Gen-T: Table Reclamation in Data Lakes

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ABSTRACT

PVLDB Reference Format:
Grace Fan, Roee Shraga, and Renée J. Miller. Gen-T: Table Reclamation in Data Lakes. PVLDB, 14(1): 50 - 60, 2021.
doi:10.14778/3421424.3421431

1 INTRODUCTION

As more tables in data lakes become openly available, users have easier access to more government, academic, and enterprise datasets. In particular, data scientists retrieve these tables to perform integration tasks, run analyses, or input into machine learning models. However, there are concerns around the origins of the tables that are directly retrieved and used for further tasks [1]. The trustworthiness of the data, when used as training data for downstream machine learning tasks for example, depends heavily on the trustworthiness of the data origins. Throughout the pipeline for which the data is used and/or reproduced, it is susceptible to malicious attacks. In data processes in which an attacker ingests malicious data into tables, or modifies them to remove data values, these tables can be unknowingly used to form the tables that data scientists retrieve, and potentially feed these changes to their downstream tasks. For example, SQL injection, in which the attacker gains access to sensitive data and proceeds to modify or delete it, is the third most dangerous and serious security risk [47, 52]. In addition, common real-world (tabular) datasets are prone to fairness issues (bias and discrimination) which may be used unknowingly by data scientists [35].

Thus, it is crucial for data scientists to trace their tables back to their originating set of tables and pipeline to verify its contained data, before continuing to use them for further downstream tasks. Oftentimes, the tables that they retrieve from data lakes are a product of prior integration over a subset of data lake tables. Consequently, the users would like to trace the tables' columns and tuples to its originating tables used in the forming integration. This is especially crucial if the users perform tasks with tables that originated from bad, noisy, inconsistent data or "flagged" data. In addition, each integration step in the original formation may have been vulnerable to injected or disappearing values. If either case is true, then their tables may contain incomplete or inconsistent instances. These tables are then directly used in data science tasks, proliferating errors throughout the pipeline.

Proceedings of the VLDB Endowment, Vol. 14, No. 1 ISSN 2150-8097.
doi:10.14778/3421424.3421431

Source Table:

ID	Name	Age	Gender	Education Level
0	Smith	27	—	Bachelors
1	Brown	24	Male	Masters
2	Wang	32	Female	High School

Table A:

ID	Name	Education Level
0	Smith	Bachelors
1	Brown	—
2	Wang	High School

Table B:

Name	Age	Status
Smith	27	applied
Brown	24	offer
Wang	32	waitlist

Table C:

Name	Gender	Status
Smith	Male	offer
Brown	Male	offer
Wang	Male	offer

Table D:

Name	Age	Gender	Education Level	Status
Smith	27	—	—	applied
Brown	24	Male	Masters	—
Wang	32	Female	—	waitlist

Figure 1: The Source Table in green contains information about applicants, including their unique ID, Name, Age, Gender, and highest Education Level. Tables A, B, C, and D are possible tables from which the Source Table's instances originated. All common columns with the Source Table are in blue, some of which contain missing (yellow '—') or inconsistent (in red) values to the Source Table's values.

To overcome this issue, we must verify the data scientist's table at hand, or the *Source Table*, by confirming its originating formation and tables. To do so, we trace the Source Table's values to the data lake tables from which they originate, or the *originating tables*, so that integrating them can reclaim the Source Table, in a process called *Table Reclamation*. In returning to the user these original tables and integrated table that reclaims the Source Table, the user can thus verify the Source Table's data values, instances, and originating tables and evaluate their trustworthiness.

Example 1. *Suppose the user has the green table in the top left of Figure 1 as training data. As this table contains instances for applicants, with sensitive values for age, gender, and education level, it is crucial to verify the values and instances. To do so, we trace its values to a subset of tables in the data lake – tables A, B, C, and D as possible originating tables. However, we see that Table C contains contradicting non-null values in the "Gender" column compared to the values in the same indices of the "Gender" column in the Source Table. Thus, to correctly verify every cell value in the Source Table, we need to refine the set of candidate originating tables to contain consistent values with those in the Source Table.*

A similar line of work is Table Discovery, in which existing systems find relevant tables to the user's table [45, 46, 54, 68]. Specifically, joinable and unionable table search find tables that can join or union with the given table, respectively [50, 70, 71]. However, retrieved tables in these searches may primarily share semantics with the columns in the given table [20, 30], or only have overlapping sets of values in individual columns. Instead, we aim to find originating tables whose values across columns for each tuple are consistent with those in the given table. Additionally, related work on Query-By-Example (QBE) or Query-By-Target (QBT) discover a query over input tables that produces an instance-equivalent table to the given example output table [4, 17, 33, 55, 62, 65]. In order to

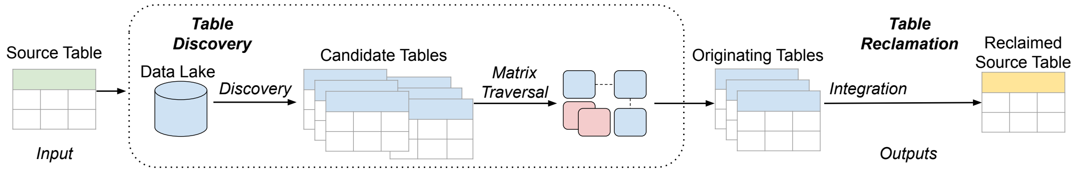


Figure 2: System Architecture of Gen-T. Given the Source Table, Gen-T finds its originating tables in the Table Discovery phase, and produces the reclaimed Source Table from the Table Reclamation phase. It returns the set of originating tables and the reclaimed Source Table to the user.

generalize to the data lake setting, we require an additional step of finding candidate tables within or across data lakes that contribute to a user's table. Also, existing systems focus primarily on discovering (Select)-Project-Join queries [8, 29, 51, 61, 67], with some using both the data values and schema of tables. Due to the noise and heterogeneity of data lake tables, these queries are not sufficient in fully integrating tables to produce the given table. So, we aim to recover Select-Project-Join-Union queries using only the data values, since metadata of data lake tables are often missing or inconsistent [2, 21, 49, 50].

We present a data-driven technique for Table Reclamation in data lakes, named Gen-T, in which we aim to discover the originating data lake tables whose integration result reclaims or reproduces the Source Table given by the user. Our contributions are

- We define the novel problem of *Table Reclamation* – finding a set of tables that can be used to best reproduce a Source Table.
- We present a solution for Table Reclamation named Gen-T. Gen-T performs data discovery to retrieve a set of candidates tables from the data lake, filters out poor candidates using novel table representations that simulate table integration without actually performing expensive integrations, and finally integrates them to produce a table whose values and instances are as close a possible to the Source Table.
- We conduct extensive effectiveness experiments with new notions of accuracy, showing that Gen-T outperforms all baseline methods when reclaiming Source Tables, reclaiming 5X more Source Tables than the best-performing baseline method.
- We show that our solution is efficient and scalable to the size of a real data lake.
- We show that Gen-T is robust when generalizing to different real-world application setting.

2 OVERVIEW

A data scientist provides a *Source Table* that she would like to verify by understanding if it can be produced by integrating any combination of tables within a data lake. Specifically, we aim to determine a set of tables from whom the Source Table's values may originate (termed *originating tables*), and use them to reclaim (regenerate) the Source Table. Given our data lake setting where tables can be changed autonomously, we formulate the problem as an approximate search of finding a set of tables that can best be used to reclaim the Source, *as close as possible.*

Unlike prior approaches to *by-example* [4, 8, 17, 29, 51, 55, 61, 62, 67] or *by-target* [65] problems, we do not assume that we know the exact set of input tables whose values first formed the Source Table or even **if** the Source Table can be reclaimed. To solve the

Source Table:

ID	Name	Age	Gender	Education Level
0	Smith	27	—	Bachelors
1	Brown	24	Male	Masters
2	Wang	32	Female	High School

Resulting table of FD(A, B, C, D):

ID	Name	Age	Gender	Education Level
0	Smith	27	Male	Bachelors
1	Brown	24	Male	Masters
2	Wang	32	Female	—
2	Wang	32	Male	High School

Resulting table of (A ⟗ B ⟗ D ⟗ C):

ID	Name	Age	Gender	Education Level
0	Smith	—	—	Bachelors
0	Smith	27	—	—
0	Smith	—	Male	Bachelors
1	Brown	—	—	—
1	Brown	24	Male	Masters
1	Brown	—	Male	—
2	Wang	—	—	High School
2	Wang	32	Female	—
2	Wang	—	Male	High School

Figure 3: Source Table about applicants' data, and the possible integrations of the data lake tables (with only shared columns with the Source Table) resulting from state-of-the-art integration method using Full Disjunction (FD) and an outer join ⟗ ordering.

problem of table reclamation, we thus use a two-step solution. First, we discover a subset of tables from the data lake that share values with the Source Table and therefore may have created portions of the Source, we call these *candidate tables.* Then, we search for ways of combining subsets of these tables to regenerate the Source Table. When considering what types of queries originally produced the Source Table, we assume that they were variations of Select-Project-Join-Union (SPJU) queries, with no aggregation or cell value-transformations involved. The subset of tables that can reproduce the Source Table using an SPJU query is called the *originating tables.* Following previous work that re-discovers (Select)-Project-Join queries that produce the Source Table by joining tables via keys [26, 29, 55, 61], we also assume that tables have unique, non-null primary and foreign keys.

Figure 2 shows the general pipeline of Gen-T, given a Source Table and outputting the Reclaimed Source Table and its originating tables. First, in the Table Discovery phase (Section 5), Gen-T discovers a set of candidate tables whose values may have contributed to the creation of the Source Table. Then, we apply our novel solution of representing table as matrices in order to simulate table integration via matrix traversal (Section 5.2). The goal of this step is to refine the set of candidate tables to a set of originating tables, and essentially filter out any tables from the set of candidate tables that are not needed in an efficient manner before performing table integration.

Once Matrix Traversal pinpoints a set of originating tables, we integrate these originating tables in the Table Reclamation phase (Section 4) and produce a reclaimed Source Table.

Example 2. *We now return to our running example to illustrate the necessity of pinpointing good originating tables. In Figure 3, the candidates are directly integrated after projecting out columns* *that do not appear in the Source Table. The bottom left, yellow table is the integration result from the state-of-the-art full disjunction (FD) method [24, 31] and the right table shows the result using one possible outerjoin order that may be learned by Auto-Pipeline [65]. The resulting tables all contain different values in the Gender column (in red) with respect to the corresponding value in the Source Table. These values originate from Table C. When possible, we need to refine the set of candidate tables to filter out tables like Table C that produce integrated tables with erroneous values that do not make the Source Table.*

The remainder of the paper is outlined as follows: we present related work in Section 3. Going into the solution pipeline of Gen-T, we first assume that we have been given an accurate set of originating tables that we need to integrate, and discuss the Table Reclamation phase in Section 4. Next, Section 5 describes the details of the Table Discovery phase, specifically the Matrix Traversal solution that finds a set of originating table. Finally, the experiments in Section 6 show the effectiveness, scalability, and generalizability of Gen-T.

