Auto-Join: Joining Tables by Leveraging Transformations

Erkang Zhu[*]
University of Toronto
ekzhu@cs.toronto.edu

Yeye He
Microsoft Research
yeyehe@microsoft.com

Surajit Chaudhuri
Microsoft Research
surajitc@microsoft.com

ABSTRACT

Traditional equi-join relies solely on string equality comparisons to perform joins. However, in scenarios such as ad-hoc data analysis in spreadsheets, users increasingly need to join tables whose join-columns are from the same semantic domain but use different textual representations, for which transformations are needed before equi-join can be performed. We developed Auto-Join, a system that can automatically search over a rich space of operators to compose a transformation program, whose execution makes input tables equi-join-able. We developed an optimal sampling strategy that allows Auto-Join to scale to large datasets efficiently, while ensuring joins succeed with high probability. Our evaluation using real test cases collected from both public web tables and proprietary enterprise tables shows that the proposed system performs the desired transformation joins efficiently and with high quality.

1. INTRODUCTION

Join performs the powerful operation of combining records from two tables together that is of key importance to data analysis. It is extensively used in relational databases, as well as data analysis tools such as Power Query for Excel [5], Informatica [3], etc.

Most existing commercial systems only support *equi-join* through exact equality comparisons. While equi-join works well in well-curated settings such as data warehousing, it falls short for a rich variety of data that is less curated. For example, analysts today increasingly need to perform *one-off*, *ad-hoc* analysis by joining datasets obtained from different sources, whose key columns are often formatted differently. Requiring support staffs to perform extensive ETL in such scenarios is often too slow and expensive. In fact, customer surveys from a Microsoft data preparation system suggest that automating join is a key feature requested by end-users. We believe that solving the auto-join problem would be an important step towards fulfilling the broad vision of *self-service data preparation* [14], a market that Gartner estimates to be worth over $1 billion by 2019.

[*]Work done at Microsoft Research.

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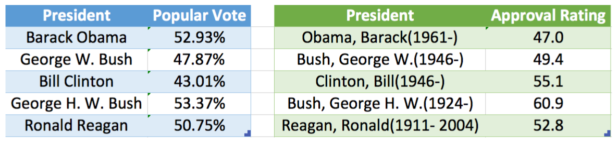
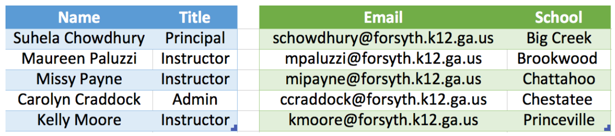


President	Popular Vote
Barack Obama	52.93%
George W. Bush	47.87%
Bill Clinton	43.01%
George H. W. Bush	53.37%
Ronald Reagan	50.75%

President	Approval Rating
Obama, Barack(1961-)	47.0
Bush, George W.(1946-)	49.4
Clinton, Bill(1946-)	55.1
Bush, George H. W.(1924-)	60.9
Reagan, Ronald(1911- 2004)	52.8

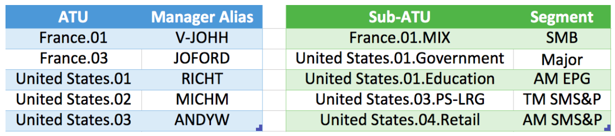
Figure 1: (left): US presidents and popular votes. (right): US presidents and job approval rating. The right table uses last-name, comma, first-name, with (year-of-birth and year-of-death).



Name	Title
Suhela Chowdhury	Principal
Maureen Paluzzi	Instructor
Missy Payne	Instructor
Carolyn Craddock	Admin
Kelly Moore	Instructor

Email	School
schowdhury@forsyth.k12.ga.us	Big Creek
mpaluzzi@forsyth.k12.ga.us	Brookwood
mipayne@forsyth.k12.ga.us	Chattahoo
ccraddock@forsyth.k12.ga.us	Chestatee
kmoore@forsyth.k12.ga.us	Princeville

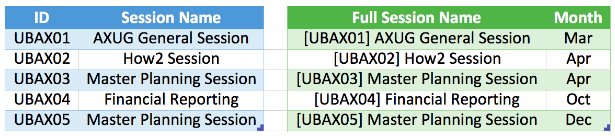
Figure 2: (left): Name and job titles in school. (right): Email and school districts. `Email` can be generated from `name` in the left by concatenating first-initials, last-names, and `'@forsynth.k12.ga.us'`.



ATU	Manager Alias
France.01	V-JOHH
France.03	JOFORD
United States.01	RICHT
United States.02	MICHM
United States.03	ANDYW

Sub-ATU	Segment
France.01.MIX	SMB
United States.01.Government	Major
United States.01.Education	AM EPG
United States.03.PS-LRG	TM SMS&P
United States.04.Retail	AM SMS&P

Figure 3: (left): `ATU` name (for area team unit). (right): `Sub-ATU` names organized under `ATU`.



ID	Session Name
UBAX01	AXUG General Session
UBAX02	How2 Session
UBAX03	Master Planning Session
UBAX04	Financial Reporting
UBAX05	Master Planning Session

Full Session Name	Month
[UBAX01] AXUG General Session	Mar
[UBAX02] How2 Session	Apr
[UBAX03] Master Planning Session	Apr
[UBAX04] Financial Reporting	Oct
[UBAX05] Master Planning Session	Dec

Figure 4: (left): `ID` and `session name` in separate fields. (right): Concatenated `full session name`.

Figure 1 shows such an example. An analyst has a table on the left in her spreadsheets about US presidents and popular votes they won in elections. She uses table search engines (such as Google Web Tables [2] or Microsoft Power Query [4]) to find an additional table on the right, that has information about their job approval rating. Now she wants to join these two tables so that she can correlate them. However, the `name` columns of the two tables use different representations – the one on the left uses first-name followed by last-name, while the one on the right uses last-name, comma, first-name, with additional year-of-birth information in parenthesis. Today's popular data analysis software such as Power Query for Excel [5] and Informatica [3] only support equi-join and would fail to work on these two tables. The analyst would have to either write her own transformation program so that the name representations become consistent for equi-join[1], or ask technology support staffs to perform such a transformation.

Figure 2 shows another case with two real tables collected from the web, where the table on the left uses teachers' full names, while the table on the right only has email addresses as the key column. Note that in this case because email aliases can be generated by taking first-initials and concatenating with last names, there exists a clear join relationship between the two tables. Equi-join, however, would again fail to work in this case.

Scenarios like these are increasingly common in ad-hoc data analysis, especially when analysts need to bring in data from different sources, such as public datasets discovered from table search engines.

