
LAKEGEN: A LLM-based Tabular Corpus Generator for Evaluating Dataset Discovery in Data Lakes

Zhenwei Dai

Amazon

zwdai@amazon.com

Chuan Lei

Amazon

chuanlei@amazon.com

Asterios Katsifodimos

Delft University of Technology

akatsifo@amazon.com

Xiao Qin

Amazon

drxqin@amazon.com

Christos Faloutsos

CMU

faloutso@amazon.com

Huzefa Rangwala

Amazon

rhuzefa@amazon.com

Abstract

How to generate a large, realistic set of tables along with joinability relationships, to stress-test dataset discovery methods? Dataset discovery methods aim to automatically identify related data assets in a data lake. The development and evaluation of such solutions for customers from a wide range of business domains, relies on diverse, high quality and domain-specific tabular benchmarks. Large language models (LLMs) are trained on a wide variety of text data, which can provide a strong foundation of general and domain-specific knowledge. In this paper, we ask the question – *can we leverage LLMs to generate a tabular benchmark adequate for evaluating the dataset discovery solutions?* In particular, we focus on the task of finding joinable tables which is the cornerstone of virtually every dataset discovery method. Current corpora for evaluating dataset discovery methods are mainly based on subsets of open data, and they suffer from three important issues: *i*) they focus on very common and generic data types (e.g., address, id, name, etc.); *ii*) they do not contain human-annotated column pairs; instead, practitioners synthesize ground truth using table splits (e.g., horizontal for table union search and vertical ones for joinability) and *iii*) they do not focus on semantic column relationships.

In this paper we present LAKEGEN, a method for creating and curating domain-specific datasets for training and evaluating dataset discovery methods, by using LLMs. LAKEGEN makes the following contributions: (a) **Novel**: it is the first to use ontologies, LLMs, as well as semantic perturbations for corpora generation. (b) **General**: we have used LAKEGEN to curate three corpora for diverse domains, including finance, pharma, and healthcare with minimal effort. (c) **Effective**: our experiments show that the generated domain-specific corpora pose multiple challenges to existing union search and joinability discovery methods, proving our intuition – current datasets fail to evaluate these methods properly.

1 Introduction

Dataset discovery tasks are a critical component of modern data-driven workflows, where finding and integrating relevant datasets in large data lakes is essential for many data analytics and machine learning tasks [1, 2]. Modern dataset discovery tasks such as the one of finding semantic joinable

columns of tables are challenging as tables in a data lake may have different way of conveying the same information [3]. Being able to understand the tabular data by appropriately profiling the syntactic and semantic rich information becomes essential for the success of a data discovery system [3, 4].

To evaluate the effectiveness of dataset discovery methods, researchers rely on corpora of datasets alongside ground truth (i.e., annotated column/table pairs) that are specifically curated for the purpose of dataset discovery. However, the existing tabular datasets [5, 6, 7, 8, 9, 10, 11] do not present the necessary semantic complexity, domain-specificity, and annotations for different discovery tasks, hindering their ability to evaluate the effectiveness and robustness of modern data discovery methods.

Pitfalls of current corpora used in dataset discovery. For instance, the recently published tabular corpus GitTables [8] comprises open data, and its semantic data types cover the commonly used ones in open knowledge bases, such as addresses, age, names, etc. This lack of semantic complexity limits its ability to evaluate methods dealing with complex and diverse domain-specific data types.

Dataset discovery in scientific domains highlights the importance of handling complex data types, such as chemical structures, genome sequences, and astronomical data. Similarly, dataset discovery in healthcare often involves handling complex medical concepts and terminologies, such as ICD codes in the Systematized Nomenclature of Medicine Clinical Terms (SNOMED CT) [12]. Such a domain-specificity is not included in GitTables. In addition, GitTables does not provide any ground truth annotations for dataset discovery. For example, it does not contain annotations of column pairs that can be used for joining tables. Smaller corpora such as TPC-H and TPC-DS [13] do offer ground-truth annotations, but they cover only *primary key/foreign key* (PK/FK) relationship, which can be easily identified using set similarity metrics over the data instances. This does not resemble complex relationships found in real-world data lakes.

Since existing corpora used for dataset discovery offer a limited amount of human-annotated ground truth, recently proposed methods attempt to create synthetic relationships via table splitting [7, 6, 4]. Vertical table splitting generates two tables that can be joined, and horizontal table splitting generates two unionable tables. However, those table splits fail to correctly evaluate dataset discovery methods, as they do not offer challenging joinability scenarios. Despite the use of naïve noise [5, 6] (e.g., typos, jitter, etc.) to make those matches more challenging to dataset discovery methods, these splits still lead to correspondences across columns (or tables), which do not reflect the real-world challenges pertaining to data discovery.

