.752	0.791	0.818	0.785	0.764	0.792	0.871	0.796	0.814	0.626	0.568	0.809	0.880	0.779	
36%	0.696	0.688	0.812	0.787	0.809	0.816	0.745	0.796	0.831	0.816	0.789	0.812	0.823	0.808	0.803	0.754	0.855	0.771	0.797	0.700	0.567	0.766	0.875	0.895	0.784
38%	0.629	0.605	0.794	0.700	0.784	0.810	0.749	0.796	0.826	0.811	0.776	0.813	0.813	0.805	0.801	0.764	0.880	0.765	0.790	0.748	0.541	0.809	0.862	0.892	0.773
40%	0.619	0.588	0.825	0.715	0.781	0.772	0.754	0.763	0.815	0.799	0.751	0.772	0.775	0.763	0.755	0.729	0.822	0.771	0.792	0.603	0.540	0.747	0.863	0.889	0.751
42%	0.705	0.722	0.822	0.805	0.809	0.808	0.757	0.734	0.822	0.822	0.739	0.775	0.782	0.783	0.764	0.760	0.865	0.777	0.780	0.730	0.558	0.762	0.856	0.884	0.779
44%	0.643	0.651	0.824	0.754	0.800	0.763	0.750	0.703	0.780	0.791	0.699	0.737	0.759	0.747	0.720	0.760	0.854	0.783	0.791	0.614	0.514	0.726	0.845	0.890	0.746
46%	0.565	0.564	0.794	0.654	0.817	0.817	0.769	0.785	0.829	0.825	0.784	0.809	0.824	0.804	0.802	0.798	0.856	0.791	0.818	0.663	0.558	0.723	0.863	0.881	0.767
48%	0.691	0.691	0.795	0.700	0.753	0.766	0.711	0.735	0.794	0.761	0.723	0.762	0.756	0.745	0.739	0.718	0.832	0.714	0.744	0.631	0.525	0.753	0.849	0.896	0.741
50%	0.591	0.557	0.778	0.678	0.745	0.728	0.678	0.689	0.752	0.744	0.681	0.712	0.724	0.704	0.683	0.695	0.818	0.706	0.736	0.673	0.514	0.739	0.874	0.893	0.712
52%	0.541	0.545	0.791	0.668	0.766	0.754	0.733	0.714	0.795	0.779	0.703	0.735	0.766	0.736	0.711	0.746	0.818	0.743	0.761	0.641	0.512	0.729	0.871	0.892	0.727
54%	0.574	0.565	0.761	0.734	0.756	0.775	0.711	0.742	0.794	0.781	0.740	0.763	0.779	0.765	0.742	0.723	0.818	0.749	0.766	0.672	0.505	0.750	0.859	0.895	0.738
56%	0.596	0.615	0.722	0.754	0.785	0.803	0.653	0.668	0.696	0.679	0.571	0.594	0.591	0.572	0.603	0.638	0.657	0.671	0.551	0.501	0.575	0.686	0.695	0.515	0.657
58%	0.618	0.595	0.758	0.768	0.748	0.769	0.680	0.726	0.788	0.762	0.730	0.758	0.755	0.757	0.738	0.703	0.795	0.701	0.738	0.552	0.569	0.711	0.850	0.875	0.724
60%	0.604	0.603	0.765	0.629	0.615	0.719	0.571	0.701	0.760	0.730	0.697	0.725	0.730	0.715	0.700	0.673	0.807	0.666	0.696	0.587	0.500	0.625	0.856	0.908	0.699
62%	0.520	0.513	0.726	0.591	0.734	0.682	0.712	0.613	0.749	0.744	0.609	0.641	0.670	0.652	0.623	0.669	0.675	0.721	0.743	0.530	0.491	0.633	0.849	0.889	0.671
64%	0.567	0.571	0.703	0.680	0.742	0.680	0.738	0.599	0.744	0.755	0.603	0.632	0.694	0.653	0.605	0.698	0.756	0.746	0.750	0.667	0.531	0.664	0.854	0.855	0.687
66%	0.670	0.698	0.724	0.670	0.703	0.644	0.661	0.564	0.715	0.699	0.562	0.589	0.669	0.595	0.538	0.649	0.797	0.673	0.699	0.562	0.508	0.674	0.888	0.886	0.666
68%	0.510	0.520	0.732	0.635	0.682	0.687	0.659	0.633	0.737	0.713	0.651	0.663	0.690	0.663	0.651	0.642	0.788	0.676	0.698	0.585	0.513	0.697	0.860	0.875	0.673
70%	0.520	0.533	0.706	0.545	0.678	0.682	0.636	0.531	0.588	0.622	0.540	0.557	0.551	0.533	0.527	0.585	0.646	0.567	0.601	0.467	0.409	0.526	0.840	0.875	0.599
72%	0.584	0.592	0.662	0.623	0.663	0.710	0.574	0.672	0.766	0.729	0.692	0.706	0.710	0.705	0.697	0.697	0.749	0.707	0.727	0.603	0.561	0.601	0.843	0.872	0.570
74%	0.520	0.501	0.699	0.545	0.654	0.602	0.650	0.568	0.648	0.609	0.575	0.585	0.604	0.595	0.576	0.573	0.784	0.567	0.585	0.557	0.500	0.569	0.832	0.885	0.599
76%	0.543	0.536	0.681	0.671	0.602	0.599	0.560	0.568	0.648	0.609	0.575	0.585	0.604	0.595	0.576	0.573	0.657	0.565	0.585	0.552	0.533	0.638	0.850	0.876	0.622
78%	0.499	0.499	0.645	0.593	0.625	0.560	0.585	0.522	0.661	0.623	0.533	0.541	0.587	0.543	0.521	0.564	0.738	0.599	0.614	0.554	0.500	0.560	0.862	0.896	0.603
80%	0.517	0.543	0.644	0.601	0.713	0.649	0.692	0.576	0.706	0.720	0.594	0.619	0.644	0.628	0.586	0.686	0.703	0.712	0.714	0.588	0.497	0.560	0.860	0.875	0.591
82%	0.500	0.499	0.623	0.606	0.629	0.554	0.582	0.531																	

**TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments**

(i) Model performance gap  $\Delta$  of RD experiment under accuracy on MiniBooNE dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE	
2%	-0.008	-0.008	-0.006	-0.009	-0.001	-0.001	0.000	-0.003	-0.002	0.000	-0.001	-0.001	-0.002	0.000	-0.001	-0.004	-0.001	-0.001	-0.001	-0.003	-0.155	-0.011	0.000	-0.001	-0.010	
4%	-0.023	-0.023	-0.014	-0.069	-0.005	-0.004	-0.001	-0.006	-0.002	-0.005	-0.002	-0.004	-0.005	-0.006	-0.001	-0.002	-0.003	-0.008	-0.005	-0.031	-0.057	-0.025	-0.003	-0.002	-0.013	
6%	-0.038	-0.026	-0.016	-0.099	-0.011	-0.013	-0.003	-0.016	-0.006	-0.012	-0.008	-0.016	-0.010	-0.015	-0.015	-0.018	-0.007	-0.016	-0.014	-0.007	-0.180	-0.020	-0.008	-0.010	-0.025	
8%	-0.081	-0.084	-0.019	-0.111	-0.016	-0.027	-0.006	-0.029	-0.007	-0.016	-0.036	-0.027	-0.020	-0.030	-0.029	-0.010	-0.006	-0.007	-0.014	-0.009	-0.264	-0.015	-0.019	-0.018	-0.039	
10%	-0.117	-0.128	-0.035	-0.042	-0.016	-0.016	-0.002	-0.023	-0.001	-0.013	-0.010	-0.020	-0.011	-0.018	-0.017	-0.023	-0.028	-0.016	-0.017	-0.017	-0.183	-0.057	-0.003	-0.006	-0.039	
12%	-0.043	-0.058	-0.033	-0.037	-0.054	-0.070	0.000	-0.090	-0.026	-0.048	-0.073	-0.079	-0.070	-0.071	-0.077	-0.026	-0.017	-0.031	-0.045	-0.058	-0.393	-0.084	-0.016	-0.023	-0.065	
14%	-0.084	-0.098	-0.042	-0.052	-0.030	-0.026	0.001	-0.033	-0.009	-0.022	-0.021	-0.028	-0.029	-0.021	-0.018	-0.026	-0.019	-0.023	-0.021	-0.315	-0.307	-0.051	-0.017	-0.021	-0.056	
16%	-0.133	-0.171	-0.056	-0.114	-0.038	-0.049	-0.004	-0.066	-0.020	-0.032	-0.054	-0.058	-0.052	-0.050	-0.054	-0.030	-0.037	-0.023	-0.031	-0.042	-0.348	-0.064	-0.017	-0.016	-0.066	
18%	-0.132	-0.130	-0.058	-0.049	-0.061	-0.066	-0.006	-0.079	-0.016	-0.046	-0.058	-0.069	-0.063	-0.066	-0.070	-0.049	-0.032	-0.035	-0.055	-0.055	-0.140	-0.183	-0.059	-0.031	-0.036	-0.067
20%	-0.180	-0.190	-0.074	-0.085	-0.060	-0.081	-0.024	-0.096	-0.038	-0.060	-0.071	-0.088	-0.079	-0.089	-0.071	-0.026	-0.047	-0.069	-0.197	-0.387	-0.060	-0.021	-0.019	-0.093		
22%	-0.273	-0.254	-0.092	-0.164	-0.060	-0.084	-0.015	-0.122	-0.026	-0.051	-0.116	-0.104	-0.100	-0.105	-0.067	-0.028	-0.043	-0.056	-0.161	-0.468	-0.060	-0.011	-0.013	-0.108		
24%	-0.160	-0.214	-0.071	-0.178	-0.093	-0.042	-0.017	-0.117	-0.044	-0.074	-0.096	-0.098	-0.101	-0.096	-0.087	-0.010	-0.089	-0.098	-0.167	-0.349	-0.131	-0.030	-0.044	-0.108		
26%	-0.249	-0.313	-0.076	-0.111	-0.055	-0.064	-0.026	-0.101	-0.020	-0.042	-0.092	-0.083	-0.067	-0.079	-0.080	-0.037	-0.049	-0.051	-0.182	-0.390	-0.089	-0.015	-0.023	-0.100		
28%	-0.187	-0.175	-0.079	-0.119	-0.046	-0.053	-0.009	-0.081	-0.018	-0.033	-0.050	-0.049	-0.048	-0.057	-0.056	-0.050	-0.026	-0.033	-0.041	-0.225	-0.434	-0.126	-0.049	-0.034	-0.089	
30%	-0.325	-0.327	-0.126	-0.149	-0.050	-0.058	-0.008	-0.078	-0.011	-0.039	-0.048	-0.064	-0.058	-0.061	-0.058	-0.035	-0.049	-0.038	-0.044	-0.200	-0.374	-0.116	-0.020	-0.023	-0.101	
32%	-0.315	-0.332	-0.118	-0.184	-0.123	-0.115	-0.120	-0.130	-0.063	-0.115	-0.111	-0.121	-0.116	-0.119	-0.127	-0.143	-0.044	-0.144	-0.128	-0.211	-0.379	-0.204	-0.047	-0.031	-0.149	
34%	-0.266	-0.303	-0.099	-0.164	-0.070	-0.102	-0.007	-0.145	-0.050	-0.062	-0.136	-0.123	-0.095	-0.117	-0.139	-0.048	-0.047	-0.034	-0.056	-0.319	-0.395	-0.123	-0.037	-0.041	-0.127	
36%	-0.248	-0.259	-0.140	-0.142	-0.074	-0.087	-0.034	-0.123	-0.032	-0.062	-0.094	-0.100	-0.089	-0.090	-0.096	-0.094	-0.065	-0.065	-0.075	-0.239	-0.397	-0.169	-0.043	-0.055	-0.122	
38%	-0.320	-0.346	-0.158	-0.236	-0.102	-0.092	-0.030	-0.122	-0.037	-0.068	-0.108	-0.098	-0.100	-0.093	-0.098	-0.081	-0.038	-0.072	-0.083	-0.187	-0.424	-0.123	-0.058	-0.133	-0.258	
40%	-0.330	-0.365	-0.126	-0.220	-0.105	-0.136	-0.024	-0.159	-0.050	-0.081	-0.137	-0.144	-0.143	-0.141	-0.149	-0.092	-0.093	-0.065	-0.080	-0.345	-0.425	-0.190	-0.056	-0.061	-0.158	
42%	-0.237	-0.219	-0.129	-0.172	-0.073	-0.095	-0.020	-0.191	-0.042	-0.055	-0.151	-0.140	-0.190	-0.188	-0.159	-0.087	-0.053	-0.058	-0.064	-0.198	-0.406	-0.174	-0.064	-0.066	-0.127	
44%	-0.305	-0.294	-0.126	-0.178	-0.084	-0.146	-0.018	-0.225	-0.080	-0.090	-0.188	-0.183	-0.160	-0.188	-0.188	-0.065	-0.060	-0.085	-0.065	-0.082	-0.333	-0.453	-0.213	-0.075	-0.060	-0.163
46%	-0.390	-0.394	-0.159	-0.227	-0.084	-0.164	-0.004	-0.135	-0.034	-0.051	-0.099	-0.103	-0.088	-0.089	-0.097	-0.040	-0.064	-0.040	-0.051	-0.279	-0.406	-0.216	-0.056	-0.069	-0.141	
48%	-0.254	-0.253	-0.158	-0.234	-0.137	-0.143	-0.079	-0.190	-0.074	-0.124	-0.169	-0.155	-0.163	-0.161	-0.168	-0.136	-0.089	-0.127	-0.136	-0.314	-0.442	-0.183	-0.072	-0.054	-0.169	
50%	-0.361	-0.397	-0.175	-0.264	-0.146	-0.185	-0.122	-0.241	-0.124	-0.144	-0.217	-0.211	-0.199	-0.207	-0.231	-0.164	-0.106	-0.143	-0.146	-0.268	-0.453	-0.198	-0.044	-0.056	-0.202	
52%	-0.416	-0.411	-0.162	-0.272	-0.122	-0.156	-0.051	-0.213	-0.074	-0.104	-0.193	-0.185	-0.152	-0.172	-0.199	-0.105	-0.096	-0.117	-0.130	-0.455	-0.209	-0.047	-0.057	-0.185		
54%	-0.379	-0.389	-0.193	-0.199	-0.134	-0.132	-0.079	-0.182	-0.072	-0.102	-0.148	-0.138	-0.139	-0.157	-0.130	-0.108	-0.121	-0.116	-0.265	-0.463	-0.187	-0.061	-0.055	-0.173		
56%	-0.355	-0.335	-0.235	-0.178	-0.125	-0.134	-0.080	-0.180	-0.129	-0.134	-0.184	-0.174	-0.160	-0.165	-0.174	-0.138	-0.148	-0.188	-0.193	-0.419	-0.453	-0.296	-0.075	-0.044	-0.263	
58%	-0.332	-0.356	-0.196	-0.249	-0.143	-0.120	-0.020	-0.220	-0.059	-0.152	-0.160	-0.165	-0.148	-0.168	-0.155	-0.130	-0.149	-0.144	-0.400	-0.395	-0.229	-0.076	-0.076	-0.188		
60%	-0.348	-0.348	-0.189	-0.314	-0.181	-0.181	-0.064	-0.227	-0.114	-0.160	-0.199	-0.197	-0.192	-0.196	-0.191	-0.118	-0.192	-0.162	-0.468	-0.322	-0.064	-0.041	-0.217			
62%	-0.438	-0.446	-0.230	-0.356	-0.159	-0.236	-0.077	-0.324	-0.126	-0.144	-0.300	-0.289	-0.223	-0.266	-0.298	-0.195	-0.164	-0.125	-0.137	-0.424	-0.477	-0.313	-0.071	-0.060	-0.248	
64%	-0.387	-0.382	-0.255	-0.259	-0.150	-0.238	-0.045	-0.339	-0.133	-0.132	-0.307	-0.299	-0.232	-0.265	-0.318	-0.160	-0.173	-0.094	-0.130	-0.275	-0.435	-0.280	-0.066	-0.096	-0.230	
66%	-0.276	-0.245	-0.233	-0.270	-0.194	-0.276	-0.143	-0.378	-0.167	-0.196	-0.354	-0.347	-0.260	-0.330	-0.394	-0.218	-0.128	-0.183	-0.189	-0.389	-0.459	-0.269	-0.086	-0.061	-0.253	
68%	-0.448	-0.438	-0.234	-0.237	-0.197	-0.236	-0.146	-0.302	-0.180	-0.180	-0.252	-0.265	-0.236	-0.263	-0.328	-0.188	-0.127	-0.188	-0.190	-0.365	-0.454	-0.244	-0.060	-0.075	-0.245	
70%	-0.438	-0.424	-0.251	-0.406	-0.223	-0.223	-0.124	-0.280	-0.160	-0.190	-0.241	-0.252	-0.246	-0.238	-0.275	-0.188	-0.197	-0.193	-0.219	-0.419	-0.453	-0.296	-0.075	-0.090	-0.255	
72%	-0.369	-0.366	-0.280	-0.230	-0.202	-0.245	-0.155	-0.259	-0.107	-0.204	-0.188	-0.212	-0.207	-0.207	-0.210	-0.157	-0.167	-0.167	-0.235	-0.337	-0.465	-0.331	-0.065	-0.059	-0.249	
74%	-0.309	-0.307	-0.240	-0.313	-0.204	-0.294	-0.152	-0.340	-0.094	-0.303	-0.244	-0.249	-0.240	-0.244	-0.240	-0.164	-0.164	-0.164	-0.240	-0.343	-0.463	-0.331	-0.065	-0.059	-0.249	
76%	-0.001	-0.001	-0.004	-0.016	-0.007	-0.005	-0.001	-0.010	-0.003	-0.005	-0.010	-0.005	-0.012	-0.005	-0.017	-0.003	-0.013	-0.010	-0.003	-0.043	-0.037	-0.008	-0.003	-0.010	-0.010	
78%	-0.015	-0.015	-0.025	-0.038	-0.041	-0.040	-0.004	-0.040	-0.024	-0.038	-0.040	-0.035	-0.035	-0.035	-0.035	-0.026	-0.035	-0.026	-0.035	-0.047	-0.048	-0.078	-0.053	-0.029	-0.029	
80%	-0.017	-0.018	-0.014	-0.052	-0.043	-0.051	-0.020	-0.057	-0.018	-0.032	-0.035	-0.034	-0.036	-0.036	-0.036	-0.024	-0.045	-0.045	-0.070	-0.107	-0.147	-0.070	-0.047	-0.045	-0.105	
82%	-0.031	-0.032	-0.014	-0.051	-0.076	-0.068	-0.004	-0.064	-0.024	-0.059	-0.041	-0.064	-0.057	-0.074	-0.061	-0.086	-0.005	-0.103	-0.083	-0.044	-0.170	-0.247	-0.080	-0.048	-0.060	-0.106
84%	-0.011	-0.012	-0.019	-0.035	-0.038	-0.041	-0.038	-0.04																		

## TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments

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**Table 18.** Model performance on Eyemovements dataset.

(a) Model performance of SC experiment under accuracy on Eyemovements dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.594	0.589	0.684	0.533	0.405	0.527	0.411	0.555	0.522	0.437	0.444	0.555	0.506	0.541	0.502	0.361	0.572	0.507	0.397	0.586	0.900	0.277	0.918	0.715	0.543
1	-0.001	0.593	0.588	0.680	0.531	0.405	0.526	0.414	0.557	0.521	0.442	0.446	0.555	0.506	0.540	0.503	0.360	0.568	0.510	0.398	0.586	0.894	0.289	0.923	0.715	0.544
2	-0.001	0.591	0.587	0.666	0.533	0.405	0.526	0.411	0.557	0.522	0.440	0.445	0.555	0.505	0.540	0.502	0.363	0.572	0.506	0.395	0.585	0.901	0.279	0.916	0.709	0.542
3	-0.005	0.594	0.591	0.679	0.532	0.405	0.525	0.412	0.556	0.520	0.437	0.443	0.553	0.507	0.542	0.502	0.358	0.573	0.507	0.396	0.588	0.900	0.287	0.918	0.723	0.544
4	0.006	0.596	0.592	0.681	0.536	0.404	0.524	0.411	0.552	0.521	0.442	0.446	0.552	0.502	0.541	0.503	0.359	0.571	0.509	0.398	0.586	0.895	0.299	0.923	0.726	0.545
5	-0.015	0.594	0.588	0.684	0.528	0.406	0.523	0.412	0.552	0.520	0.436	0.443	0.551	0.507	0.546	0.507	0.355	0.568	0.505	0.395	0.590	0.899	0.280	0.921	0.710	0.542
6	0.017	0.593	0.581	0.680	0.532	0.405	0.524	0.413	0.557	0.519	0.439	0.445	0.555	0.510	0.539	0.497	0.356	0.570	0.504	0.399	0.592	0.696	0.327	0.861	0.705	0.533
7	0.017	0.578	0.562	0.584	0.533	0.405	0.528	0.413	0.548	0.517	0.437	0.444	0.553	0.503	0.542	0.504	0.356	0.572	0.509	0.396	0.587	0.625	0.287	0.909	0.705	0.525
8	0.017	0.586	0.580	0.679	0.528	0.406	0.522	0.414	0.548	0.516	0.435	0.439	0.545	0.502	0.539	0.499	0.354	0.572	0.503	0.392	0.582	0.899	0.299	0.920	0.718	0.541
9	-0.020	0.558	0.538	0.671	0.521	0.403	0.519	0.410	0.542	0.514	0.428	0.441	0.541	0.493	0.527	0.498	0.357	0.547	0.504	0.395	0.543	0.572	0.289	0.874	0.672	0.515
10	0.021	0.591	0.588	0.674	0.534	0.407	0.530	0.413	0.557	0.517	0.440	0.438	0.553	0.504	0.543	0.504	0.358	0.572	0.510	0.399	0.585	0.897	0.296	0.924	0.702	0.543
11	0.034	0.584	0.583	0.574	0.532	0.405	0.526	0.411	0.554	0.517	0.437	0.444	0.553	0.507	0.537	0.501	0.353	0.572	0.505	0.397	0.587	0.901	0.292	0.924	0.720	0.538
12	0.052	0.594	0.588	0.683	0.525	0.402	0.524	0.413	0.554	0.523	0.438	0.443	0.552	0.507	0.543	0.502	0.357	0.570	0.508	0.395	0.584	0.901	0.299	0.920	0.729	0.544
13	0.053	0.594	0.586	0.683	0.529	0.405	0.525	0.413	0.554	0.521	0.435	0.446	0.554	0.506	0.541	0.503	0.363	0.573	0.504	0.398	0.588	0.901	0.287	0.925	0.726	0.544
14	0.081	0.595	0.590	0.683	0.530	0.404	0.529	0.412	0.560	0.523	0.436	0.442	0.553	0.508	0.542	0.503	0.357	0.566	0.511	0.399	0.583	0.877	0.299	0.920	0.708	0.543
15	-0.083	0.580	0.573	0.672	0.528	0.406	0.518	0.412	0.545	0.507	0.437	0.441	0.541	0.505	0.538	0.495	0.352	0.560	0.502	0.389	0.575	0.900	0.296	0.920	0.719	0.538
16	0.086	0.594	0.588	0.683	0.534	0.404	0.528	0.416	0.554	0.521	0.437	0.445	0.552	0.508	0.544	0.506	0.355	0.567	0.510	0.397	0.583	0.892	0.297	0.925	0.713	0.544
17	0.087	0.588	0.585	0.672	0.533	0.406	0.524	0.408	0.554	0.520	0.434	0.443	0.554	0.504	0.541	0.503	0.363	0.570	0.509	0.396	0.587	0.873	0.268	0.919	0.713	0.540
18	0.088	0.578	0.566	0.676	0.518	0.404	0.518	0.419	0.537	0.513	0.440	0.444	0.538	0.500	0.532	0.499	0.354	0.552	0.495	0.395	0.568	0.898	0.308	0.919	0.702	0.536
19	0.092	0.567	0.565	0.682	0.528	0.404	0.524	0.415	0.548	0.525	0.437	0.440	0.553	0.507	0.537	0.507	0.361	0.568	0.509	0.397	0.579	0.899	0.299	0.913	0.704	0.540
20	0.103	0.576	0.566	0.680	0.509	0.402	0.509	0.400	0.528	0.501	0.427	0.437	0.526	0.493	0.514	0.360	0.540	0.499	0.399	0.539	0.501	0.312	0.842	0.686	0.510	
21	0.122	0.578	0.576	0.678	0.525	0.403	0.523	0.412	0.551	0.514	0.436	0.445	0.547	0.498	0.536	0.500	0.357	0.565	0.504	0.395	0.579	0.890	0.277	0.923	0.718	0.539
22	0.125	0.580	0.577	0.679	0.530	0.404	0.526	0.411	0.554	0.523	0.438	0.437	0.550	0.506	0.542	0.505	0.354	0.566	0.511	0.397	0.587	0.802	0.293	0.922	0.709	0.538
23	0.155	0.587	0.589	0.678	0.527	0.406	0.518	0.411	0.547	0.518	0.444	0.446	0.546	0.506	0.528	0.506	0.346	0.567	0.504	0.400	0.583	0.896	0.280	0.920	0.720	0.541
24	0.168	0.551	0.550	0.680	0.512	0.401	0.503	0.410	0.528	0.510	0.433	0.437	0.526	0.495	0.525	0.493	0.361	0.540	0.486	0.395	0.552	0.620	0.264	0.921	0.715	0.517
25	0.213	0.592	0.588	0.678	0.528	0.404	0.514	0.414	0.544	0.522	0.440	0.445	0.540	0.500	0.530	0.507	0.355	0.569	0.503	0.393	0.584	0.899	0.275	0.920	0.719	0.540
26	0.215	0.525	0.523	0.641	0.504	0.403	0.513	0.411	0.545	0.502	0.426	0.424	0.529	0.498	0.528	0.494	0.360	0.531	0.495	0.392	0.555	0.854	0.263	0.894	0.691	0.521
27	0.228	0.569	0.583	0.620	0.525	0.406	0.517	0.409	0.545	0.512	0.427	0.437	0.539	0.523	0.497	0.357	0.565	0.494	0.394	0.581	0.898	0.257	0.914	0.706	0.532	

(b) Model performance of SC experiment under ROC-AUC on Eyemovements dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.783	0.779	0.858	0.738	0.631	0.723	0.640	0.750	0.721	0.629	0.638	0.749	0.702	0.731	0.699	0.510	0.772	0.703	0.571	0.782	0.979	0.495	0.927	0.808	0.722
1	-0.001	0.783	0.780	0.857	0.737	0.631	0.722	0.640	0.749	0.721	0.631	0.643	0.748	0.702	0.730	0.699	0.511	0.771	0.703	0.574	0.782	0.978	0.501	0.935	0.810	0.722
2	-0.001	0.782	0.779	0.846	0.738	0.632	0.723	0.640	0.750	0.721	0.631	0.637	0.749	0.702	0.731	0.699	0.513	0.772	0.703	0.572	0.782	0.979	0.500	0.927	0.802	0.721
3	-0.005	0.784	0.780	0.856	0.738	0.631	0.723	0.641	0.750	0.721	0.628	0.638	0.749	0.701	0.731	0.699	0.508	0.772	0.703	0.571	0.782	0.979	0.507	0.932	0.804	0.722
4	0.006	0.783	0.780	0.856	0.737	0.632	0.722	0.642	0.748	0.721	0.630	0.640	0.747	0.701	0.730	0.699	0.506	0.770	0.703	0.572	0.782	0.978	0.507	0.933	0.804	0.722
5	-0.015	0.783	0.779	0.859	0.732	0.633	0.720	0.641	0.744	0.720	0.630	0.633	0.748	0.701	0.729	0.699	0.513	0.771	0.702	0.570	0.783	0.978	0.506	0.933	0.805	0.721
6	0.017	0.781	0.773	0.857	0.737	0.631	0.722	0.644	0.747	0.720	0.632	0.633	0.748	0.702	0.730	0.699	0.513	0.771	0.702	0.570	0.783	0.978	0.506	0.933	0.805	0.721
7	0.017	0.775	0.769	0.777	0.737	0.630	0.722	0.645	0.748	0.720	0.629	0.639	0.748	0.700	0.731	0.699	0.507	0.771	0.703	0.571	0.783	0.978	0.502	0.920	0.798	0.709
8	0.017	0.777	0.774	0.788	0.733	0.632	0.722	0.643	0.748	0.720	0.631	0.636	0.747	0.701	0.729	0.700	0.509	0.770	0.703	0.571	0.780	0.979	0.507	0.931	0.805	0.721
9	-0.020																									

**TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments**

(d) Model performance of MC-M experiment under ROC-AUC on Eyemovements dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TFI	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.783	0.779	0.858	0.738	0.631	0.723	0.640	0.750	0.721	0.629	0.638	0.749	0.702	0.731	0.699	0.510	0.772	0.703	0.571	0.782	0.979	0.495	0.927	0.808	0.722
3.7%	0.777	0.774	0.826	0.730	0.619	0.711	0.622	0.741	0.713	0.609	0.626	0.740	0.688	0.720	0.689	0.515	0.764	0.688	0.565	0.777	0.978	0.488	0.931	0.809	0.712
7.41%	0.721	0.725	0.794	0.686	0.605	0.693	0.609	0.721	0.690	0.596	0.597	0.713	0.666	0.703	0.664	0.516	0.710	0.671	0.553	0.740	0.961	0.485	0.920	0.791	0.689
11.11%	0.715	0.718	0.792	0.666	0.589	0.675	0.591	0.699	0.678	0.579	0.567	0.687	0.652	0.688	0.654	0.503	0.690	0.654	0.538	0.718	0.952	0.501	0.920	0.777	0.675
14.81%	0.672	0.676	0.782	0.620	0.582	0.648	0.581	0.662	0.657	0.572	0.558	0.643	0.633	0.668	0.644	0.507	0.649	0.634	0.531	0.671	0.755	0.501	0.923	0.780	0.648
18.52%	0.659	0.666	0.793	0.596	0.571	0.621	0.565	0.632	0.632	0.570	0.561	0.615	0.609	0.643	0.626	0.506	0.636	0.613	0.525	0.647	0.743	0.501	0.918	0.784	0.634
22.22%	0.690	0.694	0.780	0.607	0.572	0.613	0.562	0.634	0.623	0.568	0.536	0.627	0.599	0.638	0.625	0.511	0.628	0.605	0.523	0.663	0.774	0.501	0.920	0.784	0.636
25.93%	0.679	0.687	0.768	0.592	0.571	0.596	0.555	0.614	0.600	0.561	0.572	0.606	0.585	0.627	0.616	0.507	0.645	0.591	0.513	0.643	0.763	0.501	0.917	0.781	0.627
29.63%	0.656	0.662	0.771	0.582	0.558	0.576	0.543	0.584	0.588	0.550	0.516	0.581	0.563	0.603	0.608	0.501	0.627	0.576	0.518	0.581	0.536	0.501	0.861	0.810	0.602
33.33%	0.629	0.638	0.771	0.568	0.553	0.576	0.543	0.584	0.583	0.544	0.512	0.583	0.557	0.597	0.603	0.499	0.606	0.574	0.519	0.585	0.536	0.501	0.853	0.783	0.596
37.04%	0.623	0.634	0.755	0.550	0.545	0.561	0.526	0.573	0.572	0.546	0.508	0.570	0.548	0.582	0.588	0.495	0.601	0.560	0.514	0.584	0.531	0.501	0.862	0.776	0.588
40.74%	0.609	0.619	0.746	0.562	0.535	0.558	0.519	0.571	0.564	0.542	0.497	0.569	0.539	0.575	0.578	0.496	0.596	0.553	0.518	0.580	0.522	0.501	0.853	0.784	0.583
44.44%	0.610	0.620	0.745	0.564	0.536	0.559	0.514	0.574	0.563	0.538	0.499	0.572	0.540	0.573	0.578	0.494	0.593	0.552	0.520	0.584	0.523	0.501	0.864	0.781	0.583
48.15%	0.565	0.580	0.713	0.534	0.531	0.543	0.507	0.554	0.541	0.536	0.493	0.553	0.530	0.561	0.561	0.496	0.596	0.553	0.509	0.564	0.520	0.501	0.856	0.777	0.569
51.85%	0.572	0.585	0.716	0.540	0.525	0.541	0.501	0.564	0.544	0.533	0.491	0.563	0.528	0.560	0.560	0.494	0.568	0.533	0.503	0.577	0.517	0.501	0.855	0.775	0.568
55.56%	0.573	0.587	0.716	0.538	0.525	0.545	0.500	0.559	0.545	0.533	0.493	0.561	0.526	0.559	0.556	0.494	0.590	0.534	0.507	0.571	0.517	0.501	0.856	0.773	0.569
59.26%	0.571	0.585	0.716	0.536	0.525	0.548	0.500	0.563	0.545	0.533	0.491	0.563	0.526	0.557	0.556	0.489	0.589	0.537	0.508	0.567	0.516	0.501	0.855	0.794	0.570
62.96%	0.561	0.573	0.759	0.525	0.522	0.542	0.499	0.560	0.539	0.531	0.493	0.556	0.519	0.552	0.553	0.491	0.589	0.529	0.513	0.565	0.515	0.501	0.854	0.789	0.561
66.67%	0.561	0.573	0.596	0.525	0.524	0.553	0.499	0.563	0.545	0.529	0.499	0.561	0.521	0.559	0.556	0.491	0.584	0.535	0.513	0.566	0.515	0.501	0.856	0.784	0.563
70.37%	0.523	0.525	0.525	0.511	0.516	0.534	0.492	0.533	0.527	0.511	0.495	0.532	0.506	0.539	0.539	0.489	0.586	0.523	0.507	0.530	0.512	0.501	0.863	0.813	0.550
74.07%	0.523	0.526	0.593	0.519	0.505	0.527	0.495	0.527	0.521	0.508	0.494	0.535	0.505	0.534	0.527	0.487	0.546	0.520	0.495	0.518	0.510	0.501	0.861	0.827	0.546
77.78%	0.513	0.517	0.540	0.519	0.497	0.521	0.500	0.537	0.518	0.505	0.489	0.538	0.504	0.535	0.525	0.488	0.535	0.514	0.498	0.523	0.508	0.501	0.854	0.843	0.543
81.48%	0.522	0.522	0.537	0.519	0.501	0.525	0.504	0.530	0.518	0.499	0.482	0.535	0.499	0.528	0.516	0.493	0.534	0.511	0.493	0.520	0.513	0.501	0.854	0.842	0.542
85.19%	0.523	0.523	0.533	0.514	0.504	0.526	0.500	0.518	0.503	0.503	0.487	0.527	0.502	0.527	0.519	0.494	0.526	0.510	0.486	0.522	0.514	0.501	0.852	0.856	0.542
88.89%	0.518	0.518	0.534	0.525	0.505	0.520	0.515	0.519	0.517	0.502	0.488	0.523	0.512	0.520	0.520	0.492	0.527	0.509	0.490	0.521	0.516	0.501	0.854	0.849	0.541
92.59%	0.521	0.520	0.533	0.513	0.502	0.512	0.514	0.514	0.511	0.499	0.489	0.515	0.502	0.519	0.512	0.488	0.519	0.504	0.488	0.513	0.514	0.501	0.854	0.838	0.537
96.3%	0.502	0.500	0.508	0.505	0.498	0.508	0.502	0.502	0.496	0.503	0.498	0.502	0.496	0.502	0.501	0.496	0.513	0.500	0.499	0.502	0.507	0.501	0.854	0.838	0.530
100%	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.499	0.500	0.500	0.500	0.500	0.503	0.501	0.852	0.830	0.528

(e) Model performance of MC-L experiment under accuracy on Eyemovements dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TFI	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.594	0.589	0.684	0.533	0.405	0.527	0.411	0.555	0.522	0.437	0.444	0.555	0.506	0.541	0.502	0.361	0.572	0.507	0.586	0.900	0.277	0.918	0.715	0.543	
3.7%	0.593	0.588	0.680	0.531	0.405	0.526	0.414	0.557	0.521	0.442	0.446	0.555	0.506	0.540	0.503	0.360	0.568	0.510	0.586	0.894	0.289	0.923	0.715	0.544	
7.41%	0.591	0.585	0.660	0.533	0.406	0.525	0.413	0.556	0.522	0.444	0.447	0.553	0.506	0.541	0.500	0.365	0.569	0.509	0.400	0.585	0.894	0.300	0.920	0.715	0.543
11.11%	0.592	0.587	0.657	0.531	0.404	0.525	0.414	0.557	0.518	0.443	0.445	0.550	0.505	0.541	0.499	0.360	0.570	0.509	0.584	0.895	0.288	0.920	0.701	0.541	
14.81%	0.593	0.588	0.654	0.532	0.404	0.524	0.414	0.549	0.518	0.445	0.447	0.545	0.504	0.530	0.500	0.364	0.566	0.500	0.400	0.588	0.297	0.917	0.711	0.541	
18.52%	0.590	0.587	0.654	0.530	0.407	0.522	0.414	0.547	0.520	0.441	0.444	0.546	0.504	0.538	0.500	0.364	0.564	0.500	0.400	0.587	0.297	0.917	0.711	0.541	
22.22%	0.588	0.578	0.654	0.529	0.405	0.520	0.413	0.546	0.515	0.442	0.439	0.545	0.505	0.532	0.499	0.363	0.566	0.506	0.404	0.587	0.685	0.348	0.861	0.697	0.530
25.93%	0.569	0.563	0.555	0.528	0.404	0.521	0.410	0.545	0.514	0.444	0.441	0.534	0.503	0.533	0.498	0.364	0.564	0.505	0.400	0.586	0.683	0.352	0.863	0.692	0.521
29.63%	0.575	0.564	0.553	0.521	0.405	0.520	0.416	0.548	0.508	0.448	0.450	0.538	0.503	0.533	0.498	0.364	0.565	0.505	0.396	0.581	0.615	0.315	0.854	0.691	0.518
33.33%	0.522	0.553	0.511	0.402	0.508	0.415	0.519	0.503	0.433	0.430	0.438	0.504	0.481	0.504	0.485	0.364	0.519	0.491	0.446	0.533	0.338	0.434	0.856	0.498	0.498
37.04%	0.523	0.543	0.509	0.510	0.400	0.511	0.418	0.521	0.505	0.431	0.434	0.523													

**TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments**

(g) Model performance of RD experiment under accuracy on Eyemovements dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.594	0.589	0.684	0.533	0.405	0.527	0.411	0.555	0.522	0.437	0.444	0.555	0.506	0.541	0.502	0.361	0.572	0.507	0.397	0.586	0.900	0.677	0.918	0.715	0.560
3.7%	0.584	0.582	0.668	0.527	0.404	0.520	0.411	0.548	0.510	0.436	0.436	0.546	0.504	0.536	0.502	0.357	0.561	0.505	0.395	0.581	0.856	0.669	0.912	0.708	0.552
7.41%	0.580	0.576	0.658	0.525	0.404	0.523	0.415	0.546	0.510	0.436	0.434	0.544	0.503	0.533	0.502	0.354	0.558	0.505	0.396	0.570	0.800	0.615	0.896	0.704	0.545
11.11%	0.556	0.556	0.643	0.513	0.403	0.511	0.410	0.536	0.506	0.431	0.428	0.531	0.496	0.523	0.497	0.357	0.550	0.495	0.396	0.560	0.735	0.579	0.895	0.697	0.533
14.81%	0.554	0.555	0.622	0.511	0.403	0.511	0.414	0.531	0.503	0.435	0.429	0.527	0.492	0.524	0.498	0.351	0.545	0.493	0.395	0.554	0.676	0.593	0.901	0.701	0.530
18.52%	0.542	0.527	0.601	0.510	0.403	0.510	0.411	0.529	0.501	0.434	0.428	0.529	0.492	0.518	0.498	0.353	0.543	0.494	0.398	0.556	0.673	0.529	0.888	0.682	0.523
22.22%	0.515	0.518	0.579	0.491	0.401	0.499	0.409	0.514	0.491	0.427	0.423	0.514	0.481	0.508	0.487	0.348	0.525	0.488	0.395	0.535	0.584	0.521	0.898	0.693	0.510
25.93%	0.515	0.513	0.571	0.493	0.401	0.499	0.409	0.517	0.493	0.427	0.426	0.516	0.479	0.511	0.486	0.353	0.531	0.484	0.394	0.538	0.602	0.508	0.868	0.685	0.509
29.63%	0.492	0.514	0.557	0.479	0.399	0.495	0.407	0.511	0.492	0.425	0.418	0.511	0.473	0.504	0.485	0.354	0.521	0.482	0.399	0.513	0.583	0.512	0.858	0.686	0.503
33.33%	0.493	0.509	0.548	0.481	0.401	0.496	0.411	0.512	0.487	0.431	0.422	0.507	0.478	0.507	0.485	0.354	0.518	0.479	0.396	0.511	0.559	0.504	0.861	0.671	0.501
37.04%	0.438	0.495	0.539	0.466	0.401	0.485	0.412	0.501	0.479	0.423	0.416	0.496	0.464	0.495	0.474	0.353	0.504	0.472	0.393	0.486	0.507	0.463	0.863	0.663	0.487
40.74%	0.430	0.488	0.535	0.476	0.396	0.471	0.407	0.478	0.465	0.412	0.405	0.475	0.444	0.477	0.459	0.348	0.474	0.459	0.390	0.494	0.497	0.433	0.868	0.666	0.477
44.44%	0.436	0.476	0.495	0.459	0.400	0.476	0.406	0.487	0.473	0.420	0.417	0.486	0.451	0.483	0.472	0.352	0.494	0.463	0.394	0.472	0.481	0.433	0.859	0.663	0.477
48.15%	0.436	0.480	0.503	0.462	0.398	0.479	0.407	0.486	0.476	0.419	0.414	0.489	0.456	0.484	0.475	0.349	0.494	0.463	0.395	0.472	0.462	0.413	0.833	0.656	0.475
51.85%	0.364	0.425	0.493	0.436	0.399	0.462	0.406	0.465	0.465	0.414	0.406	0.470	0.437	0.471	0.463	0.345	0.470	0.452	0.394	0.475	0.439	0.428	0.838	0.652	0.461
55.56%	0.371	0.456	0.474	0.441	0.396	0.460	0.402	0.467	0.459	0.412	0.406	0.468	0.433	0.467	0.454	0.348	0.468	0.452	0.392	0.457	0.427	0.398	0.829	0.645	0.457
59.26%	0.377	0.426	0.470	0.438	0.397	0.463	0.406	0.468	0.462	0.417	0.413	0.474	0.440	0.469	0.466	0.348	0.481	0.455	0.395	0.433	0.434	0.403	0.839	0.649	0.459
62.96%	0.337	0.397	0.462	0.418	0.398	0.454	0.404	0.454	0.443	0.412	0.402	0.454	0.413	0.456	0.446	0.348	0.453	0.442	0.390	0.461	0.436	0.372	0.833	0.634	0.447
66.67%	0.310	0.390	0.436	0.416	0.397	0.448	0.405	0.455	0.443	0.410	0.404	0.449	0.416	0.455	0.441	0.350	0.440	0.439	0.391	0.412	0.424	0.384	0.833	0.636	0.441
70.37%	0.332	0.412	0.433	0.432	0.393	0.433	0.394	0.434	0.434	0.402	0.401	0.432	0.405	0.436	0.428	0.352	0.422	0.428	0.391	0.407	0.384	0.361	0.823	0.633	0.433
74.07%	0.326	0.443	0.419	0.425	0.396	0.438	0.402	0.435	0.438	0.406	0.403	0.440	0.407	0.444	0.439	0.344	0.432	0.432	0.390	0.423	0.388	0.374	0.830	0.628	0.438
77.78%	0.330	0.413	0.401	0.422	0.392	0.425	0.394	0.423	0.419	0.400	0.398	0.424	0.382	0.426	0.418	0.346	0.401	0.421	0.390	0.365	0.366	0.347	0.826	0.610	0.422
81.48%	0.273	0.376	0.388	0.395	0.393	0.394	0.397	0.409	0.398	0.386	0.397	0.413	0.369	0.423	0.412	0.347	0.402	0.406	0.384	0.395	0.372	0.374	0.826	0.622	0.415
85.19%	0.266	0.354	0.379	0.393	0.395	0.405	0.396	0.394	0.394	0.386	0.394	0.402	0.364	0.412	0.411	0.346	0.386	0.392	0.387	0.376	0.361	0.341	0.826	0.607	0.407
88.89%	0.274	0.411	0.382	0.406	0.395	0.408	0.397	0.393	0.392	0.386	0.390	0.407	0.355	0.414	0.406	0.345	0.386	0.382	0.388	0.359	0.363	0.823	0.637	0.412	
92.59%	0.263	0.325	0.361	0.380	0.393	0.393	0.394	0.374	0.379	0.389	0.392	0.397	0.335	0.400	0.399	0.340	0.362	0.386	0.388	0.337	0.343	0.349	0.825	0.610	0.396
96.3%	0.261	0.324	0.353	0.392	0.392	0.391	0.395	0.368	0.370	0.384	0.396	0.394	0.325	0.396	0.396	0.346	0.365	0.377	0.383	0.312	0.340	0.378	0.824	0.601	0.394
100%	0.260	0.306	0.260	0.393	0.394	0.379	0.394	0.348	0.349	0.394	0.394	0.348	0.300	0.394	0.348	0.352	0.394	0.379	0.303	0.333	0.265	0.825	0.581	0.383	

(h) Model performance of RD experiment under ROC-AUC on Eyemovements dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.783	0.779	0.858	0.738	0.631	0.723	0.640	0.750	0.721	0.629	0.638	0.749	0.702	0.731	0.699	0.510	0.772	0.703	0.571	0.782	0.979	0.795	0.927	0.808	0.734
3.7%	0.779	0.776	0.847	0.733	0.629	0.718	0.638	0.743	0.713	0.626	0.625	0.742	0.698	0.725	0.697	0.509	0.763	0.699	0.570	0.776	0.949	0.746	0.924	0.797	0.726
7.41%	0.777	0.773	0.840	0.731	0.632	0.718	0.641	0.742	0.712	0.629	0.628	0.741	0.698	0.726	0.698	0.506	0.760	0.700	0.571	0.769	0.920	0.703	0.912	0.796	0.722
11.11%	0.760	0.757	0.850	0.718	0.622	0.705	0.628	0.728	0.705	0.615	0.614	0.727	0.688	0.714	0.691	0.510	0.749	0.688	0.566	0.759	0.872	0.676	0.912	0.792	0.709
14.81%	0.759	0.755	0.812	0.716	0.627	0.705	0.636	0.726	0.705	0.622	0.619	0.725	0.689	0.715	0.692	0.505	0.744	0.689	0.564	0.752	0.835	0.687	0.916	0.794	0.708
18.52%	0.745	0.740	0.797	0.712	0.624	0.706	0.634	0.726	0.704	0.620	0.619	0.726	0.688	0.713	0.692	0.506	0.741	0.691	0.570	0.747	0.828	0.644	0.907	0.787	0.703
22.22%	0.737	0.733	0.777	0.697	0.621	0.693	0.625	0.709	0.693	0.612	0.614	0.710	0.676	0.700	0.683	0.504	0.729	0.680	0.563	0.736	0.753	0.632	0.911	0.790	0.691
25.93%	0.733	0.729	0.776	0.698	0.621	0.672	0.627	0.711	0.695	0.614	0.614	0.711	0.676	0.700	0.684	0.509	0.732	0.678	0.567	0.734	0.766	0.625	0.890	0.783	0.690
29.63%	0.724	0.720	0.760	0.685	0.621	0.691	0.623	0.707	0.692	0.608	0.613	0.707	0.672	0.696	0.682	0.501	0.720	0.678	0.568	0.710	0.755	0.627	0.881	0.781	0.684
33.33%	0.716	0.713	0.752	0.685	0.624	0.691	0.613	0.706	0.690	0.618	0.614	0.704	0.675	0.697	0.682	0.510	0.718	0.677	0.569	0.713	0.737	0.623	0.886	0.784	0.684
37.04%	0.700	0.701	0.740	0.667	0.619	0.670	0.605	0.707	0.677																

(j) Model performance gap  $\Delta$  of RD experiment under ROC-AUC on Eyemovements dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TF	TABR	NCA	LMA	TLLM	UNI	AVE
3.7%	-0.005	-0.005	-0.013	-0.006	-0.004	-0.007	-0.004	-0.010	-0.011	-0.005	-0.021	-0.010	-0.005	-0.007	-0.003	-0.002	-0.011	-0.005	-0.002	-0.007	-0.031	-0.062	-0.003	-0.014	-0.011
7.41%	-0.007	-0.008	-0.021	-0.008	0.002	-0.006	0.001	-0.010	-0.012	0.000	-0.016	-0.011	-0.005	-0.007	-0.002	-0.008	-0.016	-0.004	-0.001	-0.017	-0.060	-0.116	-0.017	-0.014	-0.017
11.11%	-0.029	-0.029	-0.033	-0.027	-0.014	-0.025	-0.020	-0.030	-0.021	-0.022	-0.037	-0.029	-0.020	-0.023	-0.012	0.000	-0.030	-0.022	-0.009	-0.030	-0.109	-0.150	-0.016	-0.019	-0.034
14.81%	-0.031	-0.031	-0.055	-0.029	-0.007	-0.025	-0.008	-0.032	-0.022	-0.011	-0.030	-0.033	-0.019	-0.021	-0.011	-0.009	-0.037	-0.020	-0.011	-0.039	-0.147	-0.137	-0.011	-0.017	-0.036
18.52%	-0.048	-0.050	-0.071	-0.034	-0.011	-0.024	-0.010	-0.032	-0.023	-0.015	-0.030	-0.031	-0.020	-0.025	-0.011	-0.007	-0.039	-0.017	-0.002	-0.044	-0.154	-0.190	-0.021	-0.026	-0.043
22.22%	-0.059	-0.059	-0.095	-0.055	-0.016	-0.042	-0.024	-0.055	-0.038	-0.028	-0.038	-0.052	-0.037	-0.042	-0.023	-0.002	-0.056	-0.033	-0.014	-0.059	-0.231	-0.206	-0.017	-0.022	-0.059
25.93%	-0.064	-0.065	-0.096	-0.054	-0.015	-0.043	-0.021	-0.052	-0.036	-0.024	-0.037	-0.051	-0.037	-0.042	-0.022	-0.002	-0.052	-0.036	-0.006	-0.062	-0.217	-0.214	-0.040	-0.031	-0.060
29.63%	-0.076	-0.077	-0.114	-0.072	-0.016	-0.044	-0.027	-0.057	-0.040	-0.033	-0.039	-0.056	-0.042	-0.048	-0.025	-0.017	-0.067	-0.035	-0.005	-0.092	-0.229	-0.212	-0.050	-0.034	-0.068
33.33%	-0.085	-0.085	-0.124	-0.072	-0.012	-0.045	-0.015	-0.058	-0.042	-0.018	-0.038	-0.061	-0.038	-0.046	-0.025	-0.001	-0.070	-0.037	-0.003	-0.088	-0.247	-0.216	-0.044	-0.029	-0.068
37.04%	-0.105	-0.100	-0.137	-0.099	-0.019	-0.062	-0.025	-0.075	-0.057	-0.032	-0.048	-0.079	-0.057	-0.059	-0.038	-0.007	-0.089	-0.052	-0.018	-0.124	-0.291	-0.253	-0.043	-0.039	-0.086
40.74%	-0.097	-0.096	-0.136	-0.087	-0.049	-0.094	-0.056	-0.114	-0.086	-0.065	-0.077	-0.118	-0.089	-0.091	-0.069	-0.009	-0.140	-0.080	-0.036	-0.108	-0.317	-0.276	-0.039	-0.025	-0.104
44.44%	-0.114	-0.115	-0.174	-0.103	-0.032	-0.083	-0.046	-0.099	-0.071	-0.048	-0.053	-0.099	-0.078	-0.082	-0.047	-0.006	-0.102	-0.071	-0.020	-0.140	-0.326	-0.284	-0.045	-0.028	-0.101
48.15%	-0.115	-0.113	-0.167	-0.102	-0.014	-0.072	-0.028	-0.093	-0.061	-0.039	-0.042	-0.086	-0.063	-0.074	-0.036	-0.021	-0.098	-0.055	-0.012	-0.141	-0.339	-0.294	-0.069	-0.029	-0.098
51.85%	-0.175	-0.169	-0.182	-0.142	-0.045	-0.109	-0.062	-0.134	-0.092	-0.066	-0.078	-0.129	-0.095	-0.107	-0.062	-0.017	-0.133	-0.088	-0.043	-0.143	-0.365	-0.277	-0.061	-0.041	-0.125
55.56%	-0.148	-0.145	-0.204	-0.139	-0.046	-0.105	-0.054	-0.127	-0.095	-0.060	-0.072	-0.127	-0.099	-0.106	-0.066	-0.020	-0.142	-0.088	-0.029	-0.163	-0.382	-0.307	-0.069	-0.023	-0.125
59.26%	-0.168	-0.168	-0.201	-0.149	-0.024	-0.099	-0.042	-0.122	-0.086	-0.056	-0.051	-0.117	-0.088	-0.101	-0.054	-0.012	-0.123	-0.080	-0.023	-0.196	-0.368	-0.299	-0.064	-0.019	-0.121
62.96%	-0.211	-0.206	-0.213	-0.179	-0.071	-0.134	-0.078	-0.158	-0.129	-0.084	-0.102	-0.158	-0.133	-0.136	-0.091	-0.005	-0.165	-0.121	-0.058	-0.167	-0.371	-0.325	-0.068	-0.014	-0.148
66.67%	-0.203	-0.198	-0.247	-0.180	-0.058	-0.134	-0.074	-0.159	-0.127	-0.089	-0.098	-0.162	-0.129	-0.135	-0.095	-0.011	-0.182	-0.117	-0.049	-0.218	-0.385	-0.312	-0.068	-0.009	-0.151
70.37%	-0.193	-0.192	-0.251	-0.153	-0.076	-0.150	-0.087	-0.176	-0.141	-0.093	-0.100	-0.178	-0.140	-0.152	-0.112	-0.015	-0.195	-0.132	-0.051	-0.234	-0.431	-0.327	-0.077	-0.022	-0.162
74.07%	-0.177	-0.168	-0.265	-0.170	-0.055	-0.142	-0.071	-0.171	-0.135	-0.086	-0.086	-0.170	-0.136	-0.145	-0.099	-0.022	-0.190	-0.121	-0.040	-0.222	-0.418	-0.321	-0.074	-0.008	-0.154
77.78%	-0.218	-0.210	-0.289	-0.177	-0.090	-0.179	-0.108	-0.207	-0.173	-0.104	-0.115	-0.206	-0.169	-0.179	-0.130	-0.018	-0.218	-0.157	-0.058	-0.265	-0.445	-0.340	-0.077	0.014	-0.180
81.48%	-0.246	-0.239	-0.307	-0.227	-0.112	-0.204	-0.128	-0.229	-0.202	-0.152	-0.165	-0.233	-0.197	-0.204	-0.162	-0.026	-0.248	-0.179	-0.077	-0.251	-0.439	-0.333	-0.075	-0.005	-0.201
85.19%	-0.268	-0.263	-0.319	-0.234	-0.116	-0.222	-0.140	-0.259	-0.217	-0.142	-0.155	-0.259	-0.209	-0.225	-0.176	-0.012	-0.273	-0.196	-0.086	-0.277	-0.443	-0.352	-0.078	0.020	-0.212
88.89%	-0.239	-0.237	-0.321	-0.210	-0.123	-0.216	-0.152	-0.263	-0.216	-0.151	-0.165	-0.260	-0.211	-0.225	-0.179	-0.027	-0.274	-0.196	-0.076	-0.298	-0.449	-0.348	-0.079	-0.028	-0.214
92.59%	-0.328	-0.323	-0.364	-0.310	-0.144	-0.260	-0.174	-0.318	-0.267	-0.164	-0.173	-0.311	-0.245	-0.266	-0.214	-0.040	-0.316	-0.238	-0.102	-0.309	-0.469	-0.358	-0.080	0.024	-0.248
96.3%	-0.314	-0.311	-0.383	-0.278	-0.178	-0.280	-0.193	-0.315	-0.278	-0.180	-0.197	-0.312	-0.271	-0.287	-0.248	-0.011	-0.323	-0.260	-0.101	-0.330	-0.471	-0.357	-0.082	0.039	-0.255
100%	-0.361	-0.359	-0.418	-0.322	-0.208	-0.307	-0.219	-0.333	-0.311	-0.205	-0.216	-0.332	-0.288	-0.315	-0.285	-0.021	-0.350	-0.289	-0.124	-0.364	-0.486	-0.371	-0.081	0.027	-0.280

## TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments

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**Table 19.** Model performance on Iris dataset.