3 RELATED WORK

We now discuss related work to Table Discovery and Integration. We then discuss work related to finding the origins of a table, referred to as By-Example or By-Target approaches in the literature.

Table Discovery: Table Discovery has a rich literature, specifically keyword search over tables, unionable table search, and joinable table search. Early work such as Octopus [10] along with Google Dataset Search [9], support keyword search over the metadata of tables [2, 41] and smaller scale web-tables [58, 59]. To support data-driven table discovery, systems [22, 50, 54, 70, 71] were then developed to find schema complements, entity complements, joinable tables, and unionable tables.

For joinable table search, early systems make use of schema matching or syntactic similarities between tables' metadata, such as Jaccard similarity [38, 64]. LSH Ensemble [71] makes use of approximate set containment between column values and support high-dimensional search using LSH indexing. JOSIE [70] uses exact set containment as well to retrieve joinable tables that could be equi-joined with the columns in the user's table. MATE [19] supports multi-attribute join with a user's table in an efficient manner. These systems could be used to retrieve a set of candidate tables that have high set similarities with a given user's table.

Table union search was first supported by systems that leverage schema similarities to retrieve unionable table [42, 54]. Using data (rather than metadata), a formal problem statement was first defined by Nargesian et al. [50] who presented a data-driven solution that leverages syntactic, semantic, and natural language measures. Then, the problem was refined by SANTOS [30] to consider binary relationships in addition to column semantics when retrieving semantically unionable tables. Most recently, Starmie [20] offers a scalable solution to finding unionable tables that leverages the entire table context to encode its semantics. Although our method also retrieves relevant tables to a user's table, we aim to retrieve tables for a specific task – reclaiming the user's table. Finally, other recent work [23] presents a goal-oriented discovery for specific downstream tasks, aiming to augment additional columns. We tailor table discovery towards the goal of reclaiming the Source Table.

Table Integration: Once we have a set of candidate tables retrieved from table discovery, we continue to Table Integration. Previous work, Lehmberg et al. [36] stitches unionable tables together, but does not support join augmentation of tables. More recently, ALITE [31] performs full disjunction (FD) [24] to maximally combine tuples. Our goal is to reproduce the given Source Table, which may contain incomplete tuples, so we do not aim to maximally combine tuples if it produces a table that is not identical to the Source Table. Nonetheless, ALITE is a candidate baseline for Gen-T, as it offers the state-of-the-art integration solution.

Preceding the table integration process, there are pre-integration tasks to find alignments between table elements. First, instance-based schema matching determines how the schemas of two tables align to prepare for integration [12, 18, 34, 44, 53, 56]. Our solution implicitly aligns schemas after retrieving a set of originating tables. We rename the columns in the retrieved tables to align with the column headers of the Source Table so we can apply joins and unions. Entity matching [11, 14, 25, 27, 39, 40, 48, 66, 69] is another common pre-integration task, aiming to align tuples for cleaning or joining tables. In our solution, we assume the tables have keys, and thus align entities via their keys.

Finding Origins of Tables: Our problem setting of tracing a Source Table's values back to its origins can be related to Data Provenance [13], which given a query and its output table, explains from where the (values or) tuples originate, why and how they were produced. However, in our problem setting, we need to recover the tables and the integration required to reproduce the the Source Table and thus do not know the query that was originally used to create the Source Table.

Query-By-Example is a popular approach in which systems are given a pair of matching input and output tables, and they need to synthesize a query or transformation from the input to the output. Specifically, systems such as SQL-by-example [62], synthesize a SQL query to produce an output table, given the input table, that contains all equivalent instances of the example output table. Some systems only consider Project and Join operators [26, 29, 51, 67], whereas others also consider the Select operator [8, 61]. For example, Ver [26] aims to find Project-Join views over large tables in which the join path is not known. Some methods output a set of queries rather than one query that could reproduce the example output table, given the input table [17, 55]. AutoPandas [4] performs transformation-by-example by synthesizing Pandas programs rather than SQL queries.

Auto-Pipeline [65] defines a similar problem, Query-By-Target, with the goal of synthesizing the pipeline used to create the target table, given the target table and a set of input tables. Using the synthesized pipeline on the input tables, it then produces a table that "schematically" aligns with the input target table. As the state-of-the-art in this line of work, it is a baseline for our approach. In both By-Example and By-Target paradigms, the set of input tables on which the system synthesizes a query to generate the example or target table is known. And this set of input tables is known to contain the tuples and columns needed such that their integration can reproduce the output table. However, in our problem, we do not assume this is the case. We are only given the Source Table and a data lake as input. From the data lake, we need to search for and filter a set of candidate tables such that by integrating the filtered set of candidate tables (which we call the originating tables), we can reclaim the Source Table.

4 TABLE RECLAMATION

We now describe the Table Reclamation step of Gen-T's pipeline. We first assume that we already have the set of tables from which the Source Table originated (originating tables). In this section, we combine them to reclaim the Source Table. First, we define a set of Table Operators in Section 4.1, with which we perform table integration in Section 4.2 in order to produce an output table that reclaims the Source Table. Given the possible reclaimed table (the result of integration), we then discuss how to evaluate the quality of the reclamation of the Source Table in Section 4.3.

4.1 Table Operators

We now discuss the set of table operators we use to perform Table Integration. Consider the following table operators performed on one table.

• Projection(π): Project on specified columns of the table.
• Selection(σ): Select tuples that satisfy a specified condition.
• Complementation(κ) [5, 6]: Given tuples t_1, t_2 in the same table, t_1 complements t_2 if they share at least one non-null column value, and t_1 contains some non-null values where t_2 has nulls while t_2 contains some non-null values where t_1 has nulls. The tuples must agree on all non-null values. Applying κ on t_1 and t_2 produces a single tuple that contains all non-null values of either (both) tuples and is null only if both t_1 and t_2 are null. Applying κ on a table produces a table with no complementing tuples and involves repeatedly applying complementation to pairs of tuples that complement each other.
• Subsumption(β) [5, 24]: Given tuples t_1, t_2 in the same table, t_1 subsumes t_2 if they share some non-null column value(s) and t_1 contains some non-null values where t_2 has nulls. Applying β on a table involves repeatedly applying subsumption and discarding the subsumed tuples (t_2).

Next, we consider the following pairwise-table operators and their known derivatives that may be used in SPJU queries. For these operators, we assume the schemas of the tables have been aligned, so joinable (unionable) attributes share the same name and we use the natural version of these operators [?] These operators are applied to two tables T and S.

• Inner Union($\cup$): Union two tables that share the same schema. This operator is commutative and associative.
• Outer Union($\uplus$) [15]: Union two tables, even if their schemas are not equal. The resulting table contains the union of the columns from both tables. If a column C is missing from one table (T) but appears in the other table (S), then in the result, the tuples of S contain a null ($\perp$) in their C column. This operator is commutative and associative.
• Inner Join($\bowtie$): Two tuples t and s are joinable if they share the same values on all common attributes (attributes with the same name). The schema of the result of the inner join contains the union of the columns and the table contains all joinable tuples. If T and S contain no common attributes, then the inner join is the *Cross Product* (meaning it contains (t, s) for all tuples t and sf). This operator is commutative and associative.
• Left Join($⟕$): The left join contains the inner join and in addition, for each tuple t in T that does not join with any tuple in S, the left join contains a tuple t' that is equal to t on all attributes in T and is null on all attributes in $S - T$.
• Outer Join ($⟗$): The outer join contains the left join and in addition, for each tuple s in S that does not join with any tuple in T, the outer join contains a tuple s' that is equal to s on all attributes in S and is null on all attributes in $T - S$.

Given our set of table operators, we apply them to a set of originating tables to reclaim the Source Table. We first align the attributes of the originating tables with the source table. We can apply any schema matching algorithm for this, but given our goal of reclamation, we use the value overlap to do the alignment. Specifically, we rename each attribute of an originating table with the name of the source attribute with which it shares the most values (breaking ties arbitrarily) and remove any attributes from the originating tables that do not share values with the source table (as these attributes are not useful in reclamation.

Recall that we assume that the Source Table was first created using a SPJU query. To make our reclamation search more efficient, we will make use of the following result. Outer Union and the set of unary operators above can be used to represent any SPJU query.

Theorem 3 (Representative Operators). *Given two tables that are each in their minimal forms such that there are no duplicate tuples and no tuples that can be subsumed or complemented, for all SPJU queries, there exists an equivalent query consisting of Outer Union and the four unary operators (select, project, complementation, and subsumption).*

Proof Sketch Suppose we have two tables, T_1, T_2, that share key column K, and are in their minimal forms in which there are no duplicates and no tuples that can be subsumed or complemented. For each pairwise table operator, Inner Union, Inner Join, Left Join, Outer Join, Cross Product, there exists an equivalent query consisting of Outer Union and/or unary operators. (SP of SPJU queries are accounted for by the unary operators).

$$T_1 \bowtie T_2 = \sigma(T_1.K = T_2.K \neq \perp, \beta(\kappa(T_1 \uplus T_2))) \quad (1)$$

$$T_1 ⟗ T_2 = \beta(\beta((T_1 \bowtie T_2) \uplus T_1) \uplus T_2) \quad (2)$$

For example, Inner Join can be represented using Outer Union ($\uplus$) and selection (σ), subsumption (β), complementation (κ) operators (Equation 1), and Full Outer Join can be represented using Inner Join, showed previously to only include Outer Union and unary operators, Outer Union, and subsumption operators [24] (Equation 2). Due to space constraints, the full proofs for each pairwise table operator in SPJU are given in the technical report. Thus, $\uplus, \sigma, \pi, \kappa, \beta$ operators form queries that are equivalent to all SPJU queries.

Using our set of operators $\bigoplus = \{\uplus, \sigma, \pi, \kappa, \beta\}$, we will present an efficient way of exploring the integration space to reclaim the Source Table. Instead of traversing through all possible Join predicates (columns that two tables join on) in a space consisting of all tables, as in existing by-example and by-target work, we can simply apply Outer Union and the unary operators with conditions based on the Source Table.