LLMs as a source of semantic, and domain-specific datasets. At the same time, Large Language Models (LLMs), trained on massive amounts of data, perform well at a wide variety of tasks including text summarization, translation, text generation and many others. Recently, we have seen emerging efforts towards synthetic data generation by leveraging LLMs [14, 15]. Essentially, the off-the-shelf LLMs can be used as knowledge bases as they often capture high quality semantic relationships present in the training data. At the same time, it has been shown that factual knowledge can be recovered surprisingly well from the LLMs [16]. As we show in Section 3.2, LLMs score equally well in generating domain-specific datasets.

Corpus	Semantic Data Types		Ground Truth (joinable columns)			Targeted Problem		Value contents	
	Common	Domain Specific	Split-based	Human-annotated	PK/FK	Unionability	Joinability	Synthetic	Real-world
Open Data [7]	✓		✓	✓		✓			✓
ChemBL [10]	✓	✓			✓		✓		✓
TPC-DI [9]	✓				✓		✓	✓	
Magellan [11]	✓			✓			✓		
Valentine (WikiData) [6]	✓		✓	✓		✓	✓		
GitTables [8]	✓								✓
LAKEGEN	✓	✓	✓	✓	✓	✓	✓		✓

Table 1: **LAKEGEN wins:** Existing corpora that are used for dataset discovery evaluation.

This paper addresses the following question: *Given a set of semantic data types that describe real-world entities, how can we generate realistic, domain-specific datasets and ground truth with column relationships, for dataset discovery scenarios?*

Approach overview. The approach of LAKEGEN is to leverage the generative capabilities of LLMs to generate synthetic datasets that mimic the semantic complexity and diversity of real-world tabular data lakes. This paper presents LAKEGEN, a dataset and ground truth synthesizer for data discovery

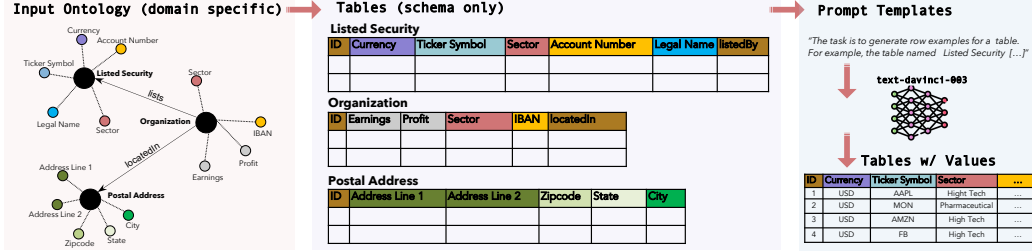


Figure 1: **LAKEGEN overview:** Base-table generation using an ontology and a LLM.

tasks. As seen in Figure 1, a user (e.g., a client or a dataset discovery method developer) can make use of an ontology to choose the entities alongside their properties in order to generate tables that resemble a given data domain. In this example, we show a simplified subset of FIBO, a widely adopted financial-domain ontology [17]. The ontology contains three entities and their data properties. In addition, it contains relationships (i.e., object properties) among those entities. LAKEGEN starts by first converting the ontology into a set of table schemata with relationships across them. It then uses those schemata, to prompt a LLM to generate values and populate those schemata. By using the data types information from the ontology (or human annotations) as shown in Figure 2, after creating tables and their values, LAKEGEN can infer relationships across tables (e.g., joinability). For instance, if two tables contain a column of the "Account Number" semantic data type, LAKEGEN can infer that those columns are joinable. After a set of perturbations (Section 4), LAKEGEN generates a set of tables, populated with values sourced from LLMs, and ground truth inferred from the given ontology. The benchmark contains a set of tables alongside their relationships, and those can be used to evaluate a given data discovery (e.g., joinable, unionable, etc.) method.

This paper proposes LAKEGEN, which has the following desirable properties:

- **Novel:** LAKEGEN is the first work to use ontologies to drive table schema generation and to utilize a LLM to populate these base tables, with minimal user input. Moreover, LAKEGEN proposes semantic perturbations to introduce noise and increase complexity at the level of column names, table shape and column values.
- **General:** LAKEGEN can generate domain-specific datasets for diverse domains. In Section 5 we generate three datasets for the domains of finance, pharma, and healthcare. These datasets present a variety of challenges for the dataset-discovery task.
- **Effective:** LAKEGEN illustrates the weaknesses of recent dataset discovery methods, as shown in our experimental study (Section 5).

2 The Column Joinability Problem

In this paper we are interested in the problem of generating domain-specific benchmarks for one critical dataset discovery task, namely joinability discovery. Joinability discovery is a form of schema matching [18] and is the process of identifying whether two columns from two different tables can be joined. We will represent two tables as R and S , and their corresponding column sets C_R and C_S . We formally define *column joinability* of two columns $c_R \in C_R$ and $c_S \in C_S$ (denoted as $c_R \bowtie c_S$) as follows.