(a) Model performance of SC experiment under accuracy on Iris dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.944	0.967	0.989	0.989	0.600	0.811	0.522	0.844	0.822	0.911	0.633	0.889	0.622	0.856	0.878	0.478	0.944	0.800	0.333	0.867	1.000	0.933	1.000	0.767	0.808
1	-0.427	0.978	0.989	0.989	0.989	0.556	0.822	0.456	0.867	0.867	0.956	0.567	0.967	0.533	0.878	0.878	0.489	0.989	0.778	0.344	0.911	1.000	0.933	1.000	0.933	0.819
2	0.783	0.956	0.978	0.989	0.978	0.556	0.833	0.500	0.833	0.744	0.811	0.644	0.833	0.500	0.856	0.744	0.400	0.856	0.722	0.144	0.856	0.811	0.967	0.733	0.759	
3	0.949	0.600	0.433	0.911	0.767	0.511	0.822	0.511	0.856	0.822	0.844	0.511	0.867	0.589	0.889	0.844	0.422	0.911	0.778	0.367	0.867	0.978	0.900	1.000	0.800	0.742
4	0.957	0.789	0.789	0.967	0.756	0.611	0.800	0.344	0.856	0.856	0.856	0.556	0.878	0.556	0.856	0.867	0.489	0.867	0.822	0.333	0.878	0.967	0.733	0.900	0.800	0.755

(b) Model performance of SC experiment under ROC-AUC on Iris dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE	
0	\	0.992	0.997	1.000	1.000	0.948	0.994	0.856	0.997	0.953	0.986	0.899	0.988	0.821	0.997	0.959	0.616	0.996	0.937	0.483	0.994	1.000	0.954	1.000	0.907	0.928	
1	-0.427	0.997	0.998	1.000	0.999	0.914	0.995	0.859	0.998	0.956	0.988	0.766	0.996	0.831	1.000	0.958	0.594	0.998	0.918	0.537	0.998	1.000	0.954	1.000	0.938	0.925	
2	0.783	0.984	0.986	1.000	1.000	0.873	0.973	0.823	0.972	0.907	0.963	0.883	0.950	0.776	0.978	0.921	0.555	0.971	0.879	0.334	0.972	0.999	0.977	1.000	0.932	0.900	
3	0.949	0.827	0.892	0.994	0.997	0.900	0.990	0.823	0.995	0.949	0.972	0.813	0.974	0.774	0.993	0.929	0.542	0.994	0.924	0.514	0.993	1.000	0.931	0.978	0.925	0.901	
4	0.957	0.956	0.977	0.995	0.996	0.939	0.987	0.717	0.979	0.944	0.971	0.841	0.974	0.780	0.992	0.989	0.706	0.986	0.928	0.478	0.990	1.000	0.811	0.957	0.891	0.908	

(c) Model performance of MC-M experiment under accuracy on Iris dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE	
0%	0.944	0.967	0.989	0.989	0.600	0.811	0.522	0.844	0.822	0.911	0.633	0.889	0.622	0.856	0.878	0.478	0.944	0.800	0.333	0.867	1.000	0.933	1.000	0.767	0.808	
25%	0.789	0.789	0.967	0.756	0.400	0.789	0.333	0.811	0.822	0.556	0.522	0.822	0.478	0.789	0.878	0.433	0.678	0.811	0.356	0.844	0.556	0.733	0.900	0.867	0.695	
50%	0.344	0.344	0.356	0.400	0.344	0.678	0.333	0.567	0.767	0.456	0.544	0.678	0.467	0.522	0.611	0.356	0.456	0.667	0.267	0.556	0.333	0.267	0.800	0.800	0.496	
75%	0.344	0.344	0.344	0.367	0.389	0.411	0.344	0.533	0.544	0.456	0.333	0.389	0.322	0.400	0.456	0.400	0.333	0.489	0.333	0.367	0.333	0.400	0.733	0.424		
100%	0.344	0.344	0.344	0.344	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.333	0.367	0.800	0.667	0.370

(d) Model performance of MC-M experiment under ROC-AUC on Iris dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.944	0.967	0.989	0.989	0.600	0.811	0.522	0.844	0.822	0.911	0.633	0.889	0.622	0.856	0.878	0.478	0.944	0.800	0.333	0.867	1.000	0.933	1.000	0.767	0.808
25%	0.789	0.789	0.967	0.756	0.400	0.789	0.333	0.811	0.822	0.556	0.522	0.822	0.478	0.789	0.878	0.433	0.678	0.811	0.356	0.844	0.556	0.733	0.900	0.867	0.695
50%	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	
75%	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	
100%	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	0.344	

(e) Model performance of MC-L experiment under accuracy on Iris dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE	
0%	0.992	0.997	1.000	1.000	0.948	0.994	0.856	0.997	0.953	0.986	0.898	0.988	0.821	0.997	0.959	0.616	0.996	0.937	0.483	0.994	1.000	0.954	1.000	0.907	0.928	
25%	0.997	0.998	1.000	0.999	0.914	0.995	0.859	0.998	0.956	0.986	0.876	0.967	0.567	0.967	0.533	0.978	0.987	0.446	0.998	0.915	0.537	0.998	1.000	0.954	0.925	
50%	0.988	0.993	1.000	1.000	0.889	0.987	0.857	0.996	0.944	0.957	0.751	0.944	0.853	0.939	0.586	0.986	0.816	0.431	0.994	1.000	1.000	0.978	0.966	0.906		
75%	0.894	0.630	0.990	0.997	0.740	0.941	0.848	0.911	0.808	0.931	0.587	0.825	0.882	0.927	0.873	0.979	0.846	0.324	0.980	0.989	0.667	0.978	0.944	0.827		
100%	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500		

(g) Model performance of RD experiment under accuracy on Iris dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.992	0.997	1.000	1.000	0.948	0.994	0.856	0.997	0.953	0.986	0.898	0.988	0.821	0.997	0.959	0.616	0.996	0.937	0.483	0.994	1.000	0.954	1.000	0.907	0.928
25%	0.941	0.963	0.996	0.998	0.878	0.979	0.778	0.974	0.889	0.894	0.781	0.957	0.789	0.974	0.597	0.998	0.918	0.446	0.973	0.998	0.932	0.970	0.945	0.897	
50%	0.872	0.870	0.951	0.955	0.828	0.946	0.728	0.934	0.844	0.907	0.733	0.922	0.769	0.926	0.578	0.995	0.828	0.466	0.966	0.987	0.874	0.937	0.945	0.859	
75%	0.764	0.710	0.832	0.819	0.758	0.846	0.674	0.831	0.778	0.826	0.709	0.851	0.729	0.8											

Table 20. Model performance on Jannis dataset.

(a) Model performance of SC experiment under accuracy on Jannis dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.680	0.682	0.715	0.629	0.657	0.669	0.560	0.693	0.666	0.633	0.626	0.694	0.661	0.678	0.685	0.530	0.705	0.638	0.636	0.731	0.725	0.560	0.582	0.850	0.662
1	0.000	0.681	0.681	0.715	0.629	0.657	0.669	0.560	0.694	0.666	0.633	0.627	0.695	0.661	0.679	0.685	0.529	0.706	0.638	0.636	0.730	0.725	0.550	0.578	0.851	0.661
2	0.000	0.681	0.682	0.715	0.629	0.657	0.669	0.561	0.693	0.666	0.633	0.626	0.694	0.662	0.679	0.685	0.531	0.705	0.638	0.637	0.731	0.725	0.530	0.581	0.849	0.661
3	0.000	0.681	0.682	0.715	0.629	0.657	0.670	0.560	0.693	0.666	0.633	0.626	0.694	0.661	0.679	0.684	0.530	0.705	0.638	0.636	0.730	0.725	0.610	0.579	0.848	0.664
4	0.000	0.680	0.681	0.715	0.630	0.657	0.669	0.560	0.693	0.666	0.632	0.627	0.695	0.660	0.678	0.685	0.531	0.707	0.638	0.636	0.731	0.725	0.450	0.584	0.848	0.657
5	-0.001	0.669	0.670	0.712	0.629	0.656	0.668	0.560	0.687	0.665	0.631	0.626	0.690	0.655	0.676	0.678	0.531	0.696	0.637	0.636	0.719	0.714	0.610	0.583	0.845	0.660
6	-0.001	0.680	0.681	0.715	0.630	0.657	0.669	0.560	0.693	0.666	0.633	0.626	0.694	0.661	0.679	0.685	0.528	0.706	0.638	0.636	0.730	0.725	0.570	0.580	0.850	0.662
7	0.001	0.680	0.681	0.715	0.630	0.657	0.669	0.560	0.693	0.666	0.633	0.626	0.694	0.662	0.679	0.684	0.531	0.706	0.637	0.635	0.731	0.725	0.590	0.585	0.850	0.663
8	0.001	0.680	0.681	0.715	0.630	0.658	0.669	0.560	0.693	0.666	0.633	0.627	0.693	0.662	0.679	0.685	0.530	0.706	0.638	0.636	0.731	0.725	0.600	0.584	0.849	0.664
9	0.001	0.681	0.681	0.715	0.630	0.658	0.669	0.560	0.692	0.666	0.632	0.626	0.694	0.661	0.678	0.684	0.530	0.706	0.638	0.636	0.730	0.725	0.520	0.582	0.847	0.660
10	-0.001	0.681	0.682	0.715	0.630	0.658	0.670	0.560	0.693	0.666	0.633	0.627	0.694	0.662	0.679	0.685	0.532	0.707	0.637	0.637	0.731	0.725	0.510	0.584	0.852	0.660
11	-0.001	0.680	0.682	0.715	0.631	0.657	0.669	0.560	0.693	0.666	0.633	0.626	0.695	0.661	0.678	0.685	0.531	0.706	0.638	0.637	0.731	0.725	0.530	0.576	0.850	0.661
12	-0.002	0.680	0.682	0.715	0.630	0.805	0.669	0.560	0.693	0.666	0.633	0.626	0.694	0.661	0.678	0.684	0.529	0.706	0.637	0.636	0.731	0.725	0.510	0.584	0.850	0.666
13	-0.002	0.681	0.681	0.715	0.630	0.657	0.669	0.560	0.693	0.666	0.633	0.626	0.694	0.662	0.678	0.685	0.531	0.705	0.638	0.636	0.731	0.725	0.710	0.584	0.847	0.668
14	0.003	0.681	0.682	0.715	0.630	0.657	0.669	0.560	0.693	0.666	0.632	0.627	0.694	0.661	0.678	0.684	0.531	0.706	0.637	0.636	0.730	0.725	0.650	0.583	0.846	0.666
15	0.003	0.681	0.681	0.715	0.630	0.658	0.669	0.560	0.693	0.666	0.632	0.626	0.694	0.661	0.678	0.684	0.530	0.705	0.637	0.636	0.731	0.725	0.740	0.582	0.846	0.669
16	0.003	0.681	0.682	0.715	0.630	0.657	0.669	0.560	0.692	0.666	0.634	0.626	0.694	0.660	0.678	0.685	0.531	0.707	0.638	0.636	0.730	0.725	0.640	0.588	0.849	0.666
17	-0.003	0.680	0.682	0.715	0.631	0.657	0.669	0.560	0.692	0.666	0.632	0.625	0.693	0.661	0.678	0.684	0.530	0.705	0.637	0.636	0.730	0.726	0.580	0.590	0.846	0.663
18	0.004	0.681	0.682	0.715	0.630	0.658	0.670	0.560	0.694	0.666	0.633	0.627	0.694	0.661	0.678	0.685	0.531	0.706	0.638	0.637	0.731	0.725	0.660	0.587	0.848	0.666
19	-0.004	0.680	0.681	0.715	0.630	0.657	0.669	0.560	0.693	0.666	0.633	0.626	0.694	0.661	0.678	0.685	0.530	0.707	0.637	0.636	0.730	0.725	0.590	0.583	0.848	0.663
20	-0.004	0.680	0.681	0.715	0.629	0.657	0.670	0.560	0.693	0.666	0.633	0.626	0.694	0.661	0.679	0.685	0.531	0.706	0.639	0.636	0.730	0.725	0.660	0.586	0.847	0.666
21	-0.004	0.680	0.682	0.715	0.630	0.657	0.670	0.560	0.693	0.666	0.633	0.626	0.693	0.660	0.678	0.684	0.531	0.706	0.638	0.636	0.730	0.725	0.600	0.583	0.851	0.664
22	-0.005	0.680	0.681	0.715	0.631	0.657	0.669	0.560	0.693	0.666	0.632	0.628	0.694	0.662	0.678	0.685	0.532	0.707	0.638	0.636	0.730	0.725	0.610	0.581	0.850	0.664
23	-0.005	0.680	0.681	0.715	0.630	0.657	0.668	0.560	0.693	0.667	0.634	0.627	0.694	0.661	0.679	0.684	0.530	0.706	0.638	0.636	0.731	0.725	0.580	0.582	0.847	0.663
24	-0.005	0.681	0.681	0.715	0.630	0.657	0.670	0.560	0.693	0.666	0.632	0.626	0.695	0.661	0.678	0.685	0.529	0.706	0.637	0.637	0.731	0.725	0.630	0.584	0.849	0.665
25	-0.005	0.681	0.682	0.715	0.629	0.658	0.669	0.560	0.693	0.666	0.633	0.626	0.694	0.661	0.678	0.685	0.530	0.705	0.637	0.636	0.731	0.726	0.550	0.579	0.846	0.661
26	-0.006	0.681	0.681	0.715	0.630	0.657	0.669	0.560	0.693	0.666	0.632	0.626	0.695	0.661	0.679	0.685	0.531	0.708	0.638	0.637	0.731	0.726	0.520	0.586	0.847	0.661
27	-0.007	0.681	0.681	0.715	0.630	0.657	0.669	0.560	0.693	0.666	0.632	0.626	0.694	0.661	0.678	0.685	0.530	0.705	0.638	0.636	0.731	0.725	0.650	0.581	0.849	0.666
28	-0.008	0.681	0.681	0.715	0.630	0.657	0.669	0.560	0.693	0.666	0.633	0.627	0.694	0.661	0.679	0.685	0.530	0.706	0.638	0.636	0.731	0.725	0.640	0.587	0.849	0.666
29	-0.009	0.672	0.672	0.705	0.627	0.654	0.661	0.560	0.683	0.662	0.628	0.625	0.688	0.653	0.673	0.678	0.531	0.697	0.634	0.633	0.719	0.713	0.590	0.583	0.846	0.658
30	-0.046	0.677	0.677	0.710	0.629	0.658	0.667	0.560	0.691	0.665	0.632	0.626	0.692	0.660	0.676	0.683	0.529	0.702	0.638	0.636	0.726	0.719	0.610	0.580	0.846	0.662
31	0.046	0.675	0.677	0.710	0.625	0.647	0.661	0.560	0.682	0.665	0.625	0.620	0.681	0.652	0.668	0.680	0.523	0.695	0.633	0.628	0.717	0.715	0.620	0.583	0.847	0.658
32	0.048	0.674	0.676	0.711	0.625	0.655	0.668	0.560	0.689	0.666	0.629	0.620	0.691	0.660	0.678	0.684	0.527	0.696	0.638	0.631	0.725	0.717	0.600	0.585	0.847	0.660
33	-0.083	0.677	0.678	0.713	0.629	0.656	0.668	0.560	0.691	0.665	0.632	0.626	0.694	0.658	0.677	0.684	0.529	0.701	0.636	0.635	0.727	0.716	0.620	0.582	0.847	0.663
34	-0.108	0.664	0.665	0.693	0.618	0.644	0.655	0.559	0.691	0.667	0.630	0.626	0.691	0.659	0.676	0.685	0.527	0.706	0.638	0.626	0.697	0.689	0.570	0.580	0.839	0.648
35	-0.108	0.676	0.677	0.711	0.624	0.654	0.664	0.559	0.689	0.662	0.629	0.625	0.690	0.657	0.675	0.683	0.527	0.696	0.635	0.631	0.725	0.719	0.600	0.579	0.849	0.660
36	-0.116	0.678	0.678	0.715	0.629	0.657	0.667	0.560	0.691	0.666	0.632	0.627	0.693	0.660	0.678	0.685	0.530	0.701	0.638	0.635	0.729	0.722	0.570	0.581	0.849	0.661
37	0.116	0.674	0.676	0.714	0.629	0.657	0.667	0.561	0.689	0.666	0.631	0.626	0.692	0.658	0.676	0.685	0.529	0.703	0.635	0.635	0.725	0.724	0.610	0.583	0.847	0.662
38	-0.131	0.677	0.678	0.714	0.629	0.657	0.668	0.560	0.693	0.666	0.632	0.627	0.694	0.661	0.678	0.685	0.530	0.705	0.638	0.636	0.720	0.725	0.590	0.583	0.847	0.663
39	-0.163	0.674	0.675	0.713	0.629	0.657	0.668	0.560	0.692	0.666	0.633	0.627</td														

(b) Model performance of SC experiment under ROC-AUC on Jannis dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.829	0.839	0.854	0.674	0.864	0.781	0.791	0.887	0.883	0.504	0.595	0.929	0.804
1	0.000	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.829	0.839	0.854	0.675	0.865	0.781	0.791	0.887	0.883	0.488	0.590	0.931	0.803
2	0.000	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.829	0.839	0.854	0.674	0.864	0.781	0.791	0.886	0.883	0.496	0.594	0.930	0.804
3	0.000	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.830	0.839	0.854	0.676	0.864	0.781	0.791	0.886	0.883	0.504	0.592	0.928	0.804
4	0.000	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.829	0.839	0.854	0.674	0.864	0.781	0.791	0.887	0.883	0.501	0.595	0.929	0.804
5	-0.001	0.842	0.843	0.873	0.790	0.816	0.831	0.747	0.850	0.834	0.766	0.793	0.851	0.826	0.836	0.848	0.674	0.858	0.781	0.791	0.880	0.877	0.508	0.595	0.928	0.802
6	-0.001	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.829	0.839	0.854	0.675	0.864	0.781	0.792	0.887	0.883	0.505	0.590	0.929	0.804
7	0.001	0.849	0.849	0.877	0.791	0.817	0.832	0.747	0.854	0.835	0.766	0.793	0.855	0.829	0.839	0.854	0.675	0.864	0.781	0.791	0.887	0.883	0.502	0.598	0.929	0.804
8	0.001	0.849	0.849	0.877	0.792	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.830	0.839	0.854	0.674	0.864	0.781	0.790	0.887	0.883	0.508	0.599	0.929	0.804
9	0.001	0.849	0.849	0.877	0.792	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.829	0.839	0.854	0.676	0.865	0.782	0.791	0.887	0.883	0.502	0.593	0.929	0.804
10	-0.001	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.829	0.839	0.854	0.674	0.865	0.781	0.791	0.887	0.883	0.501	0.594	0.931	0.804
11	-0.001	0.849	0.849	0.877	0.792	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.829	0.839	0.854	0.674	0.864	0.781	0.791	0.887	0.883	0.501	0.591	0.929	0.804
12	-0.002	0.849	0.849	0.877	0.792	0.968	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.830	0.839	0.854	0.674	0.864	0.781	0.791	0.887	0.883	0.500	0.595	0.930	0.810
13	-0.002	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.829	0.839	0.854	0.674	0.865	0.781	0.791	0.887	0.883	0.516	0.597	0.929	0.805
14	0.003	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.765	0.793	0.855	0.829	0.839	0.854	0.674	0.865	0.781	0.791	0.887	0.883	0.512	0.595	0.928	0.804
15	0.003	0.849	0.849	0.877	0.792	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.829	0.839	0.854	0.675	0.864	0.781	0.791	0.887	0.883	0.519	0.594	0.926	0.805
16	0.003	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.830	0.839	0.854	0.673	0.864	0.781	0.791	0.887	0.883	0.511	0.599	0.929	0.800
17	-0.003	0.849	0.849	0.877	0.792	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.829	0.839	0.854	0.675	0.864	0.781	0.791	0.887	0.883	0.511	0.591	0.929	0.800
18	0.004	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.830	0.839	0.854	0.674	0.864	0.781	0.791	0.887	0.883	0.512	0.600	0.928	0.805
19	-0.004	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.829	0.839	0.854	0.676	0.865	0.781	0.791	0.887	0.883	0.512	0.595	0.928	0.804
20	-0.004	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.829	0.839	0.854	0.675	0.865	0.781	0.791	0.887	0.883	0.512	0.598	0.929	0.805
21	-0.004	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.830	0.839	0.854	0.674	0.865	0.781	0.791	0.886	0.883	0.507	0.597	0.928	0.804
22	-0.005	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.830	0.839	0.854	0.673	0.864	0.781	0.791	0.887	0.883	0.509	0.595	0.929	0.804
23	-0.005	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.830	0.839	0.854	0.674	0.864	0.781	0.791	0.887	0.883	0.501	0.594	0.927	0.804
24	-0.005	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.829	0.839	0.854	0.674	0.864	0.781	0.791	0.886	0.883	0.509	0.597	0.929	0.804
25	-0.005	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.830	0.839	0.854	0.674	0.864	0.781	0.791	0.887	0.883	0.504	0.592	0.929	0.804
26	-0.006	0.849	0.849	0.877	0.791	0.817	0.833	0.748	0.854	0.835	0.766	0.792	0.855	0.830	0.839	0.854	0.675	0.865	0.781	0.791	0.886	0.883	0.501	0.601	0.928	0.804
27	-0.007	0.849	0.849	0.877	0.791	0.817	0.833	0.748	0.854	0.835	0.766	0.792	0.855	0.829	0.839	0.854	0.674	0.864	0.781	0.791	0.887	0.883	0.496	0.594	0.929	0.804
28	-0.008	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.855	0.829	0.839	0.854	0.674	0.865	0.781	0.791	0.887	0.883	0.516	0.598	0.929	0.805
29	-0.009	0.840	0.841	0.869	0.784	0.807	0.822	0.744	0.842	0.824	0.762	0.789	0.845	0.820	0.829	0.844	0.673	0.854	0.772	0.782	0.875	0.872	0.507	0.594	0.926	0.797
30	-0.044	0.848	0.848	0.875	0.790	0.816	0.831	0.747	0.853	0.834	0.765	0.793	0.854	0.828	0.838	0.853	0.674	0.862	0.780	0.790	0.886	0.880	0.509	0.590	0.929	0.803
31	0.046	0.845	0.846	0.874	0.787	0.812	0.827	0.746	0.848	0.835	0.763	0.790	0.848	0.824	0.832	0.850	0.672	0.858	0.777	0.788	0.878	0.878	0.509	0.597	0.928	0.801
32	0.048	0.844	0.845	0.874	0.788	0.816	0.831	0.747	0.850	0.834	0.764	0.798	0.853	0.828	0.837	0.853	0.672	0.860	0.781	0.789	0.883	0.877	0.508	0.600	0.928	0.802
33	-0.083	0.843	0.844	0.875	0.790	0.816	0.831	0.747	0.852	0.835	0.765	0.792	0.854	0.827	0.838	0.852	0.673	0.858	0.780	0.789	0.883	0.878	0.504	0.593	0.929	0.802
34	-0.108	0.840	0.841	0.864	0.784	0.809	0.824	0.747	0.839	0.829	0.762	0.790	0.842	0.819	0.829	0.840	0.672	0.846	0.777	0.785	0.867	0.865	0.500	0.591	0.923	0.795
35	-0.108	0.846	0.846	0.874	0.788	0.815	0.830	0.746	0.851	0.833	0.764	0.790	0.855	0.826	0.836	0.853	0.673	0.858	0.777	0.787	0.882	0.877	0.508	0.591	0.929	0.801
36	-0.116	0.847	0.848	0.876	0.790	0.817	0.832	0.748	0.853	0.835	0.766	0.793	0.854	0.828	0.838	0.853	0.675	0.862	0.782	0.790	0.886	0.881	0.505	0.594	0.929	0.803
37	0.116	0.845	0.847	0.876	0.790	0.814	0.830	0.748	0.850	0.834	0.764	0.793	0.854	0.827	0.837	0.853	0.673	0.862	0.778	0.789	0.883	0.882	0.509	0.596	0.927	0.803
38	-0.131	0.848	0.849	0.877	0.791	0.817	0.832	0.747	0.854	0.835	0.766	0.792	0.855	0.829	0.838	0.853	0.673	0.863	0.782	0.790	0.886	0.883	0.508	0.597	0.928	0.804
39	-0.163	0.846	0.847	0.875	0.790	0.817	0.832	0.748	0.854	0.835	0.765	0.793	0.854	0.828	0.838	0.8										

