Retrieve, Merge, Predict: Augmenting Tables with Data Lakes

Anonymous authors
Paper under double-blind review

Abstract

Machine-learning from a disparate set of tables, a data lake, requires assembling features by merging and aggregating tables. Data discovery can extend autoML to data tables by automating these steps. We present an in-depth analysis of such automated table augmentation for machine learning tasks, analyzing different methods for the three main steps: retrieving joinable tables, merging information, and predicting with the resultant table. We use two data lakes: Open Data US, a well-referenced real data lake, and a novel semi-synthetic dataset, YADL (Yet Another Data Lake), which we developed as a tool for benchmarking this data discovery task. Systematic exploration on both lakes outlines *1)* the importance of accurately retrieving join candidates, *2)* the efficiency of simple merging methods, and *3)* the resilience of tree-based learners to noisy conditions. Our experimental environment is easily reproducible and based on open data, to foster more research on feature engineering, autoML, and learning in data lakes.

1 Introduction: learning on data lakes needs feature engineering

New tools keep facilitating data science with machine learning, partly automating it, as with autoML (He et al., 2021; Karmaker et al., 2021; Erickson et al., 2020; Feurer et al., 2022; Hutter et al., 2019). However, they typically take a single table as an input, while data scientists often start from a data lake: a loose corpora of tables (Nargesian et al., 2019; Spotify, 2020; Phan, 2023). Learning then requires assembling multiple tables, which needs either in-depth knowledge of the data or data discovery (Fan et al., 2023a; Hulsebos et al., 2024). Data assembly is typically studied in scenarios where the schema is known (Robinson et al., 2024; Wang et al., 2024): how columns of various tables are related and which can be merged, as in a relational database. However, data lakes often come without this information. In this work, we consider a data-lake situation where the meaningful merges are unknown and where only a fraction of the tables in the data lake are relevant for the given machine learning (ML) task. Consider the following example scenario:

Alice, a data scientist, wants to predict the rating given to a movie: she has access to a table with information about movies (e.g., year of release, director, language, budget, ...). She wants to complete the table, finding more information on the subject beneficial to her task; for example, joining the table about movies with a table on the cast of those movies might help, as some actors tend to appear in movies with better ratings. Alice has access to some large repository of data, or to some search engine that she can query to find additional tables (Castelo et al., 2021; Google, 2023). However, she does not know the schema describing the relation between tables in the data repository. Her objective is to find the tables that are most relevant to her task, to merge them with the original table and finally to use the improved table to build a model that predicts the movie rating. She has limited resources (compute, RAM...), and thus cannot evaluate all potential tables.

Research on this literature is spread across the database and machine learning communities. The corresponding pipeline (Figure 1) uses retrieve, merge, and predict steps that involve four tasks: *1)* **retrieving** tables that are joinable with the original table (Fernandez et al., 2019; Zhu et al., 2019; 2016; Castelo et al., 2021; Fernandez et al., 2018; Dong et al., 2023), *2)* **selecting** which joins should be executed to improve the performance of the subsequent ML model (Esmailoghli et al., 2021; Liu et al., 2022; Galhotra et al., 2023; Deng et al., 2017a), *3)* **aggregating** results in cases of one-to-many or many-to-many joins (Chepurko

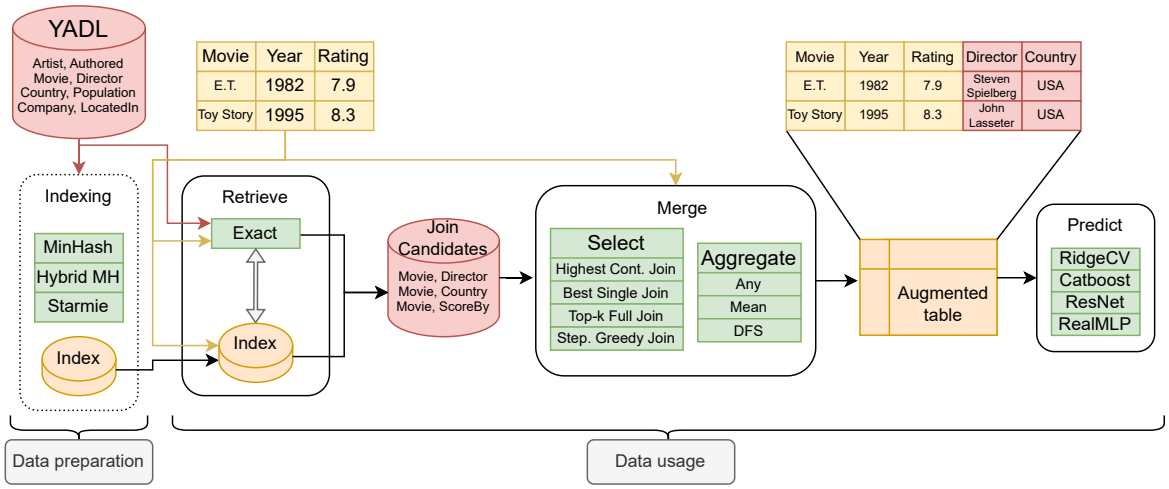

Figure 1: **The evaluation pipeline**. Given a base table, the three main steps (Retrieve, Merge, Predict) augment it with the information from the lake to improve the prediction performance. The data preparation step can be executed offline, and the resulting index may be reused across different data usage instances.

et al., 2020; Kanter & Veeramachaneni, 2015), *4)* **predicting** with supervised learning on the resulting table, a tabular learning problem (Shwartz-Ziv & Armon, 2022; Borisov et al., 2022; Grinsztajn et al., 2022). Elaborate methods have been designed for each of these tasks separately. Yet, how they contribute to the overall machine learning pipeline is often unclear. Prediction performance is not evaluated consistently in the database literature. Moreover, evaluation on data lakes is particularly challenging. First, there is no openly-available reference data suited for this purpose: both a data lake and tables with corresponding analytic tasks. Second, a solid evaluation must run the pipeline many times across loosely structured, messy ensembles of tables. State-of-the-art publications relevant to this pipeline seldom come with implementations robust and scalable enough for cross-validation loops on a data lake. Indeed, data discovery and assembly code can involve many complex elements, such as probabilistic data structures or large language models, which need careful software engineering to be production ready. The difficulty of operating those complex pipelines does beg the question of when the prediction gain is worth the operational cost. State-of-the-art research often leaves aside the question of complexity, which involves not only computational cost, but also preparation and maintenance burden (Sculley et al., 2015; Paleyes et al., 2022).

We study the full data-discovery for machine learning pipelines, with an eye on exploring the complexity gradient in a reproducible way. For this, we contribute Yet Another Data Lake (YADL), a dataset that enables systematical exploration of the aspects of the pipeline important for good prediction. Built from the YAGO knowledge base (Mahdisoltani et al., 2014), YADL provides a controlled environment to test methods. To analyze the discovery and merge pipelines across different degrees of complexity, YADL's synthesis procedure allows to vary the shape (number of rows and columns) and degree of redundancy of the resulting tables.

We investigate the impact of the main steps on the end goal of learning from data lakes: preparing the data structures needed to search for candidates, retrieving and selecting potential augmentation candidates, integrating them with the base table, and subsequently evaluating learning on this assembled data. Considering both retrieving and combining tables in a data lake and the downstream learning task, our work bridges database search and machine learning, a topic of much interest (Fey et al.; Robinson et al., 2024; Cvetkov-Iliev et al., 2023; Wang et al., 2024). It has two main objectives: first, **determine which pipeline steps are most important for prediction performance**, and second, develop an equitable playing field that facilitates **a holistic assessment of learning on data lakes**.

We analyze various methods in the four tasks, with an exhaustive empirical evaluation that required approximately 21 years or 189k CPU and GPU hours (Table 7). Our findings show that *1)* automated selection of joins is noisy, creating very messy tables for which tree-based methods are more robust than

deep learning models; *2)* better retrieval of joins reduces the amount of noise and the fraction of null values; *3)* relying on Jaccard containment (i.e., the fraction of entities of the table to augment found in a join candidate) as a criterion for retrieving joins improves downstream prediction performance; *4)* finally, simpler, metric-based join-discovery methods outpace their complex counterparts in terms of speed and the larger cost of more elaborate methods does not yield proportionate gains in prediction performance.

To validate the generality of our findings, we contrast the insights obtained from the analysis carried out via YADL with those obtained from Open Data US, a well-referenced real data lake (Nargesian et al., 2018; Galhotra et al., 2023): this comparative approach ensures that YADL is representative enough to be a benchmark. We consider 6 input base tables from the literature which pertain to multiple domains.

After outlining the problem setting and previous work in Section 2, we share our main contributions:

1. We develop YADL: a novel benchmarking data lake that allows to test retrieval and augmentation techniques in a controlled environment (Section 3). YADL, the base tables, and the pipeline are available and easily extendable to spur further research.
2. We implement a full prototype pipeline for augmenting tables from data lakes (Section 4). We then measure the prediction performance, execution time, and RAM usage of each method.
3. We conduct an experimental study on 6 base tables over various data lakes, retrieval techniques, join selection methods, aggregation solutions, and ML models (Section 5). Results provide insights on the steps of pipeline learning from data lakes.

We conclude the paper with a discussion of future research directions in Section 6.

2 Problem setting and related work

Problem setting. Consider a user training a ML model to predict some quantity. The corresponding quantity appears in the training data as a target column Y of a *base table* T. Assume our user has also access to a large collection of tables (a *data lake*) $D = \{T_1, T_2, ..., T_m\}$, some of which may contain additional information that can enrich the base table T. The data lake may be publicly available (Castelo et al., 2021; Mattmann et al., 2018; Srinivas et al., 2023; Hulsebos et al., 2023; Nargesian et al., 2018) or private (e.g., corporate data). Departing from many studies on learning on relational databases, where schemas are provided (Motl & Schulte, 2015; Fey et al., 2023; Robinson et al., 2024), we consider *unstructured* data lakes, i.e., data lakes without a schema to specify any PK-FK (Private Key - Foreign Key) relationship between the tables.

Each of these tables T_k is a bi-dimensional collection of data organized in columns $C_k^i \in T_k$ that may include categorical (names, codes etc.), numerical data (price, revenue, tax rates etc.) and text (product descriptions, user reviews etc.). While cross-table metadata such as foreign keys is not available in this setting, joining T with some of the tables in D would be beneficial for the target prediction task.

Given T and D, a table $T_k \in D$ is considered to be *joinable*, or a *join candidate* for T on a query column $Q \in T$, if at least one of the columns $C_k^i \in T_k$ has a non-empty intersection with one of the columns in table T: if $\exists Q \in T,\ \exists C_k^i \in T_k \mid Q \cap C_k^i \neq \emptyset$.

The user wants to optimize the performance of the ML model on a collection of columns (or "features") X according to the quality of the prediction for the target Y (*e.g.,* the movie rating). Columns in X may come either from T, or from joined tables in D.

Different steps. In such a scenario, the user is likely to rely on the following main steps: **Join Candidate Retrieval**, **Join Candidate Merging** (which includes the **Join Selection** and **Aggregation** tasks), and **Prediction**. Depending on the specific scenario, some of the tasks may be executed in a different order or not at all. In the following, we will drop Join from the names when clear from the context.

Another related problem, which we do not study, is that of finding new *samples* rather than *features* (called "table unionability" in databases): identifying which tables may be "appended" to T to increase the number of rows (Khatiwada et al., 2023a; Fan et al., 2023b; Nargesian et al., 2018).

Finding the join candidates Given a base table T and a data lake D, the **Candidate Retrieval** task consists in discovering join candidates (**Retrieve** in Figure 1). This task looks for tables that can be considered as "candidate joins" for the given base table. Different methods have been developed for different scenario: some "dataset search engines" tackle internet-scale crawls of tables (Castelo et al., 2021; Mattmann et al., 2018); other methods are instantiated on data stored locally (Zhu et al., 2019; Fernandez et al., 2019; Zhu et al., 2016; Fernandez et al., 2018; Khatiwada et al., 2022; 2023b).

While integrating data is not a central focus of the ML literature, augmenting features via joins is recognized as key to ML (Paleyes et al., 2022; Kumar et al., 2016). Still, the blind addition of features may lead to diminishing or negative returns, which led to the development of systems that seek to integrate only correlated features (Esmailoghli et al., 2021; Santos et al., 2021). Alternative systems seek to augment T by synthesising new features (Kanter & Veeramachaneni, 2015; Cvetkov-Iliev et al., 2023; Zhao & Castro Fernandez, 2022). Recent contributions focus on building graph representations of relational databases to leverage GNNs for learning across tables (Fey et al.; Robinson et al., 2024; Wang et al., 2024). An orthogonal research direction is concerned with the problem of search and augmentation while maintaining privacy (Huang et al., 2023a;b).

Though implementations may vary, retrieval methods used to find join candidates share some similarities: 1) they involve an offline phase to either index the data lake (Zhu et al., 2016; Fernandez et al., 2019), or train a model (Fan et al., 2023b; Dong et al., 2023), and 2) they rely on similarity metrics across columns to select candidate joins. Often, this metric is **Jaccard Containment** (JC), defined as

$$\text{Jaccard Containment} := \frac{|Q \cap C_k^i|}{|Q|}, \tag{1}$$

where $Q \in T$ is a query column in base table T, $C_k^i \in D$ is a candidate column in table T_k, $|Q \cap C_k^i|$ is the cardinality of the intersection between the two sets, and $|Q|$ is the cardinality of the query set itself. Intuitively, if this ratio is high, then a large fraction of Q is found in C_k^i, suggesting that the two columns should be joined. Approximate methods can scale JC-based retrieval to very large databases (Zhu et al., 2016; Fernandez et al., 2019; 2018). Beyond JC, other metrics have been used, such as top-k set similarity (Zhu et al., 2019), combinations of JC and embeddings-based similarities (Fan et al., 2023b), or other embeddings-based metrics (Cong et al., 2022; Habibi et al., 2020), such as approximate nearest neighbor search (Dong et al., 2023) on model embeddings. Methods based on Jaccard similarity are vulnerable to typos, which led to the development of methods that perform fuzzy or semantic matching such as Fan et al. (2023b); Mundra et al. (2023); Deng et al. (2017b); in this work, we focus on scenarios that do not involve fuzzy matching. Frequently, retrieval methods require an "indexing" step prior to their execution, which we dub "data preparation" to in our pipeline (Figure 1).

Retrieval methods are often designed for large data lakes (up to millions of tables Zhu et al., 2019; Fan et al., 2023b) and to maximize recall. However, three issues arise. First, these methods do not assess the relevance of join candidates to the downstream task. While a large containment value may indicate that a join *can* be done, it provides no guarantee that this join is actually useful (Kumar et al., 2016). Second, the number of candidate joins could become too large for practical use. Manually identifying the best candidates is time-consuming, and performing all joins might be too expensive in terms of time/memory constraints (Santos et al., 2021). A user-defined threshold on the containment can filter out the least promising joins, but deciding the correct threshold is problematic; alternatively, it is possible to select only the top-k candidates by containment. Third, Jaccard containment does not take into account the cardinality of a column: in an extreme case, if a column $Q \in T$ contains only a single value, it would have perfect overlap with any column $C_k^j \in D$ that contains the same value. While this behavior may be desirable for some specific retrieval tasks, it further expands the number of candidates with high containment. The presence of duplicate tables worsens each of these issues by introducing potential false positives.

To make retrieval readily useful, the **Join Selection** task *identifies a subset of candidate joins that maximizes the prediction performance over a downstream task* (**Select** in Figure 1). These methods use various strategies to add value to retrieval: profiling candidate joins according to various metrics (Galhotra et al., 2023; Flores et al., 2021), rules to remove joins that are not useful (Kumar et al., 2016; Shah et al., 2017), joining over sketches or coresets of the data (Wang et al., 2022; Santos et al., 2021), or executing each candidate join to find those that bring benefit (Esmailoghli et al., 2021; Chepurko et al., 2020; Liu et al., 2022; Galhotra et al.,

2023; Gong et al., 2023; Dong & Oyamada, 2022). In this work, we focus on the latter, very popular, strategy. We consider ML models that operate on rows as samples, columns forming features. Augmentation enriches features while keeping the original set of samples, thus requiring a *left join*. A resulting challenging is that un-joined rows in the left table will lead to missing (null) values in the new columns.

We split Candidate Join Retrieval and Selection to tease out the retrieval metric from the benefit for the task: the first measures similarities between columns, while the second depends on the information in the foreign table.

Merging the candidates After the set of join candidates has been retrieved, they must be merged with the base table to augment it with their columns. Depending on the join selection strategy, aggregation may be executed during the selection process, or after the set of candidates has been chosen. In any case, it is paired with the selection procedure by the need of training the ML model on the augmented tables. To represent this coupling, we combine the two tasks in a single **Merge** step in Figure 1.