Definition (Column Joinability). Two columns $c_R \in C_R$ and $c_S \in C_S$ are joinable if c_R and c_S can be joined through a mapping function h , which maps the values in c_R to the values in c_S , i.e., $(c_R \bowtie_{h(c_R)=c_S \vee c_R=h(c_S)} c_S) \neq \emptyset$

Note that if the mapping function h is the identity function, joinability refers to exact-joinability (also known as *equi-joins*) [6]. On the other hand, if we add two extra constraints to the definition of column joinability, namely *i*) $c_S \subseteq c_R$ and *ii*) c_R is the primary key of relation R , then the joinability refers to primary key/foreign key (PK/FK) joins. Finally, if the mapping function h performs some form of semantic value mapping via embeddings or a thesaurus (e.g., $h(\text{"Big Apple"}) \rightarrow \text{"New York"}$), the joinability is *semantic*. In practice, we are interested in all three joinability cases: the exact-, PK/FK-, and semantic-joinability.

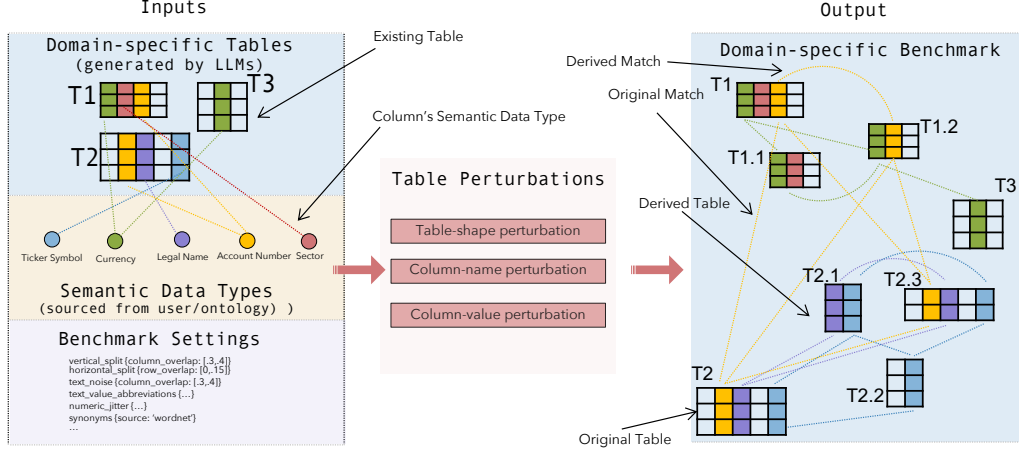


Figure 2: **LAKEGEN details:** The process of using a set of base tables and their associated semantic data types, in order to generate a set of derived tables and ground truth for dataset discovery tasks such as joinability.

3 LAKEGEN: Generating Corpora Using Ontologies and LLMs

In this section, we describe LAKEGEN, which generates a domain-specific benchmark from semantic types and relationships extracted from an ontology. LAKEGEN consists of two modules: base table generation, described in this section, and table perturbations that we describe in Section 4.

3.1 Ontologies as Sources of Domain-specific Semantic Data Types & Joinability

During the last two decades, various domain-specific ontologies have been developed. Those include FIBO for finance [17], the Gene Ontology [19] for genomics, SNOMED CT [12] and Dron [20] for healthcare, Amazon’s product knowledge graph [21] for retail, and many others. We argue that these ontologies contain rich semantic data types and relationships across different ontology classes/entities that we can leverage to generate complex datasets for data discovery tasks. However, to this date, these semantic data types and relationships have not been widely used for evaluating dataset discovery methods, mainly because real-world databases that adopt these ontologies are siloed behind corporate and governmental regulations.

Ontology to base tables generation. LAKEGEN, uses the domain-specific ontology to drive the *table schema* generation. A domain ontology, such the one depicted on the left of Figure 1, provides such a rich and expressive data model to capture a variety of real-world relationships between entities. We adopt OWL [22] for domain ontologies, where real-world entities are captured as *concepts*, each concept has zero or more *data properties*, describing the concept, and zero or more *object properties*, capturing its *relationships* with other concepts.

In LAKEGEN, we map a concept into a table and its data properties are converted to the columns in the table. For example, in Figure 1, the concept “Postal Address” has data properties such as “Address Line 1”, “Address Line 2”, “City”, “State”, “Zipcode”, etc. This information can naturally be mapped to the schema of table “Postal Address” as seen in the middle of the same figure. If a concept does not contain multiple data properties, we can group several concepts into one table, with each associated data property becoming a column.