It is worth noting that this join problem exists not only for public data sets like web tables, but also in enterprise data tables such as Excel files. Figure 3 shows a pair of real spreadsheet tables from a corpus of Excel files crawled in a large IT company. The `ATU` (area-team-unit) column on the left can be joined with `Sub-ATU` on the right by taking the first two components of `Sub-ATU`, and then equi-join with `ATU` in a hierarchical N:1 manner. Figure 4 shows another example from enterprise spreadsheets. The two tables cannot be equi-joined directly. However, if we concatenate `id` and `session name` in the left table with appropriate brackets, the two tables can then be equi-joined.

Joining tables with different representations is a ubiquitous problem. Simple syntactic transformations (e.g., substring, split, concatenation) can often be applied to make equi-join possible. However, existing commercial systems can only perform equi-joins, and users often face two main challenges: (1) For big tables with a large number of rows and columns, manually identifying corresponding rows and columns from two tables that can join using transformations is non-trivial (i.e., manually searching sub-strings in large spreadsheets is slow and does not always produce hits). (2) End-users (e.g., Excel users) may not be able to program transformations to enable equi-join. In this work, our goal is to automate the discovery of syntactic transformations needed such that two tables with different representations can be joined with the click of a button. Note that because such transformations are driven by end-user tools, a significant technical challenge is to make such transformation-based join very efficient and at interactive speed.

Existing solutions: No existing solutions can solve this problem well for end-users.

Program transformations for equi-join. A straightforward approach is to ask users to provide transformation programs (either manually or with the help of example-driven tools like FlashFill [15] and Foofah [18]). These programs can then be used to produce derived columns, with which tables can be equi-joined. This is inconvenient for users – for large tables with many columns and millions of rows, the first task of identifying rows and columns from two tables with joinable values alone is non-trivial, as users often have to pick random sub-strings from one table to search for hits in the other, which is slow and often fails to produce matches. The need to find the "best" transformation in the context of joins further complicates the problem. We aim to automate this process so that users can join two *unordered sets* of rows with the click of a button – in comparison, we no longer require users to manually specify *matching pairs* of input/output examples as in FlashFill-like systems [15].

Fuzzy join. Since rows that join under syntactic transformations typically have substantial substring overlaps, an alternative approach is to use fuzzy join [8]. The challenge is that fuzzy join has a wide range of parameters (tokenization, distance-function, thresholds, etc.) that need to be configured appropriately to work well. The ideal configuration can vary significantly from case to case, and is difficult for users to determine. For instance, for Figure 1, one should tokenize by words, but that tokenization will fail completely for Figure 2, which requires q-gram tokenization.

Furthermore, even when fuzzy join is configured perfectly, it may still produce incorrect results due to its fuzzy and imprecise nature. For example, in Figure 1, if we tokenize by words, and want to join `Ronald Reagan` and `Reagan, Ronald(1911-2004)`, then the threshold for Jaccard distance should be at least 0.66 (this pair has a distance of $1.0 - \frac{1}{3} = 0.66$). However, using a threshold of 0.66 will also join `George W. Bush` with `Bush, George H. W.(1924-)` (where the distance is $1.0 - \frac{3}{5} = 0.4$), which is incorrect. The root cause here is that fuzzy join uses an imprecise representation and a simple threshold-based decision-boundary that is difficult to be always correct. On the other hand, there are many cases where regularity of structures in data values exists (e.g. Figure 1-4), and for those cases using consistent transformations for equi-join complements fuzzy-join by overcoming its shortcomings mentioned above.

Substring Matching [23]. Warren and Tompa [23] proposed a technique to translate schema between database tables, which is applicable to joins and is the only published technique that we are aware of that can produce transformation-based joins given two tables. However, the types of transformations they considered are rather limited (e.g., no string-split and component based indexing), and as a result their approach is not expressive enough to handle many real join tasks we encountered. As we will show in our experiments, their approach can handle less than 30% of the join cases we collected.

Our contributions. We make the following contributions in Auto-Join, which is currently being integrated into a Microsoft data preparation system.

• We propose to automate transformation-based joins using a novel Auto-Join algorithm. Our technique leverages substring indexes to efficiently identify joinable row pairs, from which we automatically learn *minimum-complexity* programs whose execution can lead to equi-joins.

• In order to scale Auto-Join to large tables while still maintaining interactive speed, we design a sampling scheme that minimizes the number of rows sampled, which has a formal guarantee of success with high probability.

• We are the first to compile a benchmark of real cases requiring transformation joins. We label each case using fine-grained ground truth and make the benchmark publicly available. Our evaluation suggests that the Auto-Join produces joins with higher quality than existing approaches.

2. PROBLEM OVERVIEW

Our objective is to automate transformation-joins by generating the transformations that are needed for equi-joins.

[1]Such behavior is observed in customer surveys and logs – for certain datasets users perform sequences of transformations in order to enable equi-join.

Specifically, we want to transform columns of one table via a sequence of string-based syntactic operations, such that the derived columns can be equi-joined with another table. Example 1 gives such an example.

Example 1. In Figure 1, there exists a transformation whose application on the right table can lead to equi-joining with the left table. We illustrate the sequence of operations in the transformation using the first row $\{$[`Obama, Barack(1961-)`], [`47.0`]$\}$ as an example.

1. Input row X with two elements: $\{$[`Obama, Barack(1961-)`], [`47.0`]$\}$
2. Take the first item $X[0]$, Split by "(", produce Y: $\{$[`Obama, Barack`], [`1961-)`]$\}$
3. Take the first item $Y[0]$, Split by ",", produce Z: $\{$[`Obama`], [` Barack`]$\}$
4. Takes Substring [1:] from $Z[1]$, produce T: [`Barack`]
5. Concat T, a constant string " " and $Z[0]$, produce [`Barack Obama`]

This derived value can then be equi-joined with the first row in the left table in Figure 1. It can be verified that the same transformation can also be applied on other rows in the right table to equi-join with the `President` column of the left table.

As discussed earlier, identifying joinable rows from large tables alone is non-trivial, not to mention programming transformations. We would like to automate this problem, which we call the *transformation join problem.*

Definition 1. *Transformation Join Problem*: Given two tables T_s, T_t, and a predefined set of operators Ω, find a transformation $P = o_1 \cdot o_2 \cdot o_3 \cdot \ldots o_n$, using operators $o_i \in \Omega$, such that $P(T_s)$ can equi-join with key columns of T_t.

Here each transformation P is composed of a sequence of operators in Ω, where the output of one operator is the input of the next. For the purpose of transformation-join, we have identified a small set of operators that are sufficient for almost all join scenarios we encountered.

$$\Omega = \{\text{Split, Concat, Substring, Constant, SelectK}\} \quad (1)$$

This set of operators Ω can be expanded to handle additional requirements as needed.