4.2 Table Integration

Table Integration takes a set of originating tables ($\mathcal{T}$), a Source Table (S) and using $\bigoplus$ outputs a table (T_{result}) that reclaims S as best as possible. Note that from the previous discovery phase, each table in $\mathcal{T}$ adopts their column names from S for every column that shares values with a column in S. Our table integration method is depicted in Algorithm 1. First, as described in Section **??**, we perform pre-processing by projecting out columns not in S, and selecting tuples that values in a primary key or foreign key column in S. Hence, we only keep the columns and tuples that overlap with S (Line 3). Next, we take the Inner Union of tables that share the same schema (Line 4), to reduce the space of tables we need to explore. To prevent the over-combining of tuples that share nulls with tuples in S, for each table $T \in \mathcal{T}$, we find tuples from S that share the same key values and contain nulls. If T also contains nulls in tuples with the same key value in the same columns, then we replace these nulls with a dummy non-null value (Line 6). Before applying our set of integration operators $\bigoplus$, we take the minimal forms of each table by removing duplicate tuples, subsumed tuples (apply β), and taking the resulting tuples of complementation (apply κ) in Line 6. In the integration (Lines 8-13), we explore our set of operators $\bigoplus = \{\uplus, \sigma, \pi, \kappa, \beta\}$ As proven in Theorem 3, this is sufficient rather than considering all SPJU operators and conditions. Thus, we first apply Outer Union($\uplus$). Next, we check if applying Complementation(κ) and Subsumption(β) on the Outer Union result leads to over-combining of tuples (e.g. removing a subsumed tuple that is identical to a tuple in S) and decreases the number of values and tuples shared with S, or S coverage (we define it formally later). After iterating through all tables from the input set, we revert the previous labeling of shared nulls with S (Line 14). If the resulting integration table has fewer columns than S, we pad it with columns from S that are not currently in the resulting table, all containing null values (Line 16). This way, the resulting table shares the same schema with S. Finally, we return the resulting integration as a possible reclaimed table.

Algorithm 1: Table Integration

1 **Input**: $\mathcal{T} = \{T_1, T_2, \dots T_n\}$: tables to integrate; S: the Source Table
2 **Output**: T_{result}: integration result
3 $\mathcal{T} \leftarrow$ ProjectSelect($\mathcal{T}, S$) //σ, π ($T \in \mathcal{T}$) on columns, keys in S
4 $\mathcal{T}_{\cup} \leftarrow$ InnerUnion($\mathcal{T}$) //Inner Union tables with shared schemas
5 $\mathcal{T}_{\cup} \leftarrow$ LabelSourceNulls($\mathcal{T}_{\cup}$) //Label Nulls shared with Source Table
6 $\mathcal{T}_{\cup} \leftarrow$ TakeMinimalForm($\mathcal{T}_{\cup}$) //Apply β, κ on each table
7 $T_{\uplus} \leftarrow \emptyset$
8 **for** $T_i \in \mathcal{T}_{\cup}$ **do**
9     $T_{\uplus} \leftarrow T_{\uplus} \uplus T_i$ //Apply outer union $\uplus$
10   **if** *S coverage does not decrease* **then**
11         $T_{\uplus} \leftarrow \kappa(T_{\uplus})$ //Apply complementation κ
12   **if** *S coverage does not decrease* **then**
13         $T_{\uplus} \leftarrow \beta(T_{\uplus})$ //Apply subsumption β
14 $T_{\text{result}} \leftarrow$ RemoveLabeledNulls($T_{\uplus}$)
15 **if** T_{result} *has fewer columns than* S **then**
16   add null columns in T_{result} for each column $\in S \setminus T_{\text{result}}$
17 Output T_{result}

4.3 Aligning Tuples

Now that we have a possible reclaimed table, we compare it with the Source Table to see how close they are. Consider a Source Table S with columns C and a possible reclaimed table $\hat{S}$ that is projected on shared columns with S, now containing columns $\hat{C}$. From Algorithm 1, we padded columns in $\hat{S}$ to ensure that $\hat{C} = C$. We say that tables S and $\hat{S}$ *align* if $\hat{S}$ has at least one *aligned tuple*. An aligned tuple $t_{\text{Align}} \in \hat{S}$ is defined with respect to some tuple $t_s \in S$ such that for shared key column C_k, $t_{\text{Align}}[C_k] = t_s[C_k]$. In other words, an aligned tuple is a tuple in the reclaimed table that shares a key value with some tuple in the Source Table. If there are multiple tuples from the reclaimed table that share a key value with a Source Table's tuple, we select the aligned tuple with the largest number of shared column values with the Source Table's tuple (or the first aligned tuple upon ties). We now distinguish among three types of aligned tuples, namely a correct tuple, an erroneous tuple, and a nullified tuple. A *correct tuple* $t_{\hat{s}}$ is an aligned tuple that has all of the column values from the Source Table tuple t_s, i.e., $\forall C \in \hat{C} : t_{\hat{s}}[C] = t_s[C]$. An *erroneous tuple* $t_{\hat{s}}$ is an aligned tuple that has at least one non-null *erroneous value* (different column value than the tuple in the Source Table t_s), i.e., $\exists C \in \hat{C} : t_{\hat{s}}[C] \neq t_s[C] \wedge t_{\hat{s}}[C] \neq \perp$. Note that an erroneous value can be a non-null value where the Source Table has a null value. Finally, a *nullified tuple* $t_{\hat{s}}$ is a tuple with a *nullified value* (a null value $\perp$ in a column where the tuple from the Source Table t_s has a non-null value), i.e., $\exists C \in \hat{C} : t_{\hat{s}}[C] \neq t_s[C] \wedge t_{\hat{s}}[C] = \perp$.

Given a possible reclaimed table $\hat{S}$ that shares the same schema with Source Table S, and its aligned tuples to S, we now find how many of the values in S have been reclaimed by the aligned tuples in $\hat{S}$. To do so, we define the Value Similarity Score:

Definition 4 (Value Similarity Score). *Given a table $\hat{S}$ and a Source Table S, the Value Similarity Score (VSS_S) is a similarity score $\in [0, 1]$ with respect to S that captures how similar the values in $\hat{S}$ are to values in S.*

We would like the Value Similarity Score to have the following properties, with respect to Source Table S: *(1) $VSS_S(S) = 1$, (2) $VSS_S(\emptyset) = 0$, (3) Given table $\hat{S}$ with no aligned tuples, $VSS_S(\hat{S}) = 0$, and (4) Given table $\hat{S}_1$ containing m erroneous tuples, each with n erroneous values, and $\hat{S}_2$ with m nullified tuples, each with n nullified values, $VSS_S(\hat{S}_1) < VSS_S(\hat{S}_2)$.*

The best VSS_S of 1 results from equal tables, whereas VSS_S results in 0 if there are no aligned tuples between two tables (no key value is shared), or if an empty table is compared to a non-empty table. These properties are similar to those of the Tuple Similarity score from MapMerge [3], which measures the ratio of the number of shared column values between an aligned tuple from $\hat{S}$ and its corresponding tuple in S, vs. the total number of columns in S. Thus, the Tuple Similarity score is 1 if an aligned tuple shares all column values with its corresponding tuple in S, and 0 if no column values are shared. This is reflected in VSS_S, in which VSS_S is 1 if all tuples in $\hat{S}$ are aligned tuples that share all column values with their corresponding tuples in S ($\hat{S} = S$), and 0 if there are no aligned tuples with S (no tuple shares a key value with S), or if all aligned tuples have no columns shared with tuples in S.

Source Table:

ID	Name	Age	Gender	Education Level
0	Smith	27	—	Bachelors
1	Brown	24	Male	Masters
2	Wang	32	Female	High School

$\hat{S}_1$

ID	Name	Age	Gender	Education Level
0	Smith	27	Male	Bachelors
1	Brown	24	Male	Masters
2	Wang	32	Female	—

$\hat{S}_2$

ID	Name	Age	Gender	Education Level
0	Smith	—	—	Bachelors
1	Brown	24	Male	Masters
2	Wang	32	Female	—

Figure 4: Aligned tuples between a Source Table (left green table) and two possible reclaimed tables (right yellow tables) from Figure 3, aligned based on key column 'ID'.

Consider the fourth property, in which Source Table S is compared to table $\hat{S}_1$ with m erroneous tuples, each with n erroneous values, and also to table $\hat{S}_2$ with the same number of nullified tuples, each also with n nullified values. VSS_S is higher for $(\hat{S}_2, S)$ than for $(\hat{S}_1, S)$. This is desirable due to the fact that a table with erroneous tuples can introduce noise in later downstream tasks, whereas a table with nullified tuples can potentially be integrated with other tables to discover non-null values for the current null values. This is similar to the behavior of Kleene's three-valued logic [7] – 'true' if the degree of truth is 1, 'false' if the degree of truth is 0, and 'unknown' if the degree of truth is between 0 and 1. The maximum truth value of ('unknown', 'false') is 'unknown' since the result can be either true or false. In our case, for table $\hat{S}_2$, which contains nullified (unknown) values, and table $\hat{S}_1$ that contains erroneous (certainly false) values, we also rank the table with nullified tuples higher than the table with erroneous tuples. Consider the following example illustrating how we measure VSS_S:

Example 5. *Consider Source Table S, and two possible reclaimed table, $\hat{S}_1$ on the bottom left and $\hat{S}_2$ on the right, shown in Figure 3. We align tuples from $\hat{S}_1$ and $\hat{S}_2$ with S on key column 'ID'. If multiple tuples in $\hat{S}_1$ or in $\hat{S}_2$ share an ID value with a tuple in S, we choose the aligned tuple with the largest number of common column values. Thus, we consider the tuples in $\hat{S}_1$ and $\hat{S}_2$ shown in Figure 4 when finding VSS_S. The only difference between the alignments is the tuples with ID=0, where $\hat{S}_1$'s tuple is erroneous ("Male" in red), and $\hat{S}_2$'s tuple is nullified (yellow "—"). Thus, $VSS_S(\hat{S}_2) > VSS_S(\hat{S}_1)$.*

Recall that we evaluate Source Table S's coverage (Algorithm 1 Lines 10, 12) before and after applying Complementation(κ) and Subsumption(β) to see if the resulting table contains fewer values and tuples shared with S. With a Value Similarity score, we can evaluate the resulting table with respect to S by measuring how similar the values in the resulting table are to S's values.

Using a Value Similarity Score as a similarity measure to compare the possible reclaimed table $\hat{S}$ and Source Table S, we aim to solve the following problem:

Definition 6 (Source Table Reclamation). *Given a collection of tables $\mathcal{T}$ and a Source Table S generated from a set of tables $\mathcal{T}^* \subseteq \mathcal{T}$, find a set of originating tables $\hat{\mathcal{T}} \subseteq \mathcal{T}$ such that its integration produces $\hat{S}$ with the maximum Value Similarity Score to S.*

5 TABLE DISCOVERY

Now that we know how to integrate a set of originating tables and evaluate a possible reclamation result, let's describe how we discover a good set of originating tables. This is the Table Discovery phase of Table Reclamation. First, we discover a set of candidate tables from the input data lake in Section 5.1. Then, we discuss the novel methodology that refines this set of tables to the set of originating tables in Sections 5.2 and 5.3.

5.1 Candidate Table Retrieval

To discover a set of originating tables from a data lake, we need to discover tables that share some of the same values as the Source Table in an efficient manner. In the context of data lakes, where metadata is inconsistent or missing, searching using schema names is unreliable [2, 21, 49, 68]. Thus, we use any existing data-driven, unsupervised approach to table discovery that is scalable in a data lake setting.