It is not always possible to limit joins to one-to-one relationships; often, we join on one-to-many or many-to-many relations. For example, to join a table about movies with one that contains movie ratings on column "movie title", every movie with more than one rating is in a one-to-many relation, thus the content of all the rows in such relations gets duplicated. Sample duplication is problematic when the downstream task involves a ML or statistical analysis method, as each row corresponds to one sample. The **Aggregation** task bridges the result of the join with the downstream methods, combining the information contained from a potentially large number of rows into one (**Aggregate** in Figure 1). More precisely, given a tuple (row) t in the base table T that needs to be joined with n tuples from a table (A, B) over A, the goal is to augment t with attribute B by selecting one value that represents the information from the n joining tuples. How to select a representative value for the new attribute reminds data integration problems such as truth discovery (Dong et al., 2009) or data fusion (Bleiholder & Naumann, 2009). In this spirit, Deep Feature Synthesis (DFS) (Kanter & Veeramachaneni, 2015) takes a set of tables and a join plan to recursively aggregate replicated instances using functions such as average, median, and mode.

Learning on the augmented data Finally, the integrated table is used to train a model to **Predict** a target variable through supervised methods. Tabular machine learning is the subject of very active research, with well-established tree-based methods (Grinsztajn et al., 2022; Prokhorenkova et al., 2018) and rapidly progressing tabular deep learning (Holzmüller et al., 2024; Ye et al., 2024; McElfresh et al., 2023; Hollmann et al., 2022; Hegselmann et al., 2023; Arik & Pfister, 2021; Gorishniy et al., 2024). It is not possible in our study to explore all recent methods, in particular given that some incur compute costs incompatible with our extensive evaluation and the combinatorics of pipelines. We consider three broad range of methods: *1)* linear regression/classification (as implemented in scikit-learn Pedregosa et al., 2011), *2)* tree-based methods such as CatBoost (Prokhorenkova et al., 2018), *3)* or deep learning methods well suited for tabular data, such as ResNet (Gorishniy et al., 2021) or RealMLP (Holzmüller et al., 2024). While we present the prediction task as distinct from the prior ones, some pipelines implement learning at intermediate sections of the workflow to ensure the selection of the most appropriate candidate tables (Galhotra et al., 2023; Huang et al., 2023c).

Data preparation and data usage To model a realistic use case, we consider a scenario in which the user has prepared the data structures required to run the retrieval method in an offline manner ("Data preparation" in Figure 1), and the remaining steps of retrieval, selection and evaluation are executed online ("Data usage" in Figure 1). The online step may include cross-validation to improve the reliablility of the results: we model this in our experimental setup.

3 Building Yet Another Data Lake

Yet Another Data Lake (YADL) is a semi-synthetic data lake built by recombining the data present in the YAGO (Suchanek et al., 2007; Mahdisoltani et al., 2014) knowledge base (KB) [1] to generate a collection of tables. Our goal is to have a scalable, high-quality and consistent data lake that allows users to evaluate

[1]We use YAGO 3.0.3 (Mahdisoltani et al., 2014), which is updated to 2022.

the main steps of the pipeline in Figure 1, while avoiding some of the confounding factors that come from working with unvetted data, such as typos, inconsistent schemas and data format, and other sources of noise. These challenges can be added to YADL, e.g., by generating typos in table entries.

YAGO: the source of the original data. YAGO (Suchanek et al., 2007) is a KB composed of RDF triplets; each triplet has a *subject* connected to an *object* through a *predicate* (or relation). Subjects and objects are considered to be *entities*, e.g., in the triplet "Paris, locatedIn, France", "Paris" is the subject entity, "France" is the object entity, and "locatedIn" is the predicate that connects them. The object may also be a lexical value such as the one for the "population density". Each entity belongs to a set of *classes* (or types), arranged in a taxonomy; "Paris" belongs to the class "City", subclass of "Populated place", itself subclass of "Geographical locations".

From knowledge base to relational tables. Information in data lakes is typically stored as tables, rather than the triplet format of YAGO. For this reason, we first rearrange the YAGO triplets by converting them into binary tables, then we filter and recombine the binary tables to create multiple YADL variants (*Base*, *10k* and *50k*) that differ in their size and in the properties of the tables contained therein. YADL variants can be obtained by changing the parameters used for the synthesis, as detailed in Appendix A.

4 Implementations of the retrieve-merge-predict pipeline

We now discuss the pipeline steps in Figure 1. For the **Retrieve** step, we discuss different possible retrieval strategies; for the **Merge** step, we propose different join selectors and aggregation methods, and we explain how these two parts are intertwined; finally, for the **Predict** step, we go over the ML methods used to test the prediction performance. We explore each section in more detail in Appendix B.

Retrieving the candidates. We consider retrieval methods that work by taking a query column and return a – possibly ranked – list of candidates.

Retrieval methods usually involve offline preparation steps such as building sketches (Zhu et al., 2023; Fernandez et al., 2019), indices (Zhu et al., 2019), creating embeddings (Fan et al., 2023b), or profiling tables in the data lake (e.g., measuring the containment, or join quality Flores et al. (2021)); preparation includes persisting the data structures for future use. Afterwards, candidate joins can be obtained by accessing the pre-built data structures in a "retrieval" (or "query") operation.

For retrieval strategies that rely on Jaccard containment (Equation 1), a candidate column is a good join if its containment is large, i.e. the candidate column contains a large fraction of the entities of the query column. Alternative strategies may rely on different metrics, such as cosine similarity between embeddings (Fan et al., 2023b; Dong et al., 2023). As we consider exact joins over strings rather than fuzzy matches, an exact set metric such as containment is needed to ensure that enough keys in the base table are matched in the candidate table.

We consider four retrieval strategies that explore different approaches and trade-offs. We first distinguish between"offline" and "online" methods: methods in the first category require some degree of offline data preparation in order to be executed, such as constructing data structures, or training a specific model; methods in the latter category are instead executed directly "online" with no prior data preparation.

Exact Matching belongs to the "online" category and measures the *exact* Jaccard containment between it and every column in the data lake. The "offline" category includes **MinHashLSHEnsemble** (MinHash) (Zhu et al., 2016), **Hybrid MinHash** (a method we develop), and **Starmie** (Fan et al., 2023b). MinHash builds an index on the data lake, and when queried returns candidates whose Jaccard containment is greater than a certain threshold *without ranking them*. Hybrid MinHash combines Exact Matching and MinHash by taking the candidates returned by MinHashing and measuring their exact containment, thus limiting the number of columns to be considered and reducing the computational cost of Exact Matching, whilst introducing a candidate ranking. Finally, Starmie builds embeddings for the query column and every column in the data lake using a language model, then combines cosine and Jaccard similarity to rank candidates. More detail is provided in Appendix subsection B.1.

The "Data usage" part of the pipeline (1) is transparent to the retrieval method: given a list of join candidates, it will test each candidate regardless of how the list was constructed. To reflect practical limitations on runtime and compute resources, we introduce a *budget constraint* on the number of retrieved candidates to evaluate. We choose to keep the top-30 candidates, as we observe that almost all candidates with high containment are within this limit (Figure 8 in Appendix), and it has empirical confirmation in practice (Spotify, 2020). In Section 5, we demonstrate how even such a small budget can cause problems with scalability.

Merging base table and join candidates. In this step, the retrieved candidates are combined into a new *integrated* table that joins the information in the base table T with additional information from augmentation tables. As shown in Figure 1, the merge step combines **join selection** and **aggregation**, as both must be executed to build the augmented table used for Prediction.

Join selection We consider two different overarching strategies for selecting candidates: **metric-based selectors**, which rely on a metric to choose which candidates should be joined, and **results-based selectors**, which instead iterate over candidates and select the best by explicitly executing joins. The first category includes **Highest Containment**, which ranks candidates by containment, then joins the first, and **Top-k Full Join**, which relies entirely on the ranking provided by the retrieval method to join the first k candidates without filtering them. For the second category, we implement **Best Single Join** and **Stepwise Greedy Join**. The first works with one candidate at each iteration, during which it first joins the candidate, then it trains and evaluates a prediction model on the resulting table; after iterating over all candidates, it selects the single candidate with the best performance. The second method iterates over each candidate like in the previous case, however it retains all candidates that improve the prediction performance, so that the augmented table grows over time as new candidates are joined. Stepwise Greedy Join is related to forward feature selection (Guyon & Elisseeff, 2003), as it greedily adds new tables as features during each iteration, and represents a common approach in the database literature (Galhotra et al., 2023; Chepurko et al., 2020). Appendix subsection B.2 details the implementations.

Aggregation When joining tables for a downstream ML task, one-to-many relationships must be aggregated to avoid replicating samples in the base table, which would modify the initial data sampling. We test three aggregation strategies: **Any** selects any row at random from each group of matched tuples; **Mean** replaces all duplicated numerical (categorical) values by the mean (most frequent) of all values for that attribute in the group; finally **DFS** (Deep Feature Synthesis (Kanter & Veeramachaneni, 2015)) greedily generates new features for each column in the augmented table by aggregating groups of tuples, measuring statistics over the groups (e.g., mean, median, most frequent value), and adding said statistics as features; this is done for every join. We expand on this in Appendix subsection B.3.

Supervised learning with a ML model. The learning step is performed on the final *integrated* table on the training split returned by the join selector and evaluated on the *integrated* table on the test split.

We evaluate four predictors. We use a linear baseline: **Ridge regressor/classifier** with the RidgeCV scikit-learn (Pedregosa et al., 2011) implementation and default parameters. **CatBoost** (Prokhorenkova et al., 2018) is a state-of-the-art GBDT method, optimized to handle categorical variables. We set the number of iterations to 300. **ResNet** (Gorishniy et al., 2021) is our baseline neural method. **RealMLP** (Holzmüller et al., 2024) is a NN-based method that incorporates a number of "good defaults" to improve performance over standard NNs. For ResNet and RealMLP we use the implementation and default parameters provided by pytabkit (Holzmüller et al., 2024). We do not perform hyperparameter optimization.

5 Experimental study

5.1 Settings

For our experimental campaign, we test the different sections of the pipeline over three dimensions: prediction performance, execution time, and RAM usage. Focusing on multiple dimensions allows us to have a view of the different trade-offs across methods.

Data lakes We use four YADL variants (Binary, Base, 10k, 50k) (as detailed in Section 3) and Open Data US, a data lake employed in the literature (Galhotra et al., 2023; Zhu et al., 2019; 2016); statistics are reported in Table 1. Starmie did not run on YADL 50k (not enough RAM) and Open Data (noise in the data crashed the model), so these data lakes are excluded from figures that involve Starmie. Appendix Figure 8 reports the measured containment for the base tables used in our experiments.[2]

Table 1: **Statistics for the tables in the data lakes**. "N. cols" and "C. cols" refer to numerical and categorical columns, respectively.

	YADL	YADL			OpenData
	Binary	Base	10k	50k	US
N. tables	70	30072	10059	47223	5591
Size (MB)	629	10051	5557	27718	4062
Tot. rows	20.1M	672M	242M	1.20B	95.7M
Tot. cols	140	95.2k	127k	624k	133k
Avg rows	287k	22.3k	24.0k	25.4k	17.1k
Avg cols	2.00	3.17	12.63	13.21	23.86
Avg N. cols	0.30	0.39	3.54	3.59	11.10
Avg C. cols	1.70	2.78	9.08	9.61	12.76
Avg nulls	0.00	0.31	0.62	0.64	0.09

Base tables We evaluate five tables from sources external to the lakes: Company Employees, US Elections, 2021 US Road Accidents, and Housing Prices. As "internal" tables, derived from lakes, have been used in several previous works for evaluation (Galhotra et al., 2023; Chepurko et al., 2020), we also include one per lake: US County Population (from YADL), and Schools (from Open Data US). Statistics are reported in Appendix subsection C.8 .

For all datasets, the values of the query columns must be matched with the entities in YADL using semantic annotation solutions (Huynh et al., 2022; Nguyen et al., 2021). In our experiments, we manually performed the match to remove the noise from this task. Also, query columns are chosen based on what a user may reasonably consider as "key" (e.g., the movie title). We release the matched tables along with the data lakes for reproduciblity.

[2]The data lakes are available at `https://zenodo.org/doi/10.5281/zenodo.12607872`, while the code to prepare YADL is at `https://anonymous.4open.science/r/YADL-5064` and the pipeline is at `https://anonymous.4open.science/r/retrieve-merge-predict-6B4E/`.

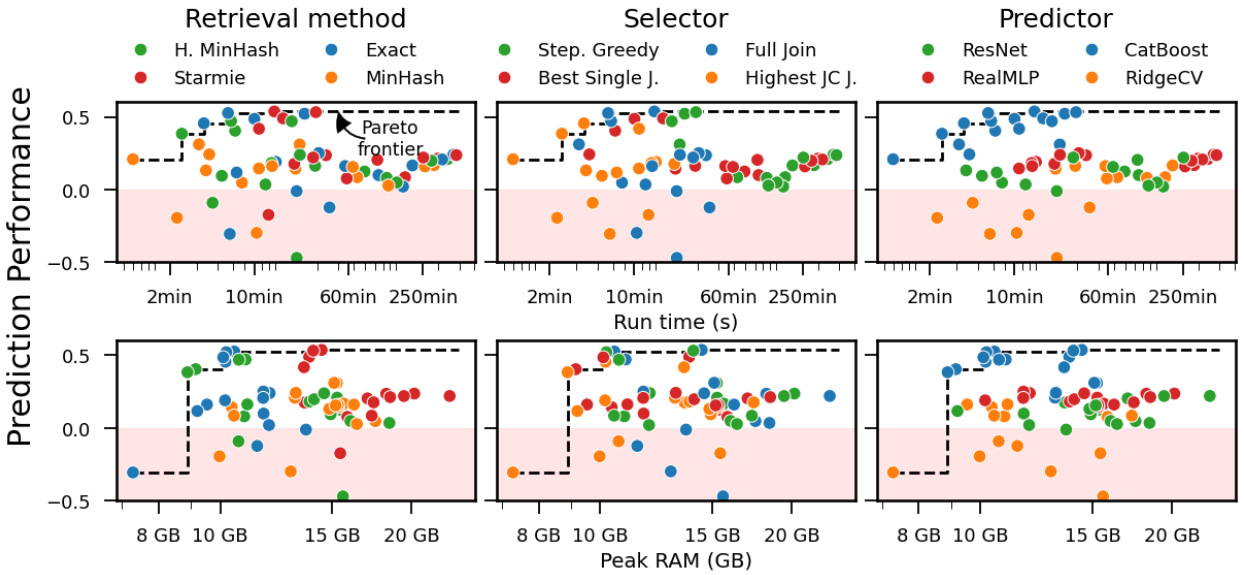

Figure 2: **Pareto frontier analysis for the pipeline steps** The prediction performance is plotted against retrieval + run time (top) and peak RAM usage (bottom). Each row presents the same results, broken down by retrieval method (left), join selector method (center) and predictor (right). Each dot represents the average prediction performance and resource cost averaged across base tables and data lakes for a specific configuration (e.g., the leftmost dot in the first row is obtaining by using MinHash, Highest Containment Join and CatBoost). Time for offline retrieval preparation for MinHash and Starmie is not reported here.

To reflect the experience of a data scientist that needs to construct a meaningful table starting from a data lake, and to highlight the effect of joins on the downstream task, we run experiments on a depleted version of the tables, i.e., the input tables include only the primary key column and the target column. We provide details on the datasets, computational resources and pipeline implementation in Appendix subsection C.2.

5.2 Results

Our first goal is to pinpoint which steps of the pipeline have the most significant impact on the studied dimensions: optimizing these influential sections can yield the greater benefits. We rely on Pareto frontier plots (Figure 2) to highlight the cost-performance trade-off for the different steps and configurations.

Reference configuration Based on Figure 2, we define a **reference configuration** that uses Exact Matching, Best Single Join, aggregation Any, and CatBoost. This configuration represents a good trade-off between performance and compute cost, and it can run on all configurations, base tables and data lakes.

Predictor: Tree-based methods perform well Supervised learning with the ML model is the pipeline step with the starkest difference between methods (Figure 2 right, Table 3): in our scenario, CatBoost is both *faster* and *more effective* than its non-tree counterparts. Indeed, CatBoost always outperforms other methods in prediction performance (by up to 26%) and run-time (33× faster than the slowest competitor), although it has a larger memory footprint.

This is likely due to two major factors: 1) imperfect joins introduce a large fraction of missing values (database "nulls"), and 2) categorical features have high cardinality. Firstly, any sample that does not find a match in a candidate will have a missing value in each new feature; in addition, any missing value *in matched rows* will remain: as a result, even "good" joins may feature a high degree of missingness. Parametric models are particularly affected by missing values, and categorical features make imputation more difficult; comparatively, tree-based models are far more resilient in presence of missing values (Josse et al., 2024). In fact, we observe that CatBoost and RealMLP are the only methods whose prediction performance never drops below 0 even in this very challenging scenario. McElfresh et al. (2023) also report that heavy missingness impedes neural networks more than tree-based models.