In this definition, because we require $P(T_s)$ to equi-join with key columns of T_t, the types of join we consider are implicitly constrained to be 1:1 join (key:key) and N:1 join (foreign-key:key). This constraint is important because it ensures that the joins we automatically generate are likely to be useful; relaxing this constraint often leads to N:M joins that are false positives (e.g., join by taking three random characters from two columns of values).

Also observe that we apply transformations on one table T_s in order to equi-join with another table T_t. We refer to the table T_s as the *source table*, and T_t as the *target table*, respectively.

Because in our problem, we are only given two tables with no prior knowledge of which table is the source and which is the target, we try to generate transformations in both directions. In Example 1 for instance, the right table is used as the source table. Changing direction in this case does not generate a transformation-join because year-of-birth is not present in the left table. Advanced handling of composite columns will be discussed the full version of this paper [24].

Table 1: Notations for analyzing q-gram matches.

Symbol	Description
T_s, T_t	T_s is the source table, T_t is the target table.
R_s, R_t	A row in T_s and T_t, respectively
C_s, C_t	A column in T_s and T_t, respectively
$\mathcal{Q}_q(v)$	The q-grams of a string value v
$\mathcal{Q}_q(C_s)$	The multi-set of all q-grams in C_s
$\mathcal{Q}_q(C_t)$	The multi-set of all q-grams in C_t

Solution Overview. Our system has three main steps.

Step 1: Find Joinable Row Pairs. In our problem, we only take two tables as input, without knowing which row from T_s should join with which row from T_t. Generating transformations without such knowledge would be exceedingly slow, due to the quadratic combinations of rows in two tables that can potentially join.

So in the first stage, we attempt to "guess" the pairs of rows from the two tables that can potentially join. We leverage the observation that unique q-grams are indicative of possible join relationships (e.g. `Obama`), and develop an efficient search algorithm for joinable row pairs.

Step 2: Learn Transformation. Once we obtain enough row pairs that can potentially join, we learn a transformation that uses rows from T_s as input and generates output that can equi-join with key columns of T_t. In Example 1 for instance, the desired transformation uses $\{$[`Obama, Barack (1961-)`], [`47.0`] $\}$ as input, and produces [`Barack Obama`] as output to join with the key column of the left table. Since there likely exists many possible transformations for one particular input/output row pair, we use multiple examples to reduce the space of feasible transformations, and then pick the one with minimum complexity that likely best generalizes the observed examples. This learning process is repeated many times using different combinations of row pairs, and the transformation that joins the largest fraction of rows in T_t is produced as the result.

Step 3: Constrained Fuzzy Join. In certain cases such as tables on the web, the input tables may have inconsistent value representations or dirty values. For example, in Figure 2, the second row of the right table uses `mipayne@forsyth.k12.ga.us`, instead of first-initial concatenated by last-name like other rows (which would produce `mpayne@forsyth.k12.ga.us`). Thus, transformations may miss this joinable row pair. As an additional step to improve recall, we develop a mechanism that automatically finds a fuzzy-join with optimized configuration to maximize additional rows to join, without breaking the join cardinality constraints (i.e., 1:1 or N:1). This improves the coverage of joins on dirty tables, and is of independent interest for the important problem of automatically optimizing fuzzy join.

3. AUTO-JOIN BY TRANSFORMATIONS

In this section we discuss the first two steps of Auto-Join: (1) finding joinable row pairs, and (2) learn transformations that generalize the examples observed in these row pairs.

3.1 Finding Joinable Row Pairs

Let P be the desired transformation, such that $P(T_s)$ can equi-join with T_t as in Definition 1. Pairs of rows that join under this transformation P is termed as *joinable row pair.*

For instance, the first row from the left and right table in Figure 1 is a joinable row pair.

Since users do not provide joinable row pair as input to our system (which is cumbersome to provide especially in large tables), in this section we explain our approach for "guessing" joinable row pairs candidates from the two table through unique q-grams matches. Note that finding such row pairs is important, because trying the quadratic number of row combinations exhaustively is too computationally expensive to be interactive.

We leverage the observation that the set of operations Ω considered for transformation-join (Equation 1) tend to preserve local *q-gram.* A q-gram [7] of a string v is a substring of v with q consecutive characters. A complete q-gram tokenization of v, denoted as $\mathcal{Q}_q(v)$, is the set of all possible q-grams of v. For example:

$$\mathcal{Q}_5(\texttt{Database}) = \{\texttt{Datab}, \texttt{ataba}, \texttt{tabas}, \texttt{abase}\}$$

q-grams have been widely used for string similarity and language modeling, among other applications.

Operations required for transformation-joins in Ω all tend to preserve sequences of local q-grams, which is the key property we exploit to find joinable row pairs.

3.1.1 1-to-1 q-Gram Match

Intuitively, if we can find a *unique* q-gram that only occurs once in T_s and T_t, then this pair of rows is very likely to be a joinable row pair (e.g., q-gram `Barack` in Figure 1). We start by discussing such 1-to-1 matches, and show why they are likely joinable row pairs using a probabilistic argument.

It is known that q-grams in texts generally follows power-law model [6, 12]. We conducted a similar experiment on a large table corpus with over 100M web tables and observed similar power law results [24]. For such power law distributions, the probability mass function for a q-gram whose frequency ranks at position k among all q-grams, denoted by $p_q(k)$, is typically modeled as [6, 12]

$$p_q(k) = \frac{\frac{1}{k^{s_q}}}{\sum_{z=1}^{N} \frac{1}{z^{s_q}}} \tag{2}$$

Here k is the rank of a q-gram by frequency, N is the total number of q-grams, and s_q is a constant for a given q. These power-law distributions empirically fit well with real data [6].

Given a pair of tables whose q-grams are randomly drawn from such a power-law distribution, we can show that it is extremely unlikely that a q-gram appears exactly once in both tables *by chance* (for reasonably large tables, e.g., $N > 100$).

Proposition 1. *Given two columns C_s and C_t from tables T_s and T_t respectively, each with N q-grams from an alphabet of size $|\Sigma|$ that follow the power-law distribution above. The probability that a q-gram appears exactly once in both C_s and C_t by chance is bounded from above by*

$$\sum_{k=1}^{|\Sigma|^q} \left((1 - p_q(k))^{N-1} \cdot p_q(k) \right)^2 \tag{3}$$

A proof this result can be found in the full version of this paper [24].