With a set of tables returned as relevant to the Source Table, we need to verify the set similarities of their values with the Source Table, especially if they were discovered primarily using table semantics. To do so, we retrieve candidate tables among the previously discovered tables using a set similarity algorithm. This could be done efficiently with a system like JOSIE [70] that computes exact set containment or MATE [19] that supports multi-attribute joins. In addition to finding candidate tables containing columns that have high set similarity with a Source Table, we also diversify the set of candidate tables such that each candidate table has minimal overlap with its previous candidate (full algorithm is included in the technical report). This is especially important since data lakes tend to have multiple versions of the same tables [32, 57]. For example, in one study (JOSIE [70]), it is found that there is a large percentage of duplicate column sets in real data lakes, specifically 98% of column sets in open data and 83% in web tables are duplicates. Duplicates, or near-duplicate tables, are typically ranked adjacent to each other in set similarity results, so we aim to diversify these tables and rank duplicates and near-duplicates lower. For efficiency, we decrease adjacently ranked tables, especially duplicate and near-duplicate tables. By diversifying the candidates, each candidate for a column in a Source Table S can overlap with different values in S's column. We illustrate this with an example:

Example 7. *Suppose we have the Source Table from our running example in Figure 1. In addition to data lake tables A, B, C, D, we also have Table E, which is an exact duplicate of Table D. If we only rank these tables using set overlap with the Source Table, we would return Tables D and (its duplicate) Table E as top candidates, since all of their columns have high set overlap with those in the Source Table. However, Table E does not add any new information when integrated with Table D. Thus, diversifying the set of candidate tables decreases Table E's set overlap score by its set overlap with the previous table in the ranked list, Table D. Consequently, as Table E is exactly Table D, Table E would now be ranked very low in the list of candidates, pushing other related tables such as Table A higher in the ranked list.*

With a diverse set of candidates found for each column in a Source Table S, we ensure that each candidate table still has high set overlap with the Source Table across all related columns. To do so, we find all tuples in a candidate table that contains column values from S. We verify that for each column that has high set overlap with a column in S, it still has high set overlap within these tuples. We then rename each candidate table's column that has high overlap with a column in S to S's column name, thus implicitly performing schema matching between a candidate table and S. Finally, we check if any candidate table can be subsumed by other candidate tables, specifically if their columns and column values are contained in other tables. If so, we remove the subsumed tables from the returned set of candidate tables.

5.2 Matrix Traversal

With the set of candidate tables, we could potentially enter the table integration phase using all candidate tables as an originating set of tables and evaluate the Value Similarity Score on the resulting table from integration. However, it may be computationally expensive to use all candidate tables to perform table integration. In order to minimize the integration cost, we need to refine the set of candidate tables to only include a set of originating tables containing the maximum set of aligned tuples with respect to the Source Table. To do so, we can emulate the table integration process without performing the expensive computations and see what candidate tables are necessary to reclaim our Source Table. By simulating the alignment of candidate tables' tuples with each other, we can uncover contradicting and erroneous aligned tuples with respect to the Source Table, and discard tables that could decrease the Value Similarity Score.

First, we need to align tuples in candidate tables to tuples in a Source Table. Recall that we assume all tables, including the Source Table, has primary and/or foreign keys. If a candidate table does not have any of the Source Table's keys, we first join it with a copy of another candidate table with which it has a foreign key relationship, and that has a key from the Source Table. This way, all tables after joining via foreign keys have a shared key column with the Source Table and can align its tuples with the Source Table using key values. Note that this pre-processing step is only to emulate table integration and refine a set of candidate tables, and is not needed to perform actual table integration.

To capture tuple alignment, we represent each candidate table and its aligned tuples with the Source Table in the form of a matrix, as illustrated in Figure 5. For each table, we encode its aligned tuples with respect to the tuples in the Source Table, for columns that the table share with the Source Table. Note that at this point, all candidate tables have been processed to contain the key column of the Source Table. To encode aligned tuples, we initialize the matrices to have the same dimensions as S, containing the same number of rows and columns as S, such that the matrix indices represent the Source Table's indices. For each key value and its associated column values in Source Table, check if the value appears in the candidate table at the corresponding column, given the corresponding key value. If so, then the matrix has 1 at the same index as the value's index in Source Table, and 0 otherwise.

Next, we simulate table integration by applying the logical Or on the matrices. Taking the logical Or of two matrices takes the maximum value at each position. This is comparable to applying

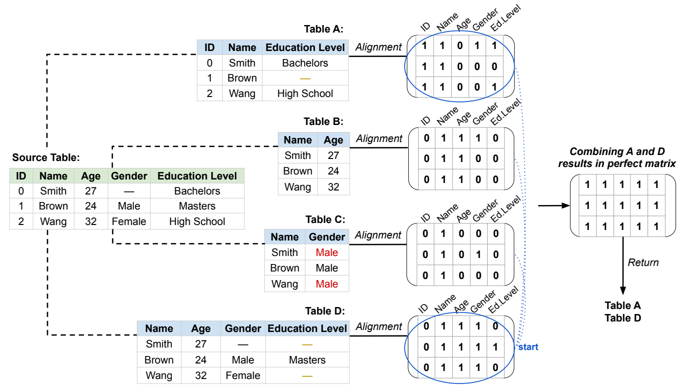


Figure 5: Matrix initialization and traversal with Source Table containing Applicants' data, and candidate tables A, B, C, D retrieved from the data lake.

the Outer Union ($\uplus$) of two tables, and applying Subsumption (β) and Complementation (κ) on the resulting table. Taking the Outer Union result of two tables, we apply β, κ such that for two tuples, t_1, t_2 that share the same non-null value at the same column, the resulting tuple t_r is formed such that for every column j,

$$t_r[j] = \begin{cases} \not\perp & \text{if } t_1[j] \neq \perp \vee t_2[j] \neq \perp \\ \perp & \text{otherwise} \end{cases} \tag{3}$$

In matrix representations, we combine two matrices by combining tuples at the same row index, since all tuples are encoded based on the order of the Source Table's keys. Recall that we encode a 1 in the matrix if the corresponding table shares the same value as the Source Table at the same index, and a 0 if it has a null where the Source Table contains a non-null value at the same index. Then, integrating tuples t_1, t_2 can be simulated with a matrix tuple m_1 and a different matrix's tuple m_2, both at row index i, that encode t_1, t_2 based on Source Table S, respectively. This way, when we combine the values in m_1, m_2 at column j, the produced tuple m_r contains the following value at position (i, j):

Suppose $S[i, j] \neq \perp$:

$$m_r[j] = max(t_1[j], t_2[j]) \tag{4}$$

Thus, matrix integration results in a 1 if there is a matching, non-null value to the Source Table's value. Similarly, table integration results in a non-null value if there exists a non-null value in the element-wise integration. In both integrations, we maximally combine the tuples such that non-null values can replace a null value at the same index.

Example 8. *In Figure 5, the matrix for table D is chosen as the start node in the matrix traversal, as it contains the largest number of values in the Source Table, which is reflected in the percentage of 1's. After exploring other tables to combine with, we find that combining matrices D and A results in a perfect matrix with all 1's, indicating a table integration between tables A and D that would perfectly reclaim the Source Table. We then return tables A and D as the only tables needed in the integration. Thus, the input set of 4 candidate tables is refined to a set containing just Tables A and D.*

Putting it all together, we show the matrix initialization and traversal in Algorithm 2. Given a ranked set of candidate tables $\mathcal{T}$ and Source Table S, we initialize each candidate table's matrix representation of its aligned tuples with respect to S (Line 3). Then, we traverse over the matrices and perform the logical Or operator to combine a pair of matrices in Combine() (Line 9). To evaluate the resulting matrix, we check the fraction of 1's in the matrix. By doing so, we check how many values in the resulting table integration are found in the Source Table, thus evaluating the Source Table's coverage or Value Similarity Score of the resulting table with respect to S. At each step of the matrix traversal (Line 13), including the start (Lines 4-5), we thus choose the matrix or resulting matrix that contains the most 1's in evaluateCoverage(). This traversal ends when either all matrices have been traversed (Line 7), or the percentage of 1's in the resulting matrix (equivalent to the number of Source Table's values found in the resulting table) converges (Lines 17-18). Note that early convergence can be achieved if the lower-ranked tables in the input set do not add new information (can replace 0's with 1's) to the resulting matrix. Finally, we return the set of tables used in the final traversal as the set of originating tables to perform the table integration.

Algorithm 2: Matrix Traversal

1 **Input**: $\mathcal{T} = \{T_1, T_2, \dots T_n\}$: set of candidate tables; S: Source Table
2 **Output**: $T_{\text{orig}} = \{T_1, T_2, \dots T_i\}$: refined set of originating tables
3 $\mathcal{M} \leftarrow$ MatrixInitialization($\mathcal{T}$), //Initialize Matrices of S shape
4 $T_{\text{start}} \leftarrow$ GetStartTable($\mathcal{M}$)
5 prevCorrect = mostCorrect $\leftarrow$ evaluateCoverage(T_{start})
6 $T_{\text{orig}} \leftarrow [\,]$
7 **while** $|T_{\text{orig}}| < |\mathcal{T}|$ **do**
8   **if** T_{orig} **then**
9         $M_c \leftarrow$ Combine(T_{orig}) //Iteratively combine each pair of consecutive matrices
10   prevCorrect = mostCorrect; nextTable = $\perp$
11   **for** *all tables* $T \in \mathcal{T} s.t. T \notin T_{\text{orig}}$ **do**
12         $M_c \leftarrow$ Combine(M_c, T)
13   percentCorrectVals $\leftarrow$ evaluateCoverage(M_c)
14   **if** *percentCorrectVals > mostCorrect* **then**
15   mostCorrect $\leftarrow$ percentCorrectVals
16   nextTable $\leftarrow T$
17   **if** *mostCorrect = prevCorrect* **then**
18   Exit, //Integration did not find more of S's values
19     $T_{\text{orig}} = T_{\text{orig}} \cup$ nextTable
20 **return** T_{orig};

5.3 Three-Valued Matrices

Previously, we use matrices populated with binary values to represent aligned tuples with respect to the Source Table. However, this representation cannot distinguish between nullified and erroneous aligned tuples with respect to the Source Table. Specifically, it does not account for cases in which a tuple in the Source Table and an aligned tuple in a candidate table have different non-null values in the same column, and if a tuple in the Source Table has a null value while the aligned tuple has a non-null value at the same column. Rather, it represents both types of values as 0 in the matrices, as shown in Figure 6(a). In actuality, when we apply Outer Union on two tables with aligned tuples containing different non-null values in the same column, we keep the tuples separate.