Retrieval: Containment is key, though imperfect A surprising result of our experiments shown in Figure 2 and Table 3 is that simple metric-based retrieval is sufficient to achieve good results, while maintaining a far lower resource cost. Relying directly (or indirectly) on Jaccard containment (Highest Containment, Full Join, Exact Matching) achieves the same results as far more thorough (and costly) retrieval (Starmie) or selection (Best Single Join, Stepwise Greedy Join).

Focusing on the reference configuration, Figure 3 relates containment to prediction performance. The plotted lines highlight the clear upwards trend in the prediction performance that follows the increase in containment. In other words, higher prediction results occur more frequently when the containment is higher. For exact joins (as in our scenario), having a high Jaccard containment leads to better results because left joins with high overlap augment a large fraction of the base table, whereas low overlap joins produce features that contain mostly empty values.

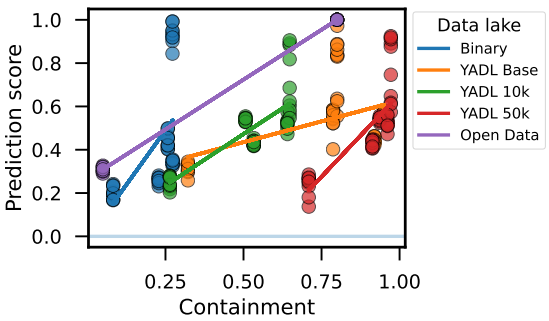

Figure 3: **Retrieval: Better containment improves prediction performance**. Regression plot relating the prediction performance with the Jaccard containment; each dot represents an experimental run for each base table.

And yet, while Jaccard containment is an effective first metric, it is not fool proof. We observe experimentally that it does not work well where there is a large degree of redundancy because in such cases many candidates may share the same containment: this is what happens with YADL 50k (Table 2, Appendix Figure 8); a larger computational budget may mitigate this issue, but it is not always an option. Furthermore, it fails in cases where the cardinality of a column is very low (e.g., with

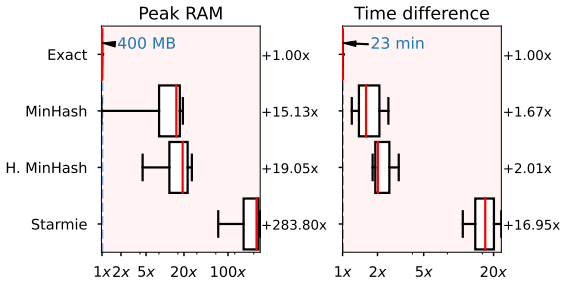

Figure 4: **Resource cost of indexing the retrieval methods**. The computational cost of each retrieval method is plotted with respect to the reference (Exact Matching). The median difference is reported on the right of each plot.

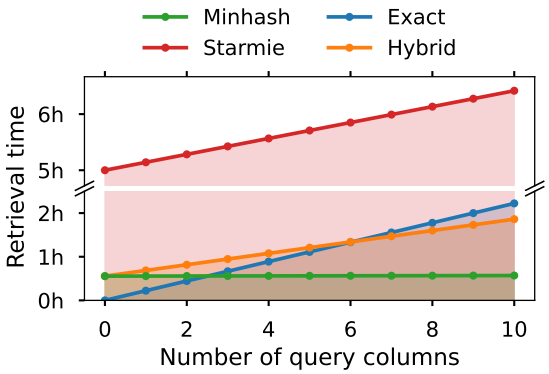

Figure 5: **Runtime as a function of the number of query columns** for the different retrieval methods.

columns that contain binary values): this is problematic if the user does not know which columns should be used for querying. In other words, *high containment means that we can join without adding too many missing values: this does not guarantee that the added features improve downstream utility.*

Retrieval: Better metrics improve performance, at a cost Pareto frontier analysis (Figure 2, left) shows that Starmie is Pareto optimal for some (resource-intensive) configurations: if resources are available for the offline preparation cost, better querying through Starmie can bring benefits. And yet, the –arguably small– improvements in downstream performance brought by Starmie come with a very large cost in both RAM and offline training time (Figure 4, Appendix Table 6, Appendix Table 10). Furthermore, we had to restrict most of our experiments (including Figure 2) as Starmie could only run on 3 out of our 5 data lakes of interest (Binary, YADL Base and YADL 10k). We had to leave out YADL 50k, where Starmie exceeded our available RAM (150GB), and Open Data which crashed Starmie, probably because it was too noisy. On the other hand, Exact matching is Pareto optimal in most cases, and runs on all data lakes we considered.

With respect to MinHash, Hybrid MinHash brings a substantial improvement in terms of downstream performance (Figure 2, Table 3, Figure 17) and top-1 retrieval performance (Appendix Figure 20, Appendix Figure 18). It leverages Exact Matching in order to produce an actual ranking of the candidates. This however comes at the cost of a substantial increase in the query time (Figure 5, Appendix Table 10).

Retrieval: Computation trade-offs Figure 4 compares resources for the different retrieval methods *at indexing and query time*[3]: Starmie is by far the most expensive method, both in run time and in peak RAM. The rapid growth of RAM usage, even for relatively small data lakes (see Appendix Table 6), is particularly problematic and prevents the method from running on GPUs, thus slowing it down even further. The other methods are far cheaper by comparison, and can run on CPU without issues.

Figure 5 shows how different retrieval methods scale with the number of query columns: the value for 0 columns shows the time required to build the index (averaged over all data lakes[4]), and the slope is the time required to query a single column (averaged over all query columns); values are reported in Appendix Table 10. The figure highlights the point at which the cost of recomputing the containment for each new query column on every column in the data lake (Exact Matching) becomes more expensive than building the index (MinHash), and then querying it.

It is clear that, as the number of query columns increases, Exact Matching scales much worse than the other solutions (except Starmie), while Hybrid MinHash and MinHash scale much better: *this is important if the*

[3]We separate retrieval proper from the pipeline execution to clearly highlight their corresponding cost and trade-offs.
[4]Open Data and YADL 50k not included.

Table 2: **Aggregated median prediction results (higher is better) for the reference configuration.** "NA" results are referring to experiments run on "internal" tables ("Schools" was sampled from Open Data, "US County Population" from YADL): if run on a different data lake, no matching entities could be found, so no new features would be added.

Base Table	Binary	YADL Base	YADL 10k	YADL 50k	Open Data US
Company Employees	0.20	0.33	**0.37**	0.25	0.26
Housing Prices	0.34	**0.57**	0.54	0.54	0.50
Schools	NA	NA	NA	NA	**1.00**
2021 US Accidents	0.26	**0.44**	**0.44**	0.43	0.31
US County Population	0.93	0.84	**0.95**	0.85	NA
US Elections	0.44	0.55	0.52	0.52	**0.59**

Table 3: **Ablation study, prediction difference (higher is better) and runtime difference (lower is better) from the reference configuration. Retrieval Method** does not include results from Open Data US and YADL 50k.

Retrieval	Diff. Prediction	Diff. Time	Selector	Diff. Prediction	Diff. Time
Exact Matching	0.00	1.00	Full Join	2.09	0.67
Starmie	-0.06	2.10	Stepwise Greedy Join	1.61	2.35
Hybrid MinHash	-3.19	0.65	Best Single Join	0.00	1.00
MinHash	-17.48	0.33	Highest Containment Join	-0.10	0.32
Aggregation	**Diff. Prediction**	**Diff. Time**	**Predictor**	**Diff. Prediction**	**Diff. Time**
DFS	2.46	4.66	CatBoost	0.00	1.00
Mean	0.02	1.02	RealMLP	-21.24	23.44
Any	0.00	1.00	ResNet	-24.11	7.07
			RidgeCV	-26.03	4.01

query column is unknown or a user would like to test multiple columns to augment one or more tables. In any case, Starmie is much slower than all other alternatives.

Aggregation: Complex aggregation improves performance with limitations Figure 6 reports aggregation results[5]. The systematic expansion of multiple aggregations in DFS leads to many features, which would make both Full Join and Stepwise Greedy Join intractable, so they are not considered here. The generated features overall bring useful information, as DFS outperforms the simpler aggregations in most cases; however, preparing and employing the new features increases noticeably the training time. This is confirmed by Table 3, which highlights both the improvement in performance (2.5%) and the major increase of compute cost (6x wrt Any).

Overall results and ablation study Table 2 reports the median prediction performance across all configurations for a pair "Base table - Data Lake". From this table it is evident that internal tables (Schools, US County Population) represent a much simpler problem to solve compared to tables that are not sampled from the data lake (all other tables). Table 3 reports the results of an ablation study where we compare the performance and runtime of the reference configuration against the other possible

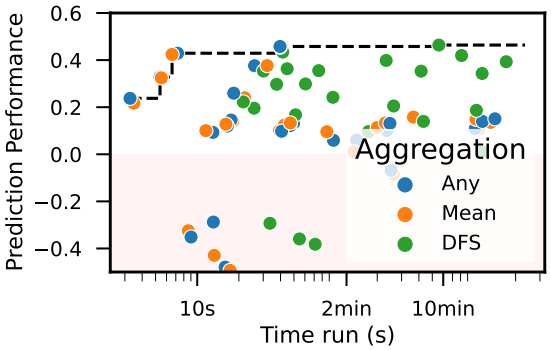

Figure 6: **Aggregation: Pareto Frontier Analysis.** DFS outperforms other methods, but is much slower to run.

[5]More detail is available in Appendix, Figure 15 and Figure 16

methods; we report the median difference in prediction and runtime. [6]

6 Discussion and conclusions

Take-away messages We build a semi-synthetic data lake based on a knowledge base to use as a reproducible test bed for evaluating methods to augment user-provided tables. We implement an easily-extendable pipeline to test the different steps of the augmentation procedure and alternative algorithms for each of their tasks. Our results uncover a number of observations important to direct research on this subject. We summarize the main take-away messages from the experiments.

1. **Tree-based models** come with significant benefits in terms of prediction and computational performance in the data-lake pipeline we studied (Figure 2 right, Table 3). Indeed, the automated selection of augmentation candidate tables generates challenging features (*e.g.,* with many missing values), which tree-based models are more effective at dealing with.
2. **Good table retrieval** affects the entire pipeline by discovering candidates that contain more useful features and introduce fewer missing values (Figure 2 left). Jaccard containment is a good metric for retrieving candidates, but it has limitations (Figure 3).
3. **Simple metric-based retrieval** (Exact matching) and candidate selection (Highest containment) produce comparable or better results than more complex methods (Starmie[7] and Best single join), while being vastly more efficient (Figure 2 left, center, Table 3).
4. Complex aggregation methods are much slower than simpler ones and do not result in commensurate gains in prediction performance (Figure 6, Table 3).
5. Combining stochastic retrieval with exact metrics (Hybrid MinHash) mitigates some of the drawbacks of basic MinHash and scales well with many query columns (Figure 3(a), Figure 5, Figure 4, Table 3).

The topic that we have studied is at the intersection of database and machine learning research. This intersection still has much open research prospect:

Merging on clean columns is only one side of the story. While we focus on columns where join keys can be matched exactly (functionally, by doing string matching), this is not possible in general because of typos, different formats, and different granularity. Similarity joins and semantic matching would help with this problem (Jiang et al., 2014; Dong et al., 2023; Deng et al., 2017b; Mundra et al., 2023) and add another dimension to the analysis. Methods that cover multiple steps, such as (Gong et al., 2023; Huang et al., 2023c), could also be considered.

To limit the search space, we keep our chain of joins for augmentation limited to one, and show that scalability is an issue even in this simplified scenario. However, some methods have considered chains of join for augmentation (Galhotra et al., 2023). Enabling join chains would also make evident the benefit of recursive methods (Cvetkov-Iliev et al., 2023; Kanter & Veeramachaneni, 2015).

"AutoRetrieval" is an exciting prospect. The overall middling-to-poor prediction results (Table 2, Table 8) suggest that the automated strategies evaluated here are not sufficient to replicate the performance achieved by a human data analyst. Automated procedures may help with discovering good candidates, but they cannot replace a human expert: fully automating this operation similarly to how AutoML tools (Hutter et al., 2019; Feurer et al., 2015) tweak ML methods represents a compelling direction for future work.

Final words. The performance-complexity trade-offs that appear are crucial for the practitioner: they suggest how to automate supervised learning on a data lake of a given size, maximizing statistical performance within a compute budget.

[6] This is expanded in Appendix subsection C.2 and Figure 17.

[7] Note that our results are not in contradiction with the Starmie study, as it was focused on *table unionability*, i.e. finding more samples rather feature augmentation which is our focus.

References

Sercan Ö Arik and Tomas Pfister. Tabnet: Attentive interpretable tabular learning. In *Proceedings of the AAAI conference on artificial intelligence*, volume 35, pp. 6679–6687, 2021.

Jens Bleiholder and Felix Naumann. Data fusion. *ACM computing surveys (CSUR)*, 41(1):1–41, 2009.

Vadim Borisov, Tobias Leemann, Kathrin Seßler, Johannes Haug, Martin Pawelczyk, and Gjergji Kasneci. Deep neural networks and tabular data: A survey. *IEEE transactions on neural networks and learning systems*, 2022.

Sonia Castelo, Rémi Rampin, Aécio Santos, Aline Bessa, Fernando Chirigati, and Juliana Freire. Auctus: a dataset search engine for data discovery and augmentation. *Proceedings of the VLDB Endowment*, 14(12): 2791–2794, 2021.

Nadiia Chepurko, Ryan Marcus, Emanuel Zgraggen, Raul Castro Fernandez, Tim Kraska, and David R. Karger. ARDA: automatic relational data augmentation for machine learning. *Proc. VLDB Endow.*, 13(9):1373–1387, 2020. doi: 10.14778/3397230.3397235. URL `http://www.vldb.org/pvldb/vol13/p1373-chepurko.pdf`.

Tianji Cong, James Gale, Jason Frantz, HV Jagadish, and Çağatay Demiralp. Warpgate: A semantic join discovery system for cloud data warehouse. *arXiv preprint arXiv:2212.14155*, 2022.

Alexis Cvetkov-Iliev, Alexandre Allauzen, and Gaël Varoquaux. Relational data embeddings for feature enrichment with background information. *Machine Learning*, pp. 1–34, 2023.

Dong Deng, Raul Castro Fernandez, Ziawasch Abedjan, Sibo Wang, Michael Stonebraker, Ahmed K Elmagarmid, Ihab F Ilyas, Samuel Madden, Mourad Ouzzani, and Nan Tang. The data civilizer system. In *Cidr*, 2017a.

Dong Deng, Albert Kim, Samuel Madden, and Michael Stonebraker. Silkmoth: An efficient method for finding related sets with maximum matching constraints. *arXiv preprint arXiv:1704.04738*, 2017b.

Xin Luna Dong, Laure Berti-Equille, and Divesh Srivastava. Truth discovery and copying detection in a dynamic world. *Proceedings of the VLDB Endowment*, 2(1):562–573, 2009.

Yuyang Dong and Masafumi Oyamada. Table enrichment system for machine learning. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 3267–3271, 2022.

Yuyang Dong, Chuan Xiao, Takuma Nozawa, Masafumi Enomoto, and Masafumi Oyamada. Deepjoin: Joinable table discovery with pre-trained language models. *Proc. VLDB Endow.*, 16(10):2458–2470, 2023. doi: 10.14778/3603581.3603587. URL `https://www.vldb.org/pvldb/vol16/p2458-dong.pdf`.

Nick Erickson, Jonas Mueller, Alexander Shirkov, Hang Zhang, Pedro Larroy, Mu Li, and Alexander Smola. Autogluon-tabular: Robust and accurate automl for structured data. *arXiv preprint arXiv:2003.06505*, 2020.

Mahdi Esmailoghli, Jorge-Arnulfo Quiané-Ruiz, and Ziawasch Abedjan. COCOA: correlation coefficient-aware data augmentation. In *Proceedings of the 24th International Conference on Extending Database Technology, EDBT*, pp. 331–336. OpenProceedings.org, 2021. doi: 10.5441/002/EDBT.2021.30. URL `https://doi.org/10.5441/002/edbt.2021.30`.

Grace Fan, Jin Wang, Yuliang Li, and Renée J. Miller. Table discovery in data lakes: State-of-the-art and future directions. In *Companion of the 2023 International Conference on Management of Data*, SIGMOD '23, pp. 69–75, New York, NY, USA, 2023a. Association for Computing Machinery. ISBN 9781450395076. doi: 10.1145/3555041.3589409. URL `https://doi.org/10.1145/3555041.3589409`.

Grace Fan, Jin Wang, Yuliang Li, Dan Zhang, and Renée J. Miller. Semantics-aware dataset discovery from data lakes with contextualized column-based representation learning. *Proc. VLDB Endow.*, 16(7):1726–1739, 2023b. doi: 10.14778/3587136.3587146. URL `https://www.vldb.org/pvldb/vol16/p1726-fan.pdf`.

Raul Castro Fernandez, Ziawasch Abedjan, Famien Koko, Gina Yuan, Samuel Madden, and Michael Stonebraker. Aurum: A data discovery system. In *2018 IEEE 34th International Conference on Data Engineering (ICDE)*, pp. 1001–1012. IEEE, 2018.

