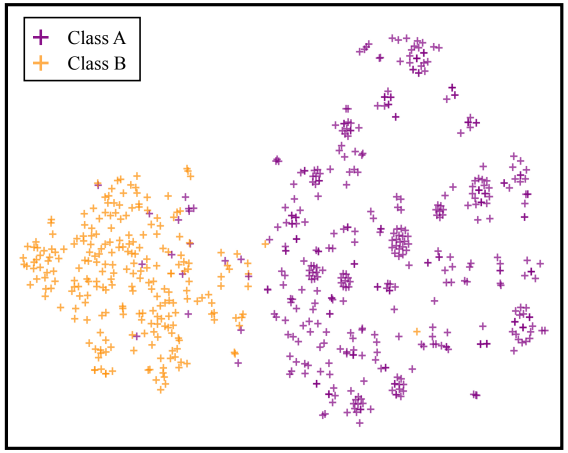
Supplementary Material

This material provides additional tables and figures that support the rebuttal of our paper. Below is a brief description of each item:

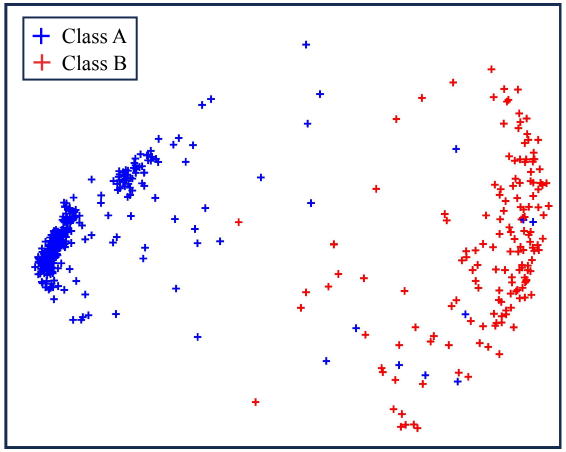
1. **Table1** extends our experiments by incorporating an established Tabular Benchmark.
2. **Figure1** visualizes the raw and transformed data distributions using t-SNE.
3. **Figure2** explores the impact of class imbalance on Meta-representations.