Example 9. *Suppose a data scientist has the left, green, Source Table in Figure 6(a), that contains applicants' data as instances, and their ID, Age, Gender, and Status of their application. For the candidate tables A, B, C, D, their matrix representations allow the integration of the start matrix D with matrices A and B, and the integration of matrices D, A, and C to result in the same perfect matrix with all 1's. In practice, when we integrate tables D, A, and C, the erroneous values in the Gender and Status columns from table C are passed on to the integration result. However, the current matrix representations do not reflect this behavior.*

Thus, we need to distinguish between nullified and erroneous aligned tuples in the matrix representation (Line 3 in Algorithm 2). To do so, we make use of three-valued matrices, in which we encode a 1 if a candidate table shares the same value with the Source Table at the same index in an aligned tuple, 0 if a candidate table contains a null where the Source Table has a non-null value at the same index, and -1 if they contain contradicting non-null values at the same index (shown in Figure 6(b)). Formally, given Source Table S and candidate table T, we populate position (i, j) for each aligned tuple $t_{\text{Align}} \in T$ in matrix M as:

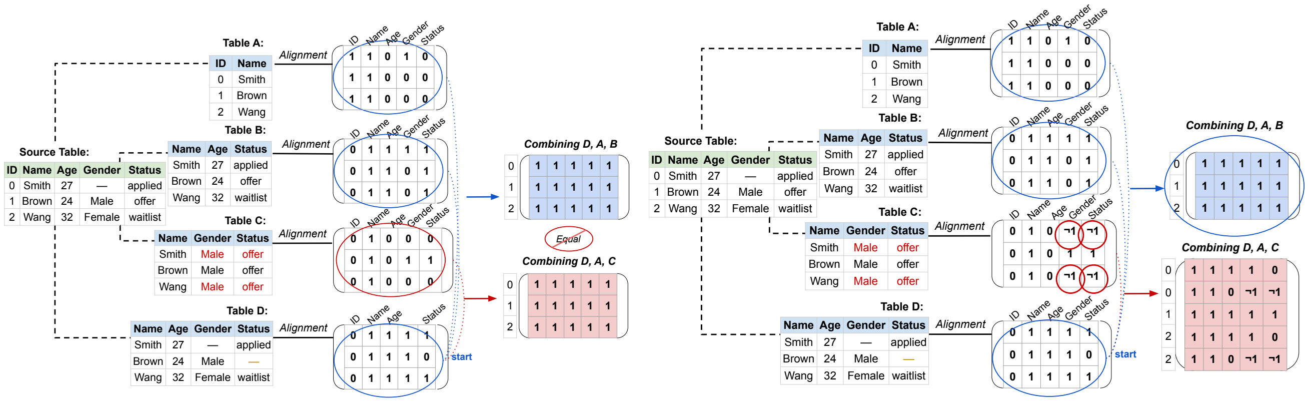
$$M[i,j] = \begin{cases} 1 & \text{if } S[i,j] = T[i,j] \\ 0 & \text{elif } S[i,j] \neq \perp \wedge T[i,j] = \perp \\ -1 & \text{otherwise} \end{cases} \tag{5}$$

Now that we have the amended matrix representations, we discuss how to combine them during matrix traversal. With three-valued matrices, taking the logical Or over two matrices takes the maximum of two truth-values at each index. Specifically, if we have two tuples from two matrices that contain a 1 and -1 at the same position, applying logical OR would choose the 1 [7]. However, in practice when applying Outer Union on two tuples with contradicting non-null values, the resulting integration would contain both tuples. Thus, we keep both tuples from the matrices if they contain different non-0 values at the same index. We re-define Combine() (Line 9) between two matrices, given tuples t_1, t_1 at the same row index accordingly.

$$\text{Combine}(t_1, t_2) = \begin{cases} \text{Return } t_1, t_2 & \text{if } t_1[j] \neq t_2[j] \neq 0 \text{ for column } j \\ \text{OR}(t_1, t_2) & \text{otherwise} \end{cases} \tag{6}$$

This way, we keep the two tuples separate if they contain contradicting, non-0 values at the same position, and otherwise apply logical Or and take the maximum of truth values element-wise.

As expected, this new Combine() could result in matrices with more rows than in the Source Table. To account for this, we encode each matrix as a dictionary, with each key value in the Source Table as the key in the dictionary, and the list of aligned tuples in the resulting matrix with respect to a tuple in the Source Table as values. In evaluating the start (Lines 4-5) and resulting matrices (Line 13) in evaluateCoverage(), we evaluate the Value Similarity Score by taking the aligned tuple with the largest number of aligned values to its corresponding tuple in the Source Table, or the largest number of 1's. Then, we check the number of correct values (1's) vs. the number of erroneous values (-1's), out of the Source Table size. Thus, we treat correct, nullified, and erroneous aligned tuples with respect to the Source Table in different manners, and combine



(a) Two-Valued Matrix Representation

(b) Three-Valued Matrix Representation

Figure 6: Suppose we have a new Source Table about applicants' data and candidate tables A, B, C, D. Figure (a) shows two-valued matrix representations, which does not distinguish between nullified and erroneous values. Figure (b) shows three-valued matrices to make this distinction.

their matrix representations depending on the behavior of applying Outer Union and unary operators.

EXAMPLE 10. *Given the same tables from Figure 6(a), Figure 6(b) now encodes nullified and erroneous values from the candidate tables differently when forming the matrix representations for the aligned tuples with respect to the Source Table. Now, when we integrate matrices D, A, and C, it produces a matrix that also contain the erroneous encoding, or* $\neg 1$*. In contrast, integrating matrices D, A, and B still results in a perfect matrix with all 1's. This exactly reflects the behavior of integrating the tables, in which integrating tables D, A, and B perfectly reclaims the Source Table whereas integrating tables D, A, and C contains the erroneous values.*

6 EXPERIMENTS

We now present evaluations on benchmarks with tables containing real instances (Source Tables) from the well-known TPC-H Benchmark [60] and also the T2D Gold [63] Benchmark. We use these benchmarks along with tables from a real data lake. For the data lakes, we use the large SANTOS benchmark [30] and a sample of WDC [37]. Effectiveness experiments in Section 6.2 show that Gen-T is able to perfectly reclaim 11-13 Source Tables, whereas all baselines only perfectly reclaim at most 1 Source Table across benchmarks. Section 6.3 shows scalability experiments in which Gen-T achieves a runtime that is 5X faster than the next-fastest baseline on a large, real data lake. Finally, Section 6.4 shows the generalizability of Gen-T to a different real-world application.

6.1 Experimental Setup

We implement Gen-T in Python on a CentOS server with Intel(R) Xeon(R) Gold 5218 CPU @ 2.30GHz processor. To evaluate both effectiveness and scalability of Gen-T, we use 6 benchmarks whose statistics are outlined in Table 1.

TP-TR Benchmarks: First, we take the 8 tables from the TPC-H benchmark [60], which contain business information including customers, products, suppliers, nations, etc. Using these tables, we create three versions of a benchmark suite titled TP-Table Reclamation (TP-TR). TP-TR Large has TPC-H tables with original sizes using scale factor of 1. TP-TR Med has TPC-H tables that are each 1/100 of its original table's rows, and TP-TR Small has TPC-H tables that are each ~1/1000 of its original table's rows. In addition, to further assess the effectiveness and scalability of our table discovery method, we embed TP-TR Med into a real, large data lake SANTOS Large [30].

To better represent a real-world scenario of a data lake, we populate the TP-TR benchmarks with both incomplete and inconsistent tables. To do so, for the three TP-TR benchmarks, we take each of the 8 tables and create 4 versions of the same table – creating 32 tables in total (detailed in Table 1). For two versions, we randomly nullify different subsets of the values, and for the other two versions, we randomly inject different non-null, or erroneous values in different subsets of values. This way, we evaluate the robustness of our approach when run on benchmarks consisting of tables that contain nullified and erroneous tuples, with respect to the original tables used to create the Source Tables for our benchmarks. Our goal in the table discovery phase is then to filter out the tables with injected non-null noise, so that the resulting reclaimed table would not contain any erroneous value. Instead, we seek to verify that our approach uses the nullified versions rather than the erroneous versions so that combining them can maximally reproduce the Source Table.

For the TP-TR Benchmarks, we create queries that produce the Source Tables that we aim to reclaim, from the 8 original tables (without injected nulls and noisy values) of each benchmark. To ensure variations of SPJU queries with no aggregations or string-transformations involved, we create 26 queries, each having a subset of operators $\{\pi, \sigma, \bowtie, ⟕, ⟗, \cup, \uplus\}$. In these 26 queries, the number of operations ranges from 2 (just π, σ), to 9, such that the query with the maximum number of unions contains 4 unioned tables, and the query with the maximum number of joins joins 3 tables. Running the same queries on each TP-TR benchmarks, we create 26 Source Tables for the TP-TR Small benchmark containing an average of 9 columns and 27 rows, and 26 Source Tables for the

TP-TR Med and TP-TR Large benchmarks that have an average of 9 columns and 1K rows.

T2D Gold Benchmark: In addition, we explore the real-world application of our method with the T2D Gold Benchmark [63], which takes web tables and matches them to properties from DBpedia. This benchmark was not originally created for the problem of Table Reclamation, so we test the generalizability of Gen-T by seeing if it can reclaim any of this benchmarks' tables. We take 515 raw tables that contain some non-numerical columns and a key column. Since we do not have prior knowledge of whether or not any of these 515 tables can be "reclaimed" as a Source, no Source is known to be able to be perfectly reclaimed from a subset of tables in the benchmark (0 Reclaimable Sources). Thus, we iterate through each of the 515 tables as potential sources. To further assess the effectiveness of Gen-T, we embed T2D Gold tables into a sample of the WDC web table corpus [37], which contains 15K relational web tables.

Benchmark	# Tables	# Cols	Avg Rows	Size (MB)
TP-TR Small	32	244	782	3
TP-TR Med	32	244	10.8K	40
SANTOS Large +TP-TR Med	11K	122K	7.7K	11K
TP-TR Large	32	244	1M	3.9K
T2D Gold	515	2,147	74	4
WDC Sample +T2D Gold	15K	75K	14	66

Table 1: Statistics on Data lakes of each benchmark

6.1.1 Baselines. For all experiments, we compare Gen-T against the current state-of-the-art for *by-target synthesis*, Auto-Pipeline [65], and the state-of-the-art for table integration, ALITE [31].

Auto-Pipeline has a similar framework to our problem in discovering the integration that reclaims the Source Table, however Gen-T does not assume to have the perfect set of input tables from which we can synthesize the query that reproduces the Source Table. Auto-Pipeline has both search and deep reinforcement learning approaches, but since we propose an unsupervised approach, we use the search variation as our baseline. Auto-Pipeline's code implementation is not openly available, so we adopted an open reimplementation of their search approach [57], which adapts the framework in Foofah [28] to perform pairwise table operations and determine which of the operators $\{\cup, \bowtie, ⟕, ⟗\}$ to perform at each edge traversal. We call this re-implemented, adapted baseline Auto-Pipeline*. Since Auto-Pipeline's benchmarks contain small tables, and most of their operators are string-transformation operators, we do not consider their benchmarks for our experiments.