(c) Model performance of MC-M experiment under accuracy on Jannis dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.680	0.682	0.715	0.629	0.657	0.669	0.560	0.693	0.666	0.633	0.626	0.694	0.661	0.678	0.685	0.530	0.705	0.638	0.636	0.731	0.725	0.560	0.582	0.850	0.662
1.85%	0.622	0.637	0.703	0.624	0.653	0.663	0.555	0.687	0.662	0.628	0.620	0.688	0.655	0.674	0.678	0.519	0.685	0.633	0.631	0.717	0.716	0.610	0.583	0.680	0.647
3.7%	0.635	0.636	0.675	0.607	0.637	0.644	0.550	0.659	0.649	0.615	0.606	0.655	0.645	0.647	0.652	0.514	0.657	0.620	0.620	0.686	0.686	0.580	0.598	0.677	0.631
5.56%	0.634	0.633	0.671	0.606	0.636	0.645	0.552	0.657	0.650	0.617	0.594	0.654	0.644	0.646	0.652	0.510	0.652	0.620	0.620	0.683	0.683	0.640	0.584	0.679	0.632
7.41%	0.622	0.620	0.662	0.603	0.635	0.641	0.548	0.647	0.649	0.613	0.584	0.646	0.642	0.639	0.652	0.502	0.626	0.618	0.615	0.664	0.655	0.700	0.582	0.678	0.627
9.26%	0.606	0.608	0.656	0.597	0.633	0.636	0.539	0.634	0.644	0.605	0.580	0.634	0.637	0.630	0.649	0.490	0.616	0.615	0.605	0.636	0.649	0.690	0.589	0.678	0.619
11.11%	0.617	0.617	0.644	0.583	0.617	0.622	0.529	0.630	0.630	0.590	0.569	0.627	0.631	0.621	0.642	0.476	0.607	0.607	0.587	0.649	0.659	0.750	0.587	0.678	0.615
12.96%	0.574	0.576	0.600	0.536	0.593	0.596	0.503	0.604	0.605	0.566	0.457	0.593	0.603	0.590	0.613	0.464	0.571	0.581	0.559	0.602	0.616	0.760	0.584	0.680	0.584
14.81%	0.489	0.497	0.578	0.533	0.590	0.579	0.504	0.543	0.594	0.567	0.456	0.545	0.577	0.555	0.591	0.453	0.541	0.587	0.555	0.588	0.590	0.850	0.585	0.677	0.568
16.67%	0.548	0.547	0.574	0.526	0.568	0.564	0.506	0.537	0.586	0.563	0.455	0.543	0.558	0.550	0.570	0.438	0.534	0.579	0.536	0.589	0.589	0.800	0.581	0.677	0.563
18.52%	0.424	0.430	0.449	0.454	0.464	0.483	0.496	0.474	0.533	0.530	0.393	0.476	0.473	0.472	0.458	0.426	0.449	0.520	0.491	0.488	0.467	0.810	0.579	0.682	0.497
20.37%	0.435	0.436	0.448	0.434	0.445	0.479	0.490	0.466	0.523	0.524	0.390	0.479	0.477	0.462	0.455	0.432	0.439	0.478	0.469	0.478	0.465	0.800	0.584	0.677	0.489
22.22%	0.432	0.433	0.448	0.423	0.438	0.456	0.479	0.458	0.508	0.513	0.390	0.466	0.439	0.452	0.445	0.423	0.436	0.451	0.450	0.466	0.457	0.760	0.578	0.679	0.478
24.07%	0.451	0.451	0.458	0.421	0.430	0.461	0.474	0.447	0.496	0.498	0.388	0.461	0.437	0.451	0.451	0.419	0.438	0.466	0.456	0.457	0.453	0.770	0.585	0.679	0.479
25.93%	0.439	0.437	0.425	0.397	0.408	0.440	0.473	0.417	0.476	0.489	0.384	0.438	0.424	0.427	0.428	0.413	0.416	0.436	0.430	0.417	0.415	0.760	0.582	0.677	0.460
27.78%	0.423	0.425	0.424	0.392	0.398	0.431	0.467	0.410	0.465	0.468	0.383	0.431	0.417	0.416	0.428	0.406	0.418	0.420	0.419	0.422	0.402	0.730	0.580	0.678	0.452
29.63%	0.396	0.399	0.416	0.387	0.389	0.412	0.467	0.404	0.457	0.461	0.385	0.413	0.403	0.411	0.414	0.400	0.408	0.409	0.408	0.407	0.397	0.660	0.581	0.679	0.440
31.48%	0.410	0.411	0.416	0.384	0.387	0.405	0.467	0.397	0.451	0.455	0.382	0.410	0.393	0.407	0.413	0.398	0.405	0.407	0.406	0.405	0.397	0.640	0.582	0.678	0.438
33.33%	0.405	0.409	0.413	0.387	0.394	0.412	0.467	0.412	0.449	0.463	0.381	0.417	0.400	0.412	0.414	0.395	0.403	0.431	0.425	0.400	0.396	0.630	0.579	0.679	0.441
35.19%	0.391	0.396	0.405	0.386	0.393	0.416	0.467	0.411	0.446	0.462	0.381	0.419	0.401	0.411	0.411	0.398	0.396	0.434	0.427	0.394	0.391	0.690	0.582	0.675	0.441
37.04%	0.358	0.362	0.383	0.361	0.371	0.391	0.467	0.387	0.420	0.435	0.363	0.398	0.376	0.388	0.381	0.394	0.380	0.402	0.392	0.375	0.378	0.760	0.574	0.679	0.424
38.89%	0.335	0.337	0.361	0.362	0.355	0.385	0.467	0.369	0.398	0.425	0.358	0.373	0.356	0.381	0.357	0.396	0.363	0.407	0.404	0.347	0.342	0.570	0.583	0.676	0.404
40.74%	0.355	0.357	0.361	0.361	0.353	0.387	0.467	0.375	0.400	0.430	0.356	0.377	0.361	0.386	0.352	0.397	0.362	0.418	0.410	0.358	0.347	0.680	0.580	0.679	0.413
42.59%	0.347	0.349	0.354	0.359	0.352	0.384	0.467	0.378	0.402	0.433	0.360	0.378	0.359	0.383	0.349	0.397	0.358	0.415	0.410	0.355	0.341	0.630	0.588	0.676	0.409
44.44%	0.342	0.342	0.343	0.360	0.349	0.385	0.467	0.361	0.399	0.446	0.360	0.365	0.338	0.383	0.322	0.396	0.353	0.428	0.411	0.336	0.317	0.650	0.578	0.678	0.404
46.3%	0.337	0.336	0.343	0.359	0.348	0.383	0.467	0.355	0.398	0.431	0.358	0.365	0.330	0.383	0.309	0.396	0.349	0.423	0.409	0.322	0.299	0.570	0.578	0.682	0.397
48.15%	0.322	0.319	0.342	0.355	0.337	0.361	0.467	0.321	0.385	0.439	0.349	0.344	0.288	0.360	0.246	0.394	0.344	0.435	0.409	0.294	0.260	0.420	0.584	0.680	0.377
50%	0.315	0.314	0.343	0.355	0.337	0.360	0.467	0.323	0.385	0.439	0.344	0.344	0.286	0.360	0.246	0.395	0.343	0.436	0.409	0.295	0.261	0.490	0.579	0.678	0.379
51.85%	0.314	0.314	0.343	0.354	0.337	0.359	0.467	0.321	0.384	0.439	0.348	0.343	0.285	0.359	0.246	0.395	0.343	0.437	0.409	0.295	0.260	0.520	0.580	0.681	0.381
53.7%	0.317	0.314	0.343	0.353	0.337	0.358	0.467	0.321	0.383	0.440	0.347	0.343	0.283	0.358	0.247	0.397	0.343	0.438	0.411	0.294	0.261	0.340	0.582	0.680	0.373
55.56%	0.317	0.314	0.343	0.353	0.337	0.358	0.467	0.319	0.383	0.443	0.347	0.344	0.284	0.360	0.247	0.399	0.343	0.438	0.413	0.294	0.261	0.410	0.582	0.680	0.376
57.41%	0.315	0.314	0.343	0.350	0.337	0.357	0.467	0.316	0.381	0.442	0.346	0.343	0.286	0.357	0.247	0.399	0.342	0.437	0.411	0.294	0.260	0.340	0.577	0.677	0.372
59.26%	0.315	0.313	0.343	0.349	0.337	0.357	0.467	0.317	0.381	0.442	0.345	0.344	0.290	0.358	0.247	0.398	0.342	0.437	0.410	0.295	0.259	0.330	0.582	0.680	0.372
61.11%	0.316	0.313	0.343	0.349	0.337	0.358	0.467	0.313	0.381	0.443	0.344	0.344	0.294	0.358	0.246	0.398	0.344	0.438	0.410	0.293	0.262	0.290	0.585	0.680	0.371
62.96%	0.319	0.315	0.343	0.347	0.337	0.359	0.467	0.311	0.380	0.444	0.345	0.344	0.295	0.357	0.246	0.398	0.343	0.438	0.411	0.293	0.262	0.350	0.583	0.676	0.374
64.81%	0.322	0.317	0.343	0.347	0.337	0.360	0.467	0.307	0.381	0.444	0.344	0.345	0.298	0.358	0.246	0.399	0.344	0.440	0.410	0.293	0.261	0.350	0.579	0.677	0.374
66.67%	0.321	0.315	0.343	0.347	0.337	0.358	0.467	0.305	0.379	0.445	0.344	0.342	0.296	0.355	0.245	0.399	0.345	0.441	0.412	0.291	0.261	0.280	0.581	0.680	0.370
68.52%	0.320	0.315	0.343	0.346	0.337	0.358	0.467	0.305	0.379	0.445	0.344	0.343	0.294	0.357	0.245	0.397	0.344	0.443	0.412	0.291	0.262	0.310	0.580	0.677	0.371
70.37%	0.318	0.313	0.343	0.345	0.337	0.360	0.467	0.304	0.379	0.445	0.344	0.342	0.288	0.357	0.244	0.399	0.344	0.443	0.417	0.292	0.263	0.320	0.578	0.678	0.372
72.22%	0.317	0.312	0.343	0.345	0.337	0.360	0.467	0.302	0.377	0.445	0.342	0.342	0.288	0.356	0.244	0.398	0.345	0.446	0.415	0.291	0.263	0.320	0.590	0.680	0.380
74.07%	0.321	0.315	0.343	0.345	0.337	0.359	0.467	0.300	0.378	0.445	0.342	0.340	0.286	0.355	0.244	0.402	0.344	0.44							

(d) Model performance of MC-M experiment under ROC-AUC on Jannis dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE	
0%	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.829	0.839	0.854	0.674	0.864	0.781	0.791	0.887	0.883	0.504	0.595	0.929	0.804	
1.85%	0.818	0.828	0.869	0.786	0.813	0.828	0.744	0.849	0.831	0.764	0.787	0.850	0.823	0.834	0.849	0.663	0.848	0.776	0.788	0.875	0.876	0.504	0.593	0.937	0.797	
3.7%	0.811	0.812	0.846	0.769	0.797	0.809	0.735	0.826	0.817	0.749	0.770	0.826	0.811	0.813	0.827	0.653	0.815	0.761	0.774	0.850	0.852	0.506	0.590	0.934	0.781	
5.56%	0.809	0.810	0.841	0.768	0.797	0.808	0.737	0.823	0.819	0.749	0.751	0.825	0.809	0.811	0.826	0.645	0.810	0.761	0.774	0.845	0.847	0.511	0.502	0.935	0.776	
7.41%	0.802	0.802	0.832	0.763	0.796	0.804	0.733	0.814	0.818	0.746	0.740	0.817	0.806	0.803	0.823	0.635	0.787	0.764	0.770	0.826	0.824	0.515	0.595	0.935	0.773	
9.26%	0.789	0.790	0.828	0.757	0.793	0.798	0.722	0.803	0.813	0.741	0.733	0.807	0.799	0.794	0.820	0.624	0.780	0.756	0.761	0.808	0.819	0.509	0.602	0.936	0.766	
11.11%	0.791	0.792	0.821	0.741	0.781	0.788	0.702	0.799	0.799	0.724	0.723	0.802	0.789	0.788	0.812	0.605	0.778	0.737	0.741	0.820	0.824	0.514	0.600	0.937	0.759	
12.96%	0.762	0.764	0.795	0.704	0.762	0.769	0.677	0.779	0.781	0.696	0.636	0.780	0.769	0.765	0.791	0.592	0.754	0.699	0.712	0.790	0.789	0.499	0.595	0.936	0.733	
14.81%	0.717	0.724	0.784	0.699	0.755	0.752	0.679	0.742	0.774	0.693	0.635	0.752	0.753	0.743	0.777	0.578	0.732	0.697	0.703	0.781	0.771	0.511	0.598	0.935	0.720	
16.67%	0.739	0.744	0.782	0.687	0.735	0.734	0.682	0.734	0.769	0.687	0.634	0.746	0.739	0.735	0.766	0.564	0.725	0.683	0.681	0.780	0.770	0.482	0.597	0.935	0.714	
18.52%	0.665	0.671	0.701	0.624	0.673	0.662	0.669	0.671	0.736	0.662	0.574	0.680	0.678	0.673	0.678	0.547	0.656	0.619	0.641	0.712	0.682	0.477	0.592	0.937	0.662	
20.37%	0.670	0.672	0.699	0.603	0.650	0.657	0.664	0.660	0.725	0.647	0.570	0.681	0.664	0.660	0.673	0.550	0.645	0.579	0.622	0.703	0.678	0.466	0.598	0.937	0.653	
22.22%	0.662	0.664	0.698	0.580	0.626	0.635	0.650	0.648	0.702	0.626	0.570	0.664	0.640	0.649	0.655	0.545	0.637	0.564	0.594	0.693	0.669	0.473	0.589	0.937	0.640	
24.07%	0.666	0.668	0.694	0.573	0.617	0.629	0.626	0.635	0.684	0.603	0.569	0.652	0.635	0.638	0.656	0.539	0.636	0.569	0.592	0.679	0.656	0.469	0.600	0.936	0.634	
25.93%	0.645	0.646	0.646	0.546	0.592	0.602	0.619	0.601	0.650	0.578	0.568	0.610	0.621	0.606	0.628	0.532	0.610	0.551	0.571	0.644	0.619	0.489	0.595	0.935	0.613	
27.78%	0.648	0.651	0.647	0.538	0.575	0.589	0.604	0.592	0.642	0.555	0.570	0.597	0.612	0.593	0.628	0.528	0.612	0.539	0.559	0.652	0.619	0.492	0.595	0.935	0.607	
29.63%	0.627	0.629	0.645	0.534	0.561	0.575	0.603	0.587	0.633	0.546	0.569	0.586	0.599	0.587	0.615	0.524	0.602	0.534	0.551	0.636	0.613	0.491	0.593	0.935	0.599	
31.48%	0.630	0.632	0.644	0.532	0.558	0.569	0.602	0.581	0.626	0.540	0.565	0.584	0.589	0.582	0.615	0.523	0.597	0.537	0.551	0.634	0.613	0.484	0.595	0.935	0.597	
33.33%	0.623	0.627	0.637	0.538	0.573	0.582	0.588	0.592	0.623	0.549	0.562	0.590	0.590	0.590	0.617	0.520	0.594	0.550	0.558	0.629	0.611	0.478	0.594	0.936	0.598	
35.19%	0.623	0.628	0.635	0.540	0.580	0.587	0.587	0.593	0.615	0.547	0.563	0.592	0.596	0.593	0.617	0.519	0.585	0.557	0.560	0.622	0.607	0.488	0.598	0.934	0.599	
37.04%	0.599	0.603	0.608	0.512	0.555	0.560	0.562	0.569	0.587	0.508	0.532	0.568	0.573	0.565	0.596	0.515	0.566	0.531	0.529	0.601	0.590	0.493	0.584	0.935	0.577	
38.89%	0.579	0.582	0.597	0.515	0.553	0.554	0.551	0.557	0.554	0.504	0.529	0.548	0.568	0.559	0.587	0.515	0.553	0.541	0.534	0.583	0.582	0.484	0.593	0.934	0.569	
40.74%	0.587	0.589	0.595	0.520	0.566	0.566	0.552	0.566	0.560	0.514	0.526	0.554	0.572	0.567	0.591	0.515	0.550	0.564	0.544	0.587	0.583	0.472	0.592	0.935	0.574	
42.59%	0.578	0.580	0.591	0.516	0.563	0.570	0.553	0.573	0.559	0.509	0.526	0.568	0.567	0.568	0.590	0.513	0.548	0.554	0.539	0.583	0.579	0.490	0.601	0.934	0.573	
44.44%	0.563	0.564	0.570	0.509	0.548	0.553	0.522	0.561	0.553	0.496	0.517	0.558	0.545	0.556	0.570	0.504	0.541	0.533	0.518	0.566	0.557	0.506	0.589	0.935	0.560	
46.3%	0.557	0.557	0.563	0.508	0.544	0.545	0.516	0.554	0.547	0.493	0.515	0.551	0.536	0.550	0.565	0.504	0.536	0.525	0.515	0.553	0.547	0.495	0.592	0.937	0.554	
48.15%	0.504	0.504	0.505	0.497	0.499	0.501	0.497	0.502	0.494	0.498	0.500	0.499	0.500	0.498	0.511	0.501	0.500	0.497	0.496	0.510	0.507	0.494	0.594	0.935	0.523	
50%	0.504	0.505	0.505	0.505	0.496	0.496	0.496	0.501	0.494	0.498	0.502	0.497	0.499	0.497	0.511	0.503	0.499	0.497	0.497	0.510	0.507	0.500	0.589	0.936	0.523	
51.85%	0.504	0.504	0.505	0.497	0.498	0.498	0.498	0.500	0.494	0.498	0.502	0.497	0.499	0.496	0.511	0.502	0.499	0.496	0.498	0.510	0.507	0.486	0.595	0.936	0.522	
53.7%	0.503	0.503	0.504	0.505	0.496	0.497	0.497	0.501	0.493	0.498	0.503	0.497	0.498	0.495	0.511	0.502	0.499	0.497	0.498	0.509	0.507	0.493	0.594	0.936	0.522	
55.56%	0.504	0.505	0.505	0.497	0.497	0.496	0.498	0.501	0.493	0.498	0.503	0.496	0.499	0.495	0.511	0.502	0.500	0.499	0.498	0.509	0.507	0.503	0.597	0.935	0.523	
57.41%	0.504	0.504	0.504	0.495	0.496	0.497	0.497	0.500	0.492	0.498	0.504	0.496	0.500	0.495	0.511	0.502	0.499	0.497	0.497	0.508	0.507	0.507	0.493	0.589	0.933	0.522
59.26%	0.503	0.504	0.504	0.496	0.496	0.497	0.497	0.499	0.491	0.494	0.498	0.505	0.497	0.495	0.511	0.502	0.499	0.497	0.497	0.508	0.507	0.507	0.493	0.593	0.936	0.522
61.11%	0.503	0.503	0.504	0.496	0.497	0.499	0.497	0.501	0.492	0.498	0.504	0.498	0.501	0.497	0.511	0.502	0.498	0.497	0.497	0.508	0.507	0.507	0.498	0.598	0.935	0.523
62.96%	0.502	0.502	0.503	0.504	0.496	0.497	0.497	0.500	0.498	0.501	0.491	0.498	0.503	0.497	0.510	0.500	0.498	0.497	0.497	0.508	0.507	0.499	0.594	0.934	0.522	
64.81%	0.503	0.503	0.504	0.504	0.496	0.496	0.498	0.500	0.491	0.498	0.502	0.496	0.502	0.495	0.511	0.500	0.497	0.499	0.496	0.508	0.507	0.494	0.590	0.934	0.522	
66.67%	0.504	0.505	0.504	0.495	0.496	0.499	0.500	0.500	0.491	0.498	0.502	0.495	0.501	0.495	0.512	0.500	0.496	0.498	0.497	0.508	0.507	0.494	0.593	0.937	0.522	
68.52%	0.504	0.505	0.505	0.494	0.495	0.499	0.500	0.498	0.490	0.494	0.499	0.501	0.494	0.499	0.511	0.498	0.493	0.499	0.497	0.509	0.508	0.501	0.590	0.936	0.522	
70.37%	0.505	0.506	0.504	0.494	0.494	0.500	0.501	0.499	0.490	0.498	0.500	0.494	0.500	0.493	0.511	0.500	0.493	0.497	0.497	0.508	0.508	0.502	0.594	0.934	0.522	
72.22%	0.505	0.506	0.504	0.494	0.495	0.500	0.500	0.499	0.490	0.494	0.500	0.494	0.500	0.494	0.512	0.500	0.492	0.497	0.496	0.508	0.508	0.502	0.594	0.934	0.522	
74.07%	0.503	0.506	0.504	0.494	0.496	0.501	0.499	0.499	0.489	0.497	0.504	0.494	0.494	0.494	0.51											

(e) Model performance of MC-L experiment under accuracy on Jannis dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.680	0.682	0.715	0.629	0.657	0.669	0.560	0.693	0.666	0.633	0.626	0.694	0.661	0.678	0.685	0.530	0.705	0.638	0.636	0.731	0.725	0.560	0.582	0.850	0.662
1.85%	0.681	0.681	0.715	0.629	0.657	0.669	0.560	0.694	0.666	0.633	0.627	0.695	0.661	0.679	0.685	0.529	0.706	0.638	0.636	0.730	0.725	0.550	0.578	0.851	0.661
3.7%	0.681	0.682	0.715	0.631	0.657	0.670	0.561	0.694	0.666	0.633	0.627	0.695	0.660	0.679	0.685	0.532	0.706	0.639	0.637	0.730	0.724	0.530	0.586	0.678	0.654
5.56%	0.681	0.682	0.715	0.631	0.657	0.671	0.561	0.694	0.666	0.634	0.627	0.695	0.660	0.680	0.684	0.532	0.707	0.638	0.637	0.730	0.724	0.510	0.581	0.682	0.653
7.41%	0.681	0.682	0.715	0.632	0.657	0.672	0.561	0.694	0.666	0.634	0.628	0.695	0.659	0.680	0.684	0.533	0.708	0.638	0.637	0.731	0.724	0.440	0.584	0.679	0.651
9.26%	0.669	0.669	0.712	0.631	0.656	0.670	0.561	0.687	0.665	0.632	0.627	0.690	0.652	0.677	0.678	0.535	0.700	0.638	0.637	0.720	0.714	0.510	0.580	0.678	0.649
11.11%	0.669	0.669	0.712	0.632	0.656	0.670	0.561	0.687	0.665	0.632	0.627	0.690	0.651	0.678	0.678	0.536	0.701	0.637	0.636	0.720	0.714	0.510	0.579	0.678	0.650
12.96%	0.670	0.671	0.711	0.632	0.656	0.670	0.561	0.688	0.665	0.633	0.627	0.690	0.652	0.678	0.678	0.538	0.701	0.637	0.636	0.720	0.714	0.490	0.577	0.679	0.649
14.81%	0.670	0.671	0.712	0.632	0.656	0.671	0.561	0.687	0.665	0.633	0.627	0.690	0.652	0.678	0.678	0.537	0.701	0.637	0.636	0.720	0.715	0.480	0.580	0.680	0.649
16.67%	0.671	0.672	0.712	0.633	0.655	0.671	0.560	0.687	0.666	0.634	0.628	0.690	0.653	0.678	0.678	0.539	0.701	0.636	0.636	0.720	0.715	0.370	0.577	0.679	0.644
18.52%	0.672	0.672	0.712	0.633	0.655	0.671	0.561	0.686	0.665	0.634	0.628	0.690	0.653	0.679	0.678	0.542	0.701	0.636	0.636	0.720	0.715	0.350	0.582	0.678	0.644
20.37%	0.671	0.671	0.711	0.635	0.656	0.671	0.560	0.687	0.666	0.633	0.627	0.690	0.654	0.679	0.678	0.543	0.701	0.636	0.636	0.720	0.714	0.360	0.584	0.677	0.644
22.22%	0.672	0.671	0.712	0.635	0.655	0.671	0.561	0.687	0.666	0.634	0.627	0.690	0.652	0.678	0.678	0.543	0.701	0.637	0.637	0.721	0.715	0.390	0.583	0.679	0.646
24.07%	0.672	0.672	0.712	0.634	0.655	0.671	0.561	0.688	0.666	0.634	0.627	0.690	0.653	0.678	0.678	0.545	0.701	0.637	0.637	0.721	0.715	0.290	0.585	0.679	0.642
25.93%	0.671	0.671	0.712	0.635	0.655	0.672	0.560	0.689	0.666	0.634	0.628	0.692	0.653	0.679	0.678	0.547	0.702	0.637	0.636	0.721	0.715	0.310	0.582	0.674	0.642
27.78%	0.672	0.671	0.712	0.636	0.655	0.672	0.560	0.688	0.666	0.633	0.628	0.692	0.651	0.678	0.678	0.548	0.702	0.636	0.636	0.722	0.715	0.340	0.580	0.679	0.644
29.63%	0.672	0.671	0.712	0.636	0.655	0.672	0.560	0.688	0.666	0.634	0.628	0.692	0.651	0.678	0.678	0.549	0.703	0.637	0.636	0.721	0.715	0.420	0.585	0.678	0.647
31.48%	0.671	0.671	0.712	0.637	0.655	0.671	0.560	0.688	0.665	0.634	0.627	0.692	0.650	0.679	0.678	0.550	0.703	0.637	0.636	0.722	0.715	0.490	0.582	0.677	0.650
33.33%	0.670	0.670	0.711	0.637	0.655	0.671	0.561	0.689	0.666	0.634	0.628	0.693	0.649	0.679	0.678	0.552	0.705	0.637	0.636	0.721	0.715	0.490	0.581	0.676	0.650
35.19%	0.670	0.670	0.712	0.638	0.655	0.672	0.561	0.689	0.666	0.634	0.628	0.692	0.648	0.680	0.679	0.553	0.706	0.637	0.638	0.720	0.716	0.520	0.581	0.682	0.652
37.04%	0.671	0.671	0.712	0.637	0.656	0.672	0.561	0.689	0.666	0.635	0.628	0.693	0.648	0.680	0.679	0.554	0.707	0.637	0.637	0.720	0.715	0.590	0.584	0.679	0.663
38.89%	0.671	0.671	0.712	0.638	0.656	0.673	0.561	0.689	0.666	0.636	0.628	0.693	0.647	0.681	0.679	0.555	0.707	0.637	0.637	0.720	0.716	0.500	0.580	0.677	0.651
40.74%	0.671	0.671	0.712	0.638	0.655	0.674	0.561	0.688	0.666	0.636	0.628	0.693	0.646	0.681	0.679	0.556	0.707	0.636	0.636	0.720	0.716	0.530	0.580	0.681	0.653
42.59%	0.671	0.671	0.712	0.638	0.655	0.673	0.561	0.689	0.666	0.636	0.628	0.695	0.645	0.682	0.679	0.558	0.708	0.636	0.636	0.721	0.715	0.290	0.580	0.680	0.643
44.44%	0.671	0.670	0.712	0.637	0.655	0.674	0.561	0.689	0.666	0.636	0.629	0.695	0.647	0.681	0.679	0.558	0.708	0.636	0.636	0.721	0.715	0.400	0.571	0.679	0.647
46.3%	0.671	0.671	0.712	0.638	0.655	0.674	0.561	0.689	0.666	0.634	0.629	0.692	0.649	0.679	0.678	0.552	0.705	0.637	0.636	0.721	0.715	0.490	0.581	0.676	0.650
48.15%	0.671	0.671	0.711	0.637	0.656	0.674	0.561	0.689	0.666	0.634	0.628	0.692	0.648	0.680	0.679	0.553	0.706	0.637	0.638	0.720	0.716	0.520	0.581	0.682	0.652
50%	0.672	0.671	0.711	0.637	0.656	0.674	0.561	0.690	0.666	0.637	0.629	0.695	0.644	0.683	0.679	0.562	0.710	0.634	0.635	0.721	0.715	0.740	0.571	0.680	0.661
51.85%	0.670	0.669	0.711	0.638	0.655	0.674	0.561	0.690	0.666	0.637	0.629	0.696	0.643	0.682	0.679	0.563	0.710	0.633	0.634	0.721	0.715	0.920	0.573	0.678	0.669
53.7%	0.656	0.656	0.702	0.635	0.652	0.665	0.560	0.675	0.661	0.632	0.627	0.689	0.631	0.673	0.671	0.562	0.700	0.630	0.630	0.710	0.700	0.880	0.574	0.678	0.660
55.56%	0.650	0.650	0.698	0.635	0.650	0.664	0.560	0.672	0.661	0.632	0.627	0.687	0.627	0.671	0.668	0.569	0.698	0.630	0.629	0.705	0.693	0.700	0.578	0.677	0.651
57.41%	0.654	0.653	0.689	0.627	0.643	0.655	0.559	0.653	0.661	0.628	0.623	0.673	0.617	0.657	0.660	0.551	0.687	0.627	0.625	0.687	0.679	0.470	0.579	0.678	0.635
59.26%	0.644	0.643	0.676	0.617	0.634	0.648	0.559	0.646	0.653	0.616	0.616	0.666	0.610	0.649	0.648	0.549	0.666	0.621	0.618	0.671	0.660	0.610	0.570	0.678	0.632
61.11%	0.641	0.641	0.673	0.615	0.633	0.646	0.558	0.643	0.652	0.614	0.616	0.663	0.607	0.647	0.645	0.550	0.662	0.618	0.614	0.664	0.647	0.340	0.572	0.678	0.618
62.96%	0.619	0.620	0.641	0.597	0.615	0.628	0.559	0.608	0.640	0.604	0.614	0.627	0.585	0.626	0.614	0.542	0.639	0.609	0.603	0.624	0.604	0.300	0.573	0.679	0.599
64.81%	0.606	0.609	0.630	0.592	0.610	0.622	0.557	0.599	0.636	0.599	0.612	0.616	0.574	0.621	0.601	0.538	0.624	0.605	0.599	0.613	0.594	0.440	0.574	0.678	0.598
66.67%	0.607	0.610	0.625	0.591	0.606	0.620	0.558	0.595	0.634	0.598	0.613	0.615	0.572	0.618	0.599	0.539	0.616	0.604	0.598	0.610	0.596	0.177	0.580	0.678	0.586
68.52%	0.604	0.609	0.622	0.587	0.601	0.614	0.559	0.584	0.633	0.593	0.613	0.608	0.565	0.613	0.597	0.536	0.612	0.600	0.594	0.596	0.592	0.400	0.583	0.675	0.591
70.37%	0.602	0.605	0.622	0.587	0.601	0.614	0.559	0.583	0.634	0.594	0.613	0.606	0.567	0.612	0.595	0.532	0.612	0.597	0.593	0.592	0.591	0.130	0.574	0.679	0.579
72.22%	0.612	0.615	0.617	0.584	0.602	0.613	0.560	0.582	0.634	0.594	0.613	0.605	0.569	0.613	0.595	0.533	0.604	0.595	0.593	0.584	0.589	0.166	0.578	0.679	0.580
74.07%	0.601	0.606	0.612	0.575	0.591	0.600	0.557	0.577	0.621	0.589	0.614	0.585	0.564	0.601	0.587	0.529	0.600	0.58							