Extracting joinable relationships from an ontology. Once we have generated the table schema based on the concepts and their data properties from the ontology, we can also obtain *joinability relationships* between tables from the object properties in the ontology. We follow the domain and range of an object property to connect two tables. For example, in Figure 1, the concept “Organization” has a relation “lists” which connects to another concept “Listed Security”. Therefore, the table “Listed Security” should include a column called “listedBy” that can be joined with a column in the table “Organization”. Here we then annotate which column in table “Organization” is related to “Listed Security”. In this case, the “listedBy” column points to the primary key column “Organization.id” of the table “Organization”.

3.2 LLMs for Table-value Generation

Traditional data generators such as Faker¹ generate the contents of each column independently from the rest of the table, with a user-defined generation function. Approaches like Faker, however, only cover common semantic types and cannot generate suitable contents for domain-specific ones. Moreover, Faker-like approaches do not maintain the value dependencies between rows, i.e., the columns “Zipcode” and “City” should match. In the case of Faker, one would have to use a user-defined dictionary of mappings between zip codes and cities.

Why LLMs. LLMs can address the above issues since they are good at generating domain-specific contents since the models are trained on a vast amount of data covering diverse domains and semantic types. Consequently, this makes them highly suitable for generating high-quality and relevant content for specific domains. In addition, LLMs are good with using *context* to generate factual data. For example, we observe that a LLM, text-davinci-003, generates nearly perfect matches between cities and zip codes in our preliminary experiments, without further actions required by a user. The contents of the table in the bottom right of Figure 1 was generated from values extracted with a simple prompt from the text-davinci-003 LLM. To the best of our knowledge, such a high-quality dataset is not possible to be generated with existing synthetic data generation pipelines. To maintain the dependency between the row entries, the table contents are generated row by row.

Joinability relationships. In LAKEGEN, the semantic type relations are naturally converted to the relations between columns with the following definition. For this paper, we mainly consider the column dependency relations, where column i from table A depends on column j from table S if $R_i \subseteq S_j$. We now exemplify how to satisfy the constraints of input column relations, i.e., how the tables should be generated according to the inter-column dependencies like Primary Key to Foreign Key relations. Namely, if the values of column R_i comes from column S_j (i.e., S_j is the primary key and R_i is the foreign key), after generating table R , we should make sure the column R_i includes all the entries of column S_j when generating table S . To achieve this goal, while generating the rows of table S , we parse the entries in column R_i to the prompt and require column S_j should include these entries. In the prompt see in Figure 3, we show how to generate table S conditional on column R_i .

For the case where multiple relations between multiple columns and tables exist, we use Algorithm 1. First, we build a graph G between tables, where table A has an edge pointing to table B if table A depends on table B (i.e., there exists a column i from table A comes from column j in table B). Then, we generate the tables one-by-one along the graph edges. Obviously, we should first generate tables with $in\_degree = 0$ since these tables can be generated without any column-wise pre-conditions. The generated tables are added to a set Q . Finally, given Q , we generate the table T whose column-wise dependencies only come from the tables in the set Q (the predecessors of T come from Q) in the next round.

4 Proposed LLM-based Table Perturbations

The column relations between the base tables offer natural exact-joinable relationships. However, more diverse semantically-joinable relationships are needed for evaluating data discovery algorithms. To this end, the joinable column pairs in the base tables need to provide semantically consistent column contents, that may not necessarily be identical. For instance, a column “country” can contain values such as “US” or “USA” while another, semantically-joinable column may contain the term “United States”. To address this, we employ LLMs to perturb the contents of the joinable column pairs, generating semantically equivalent but not identical column contents. Moreover, we can also create synthetic table pairs with ground truth through table perturbations (see table 7), which expands the dataset and enriches the inter-table relationships.

4.1 LLM-based Semantically Joinable Relationship Generation

Discovering semantically joinable column pairs is a challenging task because these pairs do not require the column contents to be identical. Instead, if the entries of two columns are semantically equivalent, the column pair is considered semantically joinable. Following the approach above to generate base tables, a group of exact-joinable column pairs can be obtained. To create more challenging semantically-joinable column pairs, we can perturb exact-joinable columns’ contents with semantically equivalent entries.

¹ <https://github.com/joke2k/faker>

Dataset	# of base tables	# of tables	avg # of rows	avg # of columns	# of exact joins	# of semantic joins
Finance	20	100	604.1	4.62	301	540
Pharma	20	100	129.7	4.97	905	1646
Healthcare	32	150	1137.4	6.22	896	6613

Table 2: Statistics of three generated datasets.

LLMs for semantically-safe value perturbations. A naive approach to perturb a column is to add noise to its entries [6, 5], such as introducing typos or replacing them with abbreviations or synonyms. However, these approaches cannot guarantee the perturbed entries still keep their original semantic meanings. In addition, naively adding typos to columns such as “URL” or “Account Number” could change the original semantics. Similarly, replacing “Address” with synonyms could lead to a different address, as “123 Main Street” is not equivalent to “123 Principal Street” or “123 Main Boulevard”. Finally, adding noise should take the context of a table schema into consideration to generate more diverse semantically equivalent variations of the column’s entries. For example, “CAD” in a column “Currency” cannot be safely expanded to “Canadian Dollar” using traditional approaches. We observed that LLMs do address the aforementioned issues and generate accurate and diverse variations of the original entries. For example, given a street name “123 Main Street” the LLM is able to abbreviate it to “123 Main St.” i.e., without breaking the semantics of its value.