Datasets	Dummy	KNN	SVM	XGB	CatB	RF	MLP	ResNet	Node	SwitchTab	TabNet	Tangos	DANets	FTT	AutoInt	DCNv2	SNN	TabTrans	PTaRL	GrowNet	TabR	Excel	ModernNCA	TuneTables	TabPFN	LoCalPFN	TabPTM
FOREX_audchf-day-High	.5068	.5940	.7520	.6627	.6398	.6554	.6901	.7464	.6523	.5232	.5135	.5010	.5370	.5179	.6567	.7480	.7262	.7424	.6191	.6754	.7520	.5297	.7544	**.7570**	.7559	.7540	.6095
taiwanese_bankruptcy_prediction	.9677	.9714	.9677	.9702	**.9718**	.9717	.9685	.9667	.9678	.9522	.9681	.9689	.9686	.9674	.9674	.9662	.9664	.9686	.9670	.9660	.9678	.9669	.9674	.9680	.9692	.9696	.9675
rl	.5000	.6549	.6308	.7993	.7858	.7295	.6562	.6592	.6475	.6227	.6281	.6596	.6665	.7196	.6822	.6488	.6490	.6282	.6429	.6258	**.8779**	.7168	.8375	.6160	.6738	.6085	.7857
pc3	.8978	.8914	.8871	.8856	.8880	.8941	.8820	.8867	.8978	.8835	.8884	.8920	.8907	.8978	.8952	.8867	.8929	.8976	.8909	.8963	.8846	.8969	.8892	**.8980**	.8950	.8965	.8978
qsar	.6635	.8057	.8464	.8673	.8613	.8708	.8654	.8894	.6768	.8657	.7912	.8970	.8547	.8537	.8641	.8720	.8720	.8761	.8720	.8569	.8569	.7953	.8635	.9000	.9087	**.9115**	.8768
eye_movements_bin	.5000	.5802	.5558	.6325	.6152	.6057	.5708	.5754	.5611	.5582	.5645	.5760	.5745	.5945	.5831	.5741	.5764	.5673	.5745	.5579	.6595	.6028	**.9088**	.5490	.5784	.5711	.6735
BNG(breast-w)	.6560	.9837	.9781	.9876	**.9878**	.9852	.9846	.9846	.9856	.9818	.9834	.9838	.9840	.9860	.9848	.9841	.9848	.9594	.9840	.9839	.9868	.9856	.9859	.9801	.9827	.9842	.9825
FOREX_cadjpy-hour-High	.5179	.5461	.7099	.6121	.6259	.5718	.7061	.7096	.5338	.5334	.6243	.5885	.6871	.6880	.6971	.7045	.6990	.7034	.7046	.6586	.6432	.6644	**.7118**	.6370	.6290	.6196	.6886
dis	.9841	.9841	.9841	**.9876**	.9866	.9841	.9852	.9841	.9841	.9832	.9837	.9849	.9835	**.9876**	.9848	.9839	.9850	.9841	.9841	.9840	**.9876**	.9858	.9868	.9840	.9841	.9841	.9868
sylvine	.4995	.8820	.9161	.9454	.9524	.9316	.9309	.9329	.9154	.9112	.9231	.9287	.9329	.9471	.9270	.9357	.8994	.9350	.9315	.9161	**.9638**	.9330	.9588	.9220	.9320	.9342	.9600
BNG(tic-tac-toe)	.6529	.7831	.7280	.8121	.8133	.8014	.8153	.8118	.8117	.7703	.7974	.7992	.8127	.8131	.8100	.8153	.8150	.8139	.8112	.8112	.8114	.8080	.8108	.8054	.7599	.7841	**.8169**
online_shoppers	.8451	.8459	.8779	.9051	**.9063**	.8633	.8803	.8871	.8875	.8905	.8908	.8958	.8864	.9019	.8976	.9032	.8969	.8868	.8989	.8829	.8965	.8998	.9053	.8910	.8969	.8543	.9025
Cardiovascular-Disease-dataset	.5003	.6737	.6878	**.7343**	.7340	.7323	.7335	.7307	.7320	.7284	.7147	.7298	.7315	.7322	.7326	.7321	.7328	.6799	.7321	.6677	.7308	.7317	.7320	.7220	.7254	.7245	.7319
credit	.5001	.6787	.7098	**.7817**	.7796	.7795	.7580	.7540	.6225	.7319	.7469	.7546	.7554	.7588	.7561	.7556	.7528	.7467	.7550	.7443	.7755	.7578	.7298	.7440	.7693	.7567	.7625
FOREX_audsgd-hour-High	.5148	.5254	.7041	.6023	.6158	.5653	.6985	.7092	.5225	.5146	.6413	.5270	.6562	.6184	.6884	.6909	.6899	.6699	.6512	.6336	.7080	.6146	**.7109**	.5150	.5813	.5660	.7019
waveform-5000	.3380	.8510	.8628	.8541	.8596	.8510	.8557	.8623	.8625	**.8637**	.8267	.8613	.8602	.8611	.8545	.8588	.8532	.8554	.8119	.4077	.8604	.8609	.8624	.8570	.8591	.8524	.8510
jungle_chess_2pcs_raw_endgame_complete	.5146	.8814	.6801	.8610	.8647	.8262	.9527	.8696	.8551	.7515	.8784	.8722	.9211	.9761	.9552	.9674	.9057	.7144	.9517	.6480	.9898	.9734	**.9950**	.7990	.8210	.8563	.9166
BNG(cmc)	.4262	.5574	.5239	.5860	**.5893**	.5730	.5790	.5791	.5881	.5624	.5772	.5819	.5795	.5850	.5829	.5838	.5780	.5273	.5475	.5281	.5823	.5801	.5682	.5399	.5558	.5597	.5462
page-blocks	.8977	.9616	.9565	**.9745**	.9667	.9703	.9669	.9668	.9295	.8715	.9527	.9679	.9694	.9671	.9711	.9663	.9661	.9640	.9661	.9638	.9677	.9632	.9668	.9550	.9727	.9713	.9680
segment	.1429	.8896	.8297	.9149	.9202	.9196	.9199	.9186	.7957	.8420	.8792	.9130	.9185	.9137	.9039	.9188	.8906	.9139	.9052	.2404	.9190	.9059	**.9277**	.8920	.9234	.9163	.9221
website_phishing	.5166	.8672	.8672	.8986	.9043	.8942	.8731	.8873	.8962	.8578	.8391	.8728	.8895	.9014	.8677	**.9087**	.8681	.8972	.8145	.8745	.8950	.8723	.8753	.8728	.8994	.8893	.8937
baseball	.9067	.9254	**.9552**	.9398	.9388	.9460	.9254	.9313	.9164	.9239	.9231	.9328	.9289	.9376	.9276	.9358	.9386	.9017	.9306	.9415	.9473	.9333	.9428	.9370	.9333	.9353	.9291