For $q = 6$, $N = 100$, $|\Sigma| = 52$, and using the s_q defined in [6], the probability of any 6-gram appearing exactly once by chance on both columns is very small (< 0.00017). This quantity will in fact grow exponentially small for larger N (typical tables have at least thousands q-grams).

Given this result, we can conclude that if we do encounter unique 1-to-1 q-gram matches from two tables, they are unlikely coincidence but the result of certain relationships.

Let $\mathcal{Q}_q(C)$ be the multi-set of all the q-grams of distinct values [2] in column C; and let $F_q(g, C)$ be the number of occurrences of a q-gram $g \in \mathcal{Q}_q(C)$. Let v_s and v_t be the cell value at row R_s column C_s in T_s and row R_t column C_t in T_t, respectively. We define *1-to-1 q-gram matches* as follows.

Definition 2. Let g be a q-gram with $g \in \mathcal{Q}_q(v_s)$ and $g \in \mathcal{Q}_q(v_t)$. If $F_q(g, C_s) = 1$ and $F_q(g, C_t) = 1$, then g is a *1-to-1 q-gram match* between row pair R_s and R_t with respect to the pair of column C_s and C_t.

As we have discussed, matches that are 1-to-1 q-gram are likely joinable row pairs.

Example 2. Given two tables in Figure 1, the 6-gram `Barack` appears only once in both tables, and the corresponding rows in these two tables are indeed a joinable row pair. The same is true for q-grams like `chowdury` in Figure 2, `France.01` in Figure 3 and `UBAX01` in Figure 4, etc.

As the reader will see in the experimental results (Section 6.3), using 1-to-1 q-gram matches as joining row pairs leads to a precision of 95.6% in a real-world benchmark.

3.1.2 General n-to-m q-Gram Match

Q-gram matches that are 1-to-1 are desirable special cases. In general we have *n-to-m q-gram matches.*

Definition 3. Let g be a q-gram with $F(g, C_s) = n \geq 1$ and $F(g, C_t) = m \geq 1$, then g is a *n-to-m q-gram match* for corresponding rows with respect to the pair of column C_s and C_t.

Compared to 1-to-1 q-gram matches that almost always identify a joinable row pair, the probability that a row pair identified by n-to-m matches is truly joinable is roughly $\frac{1}{nm}$. We use $\frac{1}{nm}$ to quantify the "goodness" of matches.

Note that the ideal q to identify n-to-m matches with small n and m can vary significantly in different cases.

Example 3. For the tables in Figure 1, if we use 6-grams for value `Barack Obama`, we get an ideal 1-to-1 match of `Barack` between the first rows of these two tables. However, if we also use 6-gram for the second row `George W. Bush`, then the best we could generate is a 2-to-2 match using the 6-gram `George`, between the second and fourth rows of these two tables, respectively.

For `George W. Bush`, the ideal q should be 9, since the 9-gram `George W.` could produce a 1-to-1 match. However, if we use 9-grams for the first row `Barack Obama`, we would fail to generate any q-gram match.

The ideal q is not known *a priori* and needs to be searched.

3.1.3 Efficient Search of q-Gram Matches

A simple algorithm for finding ideal q-gram matches (with small n and m) would conceptually operate as follows: (1) for every cell from one table, (2) for all possible settings of q, (3) for each q-gram in the resulting tokenization, (4) iterate through all values in the this table to find the number of q-gram matches, denoted as n; (5) iterate through all values in the other table to find the number of q-gram

[2]We remove possible duplicates in T_s columns since they are potentially foreign keys.

matches, denoted as m. The resulting match can be declared as an n-to-m match. This is clearly inefficient and would fail to make the desired join interactive. In this section we describe efficient techniques we use to search for unique q-gram matches.

First, we build a *suffix array index* [20] for every column in the source table and each column of the target table, so that instead of using step (4) and (5) above, we can search with logarithmic complexity. A suffix array index is built by creating a sorted array of the suffixes of all values in a column. Given a query q-gram, matches can be found by using binary search over the sorted array and looking for prefixes of the suffixes that match the query exactly. The complexity of probing a q-gram in the index is $O(\log S)$, where S is the number of unique suffixes. We probe each q-gram once in both tables, to find the number of matches n and m. An example of using suffix array index can be found in the full version of this paper [24].

Using suffix array significantly improves search efficiency for a given q-gram. However, for a cell value v, we still need to test all possible q-grams. To efficiently find the best q-gram (with the highest $\frac{1}{nm}$ score), we express the optimal q-gram g^* as the best prefix of all possible suffixes of v.

$$g^* = \underset{\forall g \in \text{PREFIXES}(u), u \in \text{SUFFIXES}(v)}{\arg\max} \frac{1}{nm} \qquad (4)$$

Where $n = F(g, C_s) > 0$ and $m = F(g, C_t) > 0$ are the number of matches in column C_s and C_t, respectively. We leverage a monotonicity property described below.

PROPOSITION 2. *Let g_u^q be a prefix of a suffix u with length q. As the length increases by 1 and g_u^q extends at the end, the $\frac{1}{nm}$ score of the longer prefix g_u^{q+1} is monotonically non-increasing, or $F(g_u^{q+1}, C_s) \leq F(g_u^q, C_s)$ and $F(g_u^{q+1}, C_t) \leq F(g_u^q, C_t)$.*

A proof of this can be found in the full paper [24].

Given Proposition 2, for every suffix u we can find $g_u^{q^*}$ by looking for the longest prefix with matches in C_t using binary search. The global optimal g^* can be found by taking the $g_u^{q^*}$ with the highest score for all u.

EXAMPLE 4. In Figure 1, for the value `George W. Bush`, we iterate through all its suffixes (e.g., "`George W. Bush`", "`eorge W. Bush`", etc.). For each suffix, we test their prefixes using binary search to find the one with the best score (the longest prefix with match), from which we select the best prefix. In this case the prefix "`George W.`" for the first suffix is the best g^*.

With this 1-to-1 match, we can determine that the first rows from the left/right tables in Figure 1 are joinable row pairs. Similarly the second rows from the two tables are also joinable row pairs, etc.

Because of the use of suffix array indexes and binary search, our overall search complexity is $O(|v| \log |v| \log S)$, which is orders of magnitude more efficient than the simple method discussed at the beginning of this section.

3.1.4 Putting it together: Find Joinable Rows

Algorithm 1 gives the high-level pseudo code for this step of finding joinable row pairs. For each pair of C_s and C_t, we iterate through distinct value $v \in C_s$, and use OPTIMALQGRAM (the procedure discussed above) to efficiently find the best q-gram match and its associated row pairs. Finally, row pairs linked by q-gram matches are grouped by C_s and C_t, and ordered by their match scores. Details of this step can be found in the full paper [24].