Raul Castro Fernandez, Jisoo Min, Demitri Nava, and Samuel Madden. Lazo: A cardinality-based method for coupled estimation of jaccard similarity and containment. In *2019 IEEE 35th International Conference on Data Engineering (ICDE)*, pp. 1190–1201. IEEE, 2019.

Matthias Feurer, Aaron Klein, Katharina Eggensperger, Jost Springenberg, Manuel Blum, and Frank Hutter. Efficient and robust automated machine learning. In *Advances in Neural Information Processing Systems 28 (2015)*, pp. 2962–2970, 2015.

Matthias Feurer, Katharina Eggensperger, Stefan Falkner, Marius Lindauer, and Frank Hutter. Auto-sklearn 2.0: Hands-free automl via meta-learning. *Journal of Machine Learning Research*, 23(261):1–61, 2022.

Matthias Fey, Weihua Hu, Kexin Huang, Jan Eric Lenssen, Rishabh Ranjan, Joshua Robinson, Rex Ying, Jiaxuan You, and Jure Leskovec. Position: Relational deep learning - graph representation learning on relational databases. In *Forty-first International Conference on Machine Learning*.

Matthias Fey, Weihua Hu, Kexin Huang, Jan Eric Lenssen, Rishabh Ranjan, Joshua Robinson, Rex Ying, Jiaxuan You, and Jure Leskovec. Relational deep learning: Graph representation learning on relational databases. *arXiv preprint arXiv:2312.04615*, 2023.

Javier Flores, Sergi Nadal, and Oscar Romero. Towards scalable data discovery, 2021. URL `https://openproceedings.org/2021/conf/edbt/p61.pdf`.

Sainyam Galhotra, Yue Gong, and Raul Castro Fernandez. Metam: Goal-oriented data discovery. In *39th IEEE International Conference on Data Engineering, ICDE 2023, Anaheim, CA, USA, April 3-7, 2023*, pp. 2780–2793. IEEE, 2023. doi: 10.1109/ICDE55515.2023.00213. URL `https://doi.org/10.1109/ICDE55515.2023.00213`.

Yue Gong, Zhiru Zhu, Sainyam Galhotra, and Raul Castro Fernandez. Ver: View discovery in the wild. In *2023 IEEE 39th International Conference on Data Engineering (ICDE)*, pp. 503–516. IEEE, 2023.

Google. Dataset search, 2023. URL `https://datasetsearch.research.google.com/`.

Yury Gorishniy, Ivan Rubachev, Valentin Khrulkov, and Artem Babenko. Revisiting deep learning models for tabular data. In M. Ranzato, A. Beygelzimer, Y. Dauphin, P.S. Liang, and J. Wortman Vaughan (eds.), *Advances in Neural Information Processing Systems*, volume 34, pp. 18932–18943. Curran Associates, Inc., 2021. URL `https://proceedings.neurips.cc/paper_files/paper/2021/file/9d86d83f925f2149e9edb0ac3b49229c-Paper.pdf`.

Yury Gorishniy, Ivan Rubachev, Nikolay Kartashev, Daniil Shlenskii, Akim Kotelnikov, and Artem Babenko. Tabr: Tabular deep learning meets nearest neighbors. In *The Twelfth International Conference on Learning Representations*, 2024.

Leo Grinsztajn, Edouard Oyallon, and Gael Varoquaux. Why do tree-based models still outperform deep learning on typical tabular data? In *Conference on Neural Information Processing Systems*, 2022.

Isabelle Guyon and André Elisseeff. An Introduction to Variable and Feature Selection. *Journal of Machine Learning Research*, 3(Mar):1157–1182, 2003. ISSN ISSN 1533-7928.

Maryam Habibi, Johannes Starlinger, and Ulf Leser. Tabsim: A siamese neural network for accurate estimation of table similarity. In *2020 IEEE International Conference on Big Data (Big Data)*, pp. 930–937, 2020. doi: 10.1109/BigData50022.2020.9378077.

Alon Y. Halevy, Flip Korn, Natalya Fridman Noy, Christopher Olston, Neoklis Polyzotis, Sudip Roy, and Steven Euijong Whang. Goods: Organizing google's datasets. In *SIGMOD*, pp. 795–806. ACM, 2016. doi: 10.1145/2882903.2903730. URL `https://doi.org/10.1145/2882903.2903730`.

Xin He, Kaiyong Zhao, and Xiaowen Chu. Automl: A survey of the state-of-the-art. *Knowledge-based systems*, 212:106622, 2021.

Stefan Hegselmann, Alejandro Buendia, Hunter Lang, Monica Agrawal, Xiaoyi Jiang, and David Sontag. Tabllm: Few-shot classification of tabular data with large language models. In *International Conference on Artificial Intelligence and Statistics*, pp. 5549–5581. PMLR, 2023.

Noah Hollmann, Samuel Müller, Katharina Eggensperger, and Frank Hutter. Tabpfn: A transformer that solves small tabular classification problems in a second. *arXiv preprint arXiv:2207.01848*, 2022.

David Holzmüller, Leo Grinsztajn, and Ingo Steinwart. Better by default: Strong pre-tuned mlps and boosted trees on tabular data. *arXiv preprint arXiv:2407.04491*, 2024.

Zezhou Huang, Jiaxiang Liu, Daniel Gbenga Alabi, Raul Castro Fernandez, and Eugene Wu. Saibot: A differentially private data search platform. *Proceedings of the VLDB Endowment*, 16(11):3057–3070, 2023a.

Zezhou Huang, Jiaxiang Liu, Haonan Wang, and Eugene Wu. The fast and the private: Task-based dataset search. *arXiv preprint arXiv:2308.05637*, 2023b.

Zezhou Huang, Pranav Subramaniam, Raul Castro Fernandez, and Eugene Wu. Kitana: Efficient data augmentation search for automl. *arXiv preprint arXiv:2305.10419*, 2023c.

Madelon Hulsebos, Çagatay Demiralp, and Paul Groth. Gittables: A large-scale corpus of relational tables. *Proceedings of the ACM on Management of Data*, 1(1):1–17, 2023.

Madelon Hulsebos, Wenjing Lin, Shreya Shankar, and Aditya Parameswaran. It took longer than i was expecting: Why is dataset search still so hard? In *Proceedings of the 2024 Workshop on Human-In-the-Loop Data Analytics*, pp. 1–4, 2024.

Frank Hutter, Lars Kotthoff, and Joaquin Vanschoren (eds.). *Automated Machine Learning - Methods, Systems, Challenges*. Springer, 2019.

Viet-Phi Huynh, Yoan Chabot, Thomas Labbé, Jixiong Liu, and Raphaël Troncy. From Heuristics to Language Models: A Journey Through the Universe of Semantic Table Interpretation with DAGOBAH. In *Semantic Web Challenge on Tabular Data to Knowledge Graph Matching (SemTab)*, 2022.

Yu Jiang, Guoliang Li, Jianhua Feng, and Wen-Syan Li. String similarity joins: An experimental evaluation. *Proceedings of the VLDB Endowment*, 7(8):625–636, 2014.

Julie Josse, Jacob M. Chen, Nicolas Prost, Gaël Varoquaux, and Erwan Scornet. On the consistency of supervised learning with missing values. *Statistical Papers*, September 2024. ISSN 1613-9798. doi: 10.1007/s00362-024-01550-4.

James Max Kanter and Kalyan Veeramachaneni. Deep feature synthesis: Towards automating data science endeavors. In *2015 IEEE international conference on data science and advanced analytics (DSAA)*, pp. 1–10. IEEE, 2015.

Shubhra Kanti Karmaker, Md Mahadi Hassan, Micah J Smith, Lei Xu, Chengxiang Zhai, and Kalyan Veeramachaneni. Automl to date and beyond: Challenges and opportunities. *ACM Computing Surveys (CSUR)*, 54(8):1–36, 2021.

Aamod Khatiwada, Roee Shraga, Wolfgang Gatterbauer, and Renée J. Miller. Integrating data lake tables. *Proceedings of the VLDB Endowment*, 16(4):932–945, dec 2022. doi: 10.14778/3574245.3574274. URL `https://doi.org/10.14778/3574245.3574274`.

Aamod Khatiwada, Grace Fan, Roee Shraga, Zixuan Chen, Wolfgang Gatterbauer, Renée J. Miller, and Mirek Riedewald. SANTOS: relationship-based semantic table union search. *Proc. ACM Manag. Data*, 1 (1):9:1–9:25, 2023a. doi: 10.1145/3588689. URL `https://doi.org/10.1145/3588689`.

Aamod Khatiwada, Roee Shraga, and Renée J Miller. Dialite: discover, align and integrate open data tables. In *Companion of the 2023 International Conference on Management of Data*, pp. 187–190, 2023b.

Arun Kumar, Jeffrey Naughton, Jignesh M Patel, and Xiaojin Zhu. To join or not to join? thinking twice about joins before feature selection. In *Proceedings of the 2016 International Conference on Management of Data*, pp. 19–34, 2016.

Jiabin Liu, Chengliang Chai, Yuyu Luo, Yin Lou, Jianhua Feng, and Nan Tang. Feature augmentation with reinforcement learning. In *2022 IEEE 38th International Conference on Data Engineering (ICDE)*. IEEE, may 2022. doi: 10.1109/icde53745.2022.00317. URL https://doi.org/10.1109/icde53745.2022.00317.

Farzaneh Mahdisoltani, Joanna Biega, and Fabian Suchanek. Yago3: A knowledge base from multilingual wikipedias. In *7th biennial conference on innovative data systems research*. CIDR Conference, 2014.

Chris A Mattmann, Sujen Shah, and Brian Wilson. Marvin: An open machine learning corpus and environment for automated machine learning primitive annotation and execution. *arXiv preprint arXiv:1808.03753*, 2018.

Duncan McElfresh, Sujay Khandagale, Jonathan Valverde, Vishak Prasad C, Ganesh Ramakrishnan, Micah Goldblum, and Colin White. When Do Neural Nets Outperform Boosted Trees on Tabular Data? *Advances in Neural Information Processing Systems*, 36:76336–76369, December 2023.

George A. Miller. WordNet: A lexical database for English. In *Human Language Technology: Proceedings of a Workshop held at Plainsboro, New Jersey, March 8-11, 1994*, 1994. URL https://aclanthology.org/H94-1111.

Jan Motl and Oliver Schulte. The ctu prague relational learning repository. *arXiv preprint arXiv:1511.03086*, 2015.

Pranay Mundra, Jianhao Zhang, Fatemeh Nargesian, and Nikolaus Augsten. Koios: Top-k semantic overlap set search. In *2023 IEEE 39th International Conference on Data Engineering (ICDE)*, pp. 1531–1543. IEEE, 2023.

Fatemeh Nargesian, Erkang Zhu, Ken Q. Pu, and Renée J. Miller. Table union search on open data. *Proceedings of the VLDB Endowment*, 11(7):813–825, mar 2018. doi: 10.14778/3192965.3192973. URL https://doi.org/10.14778/3192965.3192973.

Fatemeh Nargesian, Erkang Zhu, Renée J. Miller, Ken Q. Pu, and Patricia C. Arocena. Data lake management: Challenges and opportunities. *Proc. VLDB Endow.*, 12(12):1986–1989, 2019. doi: 10.14778/3352063.3352116. URL http://www.vldb.org/pvldb/vol12/p1986-nargesian.pdf.

Phuc Nguyen, Ikuya Yamada, Natthawut Kertkeidkachorn, Ryutaro Ichise, and Hideaki Takeda. Semtab 2021: Tabular data annotation with mtab tool. In *(ISWC*, volume 3103 of *CEUR Workshop Proceedings*, pp. 92–101. CEUR-WS.org, 2021. URL https://ceur-ws.org/Vol-3103/paper8.pdf.

Andrei Paleyes, Raoul-Gabriel Urma, and Neil D Lawrence. Challenges in deploying machine learning: a survey of case studies. *ACM computing surveys*, 55(6):1–29, 2022.

Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. Scikit-learn: Machine learning in python. *the Journal of machine Learning research*, 12:2825–2830, 2011.

Du Phan. Enhancing Data Analytics Through Intelligent Join Suggestions. https://blog.dataiku.com/joining-the-dots-enhancing-data-analytics-through-intelligent-join-suggestions, January 2023.

Liudmila Ostroumova Prokhorenkova, Gleb Gusev, Aleksandr Vorobev, Anna Veronika Dorogush, and Andrey Gulin. Catboost: unbiased boosting with categorical features. In *NeurIPS*, pp. 6639–6649, 2018. URL https://proceedings.neurips.cc/paper/2018/hash/14491b756b3a51daac41c24863285549-Abstract.html.

Joshua Robinson, Rishabh Ranjan, Weihua Hu, Kexin Huang, Jiaqi Han, Alejandro Dobles, Matthias Fey, Jan E. Lenssen, Yiwen Yuan, Zecheng Zhang, Xinwei He, and Jure Leskovec. Relbench: A benchmark for deep learning on relational databases, 2024. URL https://arxiv.org/abs/2407.20060.

Aécio Santos, Aline Bessa, Fernando Chirigati, Christopher Musco, and Juliana Freire. Correlation sketches for approximate join-correlation queries. In *Proceedings of the 2021 International Conference on Management of Data*, pp. 1531–1544, 2021.

David Sculley, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young, Jean-Francois Crespo, and Dan Dennison. Hidden technical debt in machine learning systems. *Advances in neural information processing systems*, 28, 2015.

Vraj Shah, Arun Kumar, and Xiaojin Zhu. Are key-foreign key joins safe to avoid when learning high-capacity classifiers? *Proc. VLDB Endow.*, 11(3):366–379, 2017. doi: 10.14778/3157794.3157804. URL http://www.vldb.org/pvldb/vol11/p366-shah.pdf.

Ravid Shwartz-Ziv and Amitai Armon. Tabular data: Deep learning is not all you need. *Information Fusion*, 81:84–90, 2022.

Engineering Spotify. How We Improved Data Discovery for Data Scientists at Spotify. https://engineering.atspotify.com/2020/02/how-we-improved-data-discovery-for-data-scientists-at-spotify/, February 2020.

Kavitha Srinivas, Julian Dolby, Ibrahim Abdelaziz, Oktie Hassanzadeh, Harsha Kokel, Aamod Khatiwada, Tejaswini Pedapati, Subhajit Chaudhury, and Horst Samulowitz. Lakebench: Benchmarks for data discovery over data lakes. *arXiv preprint arXiv:2307.04217*, 2023.

Fabian M Suchanek, Gjergji Kasneci, and Gerhard Weikum. Yago: a core of semantic knowledge. In *Proceedings of the 16th international conference on World Wide Web*, pp. 697–706, 2007.

Ritchie Vink, Stijn de Gooijer, Alexander Beedie, Marco Edward Gorelli, J van Zundert, Weijie Guo, Gert Hulselmans, universalmind303, Orson Peters, Marshall, chielP, nameexhaustion, Matteo Santamaria, Daniël Heres, Josh Magarick, ibENPC, Moritz Wilksch, Jorge Leitao, Jonas Haag, Marc van Heerden, cmdlineluser, Oliver Borchert, Chris Pryer, Ryan Russell, Joshua Peek, Colin Jermain, Adrián Gallego Castellanos, Jeremy Goh, and Liam Brannigan. pola-rs/polars: Python polars 0.20.6, January 2024. URL https://doi.org/10.5281/zenodo.10573881.

Jiayi Wang, Chengliang Chai, Nan Tang, Jiabin Liu, and Guoliang Li. Coresets over multiple tables for feature-rich and data-efficient machine learning. *Proceedings of the VLDB Endowment*, 16(1):64–76, sep 2022. doi: 10.14778/3561261.3561267. URL https://doi.org/10.14778/3561261.3561267.

Minjie Wang, Quan Gan, David Wipf, Zhenkun Cai, Ning Li, Jianheng Tang, Yanlin Zhang, Zizhao Zhang, Zunyao Mao, Yakun Song, et al. 4dbinfer: A 4d benchmarking toolbox for graph-centric predictive modeling on relational dbs. *arXiv preprint arXiv:2404.18209*, 2024.

Han-Jia Ye, Si-Yang Liu, Hao-Run Cai, Qi-Le Zhou, and De-Chuan Zhan. A closer look at deep learning on tabular data. *arXiv preprint arXiv:2407.00956*, 2024.

Zixuan Zhao and Raul Castro Fernandez. Leva: Boosting machine learning performance with relational embedding data augmentation. In *Proceedings of the 2022 International Conference on Management of Data*, pp. 1504–1517, 2022.

Eric Zhu, Vadim Markovtsev, aastafiev, Wojciech Łukasiewicz, Adam Foster, Sinusoidal36, Andrii Oriekhov, Joe Halliwell, JonR, Kevin Mann, Keyur Joshi, Peter Kubov, Qin TianHuan, Senad Ibraimoski, Spandan Thakur, Stefano Ortolani, Titusz, Vojtech Letal, Zac Bentley, fpug, hguhlich, long2ice, oisincar, and ronassa. ekzhu/datasketch: v1.5.9, February 2023. URL https://doi.org/10.5281/zenodo.7654815.