To show the need for our Matrix Traversal rather than directly integrating the set of candidate tables returned from Set Similarity (Section 5.1), we also compare against ALITE and give it the set of candidate tables from Set Similarity as input. Also, since Gen-T first projects and selects on the Source Table's columns and keys before performing integration, we compare with a variation of ALITE, which we call ALITE-PS, that also first performs projection and selection before the table integration. ALITE without projection and selection is much slower as it is creating a much larger integration result, hence ALITE-PS is a fairer comparison.

For each of the three baselines (Auto-Pipeline*, ALITE, and ALITE-PS), on the TP-TR benchmarks, we create another variant in which we give each method a specific integrating set of tables as input, rather than the full set of candidate tables returned from Set Similarity. Since we know what subset of tables from the 8 original tables were used to create the 26 Source Tables, we know that a perfect reclamation of each Source Table contains variants of these tables. Thus, for all original tables used to create each Source Table, the integrating set of tables includes all variations (2 tables with nullified values and 2 tables with non-null erroneous values for each original table) of these tables.

6.1.2 Metrics. For effectiveness, we evaluate how much of the values in Source Table have been reclaimed, or how similar the values in the reclaimed table are to those of the Source Table. Thus, the Source Tables are essentially our ground truth in that we see how much of its rows or values we can re-produce.

Precision and Recall: Consider a Source Table S and reclaimed table from a method $\hat{S}$. From the measure Tuple Difference Ratio (TDR) introduced in ALITE [31], we derive two similarity measures, Recall and Precision, that measure the # of tuples in the intersection of S and $\hat{S}$ relative to the # of tuples in each table:

$$\text{Recall} = \frac{|S \cap \hat{S}|}{|S|}, \text{Precision} = \frac{|S \cap \hat{S}|}{|\hat{S}|} \tag{7}$$

In addition to metrics that measure the similarity between the tuples of a reclaimed table and a Source Table, we also include finer-grain metrics that measure the number of values that do not match within aligned tuples (tuples with the same key value). If there are multiple aligned tuples with respect to one tuple in the Source Table (multiple tuples in the reclaimed table with the same key value), then we consider the tuple that contains the largest number of column values shared with the corresponding tuple in the Source Table. This way, there is at most 1 aligned tuple in the reclaimed table for each tuple in the Source Table. In these measures, which we denote as *divergence measures*, the ideal score is 0 (the reclaimed table is identical to the Source Table). Specifically, we measure how many of the tuples of the Source Table are not found in the reclaimed table (using *Instance Divergence*), and how many of the values found in reclaimed tuples differ from those in the Source Table (using *Conditional KL-Divergence*). This enables us to measure the nullified and erroneous values in the aligned tuples of the reclaimed table, with respect to the Source Table, as defined in Section 4.3.

Instance Divergence: First, we measure how many missing values there are in each aligned tuple, with respect to its corresponding tuple in the Source Table. To do so, we define Instance Divergence, which is the inverse of a measure introduced in MapMerge [3] that they refer to as Instance Similarity. Given a Source Table S and a reclaimed table $\hat{S}$, the Instance Divergence (Inst-Div.) is computed as follows.

Consider two aligned tuples s from S and $t_{\text{Align}} = match(s)$ from $\hat{S}$ with the same key value. Let $s \cap t_{\text{Align}}$ be the number of non-key columns on which s and t_{Align} agree. If t_{Align} does not exist (tuple

Method	TP-TR Small		TP-TR Med		SANTOS Large +TP-TR Med		TP-TR Large	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
ALITE	0.704	0.128	0.662	0.202	—	—	—	—
ALITE w/ integrating set	0.745	0.133	0.694	0.202	0.694	0.202	—	—
ALITE-PS	0.805	0.539	0.880	0.556	0.842	0.554	0.775	0.521
ALITE-PS w/ integrating set	0.833	0.552	0.880	0.569	0.880	0.569	0.880	0.569
Auto-Pipeline*	0.674	0.272	—	—	—	—	—	—
Auto-Pipeline* w/ integrating set	0.683	0.289	—	—	—	—	—	—
Gen-T	**0.958**	**0.839**	**0.976**	**0.867**	**0.976**	**0.867**	**0.971**	**0.816**

Method	TP-TR Small		TP-TR Med		SANTOS Large +TP-TR Med		TP-TR Large	
	Inst-Div.	D_{KL}	Inst-Div.	D_{KL}	Inst-Div.	D_{KL}	Inst-Div.	D_{KL}
ALITE	0.095	1.332	0.100	35.831	—	—	—	—
ALITE w/ integrating set	0.086	1.197	0.085	36.348	0.085	36.348	—	—
ALITE-PS	0.040	0.655	0.009	3.524	0.011	4.629	0.049	21.978
ALITE-PS w/ integrating set	0.037	0.688	0.009	3.524	0.009	3.524	0.009	3.524
Auto-Pipeline*	0.158	2.574	—	—	—	—	—	—
Auto-Pipeline* w/ integrating set	0.133	2.109	—	—	—	—	—	—
Gen-T	**0.015**	**0.130**	**0.004**	**1.326**	**0.004**	**1.326**	**0.004**	**1.490**

Table 2: Similarity Measures Recall and Precision, and Divergence Measures Instance Divergence and KL-divergence of Gen-T and baselines on all TP-TR benchmarks, given the same set of candidate tables from Set Similarity. If there are no results for some method, then it timed out for most if not all Source Tables.

s was not reclaimed), then $s \cap match(s)$ is defined as 0. Also let n be the cardinality of S defined as the number of non-key columns.

$$\text{Inst-Div.} = 1 - \frac{\sum_{s \in S, match(s) \in \hat{S}} \frac{|s \cap match(s)|}{n}}{|S|} \tag{8}$$

For each aligned tuple (see Section 4.3) in the reclaimed table, we find the fraction of overlapping values it has with its aligned tuple in the Source Table. Then, we average over all aligned tuples, with respect to the total number of tuples in the Source Table, and take the inverse to find the Instance Divergence. For a reclaimed table containing all tuples and all values from the Source Table, the Inst-Div. score is 0. Otherwise if no value from the Source Table is found in the reclaimed table, the score is 1.

Conditional KL-divergence: Finally, we want to capture how erroneous the values may be in the aligned tuples from a reclaimed table with respect to tuples in a Source Table. Thus, we also consider the Conditional KL-divergence of a reclaimed table, with respect to a Source Table, conditioned on the probability that the key values from the Source Table are found in the reclaimed table. We adopt the traditional definition of conditional KL-divergence [16, 43], and also add a penalization for erroneous values, such that the score is higher for reclaimed tables containing erroneous values as opposed to nulls in their aligned tuples with the Source Table. Given column C shared between a Source Table and a reclaimed table T, suppose we have probability distributions, $\mathcal{P}$ for C in the Source Table and $\mathcal{Q}$ for C in the reclaimed table. We condition on the key values in primary key column K. The conditional KL-divergence (or conditional relative entropy) between $\mathcal{P}$ and $\mathcal{Q}$ of sample space X of column C conditioned on key K is as follows:

$$D_{KL}(Q||P) = -\sum_{x \in X, k \in K} P(x|k) \log\left(\frac{Q(x|k)(1 - Q(\neg x|k))}{P(x|k)}\right) \tag{9}$$

Given n non-key columns C in a Source Table we take the average D_{KL} for each column divided by the probability of a key value in T matching a key value from the Source Table ($Q(K)$) and the number of non-key columns (n). Then, the conditional KL-divergence of the reclaimed table is as follows:

$$D_{KL}(T) = \frac{D_{KL}(Q_1||P_1) + D_{KL}(Q_2||P_2) + \cdots + D_{KL}(Q_n||P_n)}{Q(K) * n} \tag{10}$$

The conditional KL-divergence of the reclaimed table is a score $\in [0, \infty)$, with 0 being the ideal score. There is no upper limit on this metric since it naturally approaches ∞ when no key value from the Source Table is found in the reclaimed table.

For all effectiveness metrics, we take the average scores across all Source Tables.

Efficiency Measures: For efficiency, we measure the average runtimes for all Source Tables, as well as the average ratio of the output size of the reclaimed table to the size of the Source Table (creating a large reclaimed table can significantly increase runtimes).

6.2 Effectiveness

Table 2 reports the similarity and divergence scores, respectively, for all four TP-TR benchmarks across all methods. For all methods on TP-TR Small, TP-TR Med, and TP-TR Large benchmarks, we input candidate tables discovered from just Set Similarity (Section 5.1). For methods run on SANTOS Large +TP-TR Med, we first discover relevant tables from the large data lake using Starmie [20], a state-of-the-art self-supervised system for scalable table discovery. Hence, it can discover a set of candidate tables for the Source Table from a large data lake. Although the primary use case of Starmie was table union search, it was shown to apply to other search semantics such as table discovery to improve the performance of downstream machine learning tasks via feature discovery (join search) and column clustering. Following Starmie, we run Set Similarity to find syntactically similar tables among the returned tables from Starmie.

As the sizes of tables and/or number of tables increase across the TP-TR benchmarks, some of the baseline methods timeout for most if not all Source Tables. Specifically, Auto-Pipeline* times out for every benchmark except for TP-TR Small, and ALITE times out on SANTOS Large +TP-TR Med and TP-TR Large benchmarks. We discuss scalability and timeouts in Section 6.3.

Across all benchmarks, Gen-T outperforms the baselines for all metrics, while perfectly reclaiming 15-17 Source Tables across all benchmarks. The baselines ALITE-PS and Auto-Pipeline* only perfectly reclaim 3 Source Tables and 1 Source Table across the benchmarks on which they do not time out, respectively, and ALITE does not perfectly reclaim any. In fairness, ALITE is an integration method and does not take the Source Table into account (it is not "target-driven" like Auto-Pipeline*). In terms of similarity (top table of Table 2), Gen-T outperforms the top performing existing baseline method (ALITE) by 36-47% in Recall and by 71%-329% in Precision across all TP-TR benchmarks. For the divergence measures (bottom table of Table 2), we see that Gen-T produces tables that contain fewer nullified values in its aligned tuples with respect to the Source Table (Inst-Div.), as well as fewer erroneous values in its aligned tuples, which is reflected in the lower D_{KL} scores than the baselines.