Algorithm 1 Find joinable row pairs.

```
1: function FINDJOINABLEROWPAIRS($T_s$, $T_t$)
2:     $M \leftarrow \{\}$                                ▷ $q$-gram matches
3:     for all $C_s \in T_s$ do
4:         for all $C_t \in$ KEYCOLUMNS($T_t$) do
5:             for all $v \in C_s$ do
6:                 $\{g^*, score, R_s, R_t\} \leftarrow$ OPTIMALQGRAM($v$, $C_t$)
7:                 $M \leftarrow \cup\{(g^*, score, R_s, R_t, C_s, C_t)\}$
8:     return $M$, GROUPBY($C_s, C_t$), ORDERBY($score$)
```

It is worth noting that we group row pairs by the column pairs from which the matches are found. This is because we want to produce consistent transformations on certain columns C_s in T_s, so that the results can equi-join with columns C_t in T_t. As such, matches found in different column pairs are good indications that they belong to different transformation-join relationships, as illustrated by the following example.

EXAMPLE 5. In Figure 2, in addition to q-gram matches between the columns `Name` and `Email`, there is a q-gram match for `Princ`, which matches `Principal` in the first row in the `Title` column from the left table, and `Princeville` in the last row in the `School` column from the right table. However, matching row pairs produced between `Title` and `School` can be used to produce a transformation-join relationship between these columns (if one exists), which should be treated separately from one produced using matches between the `Name` and `Email` columns.

3.2 Transformation Learning

Given joinable row pairs $\{(R_s, R_t)\}$ produced for some column pair C_s and C_t from the previous step, we will now generate transformation programs using these pairs as examples. Specifically, we can view row R_s from T_s as input to a transformation program, and R_t projected on some key columns K of T_t as the desired output. If a transformation can take R_s as input and produce key columns K of R_t, equi-join becomes possible.

Physical Operators. Recall that we generate transformations using the following set of physical operators, Ω = {SPLIT, SELECTK, CONCAT, SUBSTRING, CONSTANT}. The detailed interface of each operator is as follows.

- `string[] SPLIT(string v, string sep)`
- `string SELECTK(string[] array, int k)`
- `string CONCAT(string u, string v)`
- `string CONSTANT(string v)`
- `string SUBSTRING(string v, int start, int length, Casing c)`

Each operator is quite self-explanatory. SPLIT splits an input string using separator; SELECTK selects the k-th element from an array; CONCAT performs concatenation; CONSTANT produces a constant string; and finally SUBSTRING returns a substring from a starting index position (counting forward or backward) for a fixed length, with appropriate casing (lower case, upper case, title case, etc.).

In designing the operator space for Auto-Join, we referred to the string transformation primitives defined in the spec of the `String` class of C# and Java. The physical operators we use are a core subset of the built-in `String` functions of these languages. More discussions on the choice of the operators can be found in a full version of the paper [24].

Disambiguate Transformations by Examples. While in Example 1 we illustrate transformations using one joinable row pair for simplicity, in practice with only one row pair there often exists multiple plausible transformations.

EXAMPLE 6. In Example 1 the input row denoted as X has two elements $\{$[`Obama, Barack(1961-)`], [`47.0`]$\}$, and the target output is [`Barack Obama`]. In addition to the transformation shown in that example, an alternative transformations that can also produce this output is:

1. Take the first item $X[0]$, SUBSTR[8:6], produce [`Barack`]
2. CONCAT with constant string " ", produce [`Barack `]
3. CONCAT with $X[0]$, SUBSTR[0:5], to produce the target output [`Barack Obama`]

There exists many candidate transformations given only one input/output example pair. However, most of transformations would fail to generalize to other example pairs. The observation here is that if we use multiple joinable row pairs as input/output examples, the space of possible transformations are significantly constrained, such that the incorrect transformations will be pruned out. For example, if we just add the second rows from Figure 1 as an example pair, with $\{$[`Bush, George W.(1946-)`], [`49.4`]$\}$ as the input and [`George W. Bush`] as the output, then the transformation discussed in Example 6 would no longer be valid, as it would produce [`eorge Bush,`], which cannot be joined with the keys in the other row.

The pruning power grows exponentially with the number of examples (details of this analysis can be found in a full version of this paper [24]). In practice we just need a few examples (3 or 4) to constrain the space of candidate programs enough and generate the desired transformations.

Learning via Logical Operators. The learning problem now is to find consistent transformations for a small set of input/output example row pairs. While the execution of transformations can be decomposed into simple physical operators defined in Ω, these are too fine-grained and do not directly correspond to our logical view of the transformation steps that humans would take. For instance, in Example 1 when we use $\{$[`Obama, Barack(1961-)`], [`47.0`]$\}$ as input to produce [`Barack Obama`] as output, humans would naturally view the required transformation as having three distinct logical steps – extract the component `Barack`, produce a space " ", extract the component `Obama`. Note that these logical operations correspond to a higher-level view that can always translate into a combination of simple physical operators – extracting the first of component `Barack` can be implemented as SPLIT by "(" followed by SPLIT by ",", and finally a SUBSTRING.

For the technical reason of learning programs from examples, by mimicking how humans rationalize transformations, we introduce a set of higher-level *logical operators* Θ, each of which can be written as a sequence of physical operators. Θ={CONSTANT, SUBSTR, SPLITSUBSTR, SPLITSPLITSUBSTR}

Unlike physical operators, each logical operator always returns a string. Each logical operator can be viewed as a "step" that contributes "progress" (partial output) to final results. It is important that logical operators all return strings, so that during automatic program generation, at each step we can decide which logical operator is more promising based on "progress". In comparison, physical operators like SELECTK often need to be used in conjunction with other operators like SUBSTR before producing partial output, thus not directly amenable to automatic program generation.