Erkang Zhu, Fatemeh Nargesian, Ken Q. Pu, and Renée J. Miller. LSH ensemble: Internet-scale domain search. *Proc. VLDB Endow.*, 9(12):1185–1196, 2016. doi: 10.14778/2994509.2994534. URL http://www.vldb.org/pvldb/vol9/p1185-zhu.pdf.

Erkang Zhu, Dong Deng, Fatemeh Nargesian, and Renée J Miller. Josie: Overlap set similarity search for finding joinable tables in data lakes. In *Proceedings of the 2019 International Conference on Management of Data*, pp. 847–864, 2019.

Table 4: "City" seed table built by flattening predicates.

Subject	locatedIn_1	locatedIn_2	owns_1	density
Paris	France	Europe	Tour Eiffel	null
Rome	Italy	null	Olympic Velodrome	2236

Table 5: "City" seed table built by left-joining binary tables.

Subject	LocatedIn	Owns	Density
Paris	France	Tour Eiffel	null
Paris	Europe	Tour Eiffel	null
Rome	Italy	Olympic Velodrome	2236

A Construction of YADL

We construct YADL by first reshaping the RDF triplets into binary tables. Then, we group subjects by their Wordnet type and construct 1015 wide-form relational "seed tables" by joining binary tables on the column that contains the triplet subjects.

Each seed table is then partitioned into "sub-tables" by selecting subsets of columns and projecting over them. Different partitioning strategies allow us to vary the characteristics of the resulting sub-tables (i.e., the number of rows and columns of each table), and the size of the resulting data lake.

Binary tables A binary table is generated for every predicate in YAGO, e.g., "hasCapital". YAGO contains 70 predicates, which result in a small data lake where some of the tables have millions of rows (e.g., "isLocatedIn") and some have few (e.g., "hasTLD"). Each table contains an attribute named "subject" and another attribute named as the actual predicate. For example, the triplet "France - hasCapital - Paris" leads to a table "hasCapital" with columns "subject" and "hasCapital"; finally, a row "France, Paris" is added to the table. The same process is applied to all 70 relations and their triplets.

Wordnet-based tables To reflect that tables typically have more than two columns, we develop a second variant of YADL where tables have a larger number of columns. To this goal, we leverage the Wordnet (Miller, 1994) classes (e.g., "Person", "Company", "Artist") to which entities belong. We use all Wordnet classes (a total of 1015) to create our *seed tables*, following the example in Table 4. Initially, the seed table includes solely the "Subject" column (e.g., the "City" table includes only values "Paris," "Rome," etc.). Then, we join every relation associated with subjects in the table: in Table 4, the subjects with type "City" are joined with relations "locatedIn", "owns", "hasPopDensity".

Transforming triplet tables into wide format tables leads to tables with null values because not all entities of a given type have the same relations. For example, column "hasPopDensity" contains null values for subject "Paris" in Table 4. The fraction of missing values in the transformed tables is reported in Table 1.

One-to-many relations A subject may be linked to many objects through the same predicate, e.g., "Paris" is linked to two objects ("France", "Europe") via the predicate "locatedIn". We address the issue in three ways. For Binary, triplets that share the same subject and predicate are transformed into tuples with the same value in the "subject" column and different values in the predicate column, e.g., the binary table has columns "Subject" and "isLocatedIn" and it contains tuples (Paris, France) and (Paris, Europe). For "Wordnet" seed tables, we build two variants. In the first case (which we dub *YADL Base* in Section 5), we flatten the group of objects by creating new columns, thus moving them on the same tuple rather than splitting them (e.g., in Table 4, column "locatedIn" is flattened over "locatedIn_1" and "locatedIn_2"). In the second variant (*YADL 10k* and *YADL 50k*), we create the new columns by executing a left join between the subject and each binary table. One-to-many matches (such as with "Paris" and "France", and "Paris" and "Europe") are

replicated with each left join; ordinarily, this would lead to an explosion in the number of rows: we limit the issue by selecting only the first two entries for each predicate (as shown in Table 5).

As a result of handling these relations differently in each version of YADL, the aggregation step in the pipeline affects them in different ways, thus exposing different problems.

Sub-tables We create supplementary tables derived from the Wordnet seed tables to augment the table count in the data lake with two different methods. In real-life lakes, numerous versions or variants of the same table are common, encompassing collections of tables that undergo slight modifications over time (Halevy et al., 2016). This redundancy poses a challenge for information retrieval methods in distinguishing between pertinent and extraneous tables. Hence, it constitutes a crucial aspect in a benchmark data lake like YADL, which incorporates it heavily in the generation of sub-tables.

For YADL Base, we generate all combinations of arity 2 and 3 for each seed table. For Table 4, these combinations would include "(isLocatedIn_1, owns_1)", "(owns_1, popDensity)", and "(isLocatedIn_1, owns_1, popDensity)". Each sub-table is then built by projecting the seed table over the generated combination; we retain rows that contain at least one non-null value and drop sub-tables with fewer than 100 rows. For YADL 10k and 50k, we drop all seed tables whose arity is lower than a minimum arity A; then, for each surviving seed table T, we generate N sub-tables by sampling a random subset of columns of size $[A-2, A]$ and projecting onto T; each parameter can be tweaked to modify the size and number of resulting sub-tables. Row-wise redundancy is provided by randomly sub-sampling a fraction p of each resulting sub-table n_s more times, thus replicating a fraction of the samples while keeping the set of columns fixed. We construct YADL 10k and YADL 50k by setting N to 10 and 50 respectively, $A = 8$, $p = 0.7$, and $n_s = 2$.

B Detailed description of the tested methods

B.1 Retrieval

Exact Matching We compute *Exact Matching* (Exact) by measuring the exact Jaccard containment for each pair (query column, candidate column) in the data lake. This can be implemented efficiently by first building a "vocabulary" on the query column, and then scanning the whole data lake to compute containment. Candidates are ranked by highest containment, then we select the "top-k" candidates in the pool. An advantage of this method is that computing the containment is an embarrassingly parallel operation.

The main drawback of Exact Matching is the computation, whose cost depends directly on the size of the data lake and the tables therein; furthermore, the operation must be repeated for every new query column. As we show in Figure 5, the cost of querying multiple columns quickly adds up. Another drawback is that containment is less reliable if the data lake features a lot of redundancy (e.g., YADL 50k in Figure 8), since unrelated tables may still feature high containment: this problem may occur if the data lake includes multiple variants of the same table, a setting commonly occurring in industry (Halevy et al., 2016). An additional drawback of Jaccard containment is that it does not consider cardinality, so that binary tables would be considered as perfect matches while being useless in practice.

MinHashLSHEnsemble (MinHash) *MinHash* (Zhu et al., 2016) relies on Locality Sensitive Hashing (LSH) to build an index subject to a user-set minimum containment threshold. At query time, all candidate columns with estimated containment larger than the threshold are returned. For consistency with the other methods, we select k candidates from this pool.

The main drawback of MinHash is that it does not feature an inherent ordering of candidates. Moreover, since MinHash returns an approximate result, it may happen that candidates with an actual containment lower than the threshold are returned as False Positives. Under tight constraints, no ordering and False Positives reduce the likelihood of retrieving good candidates (Figure 18). Finally, while the index can be updated when new data is added to the data lake, performance may deteriorate after a certain level of updates, especially depending on the skew of the new data.

Hybrid MinHash To address Minhash's lack of a candidate ranking, we propose Hybrid MinHash. *Hybrid MinHash* leverages the prebuilt index from MinHash to find candidates for a given query column, then uses Exact Matching to rank all candidates. The "top-k" candidates are then selected from the ranked list. By measuring the containment over the MinHash query result, the pool of candidates is reduced compared to testing all columns in the data lake (like with Exact Matching).

Just as it takes some of the strong suits of both MinHash and Exact, Hybrid MinHash also shares some of their disadvantages: 1) The MinHash index will degrade each time it is updated. 2) As the first filtering relies on the MinHash results, False Positives increase cost and any candidate missed by MinHash is lost. 3) Re-ranking candidates by calculating the exact containment increases the query time substantially with respect to MinHash (Table 10).

Starmie We compare the simple methods described so far against Starmie (Fan et al., 2023b), a SOTA system for table unionability and join discovery. Starmie employs a contrastive learning method to train column encoders from pre-trained language models to capture contextual information within tables. Starmie performs candidate retrieval by building embeddings for each column in the data lake and for the query column; it then ranks candidates according to the equation:

$$S_{Starmie} \;=\; |Q \cap C_k^i| \cdot S_C(vec(Q), vec(C_k^i))$$

where S_C is the cosine similarity between the embeddings of the query column Q and candidate C_k^i.

B.2 Selection

Each selector receives as input a pool of "K" candidates from a given retrieval method on a given data lake, the train and test splits of the base table, and the aggregation method to use. The train split is further split into a training (0.8) and validation set (0.2). The model is trained on the final *integrated* table (i.e., the base table joined with the candidates) produced by the selector of this training split, then the result is scored with the test split.

The reference selector is **No Join**, where the ML model is trained directly on the training split of the base table.

Highest Containment Join ranks candidates by exact containment, after measuring it for each candidate. The top-1 candidate is joined; ties are broken by taking one candidate at random.

Best Single Join iterates over each candidate one at a time, performs the aggregation and join, then trains an ML model on the joined table. The candidate with the highest model performance on the validation split is selected and joined.

Top-k Full Join aggregates and joins the first k candidates as ranked by a retrieval method, without performing any re-ranking.

Full Join aggregates and joins all candidates from the pool.

Stepwise Greedy Join aims to add more information than what is available in a single table, while reducing the amount of noise added by joining irrelevant tables. The baseline performance is measured by training a model on the base table's training split and validating on the validation split; candidates are re-ranked by their containment before iterating over each of them. During each iteration, the candidate is aggregated and merged separately with each of the two splits of the current table; a new model is trained on the training split and validated on the validation split. If the performance improves compared to the previous iteration, the newly joined table becomes the new current table, otherwise the candidate is discarded.

Highest Containment and Best Single Join produce smaller integrated tables as they only join *one* candidate, rather than *all* potential candidates like Full Join and Stepwise Greedy Join: we can therefore classify the two pairs as **single-table selectors** and **multi-table selectors** respectively. Top-k Full Join can be assigned to either class depending on the value of k.

In all selectors that involve a join, aggregation is carried out prior to executing the join itself. In our pipeline, aggregation is carried out before executing any join by grouping the "right table" by the join key, then

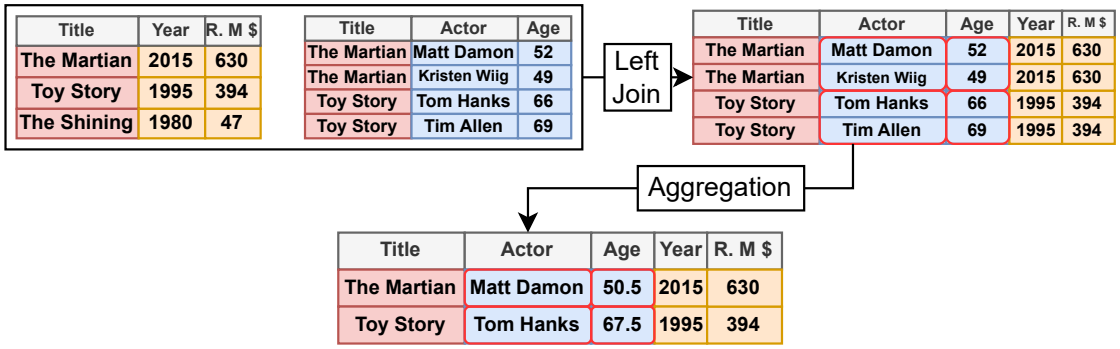

Figure 7: Example of how a left join would duplicate rows from the base table.

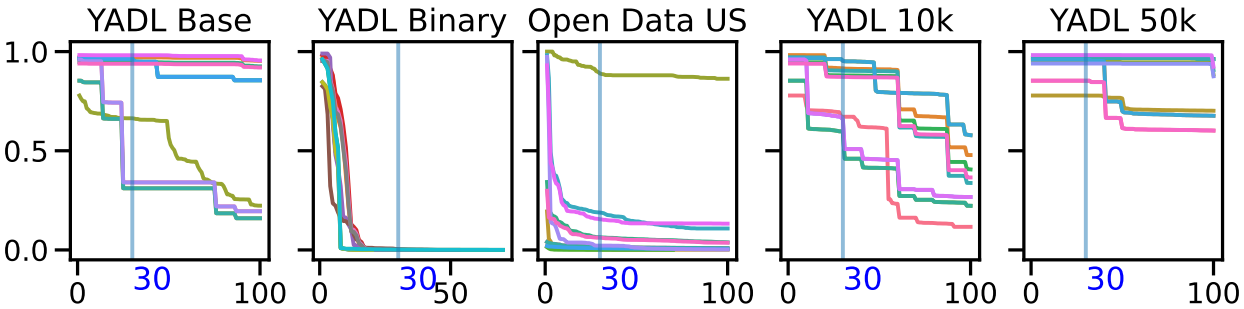

Figure 8: Exact containment measured over the top 100 join candidates for each base table (represented by a colored line) on each data lake. The x-axis reports the rank, rank 30 is the retrieval cutoff we use in our experiments.

applying one of the aggregation functions described above. This is to avoid materializing large joins, which have a huge cost in memory and time. Due to how aggregation is carried out, the final result is the same before and after the join , so executing it before materializing the joined table is more efficient.

All join selectors follow the fit-predict paradigm proposed by scikit-learn (Pedregosa et al., 2011), which simplifies extending the pipeline with new selectors.

B.3 Aggregation

When joining tables for a downstream machine learning task, one-to-many relationships must be aggregated to avoid replicating samples in the base table which would modify the initial data sampling.

Following the example in Figure 7, a join on "Title" leads to the duplication of the two first rows in the base table, as both title values appear in two rows of the candidate table. How should we aggregate the rows to obtain the best prediction over the column "Revenue"? We test three different aggregation strategies:

1. **Any** selects one row from each group, without considering the order.
2. **Mean** replaces all numerical (categorical) values by the mean (most frequent) of all values for that attribute.
3. **DFS** (Deep Feature Synthesis (Kanter & Veeramachaneni, 2015)) greedily adds new features by performing different aggregations (mean, median, count, standard deviation, etc.) over each column in the table.

C Experimental results

C.1 Choosing which baselines to use

Including recent publications often turned out to be very difficult, as the code was either unavailable, or not suited to extensive experiments on a data lake of the size that we investigate in our work. We worked on including Starmie (Fan et al., 2023b), and (partially) Lazo (Fernandez et al., 2019). We were able to test Starmie on some of the data lakes (Binary, YADL Base, YADL 10k) though we did have to adapt and optimize certain sections of the discovery code that did not scale well to our environment. We were unable to run Starmie on the larger YADL 50k, and the less structured Open Data US. Starmie results are illustrated in Section 5. The modified Starmie repository is available here: `https://anonymous.4open.science/r/starmie-50F1/README.md`, and we are contributing it upstream. These modifications are code optimizations and fixes for corner cases; they do not change the logic of Starmie.

Lazo relies on a client-server architecture that requires Elasticsearch v7. We were able to set up the backend environment and integrate the Lazo client in our pipeline, but we are unable to execute querying operations on our data lakes because the client database crashes due to out of memory errors. The wrappers we developed for testing Lazo are available in the main repository (`https://anonymous.4open.science/r/retrieve-merge-predict-6B4E`).

Additionally, for the retrieval step we considered ALITE (Khatiwada et al., 2022), KOIOS (Mundra et al., 2023), JOSIE (Zhu et al., 2019), and Saibot (Huang et al., 2023a). Each method requires substantial changes to the original codebase or very specific build configurations to run on datasets and environments different from those included in the original paper.

For the prediction pipeline, we consider ARDA (Chepurko et al., 2020) and Metam (Galhotra et al., 2023), focusing on Metam as it builds upon ARDA. Similarly to the retrieval case, Metam required substantial changes to be executed on data other than that in the paper and when tested in our environment it did not produce augmented tables. We implement some of the solutions suggested by Metam in our Stepwise Greedy Join selector, and we re-use the "Open Data US" data lake and "schools" base table in our experimental section. The modifications we made to the Metam code to interact with our pipeline are available at `https://anonymous.4open.science/r/metam-B273/README.md`.

We were not able to find an open repository for SilkMoth (Deng et al., 2017b), DeepJoin (Dong et al., 2023), Mileena (Huang et al., 2023b), or Kitana (Huang et al., 2023c).

C.2 Experimental setup

We run our experimental campaign on a SLURM cluster, fixing the number of threads to 32. Nodes have at least 256GB of RAM. Experiments that involved NNs were run on nodes equipped with GPUs. Overall, preparing the retrieval methods required about 1050 CPU hours, while the experimental results required about 189k compute hours (about 21 years of equivalent CPU time); CatBoost and RidgeCV were run on CPU, ResNet and RealMLP on GPU. Table 7 reports the equivalent CPU (GPU) time across all experiments, broken by ML model; running experiments with 32 CPUs would reduce this runtime by about 32x.