4.2 Table-level Perturbations

Table-shape perturbations. In addition to leveraging a LLM to generate diverse joinable table relations, we can also fabricate synthetic joinable relations through table-shape perturbations (see Table 7). By vertically splitting the base tables [6], we create sub-tables with joinable columns that share at least one common column. As see in Figure 2, LAKEGEN adopts this method in order to split tables while generating additional tables and joins among them.

Column-value perturbations. To introduce additional diversity to the generated benchmarks, we use column-value and schema-level perturbations (Table 7). These perturbations can pose additional challenges to the downstream data discovery algorithms. For example, our schema perturbation could rewrite the column headers with their cryptic names, i.e. “Person ID” can be encrypted to “PID”. When the data discovery algorithm (such as COMA [23]) leverages the information of column headers for column relation discovery, the cryptic column headers will significantly reduce the token-level and semantic-level similarity between joinable columns, making it more difficult to differentiate the joinable pairs.

5 Experimental Evaluation

In this section, we mainly focus on two data discovery tasks: *i*) exact-joinability and *ii*) semantic joinability detection as defined in Section 2.

Datasets. We used LAKEGEN to generate datasets for three different domains, including finance, pharma, and healthcare domains. To generate the finance and pharma domain datasets, we start with the semantic types and relations from the financial industry business ontology (FIBO) [17] and DrugBank [24] respectively. For the healthcare domain, we extract part of the MIMIC-III dataset as the base tables [25, 26] and used perturbations only, since the base tables are already provided in the original dataset. For the finance and pharma domains, we generated the 20 base tables of maximum 1,000 rows. The healthcare base tables come from a sample of MIMIC-III dataset (sampled at most 2,000 rows from each table), including 32 base tables. Table 2 describes the generated datasets.

Discovery methods. The data discovery methods are initially designed for schema matching tasks but they can also be used for the joinable relationship detection tasks where we can match the same dataset. In this experiment, we included four methods, namely: *i*) COMA [23], *ii*) Jaccard-Levenshiten (JL) [6], *iii*) Similarity Flooding (SF) [27] and *iv*) Starmie [4], a recent discovery approach that leverages column representations using a pre-trained language model.

Metrics. We evaluated the performance of these methods using precision/recall and top- k precision. While evaluating the precision/recall, column pairs with prediction score > 0.5 are treated as a positive predictions. The top- k precision is defined as: top- k precision = (# of true positives in top k predictions)/ k . The top- k predictions refer to the column pairs with largest prediction scores. In our experiments, we used $k = 1, 3, 5$.

Methods	Exact Joinable Relations			Semantically Joinable Relations		
	Finance	Pharma	Healthcare	Finance	Pharma	Healthcare
COMA	0.68 (0.55, 0.87)	0.85 (0.77, 0.96)	0.68 (0.52, 0.99)	0.64 (0.59, 0.69)	0.85 (0.77, 0.95)	0.75 (0.60, 0.98)
JL	0.74 (0.81, 0.67)	0.39 (0.87, 0.25)	0.32 (0.25, 0.43)	0.64 (0.84, 0.52)	0.38 (0.87, 0.24)	0.30 (0.26, 0.38)
SF	0.10 (0.38, 0.06)	0.22 (0.91, 0.13)	0.11 (0.52, 0.06)	0.08 (0.42, 0.05)	0.23 (0.93, 0.13)	0.11 (0.60, 0.06)
Starmie	0.12 (0.08, 0.30)	0.13 (0.10, 0.17)	0.06 (0.28, 0.03)	0.13 (0.09, 0.26)	0.13 (0.11, 0.17)	0.06 (0.32, 0.03)

Table 3: **Performance evaluation:** Four methods performance over the 3 different domains-specific datasets. For each method, the prediction score threshold is set at 0.5. In each cell, the performance is shown in the form of F_1 score (precision, recall).