Algorithm 2 Transformation learning by example.

```
Require: $R = \{I^i, O^i | i \in [k]\}$    ▷ Input/output row pairs
 1: function TRYLEARNTRANSFORM($R = \{I^i, O^i | i \in [k]\}$)
 2:     while true do
 3:         $\theta \leftarrow$ FINDNEXTBESTLOGICALOP($R$)
 4:         $P^i \leftarrow$ EXECUTEOPERATOR($\theta, I^i, O^i$), $\forall i \in [k]$
 5:         $O^i_l$ = LEFTREMAINDER($O^i, P^i$), $\forall i \in [k]$
 6:         $\theta_l$ = TRYLEARNTRANSFORM($\{I^i, O^i_l | i \in [k]\}$)
 7:         if $\theta_l$ = null then
 8:             continue
 9:         $O^i_r$ = RIGHTREMAINDER($O^i, P^i$), $\forall i \in [k]$
10:         $\theta_r$ = TRYLEARNTRANSFORM($\{I^i, O^i_r | i \in [k]\}$)
11:         if $\theta_r$ = null then
12:             continue
13:         $\theta$.left_child = $\theta_l$
14:         $\theta$.right_child = $\theta_r$
15:         return $\theta$                    ▷ current root node
```

The exact specification of each logical operator can be found in the full paper [24] in the interest of space. Here we give an example of rewriting SPLITSUBSTR as a sequence of four operators.

```
string SPLITSUBSTR(string[]array, int k, string sep,
int m, int start, int length, Casing c) :=
SUBSTRING(SELECTK(SPLIT(SELECTK(array,k), sep), m),
start, length, c)
```

Using logical operators, we can define the transformation learning problem as follows.

DEFINITION 4. *Transformation Learning*: Given a set of joinable row pairs $R = \{(R^i_s, R^i_t) | i \in [m]\}$ that can be viewed as input/output examples, and a predefined set of logical operations Θ, find a transformation $P = \theta_1 \cdot \theta_2 \cdot \theta_3 \cdot \ldots \theta_n$, $\theta_i \in \Theta$, such that
(1) P is consistent with all examples in R, namely, $\forall i \in [m]$, $P(R^i_s)$ can produce the projection of R^i_t on some key columns K of T_t, denoted as $\Pi_K(R^i_t)$;
(2) P has minimum-complexity, measured as the number of logical operators used, among all other transformation programs that are consistent with examples in R.

This definition is in spirit consistent with principles such as Minimum Description Length [21] or Occam's razor [13] – if there are multiple candidate transformations that can explain all given examples, we use the simplest one and that is likely correct. For instance, the transformation in Example 1 requires 3 logical operators, and there exist no other programs with lower complexity.

The learning problem can be viewed as a search problem – each logical operator produces a partial output and has a unit cost. Like shortest path algorithms, we want to reach the goal state by producing the required output strings but with the least cost.

This motivates a program learning algorithm that searches for the best program by recursively expanding a partial transformation program using the logical operator that yields the most progress. This algorithm is outlined in Algorithm 2 and works as follows. For the given set of input/output examples, it finds the best logical operator θ that produces the most progress towards the required output strings (which in this case is some key column of the output rows). We execute the operator θ and extract partial output produced from the target output. We get what remains to the left and right in the target output, denoted as O_l^i and O_r^i, respectively. This produces two new instances of the problem with $\{I^i, O_l^i | i \in [k]\}$ and $\{I^i, O_r^i | i \in [k]\}$, which have the same structure as the original $\{I^i, O^i | i \in [k]\}$. So we recurse and invoke TryLearnTransform on the two smaller problems. The resulting operators, θ_l and θ_r, if learned successfully, are added as the left child and right child of θ, until all remaining target output have been consumed. If at certain level in the hierarchy TryLearnTransform fails to find a consistent transformation, we can backtrack by using the next best logical operator, or terminate if enough number of candidates have been tested.

In practice we impose a limit τ on the number of logical operators that can be used in a program P to bound the search space (e.g., $\tau = 16$). We fine $\tau = 10$ to be sufficient to produce transformations needed to join all real scenarios we encountered. Setting a larger τ however has little impact on efficiency, because incorrect program generation paths are terminated quickly for failing to produce new operators consistent with the set of output examples.

We use the following example to illustrate this procedure.

Example 7. From the example in Figure 1, suppose the first three rows from the right and left tables are given as learning examples for input/output row pairs, respectively. To learn transformation, suppose we use the first row $\big\{\big[$`Obama, Barack(1961-)`$\big]$, $\big[$`47.0`$\big]\big\}$ as input and $\big[$`Barack Obama`$\big]$ as output, and we use the remaining two rows as validations. To generate the first logical operator for this row pair, we search over operators in Θ with all possible parameters (separators for Split up to a certain length, indexes for Substring that are valid for the given string, etc.), and pick the logical operator that yields the most progress. In this case it can be verified that the operator with the most progress is SplitSplitSubstr, which selects the first input element: [X = `SelectK(input, 0)`]; split by "(" and take the first element: [Y = `SelectK(Split(X, "("), 0)`]; split again by " " and take the second element: [Z = `SelectK(Split(Y, " "), 1)`]; take substring from position 1 to the end [1:-1]: [`Substr(Z, 1, -1)`]. This operator generates `Barack` for the first row, `George W.` for the second, `Bill` for the third, with a total gain of 19 characters $(6 + 9 + 4)$, and an average gain of 49% for the required outputs across three rows ($\frac{6}{12}$, $\frac{9}{14}$ and $\frac{4}{12}$, respectively).

With this first operator, the remaining required output strings to be covered are {" `Obama`", " `Bush`", " `Clinton`" }. We again search for the logical operator that yields the most progress, for which we find SplitSubstr that splits by ",", takes the first element, and returns the full string. Now the remaining output strings are {" ", " ", " " }, which can be covered by adding a Constant operator that produces a space character. Finally, by concatenating these operators, we complete a candidate transformation program that can be tested on the full input tables.

Through the following proposition, we show the success probability of transformation learning.

Proposition 3. *The learning procedure succeeds with high probability, if the transformation can be expressed using operators in Θ. The success probability is lower bounded by*

$$1 - \left(1 - \prod_{i \in [m]} \left(1 - \left(1 + (|S_I| + |S_I|^k)|S_O|^k\right) \frac{1}{|\Sigma|}^{k|S_i|}\right)\right)^T$$

where k is the number of independent examples used, T is the number of trials (each with k examples), $|S_I|$ and $|S_O|$ are the lengths of input/output examples, and $|S_i|$ is the length of the result of each intermediate step (for a logical operator).

A proof of this result can be found in the full version [24]. This proposition shows that with T independent trials we can reduce the failure probability at a rate exponential in T, thus quickly improving success probability as T increases.

Ranking of Candidate Transformations. Recall in Section 3.1.4, we generate groups of joinable row pairs, based on q-gram matches between each pair of columns C_s, C_t. For each such group, we select the top-k row pairs with the highest scores (typically 1-to-1 matches), and apply transformation learning for a fixed number of times, each of which on a random subset of the selected row pairs. We execute each learnt transformation on the original input tables, and pick the one that joins the most number of rows in the target table. By the definition of transformation join problem (Definition 1), the joining columns in the target table are key columns (1:1 or N:1 joins). A key-column join with high row coverage is likely to be meaningful in practice. Pseudocode of this step can be found in the full paper [24].