Table 7: **Total equivalent compute hours, days, months and years required to run all the experiments. Single-CPU or single-GPU equivalent time: having a 32-CPU computer divides the time by 32.**

Predictor	Platform	Total compute time
RidgeCV	CPU	4y 3m 10d 7h
CatBoost	CPU	1y 3m 29d 21h
ResNet	GPU	5y 6m 23d 0h
RealMLP	GPU	10y 7m 23d 3h
Total	Both	21y 9m 26d 8h

Implementation details The implementation of the pipeline is in Python[8]; Exact Matching, aggregation and join operations are implemented using Polars (Vink et al., 2024) as backend. For the Prediction step, RidgeCV is implemented with Scikit-

[8]Repository: `https://anonymous.4open.science/r/retrieve-merge-predict-6B4E`

Table 6: Recorded peak RAM usage for building and querying the different retrieval methods. All sizes are reported in MB. Runs that failed are marked as "NA".

Case	Data Lake Version	Exact Matching	Minhash	Minhash Hybrid	Starmie
Disk	Binary	0.0	1.4	1.4	501.1
	Open Data US	12.7	434	434	NA
	YADL 10k	21.3	515	515	522.3
	YADL 50k	28.2	2480	2480	NA
	YADL base	21.3	462	462	522.4
RAM Build	Binary	1196	226	226	19424
	Open Data US	5466	3288	3286	NA
	YADL 10k	688	3312	3290	87716
	YADL 50k	1259	13697	13697	NA
	YADL base	1061	2810	2810	38683
RAM Query	Binary	255	216	216	4567
	Open Data US	384	7789	10472	NA
	YADL 10k	388	9138	12679	134869
	YADL 50k	781	37332	37327	NA
	YADL base	412	6784	8541	145437

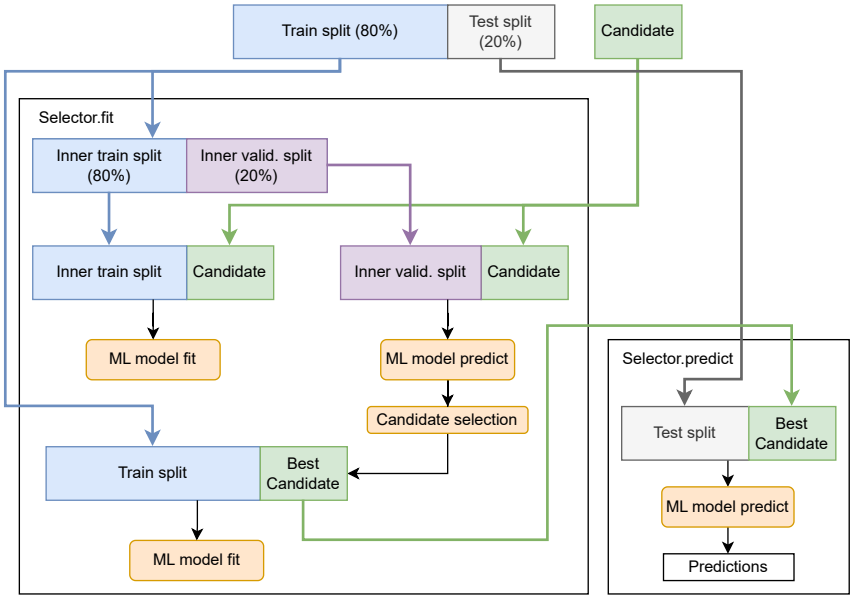

Figure 9: Schema of the cross-validation setup used in the training pipeline.

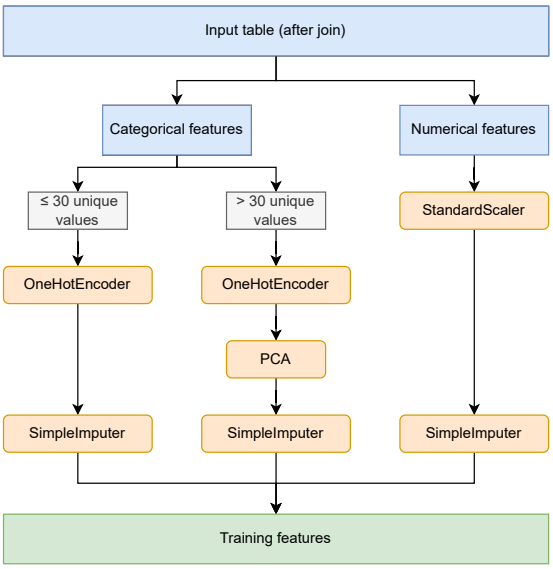

Figure 10: Pre-processing steps applied to input tables before being fed to the ML algorithms.

learn (Pedregosa et al., 2011), CatBoost using the official library
(Prokhorenkova et al., 2018), ResNet and RealMLP use pytabkit (Holzmüller et al., 2024).

We rely on the Python implementation of MinHash provided by the Datasketch package (Zhu et al., 2023). For Starmie, we optimize the original implementation so it can scale to work in our environment. We use the official DFS package. Data structures are stored by persisting on disk the ensembles for MinHash, the candidate ranking for each query column for Exact Matching, and the model checkpoints for Starmie; Hybrid MinHash relies on the MinHash data structures to work, so no additional storage is required for it.

Table 6 reports the size on disk of the data structures used for each method.

Retrieval We use a containment threshold of 0.2 for the preparation of the MinHash index, and clamp the number of candidates returned by each retrieval method to 30. These values were chosen to balance execution time and expected number of candidates given the distribution of containment encountered in the different data lakes (Figure 8). For Starmie, we use the default parameters defined in the original repository.

Selection We fix the number of Stepwise Greedy Join iterations to 30: this number is consistent with the number of candidates that are provided in the retrieval step. None of the other join selectors have parameters to tweak.

Prediction We fix the number of CatBoost iterations to 300; we stop training the model 10 iterations after the optimal metric has been detected; we set the L2 regularization coefficient to 0.01. As we are interested in evaluating the effect of each pipeline task rather than optimizing the prediction performance, we do not apply HPO to CatBoost.

We use the default parameters for RidgeCV as used in the scikit-learn implementation.

For RealMLP and ResNet we use the parameters that are set in the pytabkit package as they have been shown in Holzmüller et al. (2024) to be the "better defaults".

Table 8: **Aggregated prediction results broken by base table and data lake**. Starmie results are not reported here because it could not run on Open Data US and YADL 50k. As many ResNet and RidgeCV runs did not converge, we report a trimmed mean with cutoff 0.2.

Base Table	Binary	YADL Base	YADL 10k	YADL 50k	Open Data US
Company Employees	0.086 ± 0.036	0.081 ± 0.043	0.071 ± 0.052	0.113 ± 0.048	0.011 ± 0.019
Housing Prices	0.16 ± 0.068	0.187 ± 0.077	0.143 ± 0.074	0.199 ± 0.092	0.221 ± 0.09
Schools	NA	NA	NA	NA	0.892 ± 0.137
2021 US Accidents	0.138 ± 0.065	0.178 ± 0.054	0.199 ± 0.076	0.150 ± 0.058	0.229 ± 0.028
US County Population	0.725 ± 0.203	0.078 ± 0.064	0.075 ± 0.074	0.112 ± 0.148	NA
2020 US Elections	0.374 ± 0.062	0.373 ± 0.115	0.358 ± 0.054	0.394 ± 0.045	0.400 ± 0.06

C.3 Critical difference plot

We use critical difference plots to represent an overall ranking of the downstream prediction performance of all the configurations we considered. Specifically, the prediction metric is averaged over all base tables and data lakes, and the resulting value is used to rank each configuration.

Similarly to Figure 2 (and other Pareto plots), we present the same results after splitting them in retrieval method (Figure 11), join selector (Figure 12), and ML model (Figure 13).

C.4 Aggregated results

Figure 14 is prepared like Figure 2, however this version includes results from all data lakes and does not include Starmie as it could not run on Open Data and YADL 50k. Results are quite consistent with Figure 2: this means that the new data lakes (YADL 50k and Open Data US) do not alter the overall trends much.

In Figure 17 we report the fold vs fold difference in prediction score (R^2 and AUC) and relative execution time with respect to the reference configuration (Exact Matching, Best Single Join, aggregation Any and CatBoost) for retrieval (Figure 17 (a)), selection (Figure 17b), aggregation (Figure 17c), and prediction (Figure 17d). Individual folds are reported as dots; color palettes depend on the data lake. This is an alternative way of representing the data in Table 3. Note that as we are comparing folds against folds, the difference is 0 when a particular parameter is the same as the reference. We choose Best Single Join as a reference for the selector because DFS could not run with Full Join and Stepwise Greedy Join.

Retrieval Figure 17(a) shows that Exact Matching and Starmie have very similar performance (a median difference of 0.06%), with Starmie outperforming Exact Matching in some instances (this can also be observed in Figure 2 and Figure 11), which makes sense as the similarity metric used by Starmie combines Jaccard similarity with the cosine similarity of column embeddings. Base MinHash performs very poorly, with a median difference of -17.48% with respect to Exact Matching. This is not surprising and is likely caused by the lack of a candidate ranking combined with the presence of a candidate budget. Hybrid MinHash shows a marked improvement over base MinHash, gaining about 14% in median: this confirms that it is an effective strategy to address some of the shortcomings of the base method.

MinHash is faster than the others, despite the fact that the candidate budget k is 30 for all methods. This is because, on average, the candidates retrieved by MinHash have a much lower containment than those proposed by the other methods (Figure 3a): due to the smaller amount of data to move and use for training the models, the runtime is shorter; furthermore, imperfect recall affects the performance of both MinHash and its hybrid variant.

While Hybrid MinHash appears to be faster than Exact Matching in the pipeline, it is important to note that re-ranking candidates incurs a non-negligible additional cost (Figure 17(a), Table 10).

Overall, the two methods based on precise ranking (Exact Matching and Starmie) outperform the methods based in approximate matching (MinHash and Hybrid MinHash), suggesting that the computational cost incurred in measuring exact containment does result in better prediction performance.

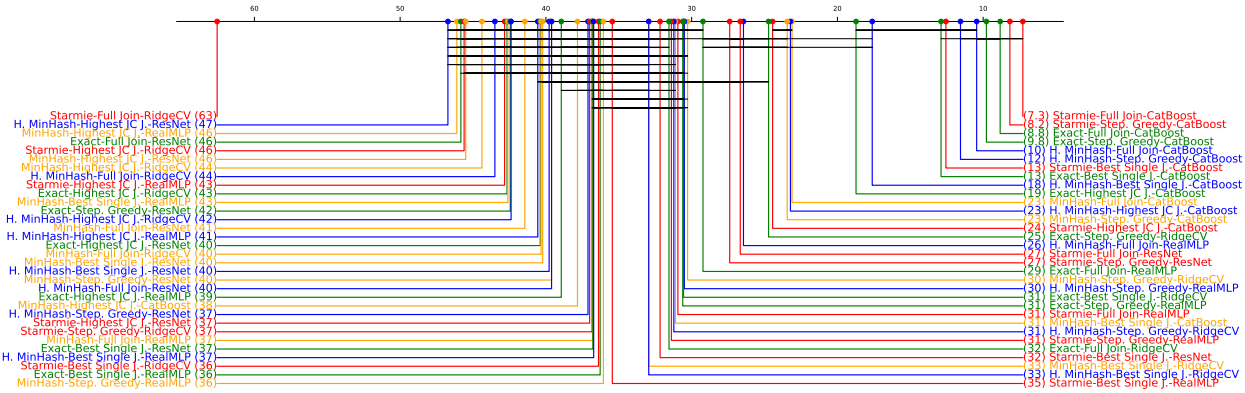

Figure 11: Critical difference plot for the retrieval methods: Exact Matching, MinHash, Starmie, Hybrid MinHash.

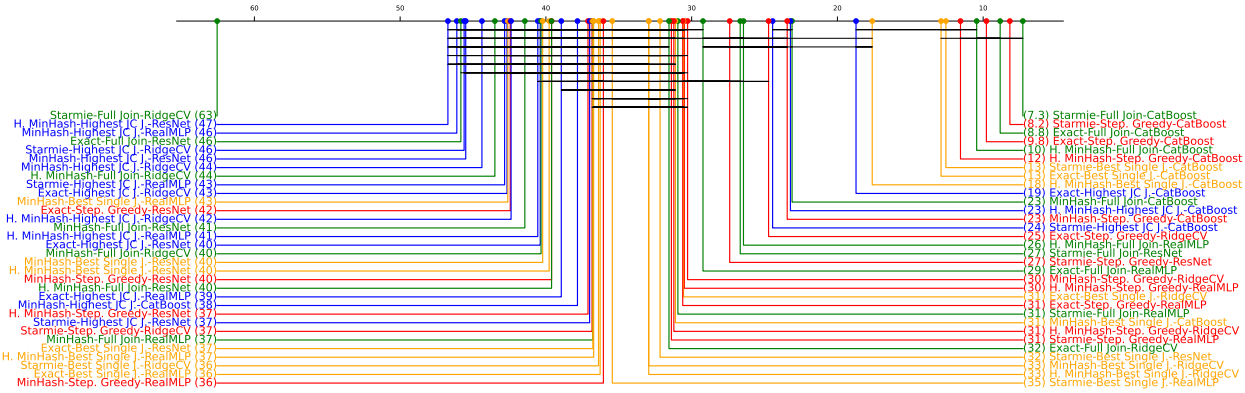

Figure 12: Critical difference plot for the join selectors: Full Join, Stepwise Greedy Join, Highest Containment Join, Best Single Join.

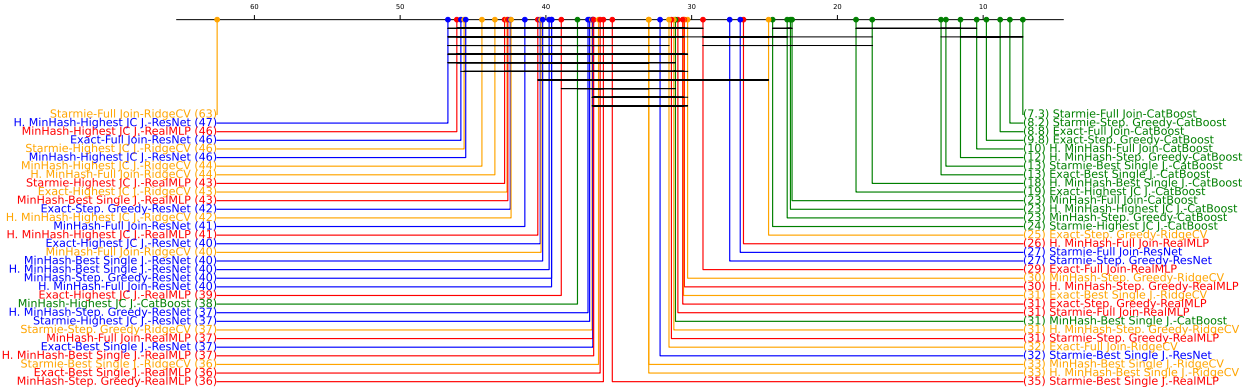

Figure 13: Critical difference plot for the predictors: CatBoost, RidgeCV, RealMLP, ResNet.

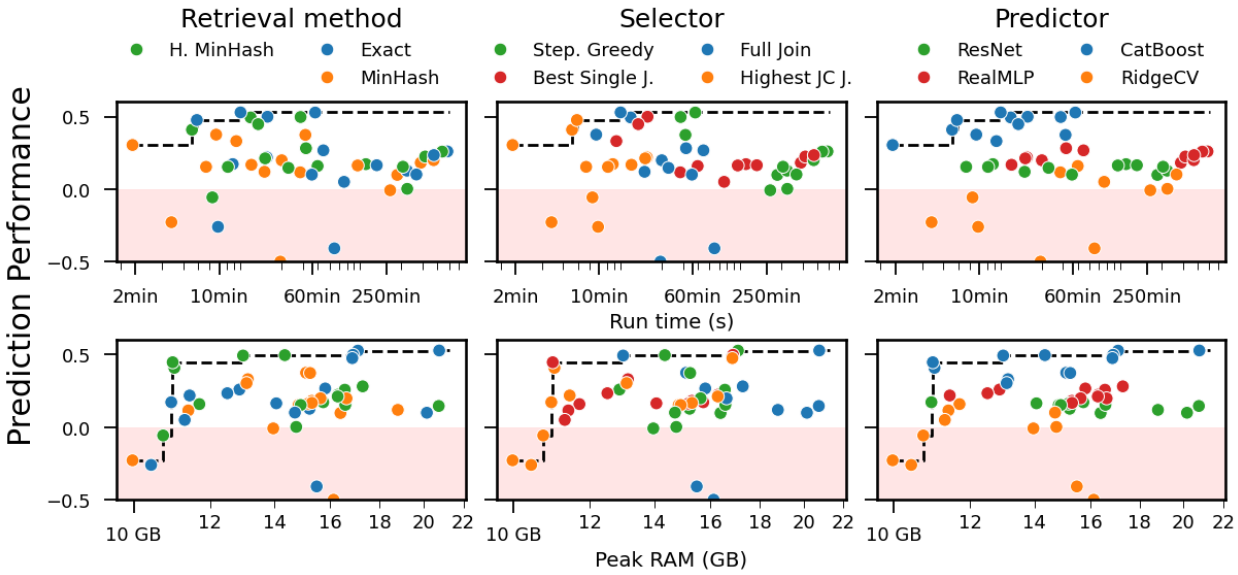

Figure 14: **Pareto frontier analysis for the pipeline steps.**

Selection The choice of selector shows a clear effect when moving from single-table selectors (Highest Containment and Best Single Join) to multi-table selectors (Stepwise Greedy and Full Join), bringing a benefit of up to 2.2% in median (Figure 17(b)).