Methods	Exact Joinable Relations			Semantically Joinable Relations		
	Finance	Pharma	Healthcare	Finance	Pharma	Healthcare
COMA	0.53, 0.40, 0.29	0.58, 0.50, 0.39	0.89, 0.78, 0.64	0.52, 0.41, 0.31	0.58, 0.51, 0.41	0.91, 0.81, 0.67
JL	0.52, 0.41, 0.31	0.55, 0.48, 0.39	0.57, 0.48, 0.38	0.52, 0.42, 0.32	0.55, 0.48, 0.39	0.51, 0.43, 0.35
SF	0.36, 0.24, 0.17	0.47, 0.35, 0.30	0.53, 0.42, 0.37	0.37, 0.25, 0.18	0.49, 0.37, 0.31	0.6, 0.45, 0.40
Starmie	0.07, 0.06, 0.05	0.13, 0.11, 0.10	0.42, 0.30, 0.25	0.08, 0.07, 0.06	0.14, 0.11, 0.10	0.42, 0.31, 0.26

Table 4: **Performance evaluation:** Top- k accuracy of baselines over the 3 different domains-specific datasets. In each cell, the performance is shown in the form of top 1, 3, 5 precision.

5.1 Results

Performance of dataset discovery methods. We evaluated the performance of 4 methods on the exact-joinable and semantically-joinable relationship detection tasks. In general, for different domains, these methods show significantly different performance, highlighting the need for methods like LAKEGEN, in order to generate diverse datasets. Tables 3 and 4 confirm that semantically joinable relation discovery is hard in most cases, achieving lower F_1 scores (dropping up to 10%). Among all these methods, traditional approaches such as COMA and Jaccard Levenshiten significantly outperform the other two. Both COMA and Jaccard Levenshiten methods mainly leverage the column cell overlaps and schema similarity to determine the joinable column pairs, which discover most of the joinable relations. In contrast, Starmie relies on column embeddings learned from a language model. Our experiments show that the similarity between embeddings is not a reliable signal for joinable relationship detection. This reveals the importance of integrating current language model-based column representations with traditional column-value/schema containment signals.

Discovering semantically joinable columns. Semantically joinable relation detection is challenging when two columns have different column headers/values that are semantically equivalent. In our experience, such semantically joinable pairs are commonplace in real-world data lakes. LAKEGEN provides a significant advantage over the traditional split-based approaches in generating such challenging semantically joinable column pairs. Since the exact-joinable pairs have covered the cases for columns with overlapping instances, here we focus on analyzing the non-exactly but semantically joinable pairs. Specifically, we divide semantically joinable pairs into two categories, “difficult” and “easy” pairs, referring to the column pairs with different or identical column headers, respectively.

Table 5 shows that all four methods fail to discover the difficult pairs, in particular Starmie, which uses a pre-trained language model to encode columns. However, the learned column embeddings cannot capture the semantic similarity between the difficult column pair cell values. Therefore, our experiments demonstrate the necessity to improve the quality of column representations in order to discover the semantic mappings between column cells. As a comparison, COMA, leveraging both schema and instance information, does better in predicting the easy joinable pairs. On the other hand, the other methods do not adequately leverage the schema information and fail to detect the easy pairs.

Dataset	Non-exact join pairs/ All semantic join pairs	Difficult Non-exactly Joinable Pairs					Easy Non-exactly Joinable Pairs				
		# pairs	Coma	JL	SF	Starmie	# pairs	Coma	JL	SF	Starmie
Finance	180/540	134	24/134	9/134	2/134	18/134	46	46/46	3/46	2/46	6/46
Pharma	50/1646	27	0/27	0/27	1/27	4/27	23	23/23	0/23	3/23	4/23
Healthcare	890/6613	70	26/70	0/70	0/70	0/70	820	820/820	35/820	56/820	30/820

Table 5: **Performance evaluation:** Four methods over the semantically joinable but not exactly joinable pairs. We decompose these pairs into two categories: 1) difficult non-exactly joinable pairs where two column headers as well as cells are different and 2) easy non-exactly joinable pairs where two column headers are identical. The table shows the number of correct predictions made by different baselines.

Methods	F_1 (Precision, Recall)			Top- k Precision ($k = 1,3,5$)		
	Finance	Pharma	Healthcare	Finance	Pharma	Healthcare
Coma	0.23 (0.19, 0.29)	0.65 (0.54, 0.82)	0.61 (0.44, 0.99)	0.41, 0.26, 0.20	0.63, 0.59, 0.58	0.94, 0.83, 0.78
JL	0.13 (0.33, 0.08)	0.32 (0.64, 0.21)	0.35 (0.24, 0.67)	0.59, 0.42, 0.29	0.89, 0.75, 0.68	0.32, 0.30, 0.28
SF	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)	0.002 (0.5, 0.001)	0.22, 0.15, 0.10	0.71, 0.59, 0.57	0.56, 0.47, 0.37
Starmie	0.05 (0.02, 0.42)	0.06 (0.04, 0.26)	0.04 (0.15, 0.02)	0.26, 0.10, 0.11	0.13, 0.10, 0.10	0.52, 0.43, 0.35
	Gosales	TPC-H	TPC-DS	Gosales	TPC-H	TPC-DS
Coma	1.00 (1.00, 1.00)	0.86 (0.75, 1.00)	0.45 (0.81, 0.31)	1.00, 0.87, 0.62	1.00, 0.83, 0.58	0.35, 0.31, 0.24
JL	0.80 (1.00, 0.60)	0.72 (1.00, 0.56)	0.37 (1, 0.23)	1.00, 0.87, 0.72	1.00, 0.82, 0.69	0.34, 0.29, 0.23
SF	0.0 (0.0, 0.0)	0.0 (0.0, 0.0)	0.00 (0.00, 0.00)	1.00, 0.83, 0.61	1.00, 0.79, 0.57	0.34, 0.25, 0.17
Starmie	1.00 (1.00, 1.00)	0.83 (0.77, 0.91)	0.84 (0.98, 0.74)	0.83, 0.67, 0.55	0.82, 0.61, 0.52	0.46, 0.33, 0.15