(f) Model performance of MC-L experiment under ROC-AUC on Jannis dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.829	0.839	0.854	0.674	0.864	0.781	0.791	0.887	0.883	0.504	0.595	0.929	0.804
1.85%	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.829	0.839	0.854	0.675	0.865	0.781	0.791	0.887	0.883	0.488	0.590	0.931	0.803
3.7%	0.849	0.849	0.877	0.792	0.817	0.833	0.747	0.854	0.835	0.766	0.793	0.856	0.829	0.840	0.854	0.675	0.865	0.781	0.791	0.887	0.883	0.501	0.598	0.936	0.805
5.56%	0.849	0.849	0.877	0.792	0.817	0.834	0.747	0.854	0.835	0.766	0.793	0.856	0.830	0.840	0.854	0.677	0.866	0.781	0.792	0.886	0.883	0.496	0.594	0.935	0.804
7.41%	0.849	0.849	0.877	0.793	0.817	0.834	0.747	0.854	0.835	0.766	0.793	0.856	0.829	0.840	0.853	0.678	0.866	0.781	0.792	0.887	0.884	0.506	0.597	0.938	0.805
9.26%	0.843	0.843	0.873	0.792	0.816	0.832	0.747	0.850	0.834	0.767	0.793	0.852	0.826	0.837	0.848	0.679	0.860	0.781	0.792	0.880	0.877	0.511	0.595	0.936	0.803
11.11%	0.843	0.843	0.873	0.793	0.816	0.832	0.748	0.851	0.835	0.767	0.794	0.853	0.825	0.838	0.848	0.681	0.860	0.781	0.793	0.880	0.877	0.511	0.588	0.937	0.803
12.96%	0.843	0.844	0.873	0.794	0.816	0.832	0.748	0.851	0.835	0.767	0.795	0.853	0.825	0.838	0.848	0.682	0.860	0.781	0.794	0.881	0.878	0.500	0.590	0.935	0.802
14.81%	0.844	0.844	0.873	0.795	0.816	0.832	0.747	0.851	0.835	0.767	0.794	0.853	0.825	0.838	0.848	0.681	0.860	0.782	0.793	0.881	0.878	0.504	0.591	0.935	0.803
16.67%	0.844	0.844	0.873	0.795	0.816	0.832	0.747	0.851	0.835	0.767	0.795	0.853	0.825	0.838	0.848	0.684	0.860	0.782	0.794	0.881	0.878	0.496	0.590	0.935	0.803
18.52%	0.844	0.844	0.873	0.796	0.816	0.833	0.747	0.851	0.835	0.767	0.795	0.853	0.825	0.839	0.848	0.685	0.861	0.782	0.794	0.881	0.878	0.484	0.594	0.935	0.802
20.37%	0.844	0.844	0.873	0.797	0.816	0.833	0.747	0.851	0.835	0.768	0.794	0.853	0.825	0.839	0.848	0.686	0.862	0.782	0.794	0.881	0.878	0.495	0.595	0.934	0.803
22.22%	0.844	0.844	0.873	0.798	0.816	0.833	0.748	0.851	0.835	0.768	0.795	0.854	0.825	0.839	0.848	0.686	0.862	0.783	0.794	0.881	0.878	0.502	0.593	0.933	0.803
24.07%	0.845	0.845	0.873	0.798	0.816	0.833	0.747	0.851	0.835	0.768	0.795	0.854	0.825	0.839	0.848	0.686	0.862	0.783	0.795	0.881	0.878	0.489	0.597	0.935	0.803
25.93%	0.845	0.845	0.873	0.799	0.816	0.834	0.748	0.852	0.835	0.768	0.796	0.854	0.825	0.840	0.848	0.687	0.863	0.783	0.795	0.881	0.878	0.491	0.593	0.935	0.803
27.78%	0.845	0.845	0.873	0.800	0.816	0.834	0.747	0.852	0.835	0.768	0.796	0.855	0.824	0.840	0.848	0.689	0.863	0.783	0.796	0.881	0.878	0.493	0.593	0.936	0.804
29.63%	0.845	0.845	0.873	0.800	0.816	0.834	0.748	0.852	0.836	0.768	0.797	0.855	0.824	0.840	0.848	0.689	0.864	0.783	0.796	0.881	0.878	0.499	0.594	0.935	0.804
31.48%	0.845	0.845	0.873	0.800	0.817	0.835	0.748	0.852	0.836	0.768	0.797	0.855	0.824	0.840	0.848	0.690	0.864	0.783	0.797	0.881	0.878	0.504	0.593	0.935	0.804
33.33%	0.845	0.845	0.873	0.801	0.817	0.835	0.748	0.852	0.836	0.769	0.797	0.855	0.824	0.841	0.848	0.690	0.865	0.783	0.797	0.881	0.878	0.499	0.595	0.934	0.805
35.19%	0.845	0.845	0.873	0.802	0.817	0.835	0.748	0.852	0.836	0.770	0.797	0.855	0.824	0.841	0.848	0.692	0.866	0.784	0.797	0.881	0.878	0.491	0.595	0.937	0.805
37.04%	0.846	0.846	0.873	0.803	0.817	0.835	0.748	0.853	0.836	0.770	0.797	0.856	0.823	0.841	0.848	0.692	0.866	0.784	0.798	0.881	0.878	0.506	0.595	0.936	0.805
38.89%	0.846	0.846	0.873	0.803	0.817	0.835	0.748	0.853	0.836	0.770	0.797	0.856	0.823	0.841	0.848	0.693	0.867	0.784	0.797	0.881	0.878	0.468	0.593	0.935	0.804
40.74%	0.846	0.846	0.873	0.804	0.817	0.836	0.748	0.853	0.836	0.771	0.798	0.856	0.823	0.842	0.848	0.693	0.867	0.784	0.797	0.881	0.878	0.502	0.592	0.938	0.805
42.59%	0.846	0.846	0.873	0.804	0.817	0.836	0.748	0.853	0.836	0.771	0.798	0.856	0.823	0.842	0.848	0.695	0.867	0.784	0.798	0.881	0.878	0.499	0.591	0.935	0.805
44.44%	0.846	0.846	0.873	0.804	0.817	0.836	0.748	0.853	0.836	0.772	0.798	0.857	0.823	0.842	0.848	0.696	0.866	0.784	0.797	0.881	0.878	0.492	0.614	0.935	0.806
46.3%	0.846	0.846	0.873	0.805	0.818	0.837	0.748	0.853	0.836	0.771	0.798	0.857	0.823	0.843	0.848	0.698	0.866	0.784	0.798	0.881	0.878	0.493	0.617	0.935	0.806
48.15%	0.846	0.846	0.873	0.805	0.818	0.837	0.748	0.854	0.836	0.771	0.798	0.857	0.823	0.843	0.848	0.700	0.867	0.785	0.798	0.881	0.878	0.505	0.610	0.934	0.807
50%	0.846	0.846	0.873	0.806	0.818	0.837	0.749	0.854	0.836	0.772	0.798	0.857	0.823	0.843	0.848	0.700	0.867	0.785	0.798	0.881	0.878	0.498	0.615	0.935	0.807
51.85%	0.846	0.846	0.873	0.806	0.818	0.837	0.749	0.854	0.836	0.772	0.798	0.857	0.823	0.843	0.848	0.699	0.868	0.785	0.799	0.881	0.878	0.484	0.614	0.936	0.806
53.7%	0.836	0.837	0.864	0.798	0.807	0.827	0.745	0.840	0.824	0.766	0.794	0.848	0.811	0.833	0.837	0.697	0.857	0.776	0.788	0.867	0.865	0.481	0.616	0.935	0.798
55.56%	0.835	0.835	0.863	0.797	0.806	0.825	0.745	0.839	0.823	0.765	0.794	0.846	0.809	0.831	0.836	0.697	0.855	0.775	0.787	0.863	0.861	0.499	0.590	0.934	0.796
57.41%	0.832	0.833	0.860	0.793	0.802	0.821	0.744	0.831	0.822	0.764	0.793	0.840	0.803	0.825	0.833	0.697	0.848	0.771	0.785	0.855	0.850	0.470	0.590	0.937	0.792
59.26%	0.828	0.829	0.852	0.786	0.797	0.817	0.742	0.825	0.816	0.758	0.787	0.834	0.799	0.820	0.828	0.695	0.835	0.767	0.781	0.844	0.841	0.502	0.611	0.935	0.789
61.11%	0.819	0.821	0.850	0.784	0.796	0.816	0.742	0.822	0.816	0.757	0.787	0.833	0.794	0.819	0.825	0.694	0.827	0.766	0.778	0.838	0.831	0.499	0.614	0.936	0.786
62.96%	0.807	0.808	0.828	0.773	0.786	0.805	0.742	0.798	0.809	0.753	0.784	0.814	0.778	0.806	0.803	0.687	0.808	0.761	0.770	0.810	0.800	0.505	0.616	0.935	0.774
64.81%	0.800	0.801	0.820	0.769	0.782	0.802	0.740	0.791	0.805	0.752	0.781	0.808	0.772	0.801	0.796	0.685	0.794	0.755	0.764	0.801	0.792	0.493	0.616	0.935	0.769
66.67%	0.800	0.802	0.817	0.767	0.781	0.799	0.740	0.790	0.804	0.751	0.781	0.807	0.768	0.800	0.794	0.687	0.792	0.755	0.763	0.791	0.790	0.520	0.594	0.935	0.768
68.52%	0.800	0.803	0.816	0.765	0.776	0.796	0.740	0.785	0.803	0.749	0.782	0.804	0.764	0.796	0.793	0.685	0.787	0.752	0.760	0.792	0.787	0.485	0.596	0.935	0.765
70.37%	0.799	0.801	0.814	0.765	0.776	0.796	0.740	0.784	0.803	0.750	0.782	0.803	0.763	0.796	0.792	0.685	0.786	0.753	0.760	0.788	0.787	0.499	0.615	0.935	0.766
72.22%	0.801	0.803	0.811	0.764	0.776	0.796	0.740	0.784	0.802	0.757	0.782	0.802	0.761	0.796	0.791	0.684	0.776	0.753	0.761	0.782	0.784	0.500	0.590	0.934	0.763
74.07%	0.801	0.802	0.807	0.757	0.770	0.786	0.738	0.775	0.795	0.748	0.782	0.788	0.756	0.787	0.784	0.684	0.779	0.74							

(g) Model performance of RD experiment under accuracy on Jannis dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.680	0.682	0.715	0.629	0.657	0.669	0.560	0.693	0.666	0.633	0.626	0.694	0.661	0.678	0.685	0.530	0.705	0.638	0.636	0.731	0.725	0.560	0.582	0.850	0.662
1.85%	0.680	0.681	0.682	0.630	0.655	0.667	0.560	0.691	0.666	0.631	0.624	0.692	0.660	0.676	0.683	0.528	0.704	0.637	0.634	0.729	0.722	0.688	0.581	0.678	0.657
3.7%	0.675	0.676	0.707	0.630	0.655	0.665	0.560	0.687	0.666	0.631	0.623	0.688	0.657	0.674	0.681	0.526	0.702	0.636	0.634	0.716	0.713	0.668	0.583	0.679	0.656
5.56%	0.651	0.656	0.707	0.620	0.652	0.661	0.560	0.679	0.663	0.629	0.620	0.682	0.654	0.670	0.678	0.526	0.698	0.632	0.631	0.714	0.703	0.674	0.579	0.678	0.651
7.41%	0.657	0.659	0.702	0.623	0.643	0.655	0.556	0.674	0.659	0.623	0.600	0.675	0.648	0.663	0.670	0.521	0.686	0.625	0.625	0.711	0.697	0.630	0.581	0.679	0.645
9.26%	0.663	0.665	0.699	0.622	0.652	0.663	0.561	0.680	0.664	0.630	0.617	0.684	0.647	0.670	0.678	0.525	0.682	0.633	0.632	0.703	0.689	0.628	0.583	0.678	0.648
11.11%	0.647	0.652	0.692	0.620	0.647	0.656	0.560	0.674	0.660	0.627	0.619	0.676	0.643	0.665	0.671	0.525	0.681	0.630	0.630	0.705	0.682	0.651	0.584	0.678	0.645
12.96%	0.635	0.642	0.695	0.622	0.640	0.649	0.556	0.665	0.655	0.621	0.607	0.667	0.642	0.656	0.664	0.520	0.677	0.622	0.623	0.682	0.691	0.656	0.582	0.679	0.640
14.81%	0.626	0.634	0.678	0.604	0.644	0.650	0.558	0.666	0.658	0.622	0.613	0.667	0.639	0.659	0.668	0.517	0.685	0.626	0.625	0.693	0.688	0.584	0.580	0.680	0.636
16.67%	0.656	0.658	0.683	0.622	0.629	0.637	0.555	0.636	0.646	0.616	0.600	0.641	0.617	0.640	0.637	0.511	0.654	0.619	0.620	0.637	0.640	0.605	0.583	0.678	0.626
18.52%	0.626	0.634	0.674	0.618	0.639	0.648	0.558	0.656	0.655	0.619	0.610	0.658	0.629	0.652	0.653	0.519	0.662	0.627	0.625	0.645	0.662	0.586	0.582	0.679	0.630
20.37%	0.623	0.628	0.672	0.607	0.625	0.634	0.553	0.648	0.648	0.613	0.595	0.649	0.617	0.641	0.513	0.664	0.612	0.614	0.656	0.642	0.574	0.582	0.679	0.622	
22.22%	0.632	0.636	0.657	0.611	0.626	0.636	0.556	0.646	0.649	0.613	0.596	0.647	0.616	0.643	0.648	0.514	0.645	0.614	0.614	0.666	0.651	0.559	0.584	0.679	0.623
24.07%	0.602	0.609	0.657	0.602	0.627	0.631	0.550	0.631	0.644	0.610	0.593	0.635	0.618	0.634	0.633	0.509	0.662	0.611	0.615	0.661	0.639	0.542	0.582	0.679	0.616
25.93%	0.581	0.591	0.642	0.587	0.613	0.614	0.547	0.626	0.636	0.602	0.579	0.621	0.603	0.619	0.628	0.510	0.623	0.602	0.604	0.659	0.625	0.512	0.583	0.679	0.604
27.78%	0.593	0.602	0.648	0.608	0.630	0.639	0.556	0.647	0.644	0.616	0.599	0.650	0.618	0.644	0.646	0.521	0.624	0.614	0.618	0.579	0.647	0.539	0.580	0.678	0.614
29.63%	0.604	0.609	0.638	0.602	0.627	0.634	0.556	0.636	0.648	0.610	0.589	0.645	0.607	0.636	0.646	0.510	0.641	0.610	0.610	0.597	0.648	0.516	0.579	0.678	0.612
31.48%	0.582	0.591	0.640	0.593	0.628	0.633	0.556	0.629	0.650	0.614	0.596	0.636	0.611	0.634	0.645	0.516	0.638	0.612	0.617	0.650	0.645	0.541	0.582	0.679	0.613
33.33%	0.594	0.602	0.631	0.589	0.611	0.618	0.554	0.622	0.635	0.604	0.575	0.630	0.590	0.624	0.620	0.513	0.632	0.598	0.603	0.585	0.604	0.541	0.583	0.678	0.601
35.19%	0.584	0.594	0.617	0.590	0.611	0.619	0.551	0.610	0.639	0.602	0.580	0.623	0.596	0.621	0.631	0.508	0.601	0.603	0.597	0.627	0.526	0.581	0.680	0.600	
37.04%	0.563	0.571	0.625	0.594	0.605	0.612	0.553	0.598	0.637	0.600	0.592	0.603	0.573	0.614	0.589	0.502	0.641	0.601	0.602	0.612	0.575	0.528	0.582	0.679	0.594
38.89%	0.561	0.567	0.606	0.585	0.591	0.596	0.534	0.596	0.620	0.587	0.537	0.599	0.547	0.605	0.580	0.489	0.608	0.583	0.585	0.563	0.552	0.474	0.582	0.679	0.576
40.74%	0.557	0.566	0.602	0.585	0.610	0.616	0.544	0.613	0.629	0.595	0.573	0.614	0.593	0.614	0.618	0.498	0.601	0.597	0.600	0.602	0.549	0.498	0.580	0.678	0.592
42.59%	0.519	0.525	0.588	0.563	0.608	0.614	0.550	0.612	0.632	0.600	0.576	0.620	0.572	0.619	0.608	0.499	0.565	0.602	0.603	0.606	0.598	0.519	0.581	0.679	0.586
44.44%	0.549	0.559	0.569	0.584	0.569	0.579	0.535	0.573	0.607	0.578	0.554	0.573	0.542	0.585	0.573	0.480	0.581	0.575	0.581	0.544	0.547	0.454	0.582	0.679	0.565
46.3%	0.515	0.527	0.590	0.573	0.584	0.596	0.542	0.578	0.617	0.589	0.558	0.589	0.554	0.592	0.574	0.493	0.567	0.585	0.588	0.562	0.543	0.473	0.583	0.679	0.569
48.15%	0.560	0.569	0.590	0.577	0.579	0.595	0.545	0.568	0.609	0.586	0.560	0.582	0.540	0.596	0.546	0.492	0.557	0.590	0.587	0.556	0.499	0.496	0.582	0.678	0.569
50%	0.501	0.509	0.543	0.543	0.579	0.592	0.548	0.585	0.627	0.594	0.571	0.595	0.549	0.593	0.592	0.490	0.567	0.587	0.591	0.565	0.582	0.498	0.582	0.677	0.569
51.85%	0.546	0.553	0.564	0.561	0.543	0.548	0.528	0.529	0.576	0.554	0.522	0.539	0.507	0.544	0.525	0.482	0.599	0.551	0.558	0.515	0.496	0.489	0.582	0.679	0.545
53.7%	0.505	0.518	0.530	0.573	0.575	0.591	0.543	0.541	0.620	0.597	0.556	0.569	0.518	0.580	0.532	0.489	0.502	0.582	0.599	0.516	0.492	0.447	0.583	0.678	0.552
55.56%	0.446	0.456	0.527	0.536	0.555	0.568	0.534	0.527	0.606	0.584	0.519	0.544	0.511	0.548	0.507	0.486	0.553	0.571	0.580	0.519	0.487	0.505	0.315	0.680	0.528
57.41%	0.506	0.516	0.540	0.549	0.571	0.572	0.549	0.547	0.604	0.581	0.560	0.558	0.513	0.569	0.543	0.496	0.503	0.575	0.582	0.542	0.508	0.470	0.316	0.850	0.547
59.26%	0.512	0.519	0.533	0.534	0.549	0.569	0.532	0.533	0.591	0.569	0.535	0.548	0.503	0.562	0.506	0.485	0.507	0.563	0.570	0.476	0.473	0.482	0.315	0.848	0.534
61.11%	0.492	0.500	0.509	0.539	0.544	0.561	0.529	0.540	0.587	0.568	0.518	0.553	0.495	0.562	0.506	0.463	0.493	0.570	0.573	0.491	0.441	0.450	0.315	0.849	0.527
62.96%	0.459	0.470	0.495	0.534	0.557	0.569	0.540	0.542	0.603	0.577	0.546	0.558	0.518	0.572	0.522	0.473	0.467	0.572	0.578	0.477	0.499	0.474	0.315	0.849	0.532
64.81%	0.453	0.461	0.481	0.507	0.516	0.542	0.537	0.494	0.588	0.557	0.502	0.528	0.456	0.537	0.486	0.470	0.502	0.544	0.557	0.443	0.440	0.448	0.315	0.679	0.502
66.67%	0.470	0.483	0.463	0.540	0.541	0.548	0.512	0.521	0.584	0.564	0.529	0.531	0.466	0.549	0.488	0.474	0.504	0.556	0.569	0.443	0.458	0.475	0.316	0.679	0.511
68.52%	0.436	0.443	0.462	0.504	0.474	0.517	0.529	0.442	0.554	0.548	0.479	0.482	0.411	0.499	0.411	0.456	0.499	0.545	0.547	0.455	0.386	0.428	0.315	0.681	0.479
70.37%	0.397	0.404	0.422	0.466	0.511	0.538	0.522	0.487	0.572	0.566	0.524	0.514	0.458	0.531	0.481	0.470	0.490	0.550	0.559	0.471	0.464	0.415	0.315	0.678	0.492
72.22%	0.463	0.468	0.449	0.495	0.531	0.517	0.461	0.573	0.558	0.490	0.506	0.441	0.533	0.452	0.456	0.462	0.540	0.559	0.441	0.414	0.454	0.315	0.680	0.490	
74.07%	0.429	0.434	0.425	0.468	0.514	0.541	0.502	0.497	0.576	0.556	0.523	0.533	0.445	0.537	0.470	0.472	0.456	0.541	0.559	0.419	0.437				

(h) Model performance of RD experiment under ROC-AUC on Jannis dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.849	0.849	0.877	0.791	0.817	0.833	0.747	0.854	0.835	0.766	0.792	0.855	0.829	0.839	0.854	0.674	0.864	0.781	0.791	0.887	0.883	0.504	0.595	0.929	0.804
1.85%	0.849	0.849	0.874	0.791	0.816	0.831	0.747	0.852	0.835	0.765	0.791	0.853	0.829	0.838	0.853	0.673	0.863	0.780	0.790	0.885	0.883	0.688	0.592	0.936	0.811
3.7%	0.846	0.847	0.872	0.791	0.816	0.830	0.748	0.850	0.835	0.765	0.790	0.852	0.827	0.836	0.851	0.669	0.863	0.779	0.789	0.878	0.876	0.668	0.595	0.935	0.809
5.56%	0.828	0.832	0.872	0.782	0.812	0.825	0.748	0.843	0.831	0.763	0.780	0.846	0.824	0.831	0.847	0.668	0.859	0.776	0.786	0.877	0.870	0.674	0.589	0.935	0.804
7.41%	0.835	0.837	0.869	0.786	0.809	0.823	0.745	0.841	0.829	0.760	0.781	0.843	0.824	0.829	0.844	0.665	0.848	0.773	0.784	0.873	0.866	0.630	0.594	0.936	0.801
9.26%	0.837	0.839	0.867	0.785	0.813	0.827	0.749	0.845	0.833	0.763	0.784	0.848	0.819	0.833	0.848	0.665	0.846	0.779	0.788	0.866	0.861	0.628	0.596	0.935	0.802
11.11%	0.821	0.826	0.862	0.783	0.809	0.822	0.746	0.838	0.827	0.762	0.786	0.841	0.817	0.828	0.841	0.668	0.845	0.774	0.784	0.873	0.855	0.651	0.595	0.935	0.799
12.96%	0.817	0.822	0.864	0.786	0.805	0.818	0.744	0.835	0.826	0.757	0.777	0.837	0.818	0.823	0.839	0.661	0.845	0.769	0.781	0.853	0.861	0.656	0.595	0.935	0.797
14.81%	0.810	0.816	0.856	0.772	0.806	0.817	0.745	0.833	0.826	0.759	0.780	0.836	0.815	0.823	0.839	0.658	0.845	0.770	0.781	0.852	0.854	0.592	0.935	0.792	
16.67%	0.835	0.836	0.857	0.787	0.796	0.804	0.741	0.808	0.817	0.753	0.766	0.814	0.790	0.807	0.814	0.646	0.828	0.761	0.775	0.826	0.818	0.605	0.596	0.935	0.784
18.52%	0.811	0.818	0.851	0.783	0.804	0.817	0.744	0.828	0.825	0.757	0.779	0.832	0.807	0.822	0.832	0.658	0.833	0.771	0.783	0.832	0.842	0.586	0.593	0.934	0.789
20.37%	0.807	0.813	0.849	0.774	0.794	0.805	0.741	0.819	0.818	0.751	0.766	0.823	0.797	0.812	0.821	0.653	0.829	0.753	0.775	0.835	0.826	0.574	0.596	0.936	0.782
22.22%	0.819	0.821	0.841	0.777	0.799	0.812	0.744	0.824	0.823	0.753	0.768	0.829	0.801	0.817	0.830	0.656	0.816	0.767	0.778	0.847	0.834	0.559	0.596	0.935	0.785
24.07%	0.795	0.801	0.841	0.770	0.787	0.796	0.737	0.802	0.811	0.747	0.758	0.808	0.788	0.800	0.809	0.642	0.831	0.754	0.768	0.840	0.814	0.542	0.594	0.935	0.774
25.93%	0.785	0.793	0.830	0.759	0.784	0.792	0.737	0.801	0.811	0.743	0.753	0.805	0.784	0.796	0.809	0.644	0.800	0.745	0.768	0.832	0.808	0.512	0.594	0.935	0.768
27.78%	0.788	0.795	0.835	0.774	0.797	0.806	0.741	0.816	0.814	0.753	0.768	0.818	0.795	0.810	0.820	0.657	0.795	0.761	0.775	0.811	0.825	0.539	0.591	0.935	0.775
29.63%	0.794	0.800	0.830	0.770	0.797	0.805	0.744	0.814	0.819	0.750	0.762	0.821	0.791	0.808	0.826	0.645	0.811	0.763	0.773	0.825	0.816	0.592	0.936	0.774	
31.48%	0.781	0.788	0.830	0.766	0.797	0.804	0.742	0.810	0.822	0.752	0.762	0.818	0.791	0.806	0.824	0.650	0.809	0.764	0.775	0.829	0.824	0.541	0.595	0.935	0.776
33.33%	0.791	0.797	0.826	0.762	0.787	0.796	0.742	0.802	0.810	0.746	0.751	0.811	0.782	0.799	0.809	0.646	0.804	0.747	0.769	0.824	0.824	0.541	0.594	0.936	0.768
35.19%	0.780	0.789	0.818	0.765	0.784	0.791	0.738	0.793	0.811	0.742	0.753	0.802	0.781	0.794	0.813	0.643	0.776	0.748	0.766	0.802	0.807	0.526	0.594	0.936	0.765
37.04%	0.769	0.776	0.821	0.763	0.781	0.785	0.741	0.781	0.808	0.745	0.761	0.790	0.767	0.788	0.793	0.637	0.810	0.751	0.766	0.802	0.778	0.528	0.594	0.935	0.761
38.89%	0.761	0.766	0.810	0.753	0.770	0.773	0.722	0.777	0.793	0.732	0.718	0.785	0.745	0.780	0.783	0.619	0.782	0.732	0.746	0.750	0.762	0.474	0.595	0.936	0.744
40.74%	0.763	0.771	0.807	0.758	0.780	0.786	0.730	0.787	0.802	0.738	0.747	0.794	0.768	0.785	0.797	0.630	0.767	0.746	0.759	0.795	0.790	0.498	0.592	0.934	0.755
42.59%	0.738	0.745	0.797	0.740	0.783	0.788	0.739	0.789	0.805	0.744	0.749	0.798	0.759	0.792	0.794	0.630	0.751	0.748	0.765	0.803	0.787	0.519	0.592	0.936	0.754
44.44%	0.751	0.759	0.790	0.758	0.752	0.757	0.724	0.757	0.788	0.725	0.727	0.766	0.736	0.765	0.766	0.615	0.768	0.728	0.742	0.762	0.753	0.454	0.593	0.935	0.736
46.3%	0.735	0.747	0.800	0.747	0.766	0.770	0.728	0.768	0.790	0.731	0.732	0.773	0.747	0.771	0.773	0.623	0.744	0.727	0.751	0.758	0.755	0.473	0.595	0.935	0.739
48.15%	0.751	0.760	0.799	0.754	0.769	0.770	0.729	0.758	0.783	0.729	0.731	0.770	0.735	0.772	0.773	0.617	0.741	0.727	0.748	0.750	0.727	0.496	0.595	0.935	0.738
50%	0.716	0.722	0.773	0.726	0.760	0.762	0.735	0.760	0.798	0.734	0.740	0.773	0.730	0.766	0.778	0.614	0.759	0.720	0.753	0.764	0.765	0.498	0.594	0.935	0.737
51.85%	0.752	0.760	0.784	0.748	0.730	0.728	0.710	0.723	0.760	0.705	0.703	0.735	0.704	0.731	0.734	0.611	0.768	0.692	0.724	0.736	0.708	0.489	0.594	0.936	0.719
53.7%	0.721	0.734	0.767	0.751	0.761	0.759	0.736	0.734	0.788	0.739	0.729	0.752	0.723	0.752	0.744	0.616	0.709	0.721	0.755	0.747	0.714	0.447	0.595	0.935	0.726
55.56%	0.700	0.708	0.768	0.730	0.752	0.751	0.728	0.734	0.786	0.725	0.769	0.751	0.711	0.743	0.741	0.607	0.739	0.712	0.743	0.757	0.709	0.505	0.496	0.935	0.718
57.41%	0.725	0.732	0.771	0.735	0.758	0.752	0.735	0.743	0.779	0.729	0.735	0.751	0.720	0.755	0.758	0.623	0.684	0.733	0.748	0.750	0.734	0.470	0.497	0.930	0.723
59.26%	0.714	0.722	0.767	0.728	0.744	0.747	0.717	0.737	0.767	0.717	0.713	0.754	0.706	0.732	0.744	0.623	0.744	0.727	0.758	0.755	0.755	0.473	0.595	0.935	0.739
61.11%	0.709	0.717	0.747	0.728	0.751	0.741	0.724	0.734	0.765	0.716	0.700	0.738	0.699	0.740	0.729	0.592	0.701	0.718	0.737	0.726	0.685	0.450	0.496	0.930	0.707
62.96%	0.697	0.707	0.741	0.722	0.738	0.739	0.730	0.713	0.766	0.720	0.722	0.736	0.699	0.741	0.722	0.595	0.666	0.722	0.730	0.706	0.707	0.474	0.496	0.929	0.705
64.81%	0.694	0.702	0.736	0.707	0.718	0.715	0.733	0.699	0.764	0.706	0.687	0.722	0.669	0.719	0.713	0.595	0.706	0.683	0.717	0.695	0.677	0.448	0.496	0.936	0.693
66.67%	0.701	0.717	0.717	0.730	0.733	0.723	0.705	0.707	0.752	0.713	0.697	0.720	0.684	0.727	0.716	0.600	0.675	0.704	0.729	0.688	0.690	0.475	0.496	0.935	0.697
68.52%	0.682	0.690	0.723	0.714	0.705	0.694	0.704	0.670	0.734	0.692	0.656	0.688	0.641	0.688	0.680	0.573	0.684	0.679	0.712	0.688	0.648	0.428	0.496	0.936	0.675
70.37%	0.651	0.660	0.705	0.675	0.732	0.714	0.713	0.693	0.751	0.711	0.697	0.706	0.676	0.711	0.715	0.586	0.695	0.690	0.727	0.694	0.684	0.415	0.496	0.935	0.685
72.22%	0.691	0.694	0.708	0.693	0.714	0.696	0.718	0.667	0.744	0.701	0.685	0.690	0.666	0.698	0.696	0.580	0.655	0.693	0.715	0.694	0.650	0.454	0.496	0.936	0.681
74.07%	0.661	0.666	0.694	0.677	0.706	0.708	0.687	0.683	0.745	0.705	0.697	0.709	0.655	0.709	0.697	0.588	0.666	0.670	0.711</td						