Stepwise Greedy Join is much slower compared to all other methods. This is not surprising, since this selector executes a join and trains a model in each iteration, then re-trains the model at the end of the fit step. In practice, while this added complexity brings an improvement of about 1.6% with respect to Best Single Join, this comes at the cost of a 2.9x increase in run time; even worse, this does not achieve the best performance as Full Join is both faster and slightly better in prediction performance. Highest Containment is significantly faster than all other solutions because it only re-ranks candidates before joining the top-1 candidate.

The difference in performance between the two single-table selectors (Best Single Join and Highest Containment) is likely due to the fact that, while Jaccard Containment is an indicator of a potentially good join, it is not sufficient for selecting the best candidate. For example, multiple candidates may have the same containment value, leading to ties. Given the lack of better information, Highest Containment breaks ties at random, thus it may select tables that are not relevant. Redundant data lakes like YADL 50k (Figure 8) are more affected by this problem. The significant difference between single- and multi-table selectors is explained by the learning model benefiting from an increased set of features: merging more than one table inherently results in a richer feature set.

An important observation is that all selectors rely on the candidates proposed by a retrieval method: if these candidates have poor quality, the selectors cannot compensate for that.

Aggregation Aggregation experiments do not include Full Join and Stepwise Greedy Join because DFS ran out of resources with those selectors. In fact, while DFS brings some benefit in its generation of new features (up to 2.46% in median wrt Any), it is also extremely slow (up to 6x wrt the simpler method), and this was in a simpler case where only one table was joined at a time. With multi-table selectors, this problem became even more noticeable and prevented us from testing the multi-table selectors. This very large memory cost is consistent with Cvetkov-Iliev et al. (2023).

For what concerns the simpler methods, Mean is slightly better than Any, and has a slightly longer runtime; we did not observe major differences between the two methods in practice.

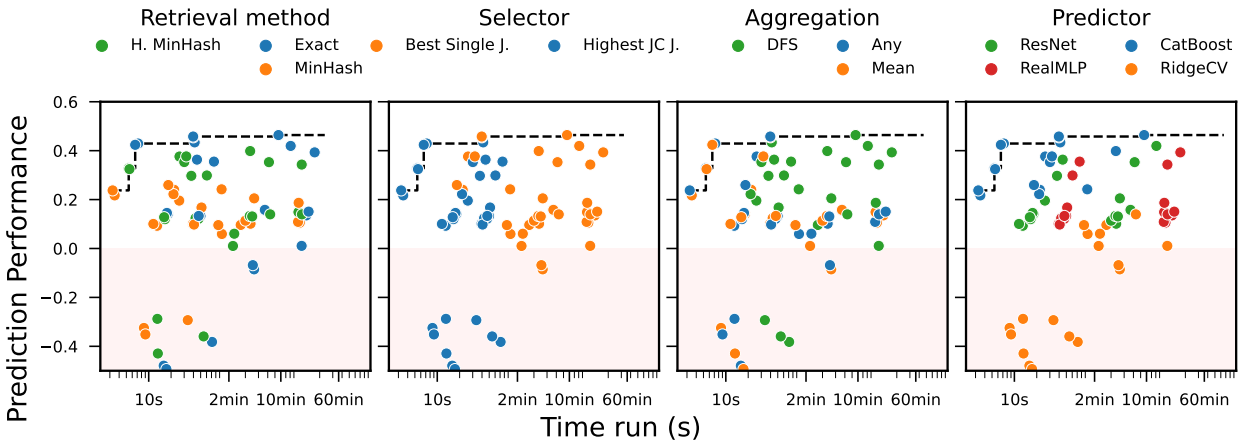

Figure 15: Aggregation trade-offs relative to run time.

Predictor The performance difference between CatBoost and all other methods already highlighted in Figure 2 and Figure 13 is confirmed in Figure 17(d), which shows CatBoost outperforming the second best model in RealMLP by about 21.2%, and the worse NN model in RidgeCV by 26%. Interestingly, CatBoost is also *faster* than all other methods by a significant amount, likely owing to the optimized preprocessing of categorical variables. RealMLP is the better performing NN model, and has shown a good resilience in the very challenging environment that we are considering; however, it is much slower than all other methods, even when run on GPUs, requiring up to 32x as much time as CatBoost.

Different Lakes Table 8 reports the trimmed average of the prediction performance across all configurations, broken by base table and data lake. We observe experimentally that many RidgeCV and ResNet runs do not converge, leading to very long run times and extremely large negative values for R^2. For this reason, we use a trimmed mean with a cutoff of 0.2. Indeed, the results are so poor because the mean across predictors is lowered substantially by the performance of the parametric models. Internal tables could were only run on the data lake they were sampled from, and other cells are reported as "NA".

Despite its lower containment compared to YADL-based data lakes (Figure 3a and Figure 8), Open Data US shows good results, outperforming the YADL variants in some cases: this may be due to the smaller fraction of nulls, and larger tables on average compared to YADL.

Prediction performance was particularly good on US demographic-adjacent tables, and on the internal dataset "Schools", which achieved perfect classification performance in most cases – also visible in Figure 3b, where highest containment leads to best performance.

YADL's internal table (US County Population) exhibits a similar, though not quite as extreme, behavior to that of Schools. This can be explained by the fact that internal tables, i.e., tables that are sampled from the data lake itself, tend to have copies in the data lake, which are likely to contain information that is correlated with the prediction task. This highlights the specific behavior of internal tables, which are routinely used in the experimental campaigns in the literature.

The different prediction performance obtained with each YADL variant suggest that the structure of each data lake impacts the actual prediction performance.

C.5 Smart aggregation brings some benefit at a major cost

While containment impacts heavily both prediction performance and execution time, aggregation has a similar impact on the execution time, without the same degree of improvement for the prediction performance (Figure 17c).

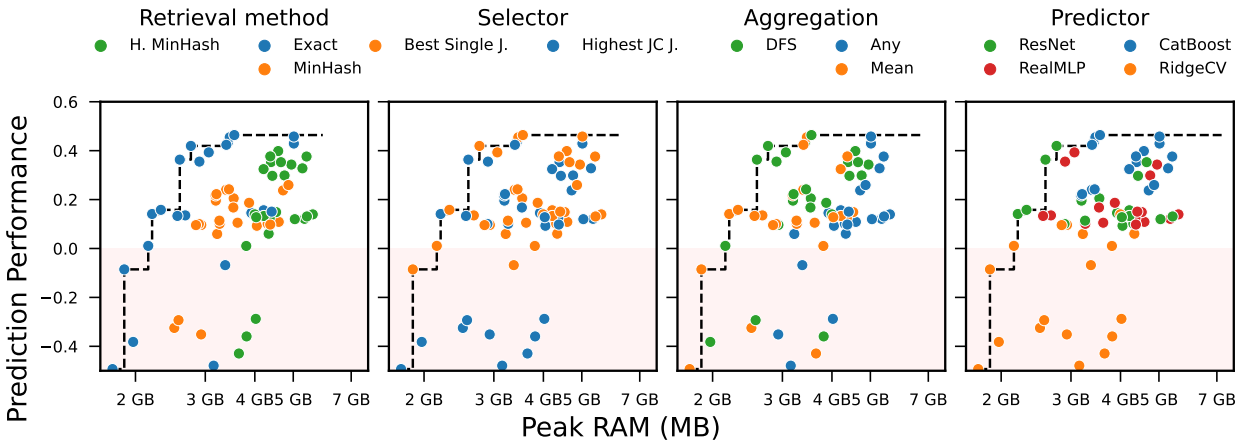

Figure 16: Aggregation trade-offs relative to peak RAM.

Aggregating values always leads to a loss of information: in exchange for a larger cost, complex aggregation methods that preserve more information (DFS) or that replace values with better representatives of a group (mean) should lead to better prediction performance. To an extent, this is what we observe: DFS does improve the downstream performance by a decent amount, however this is at a major computational cost. This problem is exacerbated by the fact that aggregation must be performed whenever a join is executed *at any point in the pipeline*, including joins executed during join selection. The result is a compounding slow-down of the entire pipeline.

The similar performance of "any" and "mean" can be explained by the execution of joins on key-like columns so that values in these columns tend to be mostly distinct, thus producing the same aggregated value for both "mean" and "any". The slight difference in performance and runtime between the two methods may be attributed to the large fraction of missing values in some of the data lakes: the "mean" method is biased towards selecting the most frequent value, which may be a null. When that happens, more values than needed become nulls, reducing the amount of features and introducing a slight speedup in the overall training.

The relatively unsatisfying performance of DFS is also explained by the fact that we are not fully exploiting its capabilities. We consider only join depth-1 chains: at each aggregation step, we join the base table with an additional table, rather than leveraging the recursive generation of features provided by DFS. As a result, DFS is not as effective at generating features as it would be with deeper join paths (Cvetkov-Iliev et al., 2023) and may benefit from integrating join path discovery systems (Deng et al., 2017a).

Figure Figure 15 and Figure 16 confirm that, while DFS improves the prediction performance, its overall cost remains problematic.

C.6 Distribution of the containment for each retrieval method

To understand the success of the different retrieval methods, we look at the containment of the joins that they suggest. Figure 18 reports top-200 containment. It highlights that, even when retrieving a large number (200) of candidates, the average containment of MinHash is very low compared to the other methods: for larger datasets, MinHash returns thousands of candidates of which only a fraction are selected. The lack of an internal ordering means that high-containment candidates are likely to be missed (Section 4). While MinHash has a threshold that can be tweaked to reduce the number of candidates that are retrieved, we observe that recall drops sharply at high thresholds. Hybrid Minhash has some success in mitigating the problem, as it improves the average containment and the overall downstream performance (Figure 2 left). [9] We were unable to obtain the containment results for Starmie on YADL 50k and Open Data US.

[9]The performance of MinHash on Binary is an artefact: the method could only retrieve about 6 candidates on average compared to the 30 found by the other two methods, thus values are averaged across fewer candidates with higher containment.

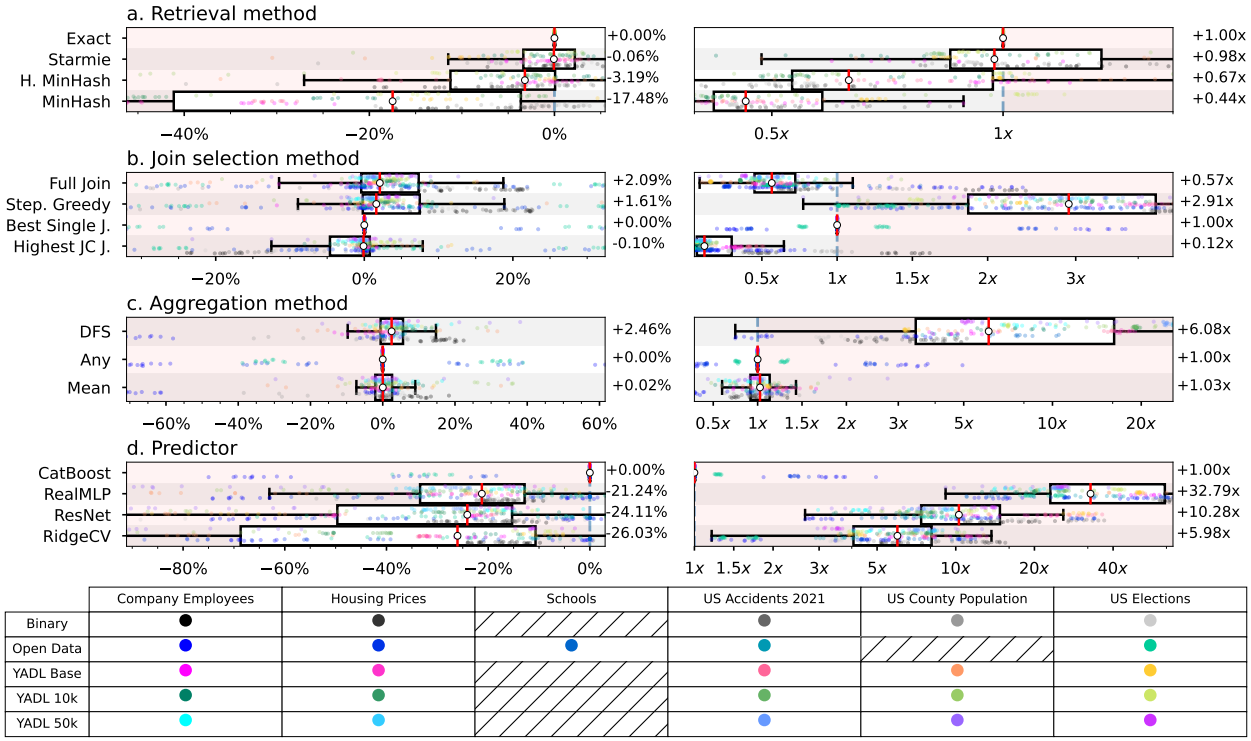

Figure 17: Experimental results across all data lakes, comparing the performance difference between evaluated methods in different steps of the pipeline. The median difference is reported on the right of each plot. (a) compares join selectors, (b) aggregation methods, and (c) ML models. In all cases, results are relative to the "average method". Starmie results are not reported in this plot as we could not run it on the larger data lakes.

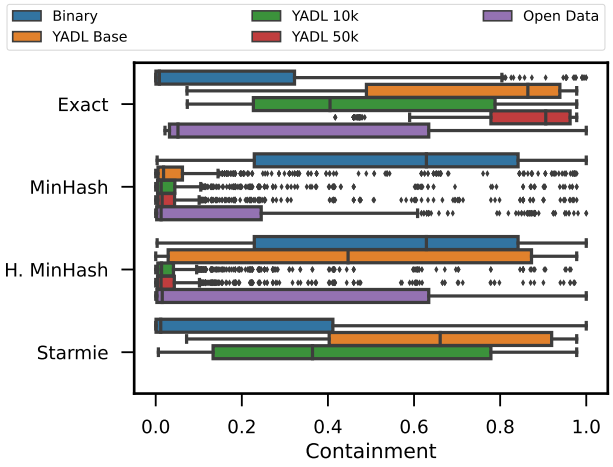

Figure 18: Distribution of containment in the top-200 candidates obtained by each retrieval method on different data lakes.

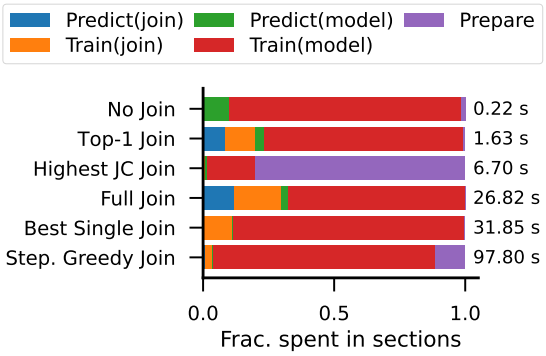

Figure 19: Breakdown of where time is spent for each selector. On the right we report the average run time of each selector.

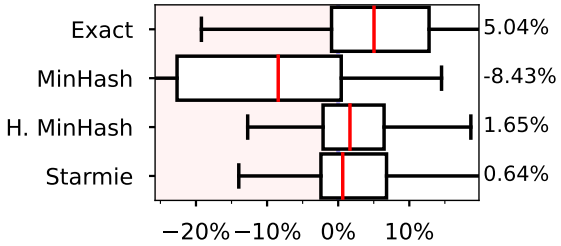

Figure 20: Relative prediction performance (median on the right) obtained selecting the (top-1) candidate according to the ranking provided by the retrieval methods. YADL 50k and Open Data are not included.