Table 6: **Performance evaluation:** Four methods’ performance on the base tables and other public datasets (Gosale, TPC-H, TPC-DS). The performance is evaluated over the semantically joinable relation discovery task.

Base table evaluation. We also examined the performance of four methods using newly generated base tables in three domains. As a comparison, all methods are also evaluated over 3 widely used data discovery corpora, including “Gosales”, “TPC-H” and “TPC-DS”. Here, we choose the semantically joinable relation detection task for the evaluation. Table 6 suggests that LAKEGEN generated base tables are much more challenging than the existing corpora, as all methods perform much worse on our base tables. As we motivated in Section 1, existing corpora lack enough schema and cell value complexity, and the joinable column pairs have similar column headers and cell-values. Our experiments demonstrate that without a realistic domain-specific dataset, the performance of data discovery methods cannot be truly stress-tested.

6 Related Work

Since we have addressed existing corpora in the introduction and Section 1, we refrain from re-iterating over those in this section. Instead, we turn to synthetic tabular data generation methods.

While the generation of images [28] and text [29] has been thoroughly studied, the generation of synthetic tabular data has received less attention in recent machine learning literature. Recent approaches to generating tabular data employ generative adversarial networks ([30, 31, 32, 33, 34]) or variational autoencoders ([33, 35, 36, 37]). The current state-of-the-art approach, CTGAN [33], emphasizes the conditional distributions among the features to generate semantically meaningful data. Transformer-based models have also been developed for tabular data classification [38, 39, 40] and for learning joint representations of tabular and textual data ([41]). [42] investigated the generation of multi-variate time series data using a transformer architecture based on BERT [43].

In contrast to these works, LAKEGEN focuses on the orthogonal problem of generating domain-specific corpora with joinable relationships, in order to evaluate dataset discovery methods. In our prototype, we have used a general LLM (text-davinci-003), using prompts to generate values for tabular data. However, our work can benefit from other general data generation frameworks like CTGAN [33] as well as GReAT [44] in order to populate the tables schemas extracted from ontologies. Finally, in the future our approach can adopt domain-specific GAN-based generation approaches for e.g., health records [45, 34, 30], or passenger records [32], etc.

7 Conclusion

In this paper, we presented LAKEGEN, the first corpus generator that leverages *i*) ontologies to extract domain-specific data types in order to create tabular dataset schemas which are then *ii*) populated using LLMs. LAKEGEN requires minimal user intervention in order to generate large complex schemata of datasets, including joinability relationships. We have used LAKEGEN to generate corpora from three different domains, namely financial, pharma and healthcare, and we have shown that such domain-specific datasets create challenges not found in existing public corpora.

Customer Problem Statement

Specializing models for clients. When we onboard new customers from various domains on Amazon DataZone², we need to deploy a highly effective dataset discovery model. In our experience, some

² <https://aws.amazon.com/datazone/>

dataset discovery methods may do well with finance databases, but not for chemical databases, etc. Ideally, the data provided by one customer should be used for training dataset discovery and matching methods, before being shipped to customers. However, due to privacy and regulatory reasons, access to real customer data can be difficult and limited. In addition, even if we had access to such customer data, we would be missing ground truth to evaluate dataset discovery methods. Currently, we are leveraging LAKEGEN to generate domain-specific datasets alongside matches, in order to train internal ML-based data discovery methods, and to establish hyper-parameters before those methods are deployed in production for both internal or external clients.

Generating corpora for training Bedrock/M* models. Modern cloud services are increasingly reliant on data-driven technologies such as machine learning and data mining. The development and operation of such services require large amounts of high quality data to harness the power of artificial intelligence to drive innovation, improve decision-making and create value for businesses and customers. Obtaining diverse, high quality and high volume datasets for developing solutions for customers from a wide range of domains can be extremely challenging due to reasons such as data quality issues, data privacy concerns, data access and ownership, data bias and data scalability. We argue that our method LAKEGEN can be used to generate large-scale realistic datasets for table representation learning. Those tasks may include table summarization, semantic data types detection on columns, knowledge graph construction, etc.