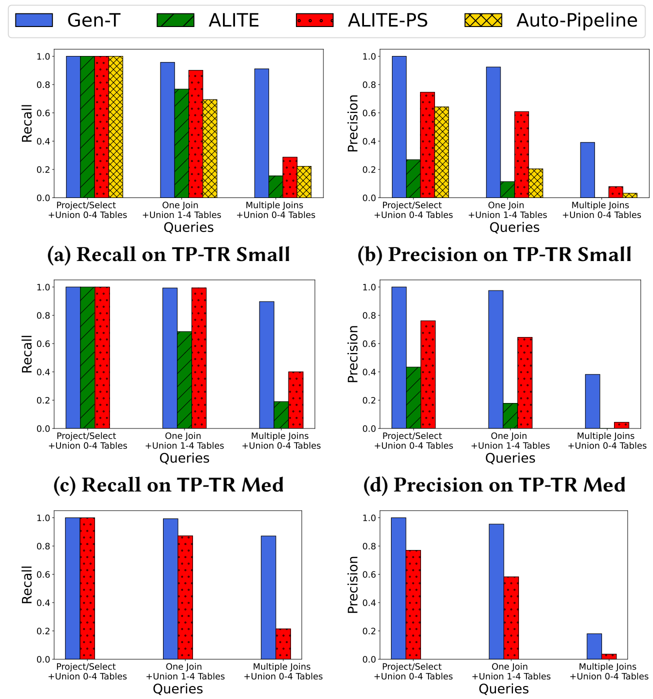
Even compared to each baseline that is given specified integrating sets of tables rather than a large set of candidates ('w/ integrating set'), Gen-T performs much better. Thus, the matrix traversal method (Section 5.3) used in Gen-T to refine the set of originating tables works well in filtering out misleading tables that could be integrated to produce tables containing erroneous values with respect to the Source Table. We provide examples and Benchmark samples corresponding to these examples in our repository.[1]

To better understand the performance of the methods on different types of queries used to initially create the Source Tables, we perform an analysis of the similarity measures for all methods on different types of queries used to form the Source Tables in TP-TR Small, TP-TR Med, and TP-TR Large benchmarks, shown in Figure 7. Ranging from simple queries (that just performing Projection, Selection, and Union) to more complex queries (joining up to 4 tables and unioning up to 4 tables), we see that Gen-T outperforms the baselines on queries of all complexities used to initially create the Source Table. Thus, not only does the matrix traversal display great effectiveness, but the set of operators used in table integration (Section 4.1) works well in representing different types of queries.

6.3 Scalability

Figure 8 shows the scalability of all methods across benchmarks as the number of tables and/or the size of tables grows larger, from the smallest TP-TR benchmark (TP-TR Small), to the tables from TP-TR Med embedded in a large data lake (SANTOS Large). Figure 8(a) reports average runtimes for all methods across all four benchmarks.

[1]https://github.com/northeastern-datalab/gen-t



(a) Recall on TP-TR Small

(b) Precision on TP-TR Small

(c) Recall on TP-TR Med

(d) Precision on TP-TR Med

(e) Recall on TP-TR Large

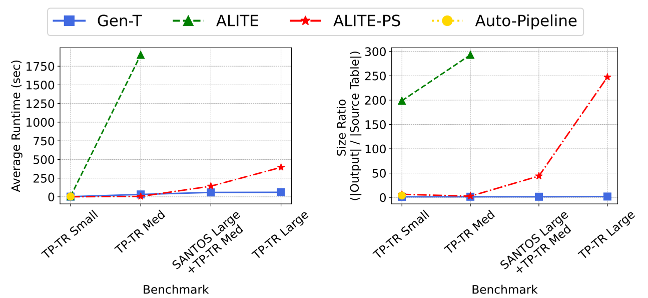
(f) Precision on TP-TR Large

Figure 7: Recall and Precision Analysis of all baselines on TP-TR Small, TP-TR Med, TP-TR Large Benchmarks, for different types of queries that produce Source Tables.

Since all methods are given the same sets of candidate tables, we report the runtimes starting from ingestion of the candidate tables. For Gen-T, this time includes the time it takes to initialize the matrix representations, traverse over matrices to refine the set of candidate tables, and integrate the originating tables to produce an output table. For the other methods, this time only includes the integration time. We find that Auto-Pipeline* only runs on TP-TR Small without timing out, and ALITE, which performs full disjunction, is exponential in time and times out for the last two benchmarks. We set the timeouts for each method according to the details reported in respective papers and with respect to the data lake size. Specifically, we use a 30min timeout for TP-TR Small benchmark, 7hrs timeout for TP-TR Med and SANTOS Large +TP-TR Med benchmarks and 24hrs timeout for TP-TR Large benchmark.

We can see that Gen-T, although having an overhead of matrix initialization and traversal, has a more consistent runtime across all benchmarks compared to all baselines. Gen-T is 2X faster in runtime compared to Auto-Pipeline* on the TP-TR Small benchmark. On the TP-TR Med, Gen-T is 60X faster than ALITE and on the TP-TR Large, Gen-T is 7X faster than ALITE-PS. Thus, the matrix representations and refinement of the set of originating tables seems to be very beneficial in cutting the cost of integration, an issue that seems prevalent as shown by the baselines.

In Figure 8(b), we report the average output sizes, or number of cell values in the reclaimed tables, with respect to the average Source Table sizes for all methods across all benchmarks. As the number and sizes of tables grow across benchmarks, the output sizes relative to the sizes of the Source Table (expected output size) can easily grow at a fast rate if the integration is among more or larger tables, especially if it includes noisy tables from the real data lake (SANTOS Large). Gen-T's produces tables' output sizes remain consistent across benchmarks, being 1.3-1.8X larger than the average Source Table's size. This trend largely accounts for the higher precision of Gen-T, compared to the other baselines, since Gen-T produces tables that mostly consist of tuples from the Source Table. Thus, Gen-T's runtimes and output sizes remain consistent across benchmarks of different sizes, even when the expected tables for integration are immersed in a large, real data lake.



(a) Average Runtimes in sec. **(b) Average Ratio of Output Size (total # values) / Source Table Size**

Figure 8: Measuring Scalability via Average Runtime (sec) and Ratio of Output Sizes to Source Table sizes for all methods on all TP-TR Benchmarks

6.4 Generalizability

In addition to the TP-TR benchmarks, we also experiment with the T2D Gold benchmark to see how well we can apply Gen-T to a real-world scenario with Web Tables. In this case, we do not know *whether* or *how* the tables were originally generated. Accordingly, we attempt to reclaim each table using a subset of other tables in the benchmark by iterating through each 515 tables as potential Source Tables, and run the methods.

Gen-T is able to successfully reclaim three Source Tables from an integration of multiple tables (5-6 tables), such that the output table has perfect Recall, Precision, Instance-Div., and near-perfect D_{KL}. Meanwhile, Gen-T also finds duplicate tables for 12 Source Tables, or 6 sets of duplicates. This indicates that we can apply Gen-T in a different domain, even if no sources are known to be reclaimed, and retrieve successful reclamations. The baseline methods are able to reclaim 12-13 Source Tables, all of which are included in the 15 Source Tables reclaimed by Gen-T. The specific results are given in a technical report [**?**].

We then run experiments on a data lake consisting of both T2D Gold and WDC Sample tables. This way, we can evaluate how well the methods perform when the set of candidate tables returned from Set Similarity may contain irrelevant or misleading tables from the WDC Sample benchmark. As shown in Table 3, we report the similarity and divergence scores for all methods on 33 of the common sources from T2D Gold for which all methods have non-empty, reasonably-sized output tables. We can see that Gen-T outperforms the baselines for all measures, even having perfect precision of 1.0. In contrast, the baseline methods that are given the candidate tables from Set Similarity integrate all candidate tables and produce tables that contain a lot of additional tuples. Thus, the matrix representation and traversal of our method proves to work well in defining the set of originating tables containing tuples that are needed to reclaim the Source Table.

Method	Recall	Precision	Inst-Div.	D_{KL}
ALITE	0.956	0.490	0.009	0.627
ALITE-PS	0.956	0.796	0.009	0.627
Auto-Pipeline*	0.881	0.725	0.088	19.261
Gen-T	0.956	1.000	0.009	0.627

Table 3: 33 Sources from T2D Gold for which all methods have non-empty output tables, and a data lake with T2D Gold tables immersed in the WDC Sample benchmark.

7 CONCLUSION

Table Reclamation in data lakes is essential in verifying the originating data lake tables and integration pipeline that first generated the user's table. Our results suggest that refining the Table discovery method for this problem is crucial in effectively reproducing, or reclaiming, the user's tables in a scalable manner.

Future work will include re-discovering the original SPJU query that was originally used to generate the user's table, from the representative set of operators that we use. We have started exploring this direction with Auto-Pipeline* (on top of our method) to discover the Join / Union operators that best combine the set of originating tables to reclaim the Source Table. This investigation will also include adapting integration methods that rediscovers SPJU queries in the scale of data lakes. Finally, we also aim to relax the assumption of table keys and align tuples via entity matching.

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8 APPENDIX

8.1 Table Operators

- Complement Union ($\boxplus$): Apply complementation on the outer union result of two tables. This operator is only commutative.
- Minimum Union ($\oplus$): Apply subsumption on the outer union result of two tables. This operator is commutative and associative.

Suppose we have two tables, T_1, T_2, that share key column K, and are in their minimal forms in which there are no duplicates and no tuples that can be subsumed or complemented. We show that for each pairwise table operator, Inner Union, Inner Join, Left Join, Outer Join, Cross Product, there exists an equivalent query consisting of Outer Union and/or unary operators. (SP of SPJU queries are accounted for by the unary operators).

Lemma 11 (Inner Union). *Inner Union($\cup$): it is known that if the schemas of two tables are equal, then Inner Union = Outer Union*

Lemma 12 (Inner Join). *Inner Join ($\bowtie$):*

$$T_1 \bowtie T_2 = \sigma(T_1.K = T_2.K \neq \perp, \beta(\kappa(T_1 \uplus T_2))) \tag{11}$$

Lemma 13 (Left Join). *Left Join (⟕) [24]:*

$$T_1 ⟕ T_2 = \beta((T_1 \bowtie T_2) \uplus T_1) \tag{12}$$

Lemma 14 (Outer Join). *Full Outer Join (⟗) [24]:*

$$T_1 ⟗ T_2 = \beta(\beta((T_1 \bowtie T_2) \uplus T_1) \uplus T_2) \tag{13}$$

Lemma 15 (Cross Product). *Cross Product($\times$): We denote columns in T_1 and T_2 as $T_1.C$ and $T_2.C$, respectively. Consider a constant column c.*

$$T_1 \times T_2 = \kappa(\pi((T_1.C, c), T_1) \uplus \pi((T_2.C, c), T_2)) \tag{14}$$

Thus, $\uplus, \sigma, \pi, \kappa, \beta$ operators form queries that are equivalent to all SPJU queries. Due to space constraints, the full proofs for each lemma are included in the technical report.

8.1.1 *Proof of Lemma 13[Left Join].*

Given two tables T_1, T_2 and join attribute a_j, such that T_1, T_2 are in their minimal forms in which there are no duplicates and no tuples can be subsumed or complemented, $T1 ⟕ T2$ produces the same result as $(T_1 \bowtie T_2) \oplus T_1$.
$T_1 ⟕ T_2 = \beta((T_1 \bowtie T_2) \uplus T_1)$

Proof. We first prove that the resulting table of $T1 ⟕ T2$ is contained in the resulting table of $(T_1 \bowtie T_2) \oplus T_1$:

There are two types of tuples that result from $T1 ⟕ T2$: tuples that appear in both T_1, T_2, or tuples that only appear in T_1:

(1) If tuples appear in both T_1, T_2, then they appear in $(T_1 \bowtie T_2)$
(2) If tuples appear in only T_1, then they are contained in the outer union result, $T_1 \uplus T_2$. Since T_1 is in its minimal form, and these tuples do not share a_j values with tuples in T_2, they are not subsumed in applying β to $T_1 \uplus T_2$, and thus also appear in $T_1 \oplus T_2$.