pendigits	.1041	.9909	.9281	.9414	.9913	.9879	**.9950**	.9948	.9807	.9854	.9874	.9947	.9929	.9935	.9935	.9942	.9916	.9924	.9927	.2276	.9943	.9937	.9940	.9941	.9888	.9904	.9932
Gender_Gap_in_Spanish_WP	.5884	.5726	.5888	.5987	.5926	.5959	**.6009**	.5961	.5917	.5868	.5874	.5956	.5900	.5986	.5951	.5895	.5957	.5809	.5966	.5884	.5914	.5941	.5925	.5729	.5900	.5902	.5716
wine-quality-white	.4490	.6337	.5306	.6242	.6315	.6235	.5779	.5790	.5430	.5235	.4956	.5752	.5498	.5517	.6093	.5586	.5884	.5308	.5531	.3165	.6265	.5327	.6327	.6287	.5795	.5980	**.6408**
satimage	.2379	.9075	.8367	.9142	.9135	.9086	.8993	.9044	.8612	.8654	.8790	.8923	.8979	.8959	.8970	.9045	.9041	.8631	.8953	.8981	.9131	.8947	.9104	.9127	.9077	**.9168**	.9098
mfeat-fourier	.1000	.8650	.8350	.8572	**.8718**	.8602	.8445	.8597	.8330	.8340	.7742	.8483	.8407	.8523	.8390	.8467	.8388	.8188	.8457	.8425	.8653	.8555	.8648	.8573	.8363	.8570	.8625
VulNoneVul$_{\times 10^{-1}}$	1.021	.9969	1.059	1.010	1.044	1.023	1.011	1.022	1.011	1.025	1.012	1.023	1.026	1.023	1.020	1.041	1.046	1.025	**.9904**	1.015	1.024	1.014	1.036				1.015
CookbookReviews$_{\times 10}$	.1536	.1491	.1532	**.1483**	.1486	.1488	.1504	.1520	.1497	.1567	.1500	.1498	.1594	.1520	.1544	.1511	.1621	.1546	.1496	.1592	.1549	.1562	.1487				.1498
kin8nm$_{\times 10^{-1}}$	2.631	1.205	2.054	1.322	.9017	1.492	.6877	.6699	.9350	2.620	.8301	.7158	4.072	.6736	.6986	.6677	.7429	2.619	.6781	1.111	**.6639**	.6924	.6968				1.784
Ailerons$_{\times 10^{-3}}$	.3993	.2047	.1696	.1527	**.1465**	.1559	.1563	.1572	.1519	.3832	.1641	.1564	.3841	.1554	.1553	.2719	.1627	.3981	.1554	.2377	.1522	.1528	.1576				.1512
Superconductivty$_{\times 10}$	3.427	1.078	1.838	.9958	**.9911**	1.057	1.044	1.050	1.269	3.361	1.276	1.088	3.713	1.065	1.080	1.031	1.127	3.417	1.079	1.478	1.032	1.061	1.038				1.046
IEEE80211aa-GATS$_{\times 10^{-1}}$	3.131	.8366	.5894	.4063	.3483	.4478	.2844	.2651	.5025	3.200	.5711	.2896	3.396	.2959	.3136	.2605	.3459	3.254	.3248	.7772	**.1991**	.3168	.2629				.6934
house_16H_reg$_{\times 10^{5}}$	.5300	.3623	.4819	.3136	**.2994**	.3278	.3175	.3137	.3483	.5397	.3533	.3187	.5458	.3067	.3123	.3133	.3280	.5404	.3158	.5156	.3054	.3223	.3102				.3276
mv$_{\times 10^{-2}}$	1045.	150.2	542.3	11.94	8.548	8.319	3.949	13.10	**.9159**	1037.	20.76	23.81	1078.	3.095	4.977	1.624	7.286	1061.	9.692	71.90	2.776	3.633	2.738				3.441
compass_reg	.5000	.4146	.4606	.3924	.3903	.4249	.4795	.4519	.4417	.5252	.4469	.4332	1.065	.4468	.4563	.4714	.4491	.5002	.4326	.5126	.3554	.4108	**.3118**				.4357
law-school-admission-bianry$_{\times 10^{-4}}$	4643.	2308.	2816.	328.3	**.1620**	.2950	116.1	61.31	6.391	4668.	115.7	41.43	7089.	2.446	28.70	6.369	6.497	5142.	20.51	2101.	1.929	8.179	183.0				8.706
KDD	1.000	.8591	.8153	**.7066**	.7070	.7168	.9204	.8083	.7371	1.036	.7339	.8121	1.023	.7158	.7812	.8344	.8100	1.044	.7902	1.003	.8765	.7193	.7224				.7330
Large-scale_Wave_Energy_Farm_Sydney_49$_{\times 10^{4}}$	7.019	1.176	1.465	.4923	.4498	.6289	.5998	.5980	.5431	7.202	1.059	.5898	9.119	.4370	.5620	.7411	.7012	6.984	.5841	1.295	**.3894**	.4144	4.740				.4183
healthcare_insurance_expenses$_{\times 10^{4}}$	1.250	.5525	.6534	.4665	.4736	**.4522**	.5049	.4790	.4677	1.283	.5636	.4869	1.673	.4616	.4721	.4874	.5219	1.248	.4763	1.116	.4624	.5255	.4699				.5296
communities_and_crime	.2213	.1348	.1380	.1325	.1336	.1337	.1338	.1425	.1363	.2294	.1530	.1355	.3889	.1369	.1386	.1361	.1366	.2218	.1414	.1449	.1437	.1327	.1390				**.1322**
bank8FM$_{\times 10^{-1}}$	1.551	.4932	.4088	.3009	.2878	.3195	.2973	.2889		1.549	.3130	.2942	1.588	.2863	.2909	.2876	.2911	1.544	**.2848**	.3879	.2925	.2856	.2921				.3240
fried$_{\times 10}$	.4958	.1854	.2643	.1079	.1010	.1395	.1022	.1029	.1007	.4945	.1032	.1041	.4949	.1009	.1018	.1010	.1048	.4935	.1026	.1144	.1017	**.1006**	.1011				.1326
archive$_{\times 10^{3}}$	.4612	.3642	.4113	.3443	**.3336**	.3466	.3629	.3936	.3448	.4598	.4307	.3739	.4612	.3907	.3730	.3986	.3598	.4653	.3611	.4067	.3875	.3812	.3944				.3733
avg. rank	23.227	16.455	18.591	8.045	7.000	10.727	10.977	11.159	13.814	21.932	18.273	12.864	17.568	8.591	11.341	10.727	13.091	18.318	12.364	19.023	7.545	10.909	8.205	15.889	12.370	13.370	9.705