4. SCALE AUTO-JOIN TO LARGE TABLES

Auto-Join is used as a data exploration feature where interactivity is critical. In deploying this into a commercial data preparation system, a practical challenge we encountered is to efficiently scale the algorithm to tables with thousands or even millions of rows. In this section, we explain how to achieve such scalability for Auto-Join.

Given two tables T_s and T_t, each with millions of rows, with commodity hardware it is unlikely that we can achieve interactive speed if all values need to be indexed and probed. On the other hand, it would actually be wasteful to index/probe all values, because for the purpose of transformation learning we only need enough joinable row pairs for learning to be successful. Intuitively, we can sample rows from input tables, where the key is to use appropriate sampling rates to minimize processing costs but still guarantee success with high probability (the danger is that we may under-sample, thus missing join relationships that exist).

For Auto-Join, we use *independent row samples* from input tables, because unlike sampling techniques for equi-join or set-intersection where join keys are known and *co-ordinated sampling* can be used, in our problem, the join keys are not known *a priori*. Co-ordinated q-gram sampling is possible, but the cost of analyzing and hashing all q-grams is still prohibitive for large tables. Given these, we study a lightweight independent sampling for Auto-Join.

Let N_s, N_t be the number of rows in table T_s, T_t, and p_s, p_t be their sampling rates, respectively. Furthermore, let r be the *join participation rate*, defined as the fraction of records in the target table T_t that participate in the desired join. Note that the join participation rate needs to be reasonably high for sampling to succeed – if only one row in a million-row table participates in a join, then we need to sample a very large fraction of it to find the joinable row pair with high probability. In practice, r is likely to be high, because joins that humans find interesting likely involve a non-trivial fraction of rows. We conservatively set r to a low value (e.g., 1%), so that as long as the real join participation is higher we can succeed with high probability.

We formulate the problem of determining p_s and p_t as an optimization problem. The objective is to minimize the total number of sampled rows that need to be indexed and queried, which is $N_s p_s + N_t p_t$. The constraint is that we need to sample enough joinable row pairs with high probability. Since the join participation rate is r, at least $N_t p_t r$ rows from the target table T_t participate in join. Because each of these participating row joins with at least one row from the source table T_s, which is sampled with probability p_s, leading to an expectation of $\mu = N_t \cdot p_t \cdot r \cdot p_s$ joinable row pairs in the sample. This can be seen as a Bernoulli process with a success probability of $p_t p_s r$ and N_t total trials.

As discussed in Section 3.2, we need a certain number of examples to constrain the space of feasible transformations enough to produce correct transformations. Let this required number be T (empirically 4 is enough in most cases). Let X be a random variable to denote the total number of joinable row pairs sampled. We want to find an upperbound for the probability that less than T joinable rows pairs are sampled, or $P(X \leq T)$.

Using the Multiplicative Chernoff Bound [9], we know X can be bounded by

$$P(X \leq (1-\delta)\mu) \leq e^{-\frac{\delta^2 \mu}{2}} \tag{5}$$

If we have $\mu \geq \frac{T}{1-\delta}$, we can upper-bound the failure probability as

$$P(X \leq T) \leq e^{-\frac{\delta^2 \mu}{2}} \tag{6}$$

For example, let $T = 4$, $\delta = 0.8$, we get $\mu = N_t p_t p_s r > \frac{T}{1-\delta} = 20$. Using Equation 6, we get $P(X \leq T) \leq e^{-\frac{0.64 \cdot 20}{2}} = e^{-6.4} < 0.0017$, or in other words, our success probability is at least 99.8%. So as long as we can ensure $\mu = N_t p_t p_s r > \frac{T}{1-\delta}$, then more than T joinable row pairs will be sampled with high probability. This becomes the constraint that completes our optimization problem:

$$\begin{aligned} \min \quad & N_s p_s + N_t p_t \\ \text{s.t.} \quad & N_t p_t p_s r \geq \frac{T}{1-\delta},\ p_t, p_s \in [0,1] \end{aligned} \tag{7}$$

Using Lagrange we obtain the following closed form optimal solution [3]:

$$p_t = \sqrt{\frac{T}{(1-\delta) r N_s}},\ p_s = \sqrt{\frac{T N_s}{(1-\delta) r N_t^2}} \tag{8}$$

The corresponding sample sizes can be written as $N_t p_t = \frac{N_t}{N_s}\sqrt{\frac{TN_s}{(1-\delta)r}}$ and $N_s p_s = \frac{N_s}{N_t}\sqrt{\frac{TN_s}{(1-\delta)r}}$, and both of them grow sub-linearly in N_s.

As a concrete example, suppose we have two tables both with 1M rows. For some fixed T and δ, such as $T = 4$ and $\delta = 0.8$ from the previous example that guarantees success with high probability, and $r = 0.1$, we can compute the sampling rates as $p_t = 0.014$ and $p_s = 0.014$, which translates to a small sample of 14K rows from the 1M-row tables. The optimized sampling significantly reduces processing costs and improves efficiency for Auto-Joinon large tables.

5. CONSTRAINED FUZZY JOIN

For datasets from the Web, inconsistencies are often found in how values are formatting and represented (e.g., with or without middle name and middle initials for names). Thus, an equi-join using transformation may miss some row pairs that should join, as Example 8 shows.

EXAMPLE 8. In Figure 2, the learned transformation that has the highest coverage on the target key column `Email` concatenates the first character of the first name with the last name in the left table, to get the email addresses. However, this transformation does not cover the target key in the third row `mipayne@forsyth.k12.ga.us` as it uses the first two characters in the first name. As a result, the third rows in the left and right tables cannot be equi-joined.

Traditionally fuzzy join is used to deal with small value inconsistencies. However, given a wide space of parameters in fuzzy join such as the tokenization, distance function, and threshold, configuring a fuzzy join that works well for a given problem instance is difficult. This is particularly true for Auto-Join, as it is intended to be a data exploration feature in spreadsheets where users may not have no the expertise on fuzzy joins.

We propose to automatically optimize a fuzzy join configuration using rows that are already equi-joinable as constraints, so that as we relax matching criteria in fuzzy join, we do not make these rows to join more than their equi-join results (which indicates that the corresponding fuzzy join is too lax). Although we use this optimization in the context of Auto-Join, the techniques here are of independent interest and can be used to optimize general fuzzy join.

Given a column C produced by transformations on the source table, and K a key column from the target table, where the join is 1:1 or N:1, our optimization objective is to maximize the number of rows in the target table that can be fuzzy-joined between C and K, subjecting to the constraint on join cardinality.