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8 Appendix

8.1 Prompt to generate base tables

We provide an example to generate the instance of table “Listed Security” with model text-davinci-003. Here, we require the table contents to be generated conditional a list of given “Legal Name” column entries.

Input:
Table Name: Listed Security
Column Names: Ticker Symbol, Legal Name, Currency and Last Traded Value Monetary Amount
Dependent Columns: Column Currency depends on Currency of table Currency Name; Last Traded Value Monetary Amount depends on Amount of table Monetary Amount;
Prompt: The task is to generate row examples for the table. For example, the table named Securities Transaction has columns: ['Type', 'Count', 'Settlement Date', 'Facilitated By Financial Service Account', 'Price Monetary Amount', 'refers To Listed Security']. And column 'Facilitated By Financial Service Account' comes from the 'Account Number' of table 'Financial Service Account'. Column 'Price Monetary Amount' comes from 'Amount' of table Monetary Amount. Column 'refers To Listed Security' comes from 'Legal Name' of table 'Listed Security'. The row examples should look like 'Example 1: Buy; 1020; 01/20/2022; 310689442; 200; Apple Inc.; Example 2: Sell; 638; 02/22/2023; 432689224; 138; Microsoft Inc.'. Now, the table named Listed Security have the following columns: ['Ticker Symbol', 'Legal Name', 'Currency', 'Last Traded Value Monetary Amount']. The entries from column 'Currency' comes from 'Currency' of table 'Currency Name'. The entries from 'Last Traded Value Monetary Amount' belong to 'Amount' of table 'Monetary Amount'. Given the entries of column 'Legal Name' are ['Apple Inc.', 'Microsoft Inc.', 'Amazon Inc.', 'Alphabet Inc.', 'Facebook Inc.']. Generate the rows for the table.
Generated Contents:
Example 1: AAPL; Apple Inc.; USD; 200
Example 2: MSFT; Microsoft Inc.; USD; 138
Example 3: GOOGL; Alphabet Inc.; USD; 150
Example 4: AMZN; Amazon.com Inc.; USD; 250
Example 5: FB; Facebook Inc.; USD; 100

Figure 3: Example prompt generates values for the “listed security” table in Figure 1.

8.1.1 Algorithm to generate base tables

Since the base tables depend on each other by the column correlations, simply generate the base tables independent could break the column correlations. The following algorithm enables the generated tables could satisfy the column correlation constrains.

Algorithm 1 Base Tables Generation with LLM

- 1: **Input:** Column dependency relationships R containing all pairs $((i, a), (j, b))$ satisfying column a (from table i) depending on column b (from table j).
 - 2: **Build relation graph:**
 - 3: For each table $i = 1, 2, \dots, n$, create a node v_i .
 - 4: For all pairs $((i, a), (j, b)) \in R$, adding an edge e_{ij} from node v_i pointing to v_j .
 - 5: **Generate tables with LLM:**
 - 6: Initialize generated tables set $Q = \emptyset$.
 - 7: For node i with in degrees = 0, generate table i with LLM. Insert v_i to Q .
 - 8: **while** $|Q| < n$ **do**
 - 9: **for** $j \notin Q$ **do**
 - 10: Let $predecessors(v_j)$ be the set of all predecessors of v_j
 - 11: **if** $predecessors(v_j) \subseteq Q$ **then**
 - 12: Retrieve the columns that table j depends on, namely $C_{i_1, a_1}, C_{i_2, a_2}, \dots, C_{i_k, a_k}$
 - 13: Generate partitions of table j with LLM conditional on the $C_{i_1, a_1}, C_{i_2, a_2}, \dots, C_{i_k, a_k}$ respectively
 - 14: Concatenate the partitions into table j . Insert v_j to Q
 - 15: **end if**
 - 16: **end for**
 - 17: **end while**
-

8.2 Data Perturbation Functions

Our pipeline also enables the following data perturbation functions on three different levels.

Table 7: LAKEGEN’s tabular data perturbation functions.

	Perturbation Type	Perturbation action
Column-values	Numeric noise	Addition of jitter, duplicates
	Text noise	Typos, synonyms, abbreviations, word removal,
	Format noise	Dates, addresses, names, etc.
	Null-values	Introduction of nulls
Schema	Cryptify column names	Cryptify business column names (e.g., abbreviate)
	Typos	Introduce typos
Table-shape	Removal of Columns	Remove columns from table
	Sampling	Sample column contents
	Vertical splitting	Split a table vertically with overlapping columns (10%, 20%, ...)
	Vertical splitting with unique column (PK/FK)	Split a table vertically with overlapping columns (10%, 20%, ...). One of the two split tables should only keep unique values.
	Horizontal Splitting	Horizontally split table with overlapping rows (0%, 10%, 20%, ...)