(i) Model performance gap  $\Delta$  of RD experiment under accuracy on Jannis dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
1.85%	0.000	0.000	-0.047	0.002	-0.003	-0.002	-0.001	-0.003	0.000	-0.002	-0.003	-0.004	-0.001	-0.003	-0.002	-0.004	-0.001	-0.002	-0.003	-0.003	-0.005	0.229	-0.002	-0.202	-0.007
3.7%	-0.008	-0.008	-0.011	0.001	-0.004	-0.005	0.000	-0.008	-0.001	-0.002	-0.005	-0.008	-0.006	-0.006	-0.005	-0.006	-0.005	-0.003	-0.020	-0.017	0.193	0.001	-0.201	-0.009	
5.56%	-0.042	-0.038	-0.011	-0.015	-0.008	-0.012	-0.001	-0.020	-0.005	-0.006	-0.010	-0.017	-0.011	-0.013	-0.010	-0.007	-0.011	-0.009	-0.008	-0.023	-0.031	0.204	-0.006	-0.202	-0.017
7.41%	-0.034	-0.033	-0.018	-0.010	-0.021	-0.020	-0.008	-0.026	-0.011	-0.015	-0.027	-0.027	-0.020	-0.022	-0.021	-0.016	-0.028	-0.020	-0.018	-0.028	-0.038	0.125	-0.002	-0.201	-0.026
9.26%	-0.026	-0.023	-0.023	-0.011	-0.008	-0.009	0.002	-0.017	-0.003	-0.004	-0.014	-0.015	-0.022	-0.012	-0.010	-0.008	-0.033	-0.007	-0.006	-0.038	-0.050	0.121	0.002	-0.202	-0.021
11.11%	-0.048	-0.043	-0.032	-0.014	-0.015	-0.019	-0.001	-0.026	-0.009	-0.008	-0.012	-0.025	-0.028	-0.019	-0.020	-0.008	-0.035	-0.012	-0.010	-0.036	-0.059	0.163	0.004	-0.202	-0.026
12.96%	-0.067	-0.058	-0.028	-0.012	-0.026	-0.030	-0.007	-0.039	-0.017	-0.019	-0.032	-0.039	-0.028	-0.033	-0.029	-0.017	-0.040	-0.024	-0.021	-0.067	-0.047	0.171	-0.001	-0.201	-0.034
14.81%	-0.076	-0.070	-0.051	-0.040	-0.021	-0.027	-0.005	-0.038	-0.013	-0.016	-0.021	-0.038	-0.034	-0.028	-0.024	-0.023	-0.028	-0.018	-0.018	-0.052	-0.051	0.043	-0.004	-0.200	-0.039
16.67%	-0.036	-0.035	-0.045	-0.011	-0.043	-0.048	-0.008	-0.081	-0.031	-0.026	-0.042	-0.076	-0.067	-0.056	-0.070	-0.035	-0.073	-0.030	-0.025	-0.128	-0.118	0.080	0.001	-0.202	-0.054
18.52%	-0.080	-0.070	-0.058	-0.017	-0.028	-0.031	-0.005	-0.052	-0.016	-0.022	-0.027	-0.052	-0.049	-0.038	-0.046	-0.021	-0.061	-0.017	-0.018	-0.118	-0.087	0.046	-0.001	-0.200	-0.048
20.37%	-0.084	-0.079	-0.060	-0.035	-0.050	-0.051	-0.012	-0.065	-0.027	-0.031	-0.051	-0.066	-0.067	-0.055	-0.064	-0.031	-0.059	-0.040	-0.034	-0.102	-0.114	0.025	0.000	-0.201	-0.060
22.22%	-0.071	-0.066	-0.081	-0.029	-0.047	-0.049	-0.008	-0.068	-0.026	-0.030	-0.048	-0.067	-0.068	-0.052	-0.054	-0.029	-0.086	-0.037	-0.035	-0.086	-0.103	-0.002	0.004	-0.200	-0.059
24.07%	-0.115	-0.109	-0.082	-0.043	-0.046	-0.056	-0.018	-0.089	-0.034	-0.035	-0.053	-0.086	-0.064	-0.066	-0.076	-0.040	-0.062	-0.042	-0.033	-0.089	-0.119	-0.032	0.000	-0.201	-0.070
25.93%	-0.146	-0.133	-0.102	-0.066	-0.068	-0.081	-0.024	-0.096	-0.046	-0.049	-0.076	-0.105	-0.088	-0.088	-0.082	-0.038	-0.116	-0.056	-0.050	-0.098	-0.138	-0.086	0.001	-0.201	-0.088
27.78%	-0.128	-0.116	-0.094	-0.033	-0.041	-0.045	-0.008	-0.066	-0.034	-0.027	-0.043	-0.064	-0.066	-0.051	-0.056	-0.017	-0.116	-0.037	-0.028	-0.207	-0.107	-0.038	-0.004	-0.202	-0.072
29.63%	-0.113	-0.109	-0.108	-0.042	-0.046	-0.052	-0.008	-0.082	-0.027	-0.035	-0.060	-0.070	-0.082	-0.062	-0.056	-0.036	-0.091	-0.043	-0.041	-0.183	-0.107	-0.079	-0.006	-0.202	-0.076
31.48%	-0.144	-0.132	-0.104	-0.057	-0.044	-0.053	-0.008	-0.092	-0.023	-0.029	-0.059	-0.083	-0.076	-0.066	-0.057	-0.025	-0.095	-0.040	-0.030	-0.111	-0.111	-0.034	0.000	-0.201	-0.074
33.33%	-0.127	-0.117	-0.117	-0.064	-0.071	-0.076	-0.012	-0.102	-0.047	-0.045	-0.083	-0.092	-0.107	-0.081	-0.094	-0.031	-0.103	-0.062	-0.053	-0.199	-0.168	-0.034	0.001	-0.202	-0.091
35.19%	-0.141	-0.128	-0.137	-0.061	-0.070	-0.075	-0.016	-0.119	-0.040	-0.048	-0.073	-0.103	-0.098	-0.085	-0.078	-0.041	-0.148	-0.054	-0.049	-0.182	-0.135	-0.061	-0.002	-0.199	-0.094
37.04%	-0.172	-0.163	-0.126	-0.055	-0.080	-0.085	-0.014	-0.137	-0.043	-0.052	-0.055	-0.131	-0.134	-0.094	-0.139	-0.051	-0.091	-0.057	-0.053	-0.162	-0.207	-0.057	-0.001	-0.201	-0.103
38.89%	-0.175	-0.169	-0.153	-0.070	-0.102	-0.108	-0.046	-0.140	-0.070	-0.072	-0.142	-0.137	-0.173	-0.108	-0.152	-0.077	-0.138	-0.086	-0.080	-0.229	-0.239	-0.154	-0.001	-0.201	-0.130
40.74%	-0.182	-0.169	-0.158	-0.070	-0.072	-0.079	-0.029	-0.115	-0.056	-0.060	-0.085	-0.115	-0.104	-0.095	-0.097	-0.060	-0.148	-0.064	-0.057	-0.169	-0.156	-0.111	-0.004	-0.202	-0.106
42.59%	-0.238	-0.229	-0.177	-0.104	-0.075	-0.082	-0.018	-0.116	-0.050	-0.052	-0.080	-0.106	-0.134	-0.088	-0.111	-0.058	-0.199	-0.056	-0.053	-0.170	-0.175	-0.073	-0.003	-0.201	-0.115
44.44%	-0.194	-0.180	-0.204	-0.071	-0.134	-0.133	-0.046	-0.173	-0.088	-0.086	-0.116	-0.174	-0.180	-0.138	-0.163	-0.094	-0.177	-0.099	-0.087	-0.255	-0.246	-0.189	-0.001	-0.201	-0.147
46.3%	-0.243	-0.227	-0.174	-0.089	-0.111	-0.108	-0.033	-0.165	-0.073	-0.069	-0.109	-0.152	-0.161	-0.128	-0.162	-0.070	-0.197	-0.082	-0.075	-0.231	-0.252	-0.155	0.001	-0.201	-0.141
48.15%	-0.177	-0.165	-0.163	-0.082	-0.119	-0.110	-0.027	-0.179	-0.086	-0.074	-0.106	-0.162	-0.184	-0.122	-0.202	-0.070	-0.210	-0.074	-0.077	-0.239	-0.311	-0.114	-0.001	-0.202	-0.141
50%	-0.263	-0.254	-0.241	-0.137	-0.120	-0.114	-0.023	-0.156	-0.058	-0.061	-0.089	-0.143	-0.170	-0.125	-0.135	-0.074	-0.196	-0.080	-0.071	-0.227	-0.198	-0.111	-0.001	-0.203	-0.140
51.85%	-0.197	-0.189	-0.212	-0.107	-0.174	-0.181	-0.058	-0.236	-0.135	-0.125	-0.167	-0.223	-0.233	-0.198	-0.233	-0.090	-0.151	-0.136	-0.123	-0.295	-0.316	-0.127	0.000	-0.201	-0.176
53.7%	-0.258	-0.239	-0.258	-0.089	-0.125	-0.117	-0.030	-0.219	-0.070	-0.056	-0.113	-0.180	-0.217	-0.145	-0.222	-0.077	-0.288	-0.087	-0.058	-0.294	-0.321	-0.202	0.001	-0.202	-0.167
55.56%	-0.345	-0.330	-0.263	-0.148	-0.156	-0.150	-0.046	-0.240	-0.090	-0.077	-0.171	-0.217	-0.227	-0.192	-0.259	-0.082	-0.216	-0.104	-0.087	-0.290	-0.329	-0.098	-0.458	-0.200	-0.203
57.41%	-0.256	-0.243	-0.244	-0.127	-0.131	-0.144	-0.020	-0.210	-0.093	-0.081	-0.106	-0.196	-0.224	-0.161	-0.207	-0.064	-0.286	-0.097	-0.084	-0.258	-0.300	-0.161	-0.458	0.000	-0.174
59.26%	-0.248	-0.239	-0.255	-0.150	-0.165	-0.149	-0.050	-0.231	-0.112	-0.101	-0.146	-0.210	-0.236	-0.172	-0.261	-0.084	-0.281	-0.117	-0.103	-0.348	-0.348	-0.139	-0.459	-0.002	-0.193
61.11%	-0.276	-0.266	-0.289	-0.143	-0.173	-0.161	-0.055	-0.220	-0.119	-0.102	-0.173	-0.203	-0.251	-0.171	-0.261	-0.125	-0.302	-0.106	-0.099	-0.328	-0.392	-0.196	-0.459	-0.001	-0.204
62.96%	-0.326	-0.311	-0.308	-0.150	-0.153	-0.148	-0.036	-0.218	-0.095	-0.088	-0.128	-0.197	-0.216	-0.157	-0.238	-0.107	-0.338	-0.103	-0.092	-0.347	-0.312	-0.154	-0.459	-0.001	-0.196
64.81%	-0.335	-0.323	-0.327	-0.195	-0.216	-0.189	-0.041	-0.287	-0.118	-0.119	-0.198	-0.239	-0.310	-0.209	-0.290	-0.113	-0.289	-0.148	-0.124	-0.394	-0.394	-0.200	-0.458	-0.001	-0.242
66.67%	-0.309	-0.291	-0.353	-0.142	-0.178	-0.181	-0.087	-0.247	-0.123	-0.108	-0.156	-0.234	-0.295	-0.191	-0.286	-0.104	-0.286	-0.129	-0.106	-0.394	-0.368	-0.152	-0.458	-0.001	-0.228
68.52%	-0.359	-0.350	-0.354	-0.199	-0.229	-0.227	-0.056	-0.362	-0.168	-0.134	-0.236	-0.306	-0.378	-0.265	-0.399	-0.139	-0.293	-0.194	-0.140	-0.378	-0.468	-0.236	-0.458	-0.001	-0.276
70.37%	-0.417	-0.407	-0.410	-0.259	-0.223	-0.196	-0.069	-0.297	-0.141	-0.105	-0.163	-0.260	-0.308	-0.217	-0.297	-0.112	-0.306	-0.137	-0.121	-0.356	-0.456	-0.259	-0.458	-0.002	-0.257
72.22%	-0.319	-0.313	-0.372	-0.209	-0.246	-0.206	-0.077	-0.334	-0.140	-0.119	-0.203	-0.270	-0.333	-0.214	-0.340	-0.140	-0.345	-0.153	-0.121	-0.396	-0.429	-0.189	-0.458	-0.002	-0.259
74.07%	-0.369	-0.364	-0.405	-0.255	-0.217	-0.191	-0.104	-0.283	-0.135	-0.120	-0.162	-0.233	-0.327	-0.209	-0.313	-0.109	-0.353	-0.151	-0.121	-0.426	-0.397	-0.200	-0.457	-0.001	-0.258
75.93%	-0.383	-0.374	-0.419	-0.265	-0.271	-0.211	-0.110	-0.314	-0.156	-0.148	-0.239	-0.280	-0.326	-0.226	-0.299	-0.150	-0.369	-0.1							

(j) Model performance gap  $\Delta$  of RD experiment under ROC-AUC on Jannis dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
1.85%	0.000	0.000	-0.003	0.001	-0.001	-0.001	-0.002	-0.001	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	0.364	-0.004	0.007	0.009	
3.7%	-0.004	-0.003	-0.005	0.001	-0.002	-0.003	0.000	-0.004	0.000	-0.001	-0.003	-0.004	-0.003	-0.003	-0.003	-0.007	-0.002	-0.002	-0.010	-0.008	0.325	0.001	0.006	0.006	
5.56%	-0.025	-0.020	-0.006	-0.011	-0.006	-0.009	-0.001	-0.012	-0.005	-0.004	-0.008	-0.010	-0.006	-0.009	-0.007	-0.009	-0.006	-0.006	-0.011	-0.015	0.337	-0.010	0.007	0.001	
7.41%	-0.016	-0.015	-0.008	-0.005	-0.010	-0.011	-0.004	-0.015	-0.007	-0.008	-0.014	-0.014	-0.010	-0.012	-0.011	-0.013	-0.018	-0.010	-0.009	-0.015	-0.020	0.249	-0.001	0.007	-0.004
9.26%	-0.014	-0.012	-0.011	-0.007	-0.004	-0.003	0.002	-0.010	-0.002	-0.004	-0.011	-0.008	-0.012	-0.007	-0.007	-0.013	-0.021	-0.003	-0.003	-0.023	-0.026	0.245	0.001	0.007	-0.002
11.11%	-0.033	-0.028	-0.016	-0.010	-0.010	-0.013	-0.002	-0.019	-0.009	-0.005	-0.008	-0.016	-0.015	-0.013	-0.014	-0.009	-0.022	-0.009	-0.008	-0.015	-0.032	0.291	0.001	0.006	-0.006
12.96%	-0.037	-0.032	-0.015	-0.006	-0.014	-0.018	-0.004	-0.022	-0.011	-0.011	-0.020	-0.021	-0.014	-0.018	-0.017	-0.019	-0.022	-0.015	-0.012	-0.038	-0.025	0.301	0.000	0.007	-0.009
14.81%	-0.045	-0.040	-0.024	-0.023	-0.013	-0.019	-0.004	-0.025	-0.011	-0.009	-0.015	-0.023	-0.018	-0.019	-0.017	-0.024	-0.022	-0.014	-0.012	-0.031	-0.027	0.158	-0.005	0.006	-0.014
16.67%	-0.017	-0.015	-0.022	-0.005	-0.026	-0.034	-0.008	-0.054	-0.022	-0.017	-0.033	-0.048	-0.040	-0.038	-0.046	-0.041	-0.041	-0.025	-0.020	-0.068	-0.074	0.200	0.001	0.006	-0.024
18.52%	-0.044	-0.037	-0.029	-0.010	-0.015	-0.019	-0.004	-0.030	-0.012	-0.011	-0.017	-0.026	-0.026	-0.026	-0.024	-0.036	-0.013	-0.010	-0.061	-0.046	0.162	-0.003	0.005	-0.018	
20.37%	-0.049	-0.043	-0.031	-0.021	-0.028	-0.033	-0.009	-0.041	-0.020	-0.019	-0.034	-0.037	-0.039	-0.032	-0.038	-0.031	-0.041	-0.036	-0.019	-0.059	-0.065	0.138	0.001	0.007	-0.027
22.22%	-0.036	-0.033	-0.041	-0.017	-0.021	-0.025	-0.005	-0.035	-0.014	-0.016	-0.031	-0.034	-0.026	-0.028	-0.026	-0.055	-0.018	-0.015	-0.045	-0.056	0.109	0.002	0.006	-0.023	
24.07%	-0.064	-0.057	-0.041	-0.026	-0.037	-0.044	-0.014	-0.061	-0.028	-0.025	-0.043	-0.054	-0.049	-0.047	-0.052	-0.047	-0.038	-0.035	-0.029	-0.053	-0.078	0.075	-0.001	0.006	-0.038
25.93%	-0.075	-0.067	-0.053	-0.040	-0.040	-0.049	-0.014	-0.062	-0.029	-0.029	-0.050	-0.059	-0.055	-0.051	-0.052	-0.044	-0.074	-0.046	-0.028	-0.062	-0.085	0.015	-0.001	0.007	-0.045
27.78%	-0.071	-0.063	-0.048	-0.021	-0.024	-0.032	-0.008	-0.044	-0.026	-0.017	-0.030	-0.043	-0.041	-0.034	-0.039	-0.024	-0.080	-0.025	-0.020	-0.120	-0.066	0.069	-0.007	0.006	-0.037
29.63%	-0.065	-0.058	-0.054	-0.026	-0.024	-0.033	-0.004	-0.047	-0.019	-0.020	-0.039	-0.046	-0.037	-0.033	-0.042	-0.062	-0.023	-0.022	-0.106	-0.066	0.023	-0.005	0.007	-0.037	
31.48%	-0.080	-0.072	-0.053	-0.031	-0.025	-0.034	-0.007	-0.052	-0.015	-0.018	-0.038	-0.043	-0.047	-0.039	-0.035	-0.064	-0.022	-0.020	-0.065	-0.067	0.073	0.000	0.007	-0.035	
33.33%	-0.068	-0.062	-0.057	-0.036	-0.037	-0.044	-0.007	-0.060	-0.030	-0.026	-0.052	-0.052	-0.058	-0.047	-0.052	-0.041	-0.069	-0.043	-0.028	-0.115	-0.098	0.073	-0.001	0.008	-0.045
35.19%	-0.081	-0.071	-0.068	-0.032	-0.040	-0.050	-0.013	-0.071	-0.029	-0.031	-0.050	-0.061	-0.059	-0.054	-0.048	-0.046	-0.102	-0.042	-0.032	-0.095	-0.086	0.043	-0.002	0.008	-0.049
37.04%	-0.094	-0.087	-0.064	-0.036	-0.044	-0.057	-0.008	-0.085	-0.032	-0.027	-0.039	-0.076	-0.076	-0.061	-0.071	-0.054	-0.062	-0.038	-0.031	-0.096	-0.119	0.047	-0.001	0.006	-0.053
38.89%	-0.104	-0.098	-0.077	-0.047	-0.058	-0.072	-0.034	-0.090	-0.051	-0.045	-0.094	-0.082	-0.101	-0.071	-0.083	-0.081	-0.095	-0.063	-0.056	-0.154	-0.137	0.060	0.000	0.007	-0.074
40.74%	-0.101	-0.092	-0.080	-0.042	-0.045	-0.056	-0.024	-0.078	-0.039	-0.036	-0.057	-0.072	-0.075	-0.064	-0.066	-0.065	-0.112	-0.044	-0.040	-0.103	-0.105	0.012	-0.005	0.005	-0.061
42.59%	-0.130	-0.123	-0.091	-0.064	-0.042	-0.053	-0.011	-0.076	-0.036	-0.028	-0.054	-0.067	-0.084	-0.056	-0.070	-0.065	-0.131	-0.042	-0.032	-0.094	-0.108	0.029	-0.005	0.008	-0.062
44.44%	-0.116	-0.106	-0.099	-0.041	-0.080	-0.090	-0.031	-0.113	-0.056	-0.053	-0.082	-0.105	-0.112	-0.088	-0.102	-0.087	-0.111	-0.068	-0.061	-0.140	-0.147	-0.100	-0.003	0.006	-0.084
46.3%	-0.134	-0.121	-0.087	-0.055	-0.063	-0.075	-0.026	-0.101	-0.054	-0.045	-0.076	-0.096	-0.099	-0.081	-0.095	-0.075	-0.139	-0.069	-0.050	-0.146	-0.145	-0.062	-0.001	0.006	-0.081
48.15%	-0.116	-0.105	-0.089	-0.047	-0.059	-0.075	-0.025	-0.113	-0.062	-0.049	-0.077	-0.099	-0.114	-0.080	-0.106	-0.084	-0.143	-0.070	-0.053	-0.145	-0.176	-0.106	0.000	0.007	-0.082
50%	-0.156	-0.150	-0.118	-0.082	-0.070	-0.084	-0.016	-0.110	-0.044	-0.042	-0.066	-0.096	-0.112	-0.087	-0.089	-0.089	-0.122	-0.078	-0.048	-0.133	-0.134	-0.012	-0.001	0.006	-0.083
51.85%	-0.114	-0.105	-0.077	-0.044	-0.054	-0.062	-0.024	-0.078	-0.039	-0.036	-0.057	-0.072	-0.075	-0.064	-0.066	-0.065	-0.112	-0.044	-0.040	-0.103	-0.105	0.012	-0.005	0.005	-0.061
53.7%	-0.151	-0.136	-0.125	-0.050	-0.068	-0.088	-0.015	-0.141	-0.056	-0.055	-0.080	-0.121	-0.128	-0.104	-0.128	-0.105	-0.179	-0.076	-0.044	-0.157	-0.192	-0.113	0.000	0.006	-0.097
55.56%	-0.176	-0.166	-0.124	-0.076	-0.080	-0.098	-0.026	-0.140	-0.059	-0.054	-0.121	-0.143	-0.144	-0.131	-0.144	-0.144	-0.209	-0.089	-0.060	-0.146	-0.198	0.002	-0.016	0.007	-0.107
57.41%	-0.146	-0.138	-0.120	-0.070	-0.073	-0.096	-0.017	-0.130	-0.068	-0.048	-0.072	-0.121	-0.132	-0.099	-0.112	-0.075	-0.209	-0.061	-0.054	-0.154	-0.169	-0.068	-0.068	0.000	-0.101
59.26%	-0.158	-0.150	-0.125	-0.079	-0.089	-0.103	-0.041	-0.137	-0.081	-0.064	-0.104	-0.149	-0.157	-0.137	-0.146	-0.146	-0.230	-0.075	-0.067	-0.167	-0.170	-0.075	-0.044	-0.017	-0.113
61.11%	-0.165	-0.155	-0.148	-0.079	-0.080	-0.110	-0.031	-0.140	-0.084	-0.065	-0.116	-0.137	-0.157	-0.118	-0.146	-0.121	-0.188	-0.081	-0.067	-0.182	-0.225	-0.108	-0.167	0.000	-0.120
62.96%	-0.179	-0.167	-0.155	-0.081	-0.096	-0.113	-0.023	-0.165	-0.083	-0.059	-0.139	-0.157	-0.177	-0.154	-0.166	-0.126	-0.230	-0.078	-0.074	-0.204	-0.200	-0.160	-0.166	-0.001	-0.123
64.81%	-0.183	-0.173	-0.161	-0.106	-0.125	-0.151	-0.051	-0.153	-0.090	-0.079	-0.113	-0.141	-0.151	-0.129	-0.140	-0.139	-0.111	-0.113	-0.084	-0.169	-0.199	-0.030	-0.001	0.007	-0.105
66.67%	-0.174	-0.162	-0.182	-0.077	-0.103	-0.131	-0.056	-0.187	-0.099	-0.068	-0.120	-0.158	-0.176	-0.133	-0.161	-0.109	-0.219	-0.098	-0.078	-0.226	-0.219	-0.058	-0.166	0.006	-0.133
68.52%	-0.197	-0.187	-0.175	-0.097	-0.137	-0.167	-0.057	-0.215	-0.121	-0.106	-0.172	-0.196	-0.227	-0.180	-0.204	-0.150	-0.208	-0.131	-0.100	-0.224	-0.266	-0.151	-0.166	0.007	-0.160
70.37%	-0.233	-0.223	-0.196	-0.147	-0.104	-0.142	-0.046	-0.189	-0.101	-0.072	-0.121	-0.175	-0.185	-0.163	-0.162	-0.130	-0.195	-0.117	-0.081	-0.218	-0.226	-0.177	-0.166	0.006	-0.149
72.22%	-0.186	-0.182	-0.193	-0.123	-0.126	-0.164	-0.039	-0.218	-0.110	-0.085	-0.136	-0.193	-0.197	-0.167	-0.185	-0.139	-0.242	-0.113	-0.096	-0.217	-0.264	-0.100	-0.166	0.007	-0.153
74.07%	-0.221	-0.216	-0.206	-0.144	-0.136	-0.150	-0.080	-0.199	-0.108	-0.080	-0.120	-0.171	-0.210	-0.155	-0.184	-0.127	-0.230	-0.142	-0.100	-0.259	-0.228	-0.111	-0.164	0.006	-0.158
75.93%	-0.243	-0.233	-0.210	-0.132	-0.149	-0.157	-0.071	-0.202	-0.118	-0.106	-0.170	-0.178	-0.208	-0.155	-0.184	-0.127	-0.254	-0.157	-0.129	-0.258	-0.228	-0.117	-0.166	0	

Table 21. Model performance on Penguins dataset.