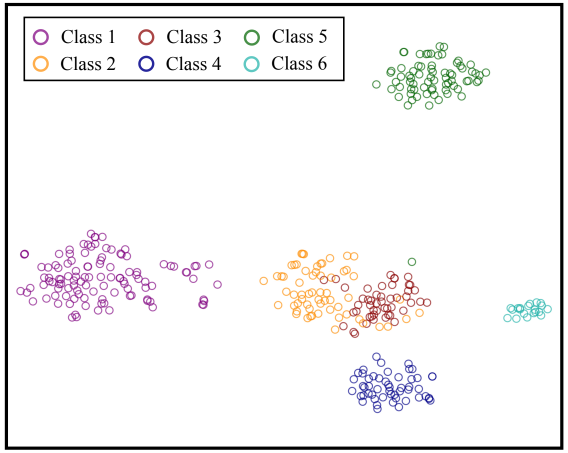
Table 1: We extend our experiments by incorporating the recently introduced Tabular Benchmark. Specifically, we utilize the official "Tiny Benchmark subset for Rank Consistent Evaluation" from TabBench, which comprises 44 datasets (27 for classification and 17 for regression). These datasets demonstrate consistency in method ranking across a larger pool of 300 datasets. While other methods require 100 trials of hyperparameter tuning, TabPTM achieves competitive results through lightweight fine-tuning alone. (Note that TabPFN, TuneTables, and LoCalPFN primarily focus on classification tasks, and when ranking regression datasets, they report the median score. **TabPTM outperforms the KNN-based improved version of PFN in ranking.**)