C.7 Execution time breakdown

Figure 19 breaks down where the time is spent by each join selector, with the corresponding average total time on the right. *Prepare* tracks the time spent building data structures (including any ranking operation), and loading data. *Train(model)* and *Predict(model)* track the time spent inside the ML model for training and prediction, respectively. Finally, *Train(join)* and *Predict(join)* track the time spent executing a merge operation, combining join and aggregation. Results are aggregated over all experiments with "first" as aggregation. The time distribution follows our expectations: most of the time is spent fitting models, with time spent joining (and aggregating) in second place. Highest Containment Join spends a relatively long time in the "Prepare" step due to the need to re-rank candidates before joining: since the join and train steps involve only one table, they are faster in comparison. Stepwise Greedy Join has a similar re-ranking step, however training the models in each iteration dominates the other steps. Full Join merges all candidates at the same time, then trains a single model on the result: this explains how the fraction of time spent joining is larger than in other methods. Top-1 Full Join is a reference of how long it would take to simply join one candidate and train on that, without any additional operation: as expected, it is very fast.

C.8 Effectiveness of top-1 join with different retrieval methods

Figure 20 reports the prediction performance across different data lakes obtained by joining each base table on the top-1 candidate according to each retrieval method's internal ranking (here, Exact is equivalent to top-1 Highest Containment Join). Unsurprisingly, MinHash is far worse than all other methods (up to 13.5% in median) due to the lack of an inherent ordering, and budget constraints; Hybrid MinHash successfully mitigates some of the issues of MinHash, however the imperfect retrieval performance penalizes it. It appears that the first candidate retrieved by Starmie is not as good as what is selected by Exact Matching. We observe that the performance of Starmie drops on YADL 10k: this is likely due to the larger width of the candidate tables, which affects the cosine similarity, and thus worsens the ranking. However, the situation improves for multi-table selectors, suggesting that this issue is mitigated by selecting multiple candidates at once.

C.9 Trade-off

Figure 5 is prepared assuming that query retrieval time increases linearly with the size of a table and that the cost of creating the MinHash index is fixed for the data lake at hand; we use Table 10 as reference to build the figure. We observe that the MinHash indexing cost pays itself off after as few as three queries on average thanks to the fast query time; Hybrid MinHash requires more queries to break even due to its slower query time, yet it remains faster than Exact Matching when the number of query columns is larger. While the assumptions may not hold in general, the plot gives a reasonable estimate of the break-even points. Starmie

Table 9: Statistics for the base tables.

Base Table	Target	# Num. Att.	# Cat. Att.	# Rows
Company Employees	Number of Employees	2	7	3109
Housing Prices	House Price	3	7	22250
Movies	Movie Revenue	8	10	7397
Schools	School Class	4	3	1774
2021 US Accidents	Accidents by County	1	3	14850
US County Population	County Population	1	1	3059
2020 US Election Results	Vote % by County	3	6	22093

scales much worse than other methods as it has a much slower build and query time, and a much larger memory footprint (Figure 4, Table 6).

Although dependent on implementation, another factor that should be considered is the size on disk of the indices: the MinHash index occupies a much larger space on disk compared to the data required to hold the Exact matching ranking. Starmie needs to store model checkpoints, which occupy roughly 500MB regardless of the size of the base data lake (Table 6).

Table 10: **Average time required to prepare retrieval methods**. Build and query time are separate as index construction can be done offline.

Method	Avg. Index time	Avg. Query Time
Exact	-	826.4
MinHash	2107	2.92
H. MinHash	2107	473.0
Starmie	18196	512.4

Exhaustive computation of the containment is a net gain in performance at the expense of an execution time that increases quickly as the number of columns to query increases. This may not be a problem if the user is aware of which columns should be queried; if, instead, the user is trying to conduct an exhaustive search over all columns, a method such as MinHash should be favored. These observations are consistent with Zhu et al. (2019). Finally, in scenarios where the query table and the data lake do not change, query results can computed offline and reused; in these scenarios, the additional cost of Exact Matching would be less problematic. In situations where the data lake tends to evolve over time, methods that support updating the index such as Fernandez et al. (2019) or Fernandez et al. (2018) should be considered.

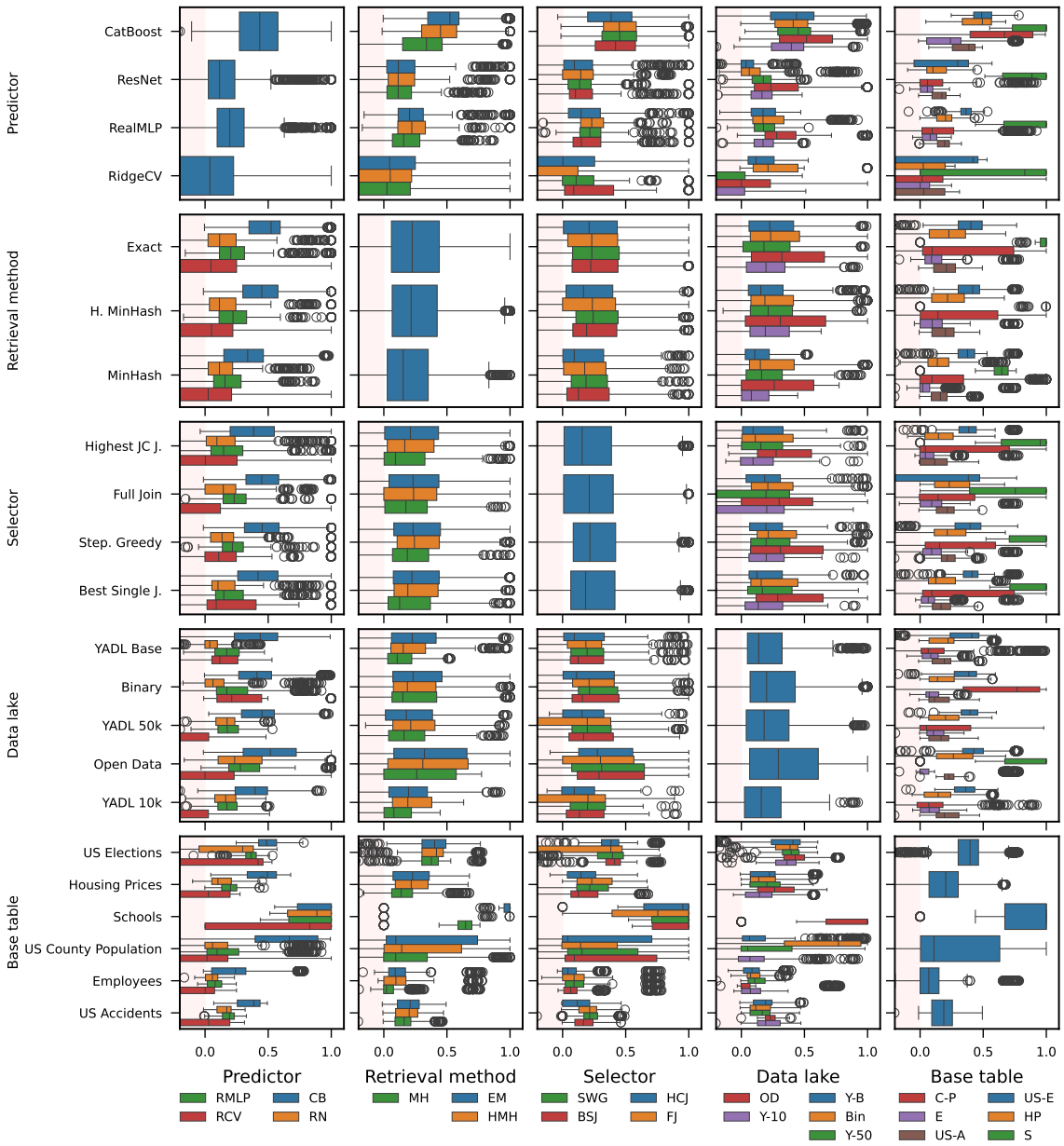

Figure 21: Effect of different variables on the (absolute) prediction performance. Each row reports one variable (e.g., Predictor) and breaks it down by another variable on each column (e.g., by Retrieval method). This plot does not include Starmie.

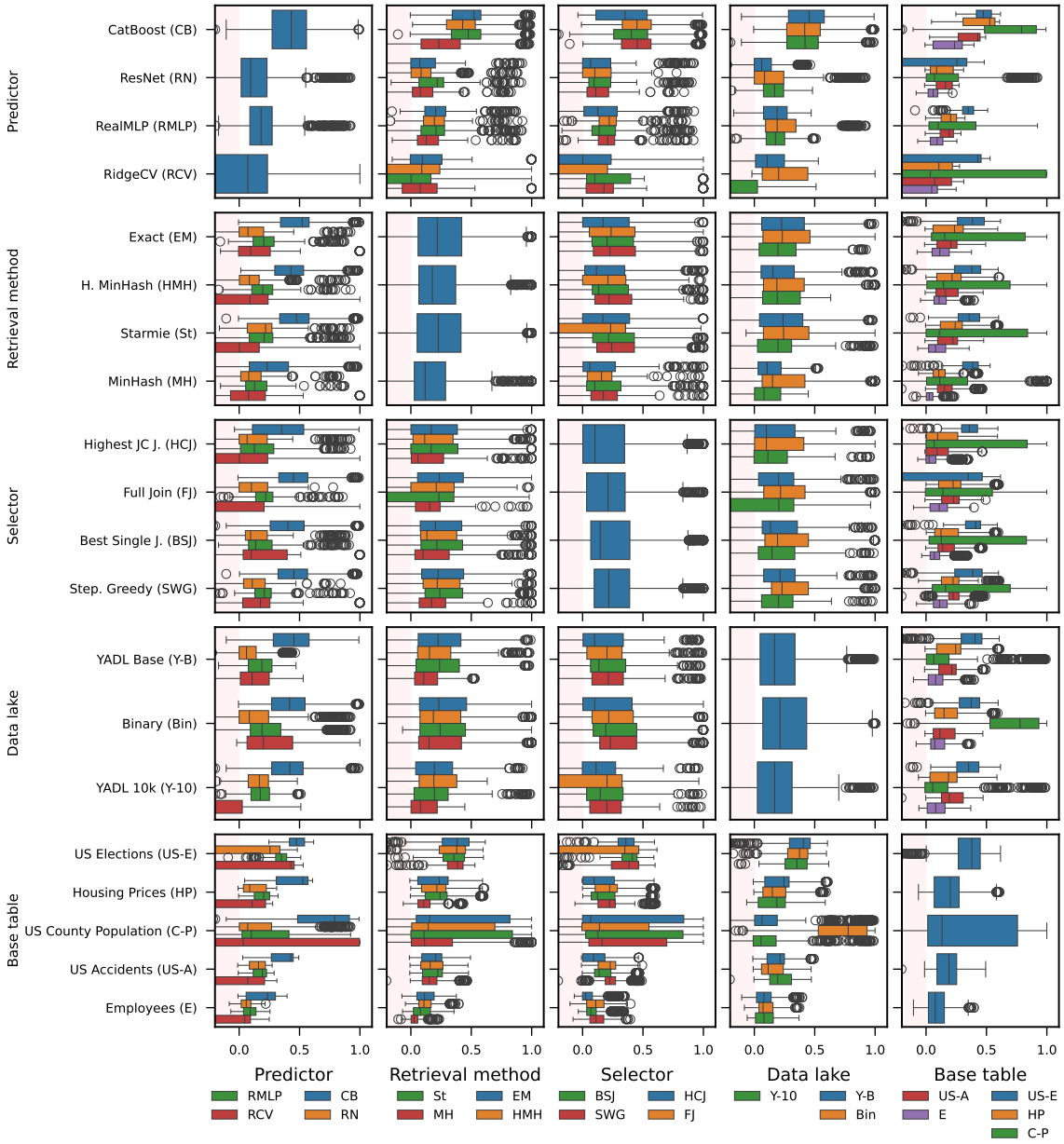

Figure 22: Effect of different variables on the (absolute) prediction performance. Each row reports one variable (e.g., Predictor) and breaks it down by another variable on each column (e.g., by Retrieval method). This plot does not include YADL50k and Open Data US.

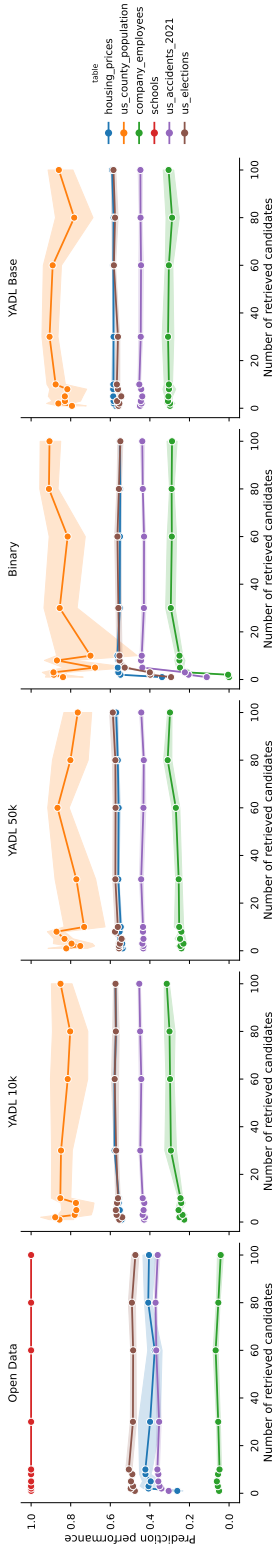

Figure 23: Prediction performance as a function of the number of candidates obtained in the retrieval step, broken by data lake.

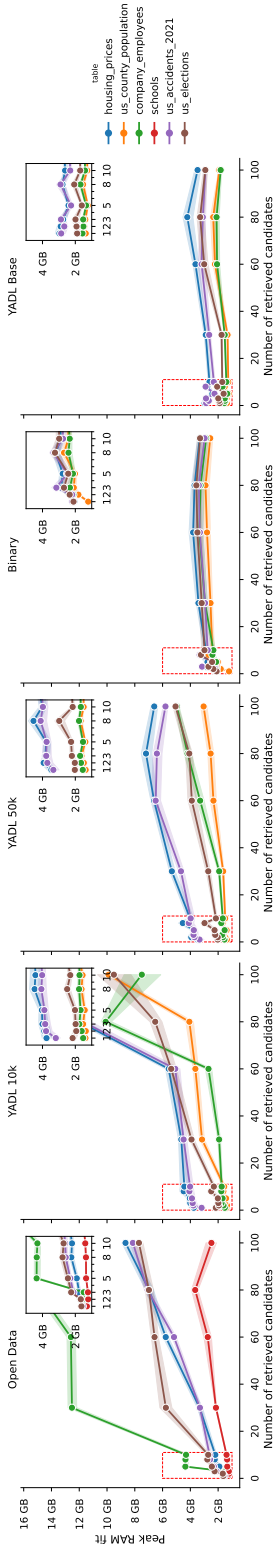

Figure 24: Peak RAM required at fit time as a function of the number of candidates obtained in the retrieval step, broken by data lake.

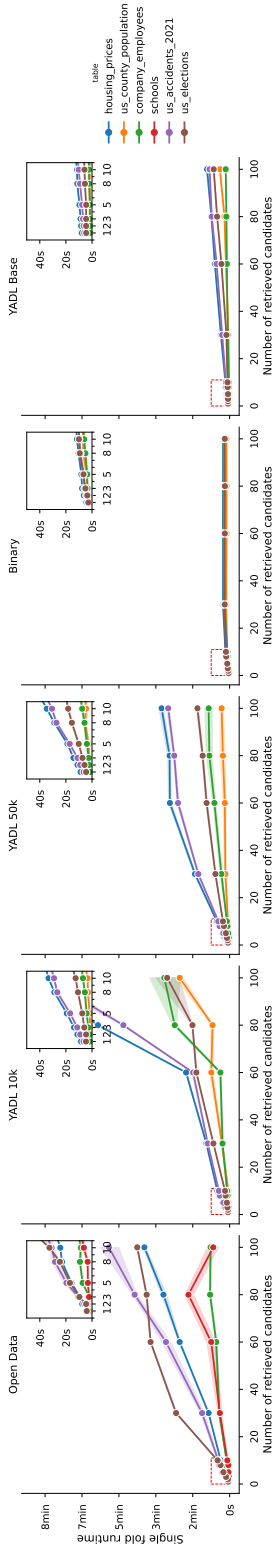

Figure 25: Fold runtime in seconds as a function of the number of candidates obtained in the retrieval step, broken by data lake.

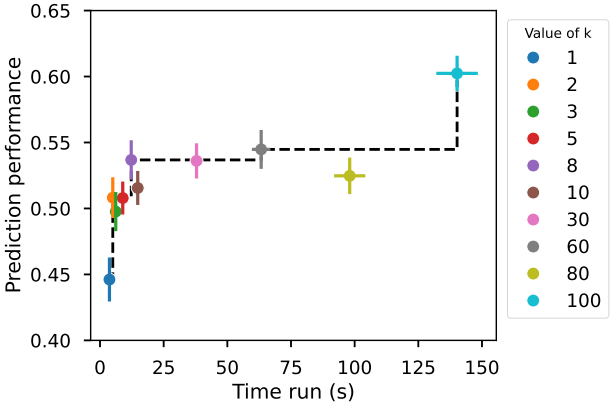

Figure 26: Pareto plot reporting the trade-off in prediction performance as the number of candidates increases for the Full Join selector. Results are averaged over all base tables and data lakes.