(a) Model performance of SC experiment under accuracy on Penguins dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.981	0.971	0.961	0.990	0.478	0.884	0.614	0.966	0.976	0.792	0.541	0.754	0.319	0.928	0.749	0.246	0.754	0.841	0.256	0.860	1.000	0.826	0.826	0.986	0.771
1	0.015	0.971	0.966	0.966	0.986	0.473	0.821	0.609	0.952	0.981	0.797	0.444	0.754	0.377	0.942	0.749	0.256	0.754	0.841	0.261	0.860	1.000	0.855	0.826	0.986	0.768
2	-0.636	0.865	0.957	0.952	0.986	0.483	0.865	0.628	0.961	0.976	0.773	0.556	0.754	0.353	0.937	0.739	0.246	0.754	0.850	0.242	0.855	0.986	0.754	0.826	0.855	0.756
3	0.731	0.715	0.715	0.758	0.734	0.483	0.754	0.609	0.710	0.715	0.681	0.512	0.754	0.300	0.720	0.739	0.304	0.749	0.696	0.256	0.749	0.734	0.725	0.841	0.957	0.663
4	-0.744	0.971	0.952	0.947	0.981	0.430	0.826	0.604	0.928	0.961	0.768	0.517	0.734	0.357	0.903	0.725	0.251	0.739	0.831	0.271	0.845	0.971	0.826	0.841	0.971	0.756
5	0.750	0.961	0.957	0.966	0.961	0.430	0.874	0.585	0.889	0.952	0.739	0.473	0.758	0.406	0.932	0.744	0.271	0.754	0.826	0.275	0.870	1.000	0.841	0.812	0.986	0.761
6	0.854	0.976	0.966	0.961	0.990	0.430	0.884	0.618	0.957	0.981	0.807	0.527	0.754	0.348	0.928	0.744	0.304	0.749	0.816	0.213	0.874	0.995	0.797	0.841	0.986	0.769

(b) Model performance of SC experiment under ROC-AUC on Penguins dataset.

Column	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0	\	0.990	0.990	0.997	1.000	0.856	0.989	0.911	0.997	0.999	0.919	0.690	0.998	0.546	0.999	0.991	0.228	0.992	0.947	0.498	0.999	1.000	0.823	0.857	0.986	0.883
1	0.015	0.989	0.989	0.997	1.000	0.859	0.995	0.925	0.997	0.999	0.911	0.621	0.998	0.530	0.999	0.994	0.219	0.993	0.950	0.508	1.000	1.000	0.856	0.843	0.986	0.882
2	-0.636	0.979	0.987	0.983	1.000	0.869	0.987	0.892	0.998	0.999	0.925	0.775	0.996	0.541	0.999	0.995	0.230	0.993	0.944	0.492	0.996	1.000	0.759	0.874	0.894	0.879
3	0.731	0.879	0.883	0.906	0.889	0.838	0.919	0.864	0.914	0.817	0.700	0.617	0.956	0.528	0.877	0.860	0.346	0.923	0.824	0.374	0.944	0.898	0.726	0.861	0.984	0.805
4	-0.744	0.991	0.992	0.987	1.000	0.868	0.970	0.910	0.993	0.992	0.886	0.667	0.993	0.522	0.995	0.988	0.319	0.989	0.924	0.492	0.994	1.000	0.823	0.871	0.971	0.881
5	0.750	0.989	0.988	0.997	1.000	0.829	0.994	0.877	0.989	0.997	0.890	0.624	0.999	0.558	0.999	0.981	0.246	0.990	0.960	0.505	0.998	1.000	0.841	0.857	0.986	0.879
6	0.854	0.991	0.989	0.994	1.000	0.705	0.977	0.886	0.996	0.996	0.890	0.762	0.998	0.601	0.999	0.991	0.297	0.986	0.935	0.366	1.000	1.000	0.799	0.871	0.986	0.876

(c) Model performance of MC-M experiment under accuracy on Penguins dataset.

Degree	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.981	0.971	0.961	0.990	0.478	0.884	0.614	0.966	0.976	0.792	0.541	0.754	0.319	0.928	0.749	0.246	0.754	0.841	0.256	0.860	1.000	0.826	0.826	0.986	0.771	
16.67%	0.976	0.966	0.961	0.990	0.430	0.884	0.618	0.957	0.981	0.807	0.527	0.754	0.348	0.928	0.744	0.304	0.749	0.816	0.213	0.874	0.995	0.797	0.841	0.986	0.769	
33.33%	0.957	0.952	0.961	0.982	0.382	0.860	0.546	0.870	0.932	0.618	0.604	0.754	0.420	0.884	0.729	0.338	0.734	0.826	0.232	0.870	1.000	0.812	0.841	0.986	0.753	
50%	0.686	0.860	0.763	0.845	0.382	0.671	0.478	0.855	0.928	0.517	0.536	0.715	0.435	0.749	0.633	0.382	0.671	0.768	0.256	0.783	0.986	0.899	0.841	0.971	0.685	
66.67%	0.382	0.493	0.483	0.488	0.382	0.676	0.473	0.512	0.556	0.319	0.444	0.527	0.401	0.512	0.483	0.343	0.430	0.643	0.227	0.517	0.556	0.551	0.841	0.957	0.495	
83.33%	0.329	0.353	0.314	0.309	0.382	0.391	0.367	0.362	0.353	0.362	0.377	0.372	0.372	0.372	0.372	0.372	0.372	0.372	0.372	0.372	0.372	0.372	0.372	0.372	0.372	
100%	0.271	0.357	0.271	0.232	0.382	0.391	0.382	0.362	0.382	0.391	0.382	0.391	0.382	0.391	0.382	0.391	0.391	0.391	0.391	0.391	0.391	0.391	0.391	0.391	0.391	

(d) Model performance of MC-M experiment under ROC-AUC on Penguins dataset.

Degree	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.990	0.990	0.997	1.000	0.856	0.989	0.911	0.997	0.999	0.919	0.690	0.998	0.546	0.999	0.991	0.228	0.992	0.947	0.498	0.999	1.000	0.823	0.857	0.986	0.883	
16.67%	0.991	0.989	0.994	1.000	0.705	0.977	0.886	0.996	0.996	0.890	0.762	0.998	0.601	0.999	0.991	0.297	0.986	0.935	0.366	1.000	1.000	0.799	0.857	0.986	0.875	
33.33%	0.991	0.979	0.988	1.000	0.667	0.981	0.832	0.987	0.990	0.816	0.725	0.998	0.626	0.989	0.972	0.328	0.981	0.948	0.432	0.994	1.000	0.823	0.857	0.986	0.870	
50%	0.985	0.974	0.981	0.993	0.675	0.957	0.803	0.962	0.985	0.766	0.712	0.994	0.587	0.963	0.962	0.449	0.979	0.885	0.473	0.991	0.999	0.908	0.885	0.986	0.869	
66.67%	0.735	0.801	0.811	0.780	0.648	0.790	0.699	0.749	0.725	0.515	0.631	0.832	0.494	0.789	0.773	0.584	0.821	0.704	0.440	0.834	0.845	0.613	0.847	0.984	0.727	
83.33%	0.492	0.486	0.498	0.491	0.489	0.492	0.501	0.510	0.470	0.464	0.508	0.478	0.499	0.494	0.492	0.493	0.504	0.496	0.500	0.463	0.455	0.498	0.847	0.987	0.525	
100%	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	

(e) Model performance of MC-L experiment under accuracy on Penguins dataset.

Degree	PCC	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
0%	0.981	0.971	0.961	0.990	0.478	0.884	0.614	0.966	0.976	0.792	0.541	0.754	0.319	0.928	0.749	0.246	0.754	0.841	0.256	0.860	1.000	0.826	0.826	0.986	0.771	
16.67%	0.971	0.966	0.961	0.990	0.430	0.884	0.618	0.957	0.981	0.807	0.527	0.754	0.348	0.928	0.744	0.304	0.749	0.816	0.213	0.874	0.995	0.797	0.841	0.986	0.769	
33.33%	0.972	0.952	0.957	0.976	0.483	0.812	0.609	0.942	0.966	0.768	0.484	0.758	0.401	0.952	0.749	0.295	0.754									

(i) Model performance gap  $\Delta$  of RD experiment under accuracy on Penguins dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
16.67%	-0.072	-0.054	-0.037	-0.051	-0.049	-0.053	-0.008	-0.069	-0.048	-0.040	-0.063	-0.003	0.119	-0.036	-0.012	0.105	-0.005	-0.036	-0.013	-0.021	-0.052	0.105	0.006	-0.027	-0.026
33.33%	-0.188	-0.107	-0.115	-0.100	-0.090	-0.103	-0.035	-0.098	-0.070	-0.093	-0.120	-0.008	0.191	-0.057	-0.033	0.137	-0.017	-0.075	0.025	-0.023	-0.084	0.053	0.018	-0.072	-0.061
50%	-0.346	-0.178	-0.240	-0.175	-0.145	-0.203	-0.119	-0.177	-0.164	-0.218	-0.142	-0.037	0.217	-0.161	-0.081	0.298	-0.063	-0.152	-0.038	-0.113	-0.176	0.246	0.021	-0.085	-0.143
66.67%	-0.496	-0.288	-0.408	-0.318	-0.183	-0.302	-0.163	-0.299	-0.267	-0.260	-0.134	-0.060	0.211	-0.255	-0.157	0.461	-0.176	-0.233	0.023	-0.174	-0.373	-0.281	0.016	-0.094	-0.223
83.33%	-0.631	-0.430	-0.595	-0.514	-0.199	-0.465	-0.272	-0.449	-0.408	-0.380	-0.226	-0.193	0.230	-0.398	-0.273	0.552	-0.425	-0.366	0.000	-0.313	-0.564	-0.526	0.015	-0.120	-0.355
100%	-0.724	-0.632	-0.719	-0.766	-0.202	-0.557	-0.378	-0.625	-0.609	-0.506	-0.295	-0.494	0.227	-0.589	-0.477	0.588	-0.481	-0.534	-0.038	-0.545	-0.754	-0.404	0.018	-0.191	-0.484

 (j) Model performance gap  $\Delta$  of RD experiment under ROC-AUC on Penguins dataset.

Degree	LGB	XGB	CATB	PFN	DAN	MLP	NODE	RES	SWI	CAP	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	TLLM	UNI	AVE
16.67%	-0.020	-0.018	-0.020	-0.018	-0.033	-0.015	-0.021	-0.016	-0.032	-0.057	-0.017	-0.008	0.001	-0.021	-0.023	0.213	-0.013	-0.026	-0.085	-0.010	-0.017	0.132	0.004	-0.017	-0.012
33.33%	-0.054	-0.044	-0.046	-0.045	-0.029	-0.026	-0.037	-0.027	-0.039	-0.072	-0.013	-0.016	0.013	-0.031	-0.032	0.315	-0.019	-0.041	-0.055	-0.009	-0.027	0.047	0.010	-0.039	-0.025
50%	-0.103	-0.073	-0.086	-0.078	-0.131	-0.064	-0.087	-0.079	-0.098	-0.194	-0.029	-0.040	0.023	-0.078	-0.081	0.647	-0.053	-0.102	-0.147	-0.059	-0.056	-0.135	0.005	-0.016	-0.069
66.67%	-0.175	-0.126	-0.162	-0.145	-0.116	-0.120	-0.157	-0.141	-0.163	-0.226	-0.065	-0.095	-0.021	-0.140	-0.137	0.797	-0.099	-0.163	-0.132	-0.091	-0.155	-0.168	-0.011	-0.019	-0.116
83.33%	-0.273	-0.238	-0.292	-0.271	-0.190	-0.233	-0.243	-0.242	-0.265	-0.322	-0.172	-0.211	-0.027	-0.259	-0.234	0.911	-0.201	-0.270	0.003	-0.223	-0.273	-0.356	-0.013	-0.003	-0.206
100%	-0.495	-0.495	-0.499	-0.500	-0.416	-0.494	-0.451	-0.498	-0.499	-0.456	-0.276	-0.499	-0.084	-0.500	-0.495	1.194	-0.496	-0.472	0.004	-0.499	-0.500	-0.360	-0.012	0.002	-0.393

Table 22. Model performance on Abalone dataset.

(a) Model performance of SC experiment under RMSE on Abalone dataset.

Column	PCC	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0	\	2.184	2.183	2.122	3.103	2.367	3.076	2.233	3.124	2.639	2.237	2.674	2.509	2.606	3.048	2.487	3.003	3.172	2.174	2.194	2.922	2.603
1	-0.035	2.233	2.227	2.169	3.102	2.391	3.076	2.318	3.123	2.731	2.274	2.831	2.616	3.065	3.009	2.510	2.957	3.185	2.357	2.238	6.674	2.854
2	0.421	4.806	4.846	3.640	3.099	2.534	3.078	2.659	3.119	2.701	2.931	2.704	2.595	2.959	3.015	2.526	3.968	3.204	2.782	3.377	4.411	3.248
3	0.504	2.411	2.429	2.265	3.103	2.374	3.081	2.241	3.116	2.755	2.257	2.706	2.574	3.065	3.023	2.487	3.069	3.175	2.201	2.202	4.199	2.737
4	0.540	4.931	4.996	2.536	3.104	2.377	3.082	2.415	3.123	2.783	2.246	2.639	2.562	3.109	3.026	2.492	2.715	3.151	2.215	2.244	5.988	3.087
5	0.557	2.260	2.267	2.188	3.110	2.388	3.085	2.239	3.123	2.621	2.254	2.661	2.574	3.062	3.026	2.497	2.995	3.148	2.236	2.217	9.585	2.977
6	0.557	2.245	2.239	2.231	3.103	2.443	3.082	2.320	3.123	2.824	2.310	2.675	2.602	3.046	3.026	2.537	2.891	3.152	2.240	2.270	5.466	2.791
7	0.575	2.277	2.287	2.198	3.107	2.416	3.084	2.326	3.124	2.805	2.251	2.668	2.577	3.114	3.024	2.497	2.949	3.206	2.207	2.210	7.703	2.901
8	0.628	3.107	3.079	2.827	3.106	2.578	3.084	2.844	3.125	2.807	2.871	2.695	2.615	3.037	3.031	2.622	2.833	3.177	2.620	2.917	8.728	3.185

(b) Model performance of MC-M experiment under RMSE on Abalone dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0%	2.184	2.183	2.122	3.103	2.367	3.076	2.233	3.124	2.639	2.237	2.674	2.509	2.606	3.048	2.487	3.003	3.172	2.174	2.194	2.922	2.603
12.5%	3.107	3.079	2.169	3.106	2.580	3.085	2.836	3.126	2.789	2.871	2.691	2.616	2.616	3.038	2.617	2.836	3.176	2.620	2.903	4.730	2.930
25%	3.452	3.431	3.647	3.110	2.743	3.092	3.138	3.126	3.136	3.126	2.727	2.859	2.644	3.078	2.712	2.912	3.198	2.795	3.007	4.315	3.112
37.5%	3.868	3.846	4.099	3.112	3.024	3.097	3.477	3.130	3.045	3.590	2.806	2.895	2.754	3.027	2.914	3.162	3.170	3.144	3.332	3.819	3.266
50%	3.461	3.415	2.809	3.120	3.151	3.105	3.326	3.129	2.906	3.732	2.888	3.039	2.865	3.015	3.000	3.661	3.121	3.237	3.615	4.014	3.230
62.5%	6.941	6.997	2.879	3.121	3.267	3.110	3.750	3.131	2.988	3.956	3.137	3.153	3.006	3.089	3.119	3.994	3.119	3.523	4.297	5.614	3.810
75%	6.303	6.344	2.783	3.123	3.353	3.115	3.869	3.125	3.086	4.021	3.068	3.190	3.083	3.135	3.180	4.237	3.136	3.579	4.516	5.955	3.810
87.5%	3.309	3.309	2.825	3.119	3.087	3.116	3.025	3.125	3.097	3.098	3.259	3.075	3.110	3.079	3.111	3.332	3.192	3.047	3.025	5.989	3.266
100%	3.314	3.315	3.277	3.118	3.121	3.116	3.123	3.125	3.128	3.124	3.809	3.136	3.118	3.142	3.123	3.197	3.134	3.123	6.292	3.348	

(c) Model performance of MC-L experiment under RMSE on Abalone dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0%	2.184	2.183	2.122	3.103	2.367	3.076	2.233	3.124	2.639	2.237	2.674	2.509	2.606	3.048	2.487	3.003	3.172	2.174	2.194	2.922	2.603
12.5%	2.233	2.227	2.169	3.102	2.391	3.076	2.318	3.123	2.731	2.274	2.831	2.616	3.065	3.009	2.510	2.957	3.185	2.357	2.238	6.674	2.854
25%	4.709	4.755	3.110	3.098	2.541	3.078	2.725	3.119	2.749	2.938	2.822	2.604	2.981	3.016	2.548	4.019	3.213	2.894	3.344	4.561	3.241
37.5%	5.394	5.455	3.726	3.099	2.521	3.083	2.714	3.116	2.789	2.983	2.833	2.578	2.987	3.029	2.553	3.802	3.233	2.962	3.523	4.644	3.351
50%	2.545	2.535	3.843	3.101	2.498	3.089	2.502	3.117	2.680	2.794	2.722	2.564	3.088	3.048	2.595	3.182	3.196	2.789	3.044	4.086	2.951
62.5%	2.713	2.702	5.306	3.108	2.514	3.097	2.585	3.118	2.683	2.821	2.724	2.608	3.160	3.064	2.658	2.906	3.146	2.852	3.269	4.283	3.066
75%	2.568	2.559	5.316	3.110	2.607	3.102	2.586	3.120	2.635	2.732	2.853	2.722	3.189	3.081	2.797	2.797	3.126	2.733	3.174	5.461	3.113
87.5%	2.501	2.503	3.245	3.116	2.709	3.108	2.612	3.120	2.654	2.708	3.054	2.829	3.196	3.094	2.878	2.628	3.147	2.804	3.328	5.550	3.039
100%	3.314	3.315	3.277	3.118	3.121	3.116	3.123	3.125	3.128	3.124	3.809	3.136	3.118	3.142	3.123	3.197	3.134	3.123	6.292	3.348	

(d) Model performance of RD experiment under RMSE on Abalone dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0%	2.184	2.183	2.122	3.103	2.367	3.076	2.233	3.124	2.639	2.237	2.674	2.509	2.606	3.048	2.487	3.003	3.172	2.174	2.194	2.922	2.603
12.5%	3.034	3.046	2.510	3.104	2.438	3.081	2.419	3.122	2.692	2.424	2.700	2.564	2.590	3.057	2.520	3.048	3.175	2.357	2.469	3.030	2.769
25%	3.603	3.624	2.868	3.106	2.517	3.087	2.584	3.122	2.789	2.495	2.733	2.631	2.598	3.069	2.587	3.100	3.176	2.463	2.713	3.189	2.903
37.5%	3.955	3.979	3.166	3.109	2.602	3.092	2.725	3.123	2.844	2.755	2.777	2.705	2.629	3.077	2.678	3.158	3.175	2.651	2.931	3.394	3.026
50%	4.124	4.150	3.384	3.111	2.692	3.097	2.843	3.123	2.888	2.825	2.829	2.783	2.684	3.086	2.777	3.199	3.173	2.759	3.110	3.569	3.110
62.5%	4.132	4.157	3.508	3.112	2.788	3.102	2.940	3.124	2.925	3.310	2.890	2.864	2.763	3.096	2.877	3.233	3.171	2.873	3.238	3.761	3.193
75%	3.993	4.015	3.532	3.114	2.886	3.107	3.019	3.124	2.954	3.015	2.958	2.950	2.859	3.107	2.964	3.240	3.167	2.912	3.315	3.466	3.185
87.5%	3.718	3.732	3.458	3.116	2.996	3.112	3.079	3.127	3.029	3.084	3.089	3.031	2.988	3.108	3.056	3.216	3.167	3.022	3.272	3.469	3.194
100%	3.314	3.315	3.277	3.118	3.121	3.116	3.123	3.125	3.128	3.124	3.809	3.136	3.118	3.142	3.123	3.197	3.134	3.123	6.292	3.348	

 (e) Model performance gap  $\Delta$  of RD experiment under RMSE on Abalone dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
12.5%	0.389	0.396	0.183	0.001	0.030	0.002	0.083	0.000	0.020	0.084	0.010	0.022	-0.006	0.003	0.013	0.015	0.001	0.084	0.126	0.037	0.064
25%	0.650	0.660	0.351	0.001	0.063	0.003	0.157	0.000	0.057	0.116	0.022	0.048	-0.003	0.007	0.040	0.032	0.001	0.133	0.2		

Table 23. Model performance on Bike dataset.

(a) Model performance of SC experiment under RMSE on Bike dataset.

Column	PCC	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0	\	144.013	143.939	135.000	179.892	145.766	175.822	144.337	180.375	151.729	145.031	148.959	144.767	148.750	177.111	145.135	179.243	180.104	142.964	130.901	111.751	152.779
1	-0.005	148.964	149.001	140.776	179.902	150.693	175.880	150.353	180.385	155.370	150.630	152.540	150.503	153.774	177.833	151.771	193.594	179.962	149.755	160.489	113.245	158.271
2	-0.005	144.180	143.941	135.075	179.882	145.753	175.828	144.359	180.381	151.171	145.039	149.078	144.650	148.708	177.324	145.186	179.480	180.149	142.888	131.347	135.208	153.981
3	0.012	144.015	143.941	138.264	179.890	146.791	175.856	145.937	180.413	153.449	146.276	150.427	145.938	148.822	176.601	146.332	181.988	180.030	144.048	144.339	147.834	156.060
4	-0.088	144.049	143.964	136.685	179.903	146.308	175.878	145.083	180.359	155.157	145.889	150.207	145.609	149.005	176.953	146.239	183.238	179.976	143.777	134.750	148.900	155.596
5	0.101	144.332	144.238	136.368	179.873	146.203	175.978	144.672	180.386	152.004	149.735	145.198	148.950	167.923	145.485	180.919	179.815	143.947	133.936	157.922	155.614	
6	0.311	157.476	157.323	149.682	179.897	152.234	176.732	154.015	180.318	157.863	152.284	154.775	152.378	154.071	177.097	152.476	175.218	180.148	152.523	160.483	203.215	164.010
7	-0.317	153.510	153.440	152.533	179.951	156.511	176.351	156.419	180.353	161.478	155.400	157.483	156.460	157.827	179.132	156.135	175.000	180.260	153.860	152.418	188.628	164.158
8	0.390	149.394	149.416	143.541	180.114	150.822	177.142	149.121	180.367	161.971	149.869	154.565	148.653	154.070	181.465	152.763	175.270	180.446	150.715	135.680	188.731	160.706
9	0.394	164.242	164.828	150.317	179.716	150.002	177.113	151.897	180.355	158.381	150.132	154.216	151.194	153.906	175.954	151.951	175.835	180.194	150.017	170.393	188.774	163.971

(b) Model performance of MC-M experiment under RMSE on Bike dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0%	144.013	143.939	135.000	179.892	145.766	175.822	144.337	180.375	151.729	145.031	148.959	144.767	148.750	177.111	145.135	179.243	180.104	142.964	130.901	111.751	152.779
11%	164.242	164.828	140.776	179.716	150.002	177.113	151.897	180.355	158.381	150.132	154.216	151.194	153.906	175.954	151.951	175.835	180.194	150.017	170.393	125.146	160.312
22%	182.556	184.250	140.775	179.956	163.080	178.474	162.467	180.366	166.727	164.787	167.488	162.138	165.598	180.110	167.434	183.833	180.743	166.408	172.426	120.337	168.498
33%	191.637	193.101	143.928	180.048	173.435	178.943	174.119	180.331	175.796	175.973	174.629	173.515	174.072	181.638	178.186	180.593	181.214	180.678	189.662	117.097	174.930
44%	184.897	184.919	145.306	180.002	184.204	179.860	184.529	180.307	181.610	186.473	184.915	182.692	183.407	182.199	184.849	195.386	181.362	191.660	188.502	209.086	183.808
55%	186.125	185.723	146.084	180.006	184.696	180.002	185.613	180.308	183.222	187.805	188.132	183.234	184.400	182.868	185.901	196.748	181.031	193.716	188.982	197.294	184.094
66%	185.800	185.590	157.219	180.023	184.194	180.044	186.658	180.201	181.477	187.596	189.043	182.983	184.543	182.937	186.273	189.902	180.588	195.903	189.614	193.764	184.668
77%	185.773	185.577	169.450	180.020	184.017	180.050	188.346	180.144	179.526	187.626	191.601	182.591	184.533	183.522	186.466	200.974	180.798	197.340	191.479	189.001	185.442
88%	185.615	185.566	169.532	180.022	183.988	180.050	188.304	180.128	179.214	187.659	191.322	182.708	184.445	183.604	186.574	200.988	180.992	197.969	191.216	188.823	185.436
100%	182.151	183.123	182.720	180.029	180.234	180.045	181.909	180.175	181.311	180.534	190.541	180.153	181.940	181.619	186.534	180.036	180.638	188.483	181.918	188.774	182.643

(c) Model performance of MC-L experiment under RMSE on Bike dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0%	144.013	143.939	135.000	179.892	145.766	175.822	144.337	180.375	151.729	145.031	148.959	144.767	148.750	177.111	145.135	179.243	180.104	142.964	130.901	111.751	152.779
11%	148.964	149.001	140.776	179.902	150.693	175.880	150.353	180.385	155.370	150.630	152.540	150.503	153.774	177.833	151.771	193.594	179.962	149.755	160.489	113.245	158.271
22%	149.291	148.973	172.668	179.893	150.578	175.885	150.417	180.393	154.688	150.465	152.820	150.083	153.742	178.262	151.757	193.788	179.991	154.350	160.457	135.208	161.185
33%	149.330	148.897	191.500	179.890	151.530	175.921	151.848	180.444	155.529	151.573	154.444	150.739	153.807	178.056	153.191	196.496	179.879	154.233	159.176	147.834	163.216
44%	149.635	149.145	185.565	179.905	151.967	175.979	153.167	180.423	159.271	152.086	156.401	151.712	154.249	177.843	154.937	200.971	179.724	156.412	159.096	148.900	163.869
55%	149.108	148.707	187.372	179.873	152.590	176.133	153.811	180.447	158.606	152.692	152.295	154.411	177.282	154.836	180.289	179.289	156.206	159.105	157.922	164.693	
66%	163.929	163.682	185.912	179.867	154.977	177.024	157.874	180.406	161.401	155.577	164.894	165.244	165.733	177.214	159.075	188.298	179.186	162.207	167.468	203.215	169.696
77%	172.150	171.878	185.944	179.900	164.923	177.540	166.636	180.370	170.063	164.812	176.441	165.584	179.594	179.336	179.737	179.700	179.398	175.476	173.204	188.628	174.414
88%	168.620	168.633	185.947	180.132	170.632	178.798	169.028	180.250	176.424	168.054	168.823	168.517	170.979	181.511	177.866	173.676	180.634	186.744	174.927	188.731	176.129
100%	182.151	183.123	182.720	180.029	180.234	180.045	181.909	180.175	181.311	180.534	190.541	180.153	181.940	181.619	186.534	180.036	180.638	188.483	181.918	188.774	182.643

 (e) Model performance gap  $\Delta$  of RD experiment under RMSE on Bike dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
11%	0.042	0.042	0.058	0.000	0.025	0.003	0.032	-0.001	0.027	0.027	0.024	0.028	0.015	0.003	0.032	0.005	0.000	0.048	0.130	-0.077	0.022
22%	0.080	0.081	0.111	0.000	0.051	0.005	0.064	-0.001	0.055	0.056	0.049	0.058	0.039	0.002	0.065	0.009	0.000	0.048	0.211	24.834	0.954
33%	0.114	0.116	0.160	0.000	0.078	0.008	0.095	-0.001	0.082	0.084	0.075	0.087	0.064	0.008	0.099	0.014	0.000	0.058	0.271	0.332	0.078
44%	0.146	0.148	0.203	0.000	0.106	0.011	0.128	-0.001	0.091	0.114	0.102	0.116	0.090	0.004	0.130	0.024	0.000	0.063	0.330	1.937	0.155
55%	0.175	0.178	0.243	0.001	0.134	0.011	0.153	-0.001	0.123	0.143	0.133	0.141	0.117	0.012	0.172	0.028	0.001	0.			