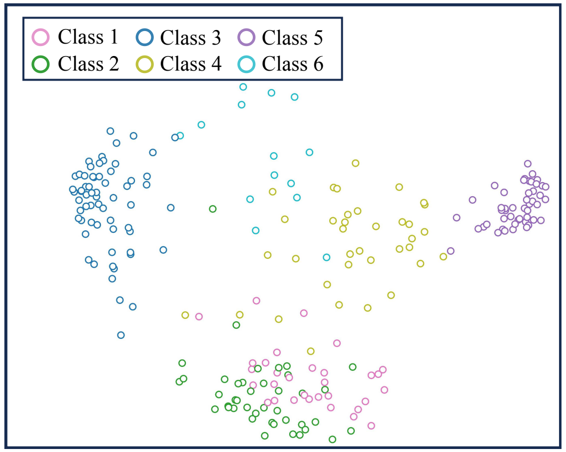
(a) Dataset breast-cancer-wisc (raw data t-SNE)



(b) Dataset breast-cancer-wisc (XTab)



(c) Dataset dermatology (raw data t-SNE)



(d) Dataset dermatology (XTab)

Figure 1: In subfigures (a) and (c), we visualized the distribution of the raw data using t-SNE. To extend visualizations to other methods, we specifically examined XTab, another pre-trained method for tabular data. We applied average pooling to the transformer's output to obtain a condensed 32-dimensional representation for each sample. These processed representations, which are input into the classification heads, are shown in subfigures (b) and (d). However, the representations from XTab did not show a significant improvement over the raw data. This suggests that much of the representational learning in XTab may rely heavily on the model's top layers (the classification module), rather than developing robust intermediate representations. In contrast, as shown in Figure 3c of the main paper, the meta-representations generated by TabPTM successfully capture relational patterns within the dataset.

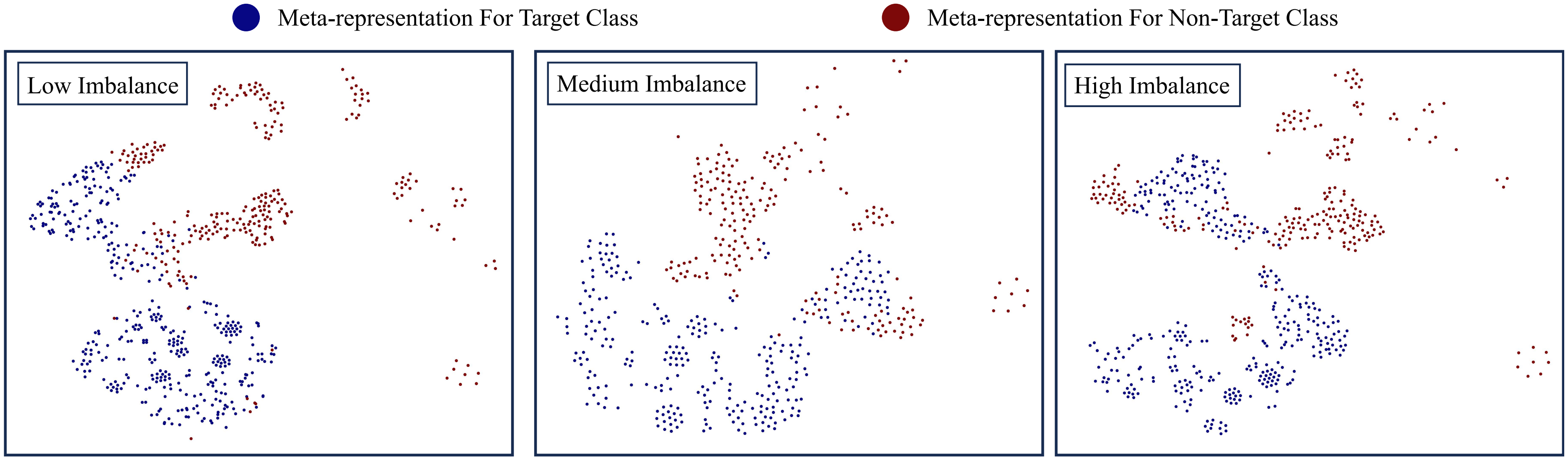


Figure 2: To explore the effect of class imbalance on Meta-representation, we utilized the"breast-cancer-wis" binary classification dataset. We manipulated the dataset to reflect three levels of class imbalance: Low (majority:minority = 0.6), Medium (majority:minority = 0.4), and High (majority:minority = 0.2). The Meta-representations for both the Target and Non-Target classes were visualized under these varying conditions. Despite the imbalance, Meta-representations maintained a good level of discriminative ability. As the imbalance intensified, the discriminative effectiveness for challenging-to-classify samples decreased. This was visually apparent as the red (Target) and blue (Non-Target) points became more intermixed, indicating that the neighboring space, dominated by the majority class, diminishes distinctiveness between classes. The model's exposure to diverse distributions from large-scale datasets helps it capture essential patterns even under imbalanced conditions. Thus, while class imbalance poses challenges, TabPTM's performance remains comparatively stable.