Thus, all tuples from $T1 ⟕ T2$ are contained in the resulting table of $(T_1 \bowtie T_2) \oplus T_1$.

Next, we show that and the resulting table of $(T_1 \bowtie T_2) \oplus T_1$ is contained in the resulting table of $T1 ⟕ T2$.

Again, let's consider two types of tuples that result from $(T_1 \bowtie T_2) \oplus T_1$: tuples that appear in both T_1, T_2, and those that do not:

(1) If tuples appear in both T_1, T_2, then they appear in $(T_1 \bowtie T_2)$, whose result is contained in that of $T1 ⟕ T2$.
(2) All tuples in $(T_1 \uplus T_2) \setminus (T_1 \bowtie T_2)$ either contain tuples that can be subsumed by tuples from $(T_1 \bowtie T_2)$, or tuples that are only in T_1 and not in $(T_1 \bowtie T_2)$. Thus, the only tuples in $(T_1 \oplus T_2) \setminus (T_1 \bowtie T_2)$ are tuples in $T_1 \setminus (T_1 \bowtie T_2)$.

Thus, all tuples from $(T_1 \bowtie T_2) \oplus T_1$ are contained in the resulting table of $T1 ⟕ T2$.

Now that we have shown that tuples from $T1 ⟕ T2$ are contained in the resulting table of $(T_1 \bowtie T_2) \oplus T_1$ and vice versa, we have shown that the resulting table of $T1 ⟕ T2$ is equivalent to the resulting table of $(T_1 \bowtie T_2) \oplus T_1$.

□

8.2 Set Similarity

Algorithm 3: Set Similarity

1 **Input**: $\mathcal{T} = \{T_1, T_2, \ldots T_n\}$: set of data lake tables; S: Source Table; C_k: primary key column of Source Table; τ: Similarity Threshold
2 **Output**: $\mathcal{T}' = \{T_1, T_2, \ldots T_n\}$: a set of candidate tables with high syntactic overlap with S
3 $\mathcal{T}'_{\text{scores}} \leftarrow \{\}$ //Store a list of scores for each candidate table
4 **for** *all S columns $c \in C$* **do**
5     $\mathcal{T}_C$, overlapScores $\leftarrow$ SetOverlap$(\mathcal{T}, c, \tau)$
6     $\mathcal{T}_C$, diverseOverlapScores $\leftarrow$ diversifyCandidates$(\mathcal{T}_C, c, \tau)$
7   **for** *all tables $T \in \mathcal{T}_C$* **do**
8         $\mathcal{T}'_{\text{scores}}[T]$+= diverseOverlapScores$[T]$
9 Order $\mathcal{T}'_{\text{scores}}$ by average diverseOverlapScores, in descending order
10 $\mathcal{T}' \leftarrow$ keys$(\mathcal{T}'_{\text{scores}})$
11 **for** *all tables $T \in \mathcal{T}'$* **do**
12   alignedTuples $\leftarrow$ tuples in T that contain S's column values
13   **if** *set overlap of T values in alignedTuples with $S < \tau$* **then**
14   Discard T;
15   Remove T if its values are contained in another table $T' \in \mathcal{T}'$
16   Rename T columns to aligned S columns
17 **return** $\mathcal{T}'$;

We find candidate tables with values that have high set overlap with those in a Source Table. As shown in Algorithm 3, we perform Set Similarity with an input set of data lake tables $\mathcal{T}$, the Source Table S, primary key column in the Source Table C_k, and a similarity threshold τ (Line 1), and output a set of candidate tables (Line 2). We first find a set of candidate tables where each table contains a column whose set overlap with a column from S (overlapScore) is above a specified threshold (Lines 4-8). This can be done efficiently with a system like JOSIE [70] that computes exact set containment or MATE [19] that supports multi-attribute joins. In addition, when finding tables with columns that have a high set overlap with columns in S, we call diversifyCandidates() (Line 6) to ensure that each candidate table not only has a high overlap with S, but also has minimal overlap with the previous candidates, shown in Diversify Candidates Algorithm 4.

Formally, given candidate table $T_i \in \mathcal{T}$ s.t. $i > 0$, the previous candidate table, T_{i-1}, and Source Table S, we diversify a set of candidate tables uses the following formula to rank the candidates, in descending order:

$$\text{diverseOverlapScore} = \frac{|T_i \cap S|}{|S|} - \frac{|T_i \cap T_{i-1}|}{|T_i|} \tag{15}$$

When finding diverseOverlapScore, we find the set overlap of T_i with S vs. the set overlap of T_i with the previous candidate T_{i-1}. This way, we arrange the set of candidate tables to ensure diversification of candidates.

Algorithm 4: Diversify Candidates

1 **Input**: c: column from Source Table; $\mathcal{T}_C = \{T_1, T_2, \ldots T_n\}$: set of candidate tables with columns having high overlap with c; τ: Similarity Threshold

2 **Output**: $\mathcal{T}'_C = \{T_1, T_2, \ldots T_n\}$: a set of diverse candidate tables

3 $\mathcal{T}_{\text{scores}} \leftarrow \{\}$

4 **for** *all tables* $T \in \mathcal{T}_C$ **do**

5 $\quad C \leftarrow$ column from T with highest set overlap with c

6 $\quad \text{Ind}_T \leftarrow$ index of T in $\mathcal{T}_C$

7 $\quad$ **if** $Ind_T = 0$ **then**

8 $\quad\quad$ Continue;

9 $\quad C_{\text{prev}} \leftarrow$ column from $\mathcal{T}_C[\text{Ind}_T - 1]$ with highest set overlap with c //Get column from previous candidate table with high overlap with c

10 $\quad \text{prevColOverlap} \leftarrow (C \cap C_{\text{prev}})/|C|$ //Set overlap with previous column

11 $\quad \text{sourceColOverlap} \leftarrow (C \cap c)/|c|$ //Set overlap with column from Source table

12 $\quad$ **if** *sourceColOverlap* $< \tau$ **then**

13 $\quad\quad$ Continue;

14 $\quad \text{overlapScore} \leftarrow \text{sourceColOverlap} - \text{prevColOverlap}$

15 $\quad \mathcal{T}_{\text{scores}}[T] \leftarrow \text{overlapScore}$

16 Order $\mathcal{T}_{\text{scores}}$ by values in descending order

17 $\mathcal{T}'_C \leftarrow \mathcal{T}_{\text{scores}}.\text{keys}$

18 **return** $\mathcal{T}'_C$;

After we find candidate tables for each column in the Source Table, we average over all overlap scores, each for a Source Table's column with which they share many values, and rank them in descending order of averaged scores (Line 9). With a set of candidate tables, we find tuples in each candidate table that contain column values from S. Within these aligned tuples, we check if each aligned column in a candidate table, with respect to a column in S, still has high set overlap (above threshold τ). If not, we remove them (Line 14). Next, we remove any subsumed candidate table, whose columns and column values are all contained in another candidate table (Line 15). We then rename each candidate tables' columns to the names of S's columns with which they align (Line 16), thus implicitly performing schema matching between S's columns and the columns from the candidate tables that have overlapping values with S's columns. Finally, we return the set of candidate tables.

8.3 Effectiveness Examples

Example 16. *Consider one Source Table from TP-TR Large benchmark that was generated from the "Customers" table ⟗ the "Orders" table from the TPC-H tables. Gen-T discovers 2 nullified "Customers" tables and 2 nullified "Orders" tables as its set of originating tables (recall dataset description in Section 6.1). During integration, non-null values replace the nullified values from the originating tables, thus recovering the Source Table's values. This results in an integrated table that has 100% Recall and Precision. ALITE-PS, the only baseline that does not time out on this benchmark, integrates all 11 discovered tables: all 4 versions of the "Customers" table, all 4 of the "Orders" tables, and 3 of another tables that happens to*

Method	Recall	Precision	Inst-Div.	D_{KL}	# Sources
ALITE	0.195	0.142	0.588	38.852	109
ALITE-PS	0.186	0.213	0.600	46.390	111
Auto-Pipeline*	0.172	0.179	0.631	80.797	112
Gen-T	0.218	0.249	0.574	45.994	95

Table 5: All T2D Gold with non-empty reclaimed tables results.

share some of the same key values and columns as the Source Table. This integration results in a nearly 0% Recall and Precision, with an output size that is 5.5X the output size from Gen-T. Thus, by filtering out noisy tables from the 11 discovered tables using matrix traversal, Gen-T is able to discover the exact set of originating tables , and integrate it to perfectly reclaim the Source Table.

Example 17. *Consider a Source Table from TP-TR Large benchmark that was generated from "Customers" ⟗ "Orders" ⟗ "Lineitem" ⟗ (∪ 4 samples of "Nations") from the TPC-H benchmark. Gen-T has 99% Recall and 6% Precision on this Source Table, from a set of 9 originating tables retrieved from a set of 15 candidate tables. Although Gen-T outputs a table that is almost 9X larger than the Source Table, it contains almost all tuples from the Source Table. ALITE-PS integrates all 15 tables discovered from the data lake, including ones with non-null noisy values. This integration results in a nearly 0% Recall and Precision, with an output size that is 10X the size of the Source Table. Thus, even though Gen-T is not able to reclaim only the Source Table's tuples, its integration result contains most of the Source Table's tuples as a result of its near-perfect set of originating tables returned from matrix traversal, which filters out all the non-null noisy tables discovered from the data lake.*

8.4 Generalizability Results

Method	Recall	Precision	Inst-Div.	D_{KL}
ALITE	1.000	0.821	0.000	0.375
ALITE-PS	1.000	0.998	0.000	0.375
Auto-Pipeline*	0.946	0.871	0.034	2.526
Gen-T	1.000	1.000	0.000	0.375

Table 4: Reclamation of 3 Source Tables (integrating 5-6 tables for each Source Table) and 12 Source Tables (with a duplicate found for each Source Table).

Since the baseline methods are able to reclaim a subset of these 15 Source Tables, and no other Source Table that Gen-T does not successfully reclaimed with perfect similarity scores, we report the similarity and divergence scores for these 15 tables in Table 4. We can see that even in a benchmark where there are no sources known to be reclaimed, Gen-T can still reclaim 15 Source Tables with perfect similarity scores while outperforming the baseline methods. Thus, we can apply Gen-T in a different domain and it is able to retrieve successful reclamations.

When experimenting on the T2D Gold benchmark, we also report the evaluation scores and number of Source Tables for which each method returns a non-empty table in Table 5. We can see that Gen-T's performance is comparable to the baselines. For the Source Tables that the baselines produce non-empty output tables and Gen-T do not, the baselines' outputs contain few, if any, of the Source Table's tuples, resulting in very low similarity scores and high divergence scores.