Table 24. Model performance on Concrete dataset.

(a) Model performance of SC experiment under RMSE on Concrete dataset.

Column	PCC	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0	\	5.003	5.033	3.936	17.102	14.138	17.054	12.976	17.138	18.134	12.597	16.126	12.814	15.955	17.150	15.210	16.088	17.699	12.451	7.374	33.711	14.385
1	-0.106	5.294	5.157	4.092	17.103	14.189	17.058	13.120	17.132	17.508	12.696	16.352	12.902	15.966	17.113	15.233	16.511	17.744	12.366	7.517	30.438	14.274
2	0.135	7.600	7.520	6.101	17.108	14.313	17.061	13.291	17.140	19.277	12.816	16.419	13.101	16.012	17.169	15.272	16.765	17.715	12.574	8.773	123.950	19.499
3	-0.165	5.426	5.384	4.480	17.106	14.280	17.056	13.170	17.146	18.068	12.815	16.011	12.990	16.040	17.154	15.318	16.291	17.635	12.253	7.558	25.855	14.102
4	-0.167	5.512	5.562	4.853	17.094	14.268	17.054	13.173	17.128	17.516	12.743	16.242	12.804	16.013	17.135	15.268	16.766	17.666	12.658	7.793	19.141	13.820
5	-0.290	7.743	8.026	6.562	17.090	14.565	17.059	13.489	17.136	19.418	13.096	16.294	13.183	16.105	17.155	15.468	17.053	17.680	13.119	9.359	24.401	14.700
6	0.329	14.759	12.448	14.823	17.116	14.834	17.068	14.017	17.155	18.899	13.879	16.367	14.046	16.264	17.164	15.633	17.230	17.709	14.356	14.359	22.994	16.056
7	0.366	5.749	5.993	4.870	17.111	14.866	17.078	13.888	17.136	17.796	13.446	16.533	13.206	16.357	17.199	15.655	16.144	17.658	12.101	8.700	35.539	14.851
8	0.498	11.116	10.919	9.723	17.100	14.878	17.080	14.287	17.113	18.778	13.414	15.983	13.602	16.293	17.224	15.672	15.980	17.728	13.090	11.080	19.313	15.019

(b) Model performance of MC-M experiment under RMSE on Concrete dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0%	5.003	5.033	3.936	17.102	14.138	17.054	12.976	17.138	18.134	12.597	16.126	12.814	15.955	17.150	15.210	16.088	17.699	12.451	7.374	33.711	14.385
12.5%	11.116	10.919	4.092	17.100	14.878	17.080	14.287	17.113	18.778	13.114	15.983	13.602	16.293	17.224	15.672	15.980	17.728	13.090	11.080	30.439	15.293
25%	11.441	11.157	6.279	17.109	15.685	17.105	15.343	17.120	19.424	14.526	16.651	14.620	16.703	17.255	16.145	16.136	17.700	13.049	11.643	38.483	16.179
37.5%	20.014	16.971	6.686	17.121	16.263	17.118	16.188	17.142	19.998	15.736	17.030	15.610	16.993	17.264	16.571	17.382	17.717	16.044	17.057	72.247	19.358
50%	20.181	17.742	7.655	17.106	16.770	17.120	16.774	17.132	20.136	16.574	17.245	16.596	17.153	16.887	19.937	17.688	18.390	18.043	36.586	18.147	
62.5%	20.812	18.127	8.404	17.103	16.874	17.118	16.952	17.127	19.227	16.794	17.452	16.800	17.218	17.215	16.952	19.828	17.651	18.873	18.105	38.918	18.378
75%	20.358	18.010	16.465	17.112	17.019	17.117	17.109	17.124	17.382	17.002	17.306	17.000	17.317	17.213	17.081	19.855	17.576	18.449	18.100	93.046	21.382
87.5%	21.494	18.665	18.084	17.118	17.116	17.124	17.231	17.115	17.404	17.146	17.553	17.172	17.392	17.228	17.154	19.949	17.569	18.079	18.735	91.190	21.526
100%	20.876	18.556	20.782	17.117	17.124	17.125	17.131	17.112	17.277	17.124	17.414	17.117	17.399	17.204	17.151	17.325	17.538	17.476	19.085	46.866	19.240

(c) Model performance of MC-L experiment under RMSE on Concrete dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0%	5.003	5.033	3.936	17.102	14.138	17.054	12.976	17.138	18.134	12.597	16.126	12.814	15.955	17.150	15.210	16.088	17.699	12.451	7.374	33.711	14.385
12.5%	5.294	5.157	4.092	17.103	14.189	17.058	13.120	17.132	17.508	12.696	16.352	12.902	15.966	17.113	15.233	16.511	17.744	12.366	7.517	30.438	14.274
25%	7.316	7.314	10.455	17.112	14.376	17.064	13.416	17.129	17.794	12.949	16.543	13.192	16.023	17.126	15.301	16.505	17.763	12.325	8.895	21.149	14.487
37.5%	7.586	7.454	18.683	17.120	14.529	17.067	13.608	17.133	17.231	13.176	16.365	13.422	16.114	17.137	15.405	16.158	17.684	12.102	9.107	25.217	15.115
50%	7.949	7.977	19.251	17.108	14.641	17.066	13.804	17.124	17.041	13.356	13.650	13.531	16.174	17.097	15.469	16.585	17.659	12.288	9.517	25.540	15.276
62.5%	9.245	9.277	19.952	17.093	14.998	17.069	14.171	17.123	18.825	13.672	16.716	14.056	16.330	17.143	15.714	15.154	17.764	11.568	10.435	24.127	15.522
75%	16.159	14.542	19.809	17.098	15.589	17.083	15.069	17.168	18.549	14.751	16.397	14.903	16.641	17.179	16.141	15.981	17.726	14.605	15.575	26.126	16.855
87.5%	17.935	15.825	20.698	17.104	16.309	17.100	15.824	17.159	15.704	17.192	15.726	17.042	17.198	16.627	17.338	17.626	16.036	17.265	24.189	17.372	
100%	20.876	18.556	20.782	17.117	17.124	17.125	17.131	17.112	17.277	17.124	17.414	17.117	17.399	17.204	17.151	17.325	17.538	17.476	19.085	46.866	19.240

(d) Model performance of RD experiment under RMSE on Concrete dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0%	5.003	5.033	3.936	17.102	14.138	17.054	12.976	17.138	18.134	12.597	16.126	12.814	15.955	17.150	15.210	16.088	17.699	12.451	7.374	33.711	14.385
12.5%	7.900	6.931	14.527	17.013	14.527	17.065	13.571	17.139	18.406	13.113	16.268	13.226	16.130	17.162	15.441	16.663	17.690	12.815	9.437	9.514	13.886
25%	10.317	9.764	9.484	17.103	14.944	17.078	14.268	17.132	18.365	13.771	16.393	13.857	16.308	17.172	15.677	16.968	17.681	12.905	11.340	16.413	14.847
37.5%	12.435	11.604	11.722	17.105	15.294	17.083	14.701	17.128	18.433	13.924	16.586	14.356	16.477	17.178	15.918	17.405	17.670	13.979	12.788	13.210	15.250
50%	14.345	13.234	13.729	17.107	15.673	17.093	15.238	17.124	18.407	14.685	16.763	14.959	16.653	17.183	16.163	17.671	17.659	14.882	14.250	15.029	15.892
62.5%	16.110	14.712	15.560	17.109	16.053	17.101	15.759	17.120	18.266	15.336	16.959	15.552	16.831	17.187	16.409	17.834	17.645	15.251	15.620	16.683	16.455
75%	17.770	16.077	17.249	17.112	16.415	17.109	16.251	17.115	17.969	16.080	17.173	16.118	17.009	17.194	16.655	17.864	17.621	16.156	16.928	25.465	17.367
87.5%	19.353	17.352	18.814	17.114	16.771	17.117	16.718	17.113	17.662	16.520	17.540	16.644	17.190	17.202	16.900	17.687	17.577	17.191	18.222	19.219	17.495
100%	20.876	18.556	20.782	17.117	17.124	17.125	17.131	17.112	17.277	17.124	17.414	17.117	17.399	17.204	17.151	17.325	17.538	17.476	19.085	46.866	19.240

 (e) Model performance gap  $\Delta$  of RD experiment under RMSE on Concrete dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE


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## TabFSBench: Tabular Benchmark for Feature Shifts in Open Environments

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**Table 25.** Model performance on Laptop dataset.

(a) Model performance of SC experiment under RMSE on Laptop dataset.

Column	PCC	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0	\	271.935	278.929	255.116	719.433	554.012	714.388	475.469	726.168	764.760	478.342	656.838	507.616	677.269	705.867	671.807	665.836	709.988	494.823	325.431	368.688	551.136
1	0.067	281.552	288.477	263.324	719.364	555.705	714.412	477.871	725.889	837.923	480.571	657.637	515.006	677.744	707.521	673.616	665.121	710.146	487.019	335.495	370.561	557.248
2	0.087	285.064	278.829	255.109	719.194	554.739	714.373	477.734	726.086	746.466	481.354	654.238	509.706	676.493	706.643	671.884	674.010	710.019	499.864	325.009	355.379	551.110
3	-0.125	300.896	301.055	264.208	719.484	553.686	714.446	475.840	726.131	752.968	479.137	656.171	510.054	677.522	705.809	672.508	649.796	710.351	496.776	326.861	384.295	553.900
4	-0.126	300.087	307.616	276.128	719.311	553.885	714.400	473.727	726.015	769.002	479.056	660.375	507.391	677.704	707.161	675.299	659.820	709.192	491.430	340.899	347.930	554.821
5	0.137	289.799	297.917	267.554	719.391	555.841	714.459	476.297	726.094	755.516	482.298	656.155	504.844	678.034	702.927	673.120	650.069	711.146	496.102	333.625	451.650	557.292
6	0.142	294.557	299.855	279.177	719.349	554.075	714.401	478.592	726.329	756.299	477.172	658.370	507.794	677.222	705.463	673.711	668.897	711.450	493.818	339.167	343.535	553.962
7	0.143	322.949	324.296	291.568	719.430	555.165	714.439	474.303	726.198	787.555	479.137	660.976	509.914	677.411	704.954	674.029	648.234	710.528	495.998	327.259	477.235	564.079
8	0.178	272.432	282.140	256.613	719.431	555.405	714.490	476.895	726.286	759.677	480.947	677.074	507.921	672.273	706.155	672.058	649.796	709.795	494.822	326.604	356.739	550.278
9	0.189	271.937	278.622	257.275	719.403	558.474	714.452	477.755	726.499	808.723	482.064	651.960	516.953	677.845	705.811	670.735	673.934	710.568	495.193	328.577	435.839	558.131
10	0.212	300.526	304.860	285.336	719.197	558.594	714.651	485.024	726.232	804.611	482.982	650.883	535.150	678.453	704.453	676.727	673.313	711.034	492.846	379.397	401.760	564.299
11	0.251	273.798	278.748	269.791	719.614	556.829	714.520	475.991	725.611	794.972	480.674	662.760	511.578	678.711	708.518	672.047	665.019	710.170	502.434	322.522	365.862	554.395
12	0.290	279.238	310.642	264.253	719.621	561.423	714.471	488.167	727.266	816.289	488.264	661.099	511.195	677.997	707.370	673.511	675.150	709.899	500.685	344.459	380.568	560.577
13	0.291	271.428	278.741	256.662	719.623	557.942	714.671	480.068	726.015	780.365	477.043	669.050	510.299	677.266	705.731	673.669	659.950	708.378	473.214	333.448	413.873	554.374
14	-0.297	271.935	278.929	255.878	719.400	558.659	714.503	476.815	725.721	815.280	482.038	658.002	511.194	678.306	707.410	674.514	654.427	710.856	472.314	330.378	356.723	552.372
15	0.324	276.861	286.951	260.650	719.285	558.387	714.515	485.352	725.745	774.346	481.000	658.050	510.045	677.791	703.761	673.653	659.957	710.853	495.679	329.540	372.637	553.942
16	-0.404	276.722	282.887	257.749	719.256	563.763	714.477	488.456	726.668	731.100	485.548	661.605	511.329	679.647	704.363	677.622	669.184	707.974	489.480	328.053	395.729	553.581
17	0.429	299.028	309.114	315.451	719.445	563.025	714.747	490.969	727.341	808.399	489.992	657.007	516.428	682.567	704.803	679.589	712.082	730.503	566.536	371.029	376.503	566.546
18	0.474	298.308	308.380	281.084	719.188	564.519	714.806	493.363	721.311	782.013	493.595	673.669	519.268	681.233	707.968	614.189	679.708	510.288	509.480	361.037	354.327	562.916
19	0.504	319.404	324.919	274.305	719.111	564.530	714.778	487.918	726.742	782.433	488.281	669.113	519.726	683.714	707.422	682.337	686.738	710.410	483.400	348.089	385.282	563.033
20	0.549	278.134	284.193	260.409	719.500	570.466	714.886	495.240	725.407	718.447	496.009	656.635	534.507	681.134	709.948	676.656	674.365	712.842	500.177	344.916	392.021	567.794
21	0.552	272.797	281.972	264.028	719.650	568.816	714.909	498.668	725.552	758.988	493.812	668.550	539.395	683.476	705.639	677.494	705.684	708.052	505.721	345.780	428.978	563.398
22	0.740	319.404	322.546	343.236	719.486	575.909	714.787	525.524	726.231	804.326	509.039	662.112	532.376	682.721	712.587	684.983	691.624	709.901	507.367	410.556	396.972	577.584

(b) Model performance of MC-M experiment under RMSE on Laptop dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FIT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE	
0%	271.935	278.929	255.116	719.433	554.012	714.388	475.469	726.168	764.760	478.342	656.838	507.616	677.269	705.867	671.807	665.836	709.988	494.823	325.431	368.688	551.136	
4.55%	519.404	322.546	263.324	719.364	575.909	714.787	525.524	726.231	804.326	509.039	662.112	532.376	682.721	725.387	684.983	691.624	709.901	487.019	410.556	370.561	571.251	
9.09%	319.676	329.158	263.336	719.716	591.657	715.307	550.479	725.581	754.828	526.691	747.530	571.388	688.921	712.888	690.630	733.420	708.078	491.465	419.023	341.896	576.443	
13.64%	333.898	344.029	274.307	719.470	616.716	715.732	571.491	724.722	734.300	560.176	675.712	584.280	692.298	729.698	696.026	709.660	711.233	492.045	451.527	392.705	585.527	
18.18%	397.074	419.643	289.909	719.233	628.667	716.119	586.742	725.424	718.378	576.966	689.054	602.111	699.579	716.842	706.592	697.107	712.574	486.280	503.114	409.548	600.048	
22.73%	431.738	446.690	305.397	719.858	640.332	716.516	607.902	726.456	760.851	597.525	707.217	614.776	703.655	714.629	721.206	721.777	712.478	489.434	560.574	406.532	515.082	
27.27%	491.612	511.922	332.357	719.041	649.528	716.902	624.291	727.797	730.560	613.555	710.797	723.201	730.201	733.594	748.693	717.231	723.594	748.693	717.231	482.734	649.663	613.622
31.82%	504.537	523.888	371.339	718.811	663.654	716.999	646.573	728.671	720.367	618.558	711.584	726.681	727.681	730.220	771.224	716.105	484.729	637.564	604.302	646.764	646.764	
36.36%	527.398	555.978	372.700	718.677	668.681	717.114	658.016	728.095	722.770	640.714	714.558	627.799	714.342	713.489	732.074	714.732	716.213	484.226	650.860	589.668	652.087	
40.91%	527.398	555.978	373.571	718.694	678.330	717.217	668.489	727.812	727.356	652.680	718.995	639.449	715.491	716.498	735.669	784.393	717.478	489.635	659.233	595.908	656.509	
45.45%	533.312	567.339	413.065	718.792	685.747	717.443	673.459	727.548	711.255	667.649	722.756	648.654	715.503	715.103	737.402	786.732	713.337	498.400	652.545	593.791	660.002	
50.00%	543.082	636.054	410.997	718.692	693.128	715.730	686.698	728.909	700.121	680.888	724.278	664.513	706.644	716.044	739.008	780.885	713.389	508.136	678.667	602.131	668.579	
54.55%	457.993	499.148	578.424	719.036	580.293	715.197	508.824	726.062	694.308	513.161	649.983	576.241	683.628	715.689	689.049	629.239	714.693	684.432	451.584	431.868	610.943	
59.09%	462.278	504.061	619.884	719.202	582.524	715.394	511.506	725.519	675.095	515.347	674.497	589.292	683.547	708.799	715.867	650.560	705.399	517.153	374.190	431.372	548.283	
63.64%	462.278	504.061	622.461	719.254	589.019	715.478	514.267	724.645	712.780	519.												

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
0%	271.935	278.929	255.116	719.433	554.012	714.388	475.469	726.168	764.760	478.342	656.838	507.616	677.269	705.867	671.807	665.836	709.988	494.823	325.431	368.688	551.136
4.55%	281.552	288.477	263.324	719.364	555.705	714.412	477.871	725.889	837.923	480.571	657.637	515.006	677.744	707.521	673.616	665.121	710.146	487.019	335.495	370.561	557.248
9.09%	305.314	287.935	361.772	719.123	556.647	714.397	480.264	725.810	746.672	483.981	654.201	515.292	676.962	708.103	673.656	673.668	710.126	521.949	334.427	385.716	561.814
13.64%	364.303	310.210	373.953	719.173	556.180	714.447	480.706	725.755	717.559	484.264	652.370	517.377	677.208	708.179	674.296	660.817	710.171	532.843	333.534	366.501	563.992
18.18%	356.501	331.404	403.788	719.012	556.366	714.453	480.635	725.657	725.013	484.997	656.016	519.823	677.683	710.735	677.786	653.097	709.110	527.027	335.716	384.221	568.452
22.73%	395.752	341.703	452.400	718.954	558.298	714.514	480.727	725.631	721.388	487.982	655.956	517.220	678.456	710.259	679.408	639.222	710.474	544.044	359.790	402.804	574.749
27.27%	408.885	368.007	529.694	718.951	558.858	714.554	483.095	725.743	707.399	487.834	654.172	519.867	678.533	708.979	681.158	650.862	712.372	571.153	374.190	431.372	584.283
31.82%	416.139	396.976	537.211	718.949	559.601	714.591	482.790	725.705	713.362	489.180	655.576	521.679	678.680	708.760	683.173	620.822	712.520	586.359	377.450	425.132	586.233
36.36%	417.843	401.032	544.265	718.953	561.577	714.696	484.521	725.855	703.689	490.547	652.483	528.024	679.792	711.316	683.603	603.579	712.973	592.705	378.172	425.219	586.542
40.91%	425.947	402.420	546.516	718.840	566.101	714.755	486.575	726.124	702.610	494.334	650.248	536.557	680.404	713.000	682.418	598.341	714.058	587.266	378.580	431.492	587.830
45.45%	447.380	450.738	550.955	718.605	569.808	714.949	495.451	725.764	704.040	499.149	647.056	565.989	681.516	711.427	686.824	615.812	713.784	648.605	424.811	419.450	599.606
50.00%	440.090	444.300	563.921	718.838	573.273	715.088	496.056	724.657	701.605	502.130	648.643	571.543	682.946	714.431	687.505	615.845	714.134	665.873	419.491	437.362	601.887
54.55%	457.993	499.148	578.424	719.036	580.293	715.197	508.824	726.062	694.308	513.161	649.983	576.241	683.628	715.689	689.049	629.239	714.693	684.432	451.584	431.868	610.943
59.09%	462.278	504.061	619.884	719.202	582.524	715.394	511.506	725.519	675.095	515.347	674.497	589.292	683.547	716.560	690.847	632.714	714.819	701.307	445.467	427.511	615.369
63.64%	462.278	504.061	622.461	719.254	589.010	715.478	514.267	724.645	671.881	519.417	669.896	601.444	684.461	716.292	692.910	566.915	714.334	709.741	443.954	442.514	614.261
68.18%	462.920	524.860	623.435	719.107	593.947	715.586	521.160	723.721	675.823	524.600	669.974	608.763	687.021	712.529	694.750	559.421	716.710	711.854	448.716	447.013	617.095
72.73%	468.726	535.044	651.540	718.993	605.571	715.665	538.270	724.321	690.654	553.801	665.102	607.093	689.546	709.979	701.195	567.206	716.327	714.518	454.383	555.886	628.291
77.27%	508.036	606.168	666.173	719.017	616.965	716.034	558.745	726.161	696.295	553.803	671.700	614.081	695.019	707.606	708.310	591.356	723.801	728.421	515.724	569.823	644.662
81.82%	566.058	625.084	666.652	718.732	629.135	716.439	580.352	729.083	694.190	577.323	688.388	631.974	699.288	708.288	717.819	637.420	720.460	732.975	564.484	642.917	662.353
86.36%	597.169	717.468	719.329	718.267	643.964	716.807	600.324	731.241	700.238	599.542	703.551	646.433	706.211	708.927	728.940	641.012	721.224	754.103	617.210	752.556	686.226
90.91%	620.045	749.928	723.150	718.251	666.422	717.277	623.659	729.750	703.233	629.686	713.541	672.881	710.390	708.863	733.672	659.551	726.512	761.955	625.244	757.463	697.574
95.45%	620.872	764.271	723.157	718.278	686.094	717.702	654.355	728.327	702.228	663.033	733.921	691.897	716.898	707.550	739.619	658.381	724.987	764.109	679.871	760.146	707.785
100%	733.084	865.660	729.423	718.364	717.024	718.069	718.618	729.607	720.568	718.535	737.503	716.832	722.873	720.970	753.144	723.708	745.945	784.034	849.592	742.227	

 (e) Model performance gap  $\Delta$  of RD experiment under RMSE on Laptop dataset.

Degree	LGB	XGB	CATB	DAN	MLP	NODE	RES	SWI	NET	GOS	INT	DCN	FTT	GRO	SAT	SNN	TTF	TABR	NCA	LMA	AVE
4.55%	0.063	0.061	0.073	0.000	0.011	0.000	0.019	0.000	0.003	0.009	0.004	0.017	0.003	0.001	0.006	0.004	0.001	0.000	0.053	-0.342	-0.001
9.09%	0.128	0.129	0.139	0.000	0.024	0.001	0.049	0.000	0.003	0.025	0.011	0.043	0.007	0.004	0.013	0.016	0.001	-0.007	0.137	-0.300	0.013
13.64%	0.195	0.204	0.221	0.000	0.024	0.001	0.039	0.000	-0.026	0.016	0.005	0.045	0.006	0.002	0.013	-0.002	0.002	0.010	0.111	-0.194	0.018
18.18%	0.264	0.283	0.314	0.000	0.057	0.001	0.112	0.001	-0.013	0.061	0.018	0.087	0.015	0.006	0.029	0.021	0.004	-0.011	0.305	-0.039	0.047
22.73%	0.338	0.350	0.399	-0.001	0.056	0.001	0.097	0.001	-0.017	0.071	0.022	0.092	0.016	0.004	0.031	0.003	0.003	-0.013	0.287	-0.084	0.051
27.27%	0.422	0.468	0.425	0.000	0.076	0.002	0.146	0.001	-0.030	0.086	0.029	0.123	0.021	0.005	0.037	0.050	0.003	0.026	0.328	-0.006	0.069
31.82%	0.483	0.533	0.517	0.000	0.078	0.002	0.142	0.000	-0.028	0.115	0.024	0.150	0.020	0.005	0.035	0.036	0.004	-0.001	0.338	0.002	0.075
36.36%	0.544	0.641	0.580	-0.001	0.116	0.002	0.178	0.000	-0.049	0.133	0.035	0.180	0.028	0.009	0.050	0.022	0.007	0.012	0.415	0.230	0.097
40.91%	0.653	0.725	0.753	-0.001	0.124	0.002	0.223	0.002	-0.054	0.164	0.047	0.181	0.029	0.013	0.056	0.061	0.003	0.027	0.540	0.196	0.116
45.45%	0.722	0.830	0.879	-0.001	0.106	0.002	0.175	0.001	-0.076	0.198	0.037	0.167	0.026	0.007	0.050	0.012	0.005	0.079	0.475	0.298	0.119
50.00%	0.835	0.985	0.951	-0.001	0.134	0.003	0.237	0.003	-0.074	0.208	0.056	0.225	0.034	0.010	0.064	0.071	0.004	0.114	0.642	0.337	0.149
54.55%	0.930	1.087	1.014	-0.001	0.139	0.003	0.231	0.001	-0.064	0.247	0.046	0.238	0.032	0.010	0.062	0.021	0.005	0.132	0.587	0.398	0.156
59.09%	0.922	1.078	1.119	-0.001	0.161	0.003	0.280	0.002	-0.068	0.262	0.049	0.272	0.038	0.011	0.070	0.067	0.006	0.119	0.762	0.545	0.176
63.64%	1.032	1.265	1.177	-0.001	0.187	0.004	0.312	0.002	-0.079	0.264	0.070	0.283	0.045	0.014	0.083	0.030	0.010	0.161	0.815	0.543	0.192
68.18%	1.128	1.384	1.235	-0.001	0.187	0.004	0.324	0.002	-0.075	0.255	0.068	0.307	0.044	0.017	0.084	0.046	0.009	0.262	0.878	0.666	0.211
72.73%	1.178	1.389	1.416	-0.001	0.207	0.004	0.363	0.001	-0.075	0.338	0.074	0.346	0.049	0.016	0.092	0.047	0.010	0.292	1.029	0.674	0.232
77.27%	1.335	1.632	1.384	-0.001	0.223	0.004	0.394	0.003	-0.066	0.390	0.079	0.345	0.054	0.018	0.099	0.099	0.006	0.276	1.071	0.702	0.252
81.82%	1.362	1.675	1.506	-0.001	0.239	0.004	0.415	0.001	-0.068	0.392	0.098	0.356	0.056	0.018	0.105	0.079	0.009	0.338	1.115	0.706	0.264
86.36%	1.453	1.779	1.586	-0.001	0.243	0.004	0.427	0.001	-0.064	0.422	0.085										