Specifically, given a tokenziation scheme t from a space of possible configurations (e.g., word, 2-gram, 3-gram, etc.), a distance function d (e.g., Jaccard, Cosine), and a distance threshold (normalized into a fixed range, e.g., [0,1]). The rows that can fuzzy join for some given t, d, s, denoted as $F_{t,d,s}(C, K)$, is defined as follow.

$$F_{t,d,s}(C, K) = \{v_k \mid \exists v_k \in K, v_c \in C, d_t(v_k, v_c) \leq s\} \tag{9}$$

where d_t is the distance d using a given tokenization t.

This objective alone tends to produce overly lax matches. The counteracting constraint is to respect join cardinality. Specifically, after using fuzzy join every value $v_c \in C$ cannot join with more than one value $v_k \in K$. This can be viewed as a key-foreign-key join constraint – a foreign-key value should not join with two key values (even with fuzzy join).

Additionally, we can optionally require that each $v_k \in K$ cannot join with more than one distinct $v_c \in C$. This is an optional constraint assuming that on the foreign key side, each entity is only represented with one distinct value. E.g., if we already have "`George W. Bush`" in a table, we would not have "`George Bush`" or "`George W. Bush Jr.`" for the same person. On the other hand a very close value "`George H. W. Bush`" in the same column likely corresponds to a different entity and should not join with the same key as "`George W. Bush`". This optional requirement helps to ensure high precision.

These requirements lead to the following two constraints in the optimization problem.

[3]When N_s and N_t are small, there may not be feasible solutions (the required p may be greater than 1). In such cases we use full tables.

$$\begin{aligned} &\arg\max_{t,d,s} |F_{t,d,s}(C, K)| \\ &\quad s.t.\ |\{v_k \mid v_k \in K, d_t(v_c, v_k) \leq s\}| \leq 1, \forall v_c \in C \\ &\quad\quad |\{v_c \mid v_c \in C, d_t(v_c, v_k) \leq s\}| \leq 1, \forall v_k \in K \end{aligned} \quad (10)$$

We can search over possible t, d, and s from a given parameterization space. The following example illustrates how fuzzy join optimzation is used for joining tables in Figure 1.

EXAMPLE 9. Continue with Example 8, after applying the transformation, the output for `Missy Payne` in the left table is `mpayne@forsyth.k12.ga.us`, which cannot be equi-joined with `mipayne@forsyth.k12.ga.us` in the right table. Using 3-gram tokenizer and Jaccard distance, the distance between the two is 0.125. Thus, a distance threshold above 0.125 would join these two rows. On the other hand, if we use a larger distance threshold such as 0.4, `kmoore@forsyth.k12.ga.us` (transformation output from the left table) would join `mipayne@forsyth.k12.ga.us` (in the right table), breaking the second constraint in Equation 10 as `mipayne@forsyth.k12.ga.us` is joined with two distinct values. The fuzzy join optimization algorithm finds the maximum threshold that still satisfies the join constraints, thus the optimal threshold in this case is 0.2 or 0.3.

Due to the monotonicity of the objective function with respect to the distance threshold, we use binary search to find the optimal distance threshold. The pseudo code for fuzzy join optimzation can be found in the full paper [24].

6. EXPERIMENTS

In this section we discuss experimental results on join quality (precision/recall) as well as scalability.

6.1 Benchmark Datasets

Benchmarks. We constructed two benchmark, `Web` and `Enterprise`, using test cases from real datasets; as well as a synthetic benchmark `Synthetic`. The `Web` benchmarks is made available online[4] to facilitate future research.

The `Web` benchmark is constructed using tables on the Web. We sampled table-intent queries from the Bing search engine (e.g., "list of US presidents"). We then used Google Tables [2] to find a list of tables for that query (e.g., U.S. presidents), and selected pairs of tables that use different representations but are still joinable under transformation (e.g., Figure 1). We searched 17 topics and collected 31 table pairs. We observe that tables on the Web often have minor inconsistencies (e.g., formatting differences, with or without middle initials in names, etc.) for the same entity mentions, which cannot be easily accounted for using transformations alone. This makes `Web` a difficult benchmark.

The `Enterprise` benchmark contains 38 test cases, each of which has a pair of tables extracted from spreadsheet files found in the intranet of a large enterprise (e.g., Figure 3 and Figure 4). The test cases are constructed by grouping tables with common topics. Comparing to `Web` that has mostly 1-to-1, entity-to-entity joins, `Enterprise` also has cases with hierarchical N:1 joins (e.g., Figure 3).

Lastly, since the authors in [23] studied a close variant of the auto-join problem and used synthetic datasets for evaluation, as a validation test we reconstruct 4 datasets used in [23] as the `Synthetic` benchmark. The 4 test cases, `UserID`, `Time`, `NameConcat`, and `Citeseer`, either split or merge columns to produce target tables [23].

In all these benchmark cases, equi-join would fail. We manually created the ground truth join result for each pair of tables, by determining what rows in one table should join with what rows from the other table.

Evaluation metrics. We use the following metrics to measure join quality. Denote by G the row pairs in the ground truth join results, J the joined row pairs produced by an algorithm. We measure join quality using the standard *precision* and *recall*, defined as:

$$precision = \frac{|G \cap J|}{|J|},\ recall = \frac{|G \cap J|}{|G|}$$

We also report *F-score* that is the harmonic mean of precision and recall. When an algorithm produces empty join results, we do not include it in computing average precision, but we include it in average recall and F-score.

6.2 Methods Compared

We implemented 8 methods for comparison.

Substring Matching (`SM`). We implemented the algorithm by Warren and Tompa based on their paper [23]. This algorithm uses a greedy strategy to find a *translation formula*, which is a sequence of indexes of the source columns' substrings that matches parts of the target column.

Fuzzy Join - Oracle (`FJ-O`). It is known that a major difficulty of using fuzzy join is the need to find the right configuration from a large space of parameters, which includes different tokenization schemes, distance functions, and distance thresholds, etc. To be more favorable to fuzzy join based methods, we consider an extensive combination of configurations. Specifically, for tokenization we use {Exact, Lower, Split, Word, and q-gram for $q \in [2, 10]$} (similar to ones used in [16]); for distance functions we consider {Intersect, Jaccard, Dice, MaxInclusion}; and for thresholds we use 10 equally-distanced values (e.g., {0.1, 0.2, ..., 1} for Jaccard). This creates a total of 520 unique parameter configurations. We execute each of these fuzzy joins on columns that are used in the ground truth as if they are known *a priori*, and we join each row with top-1 fuzzy match in the other table to maintain high precision. We report the best configuration that has the highest average F-score across all cases.

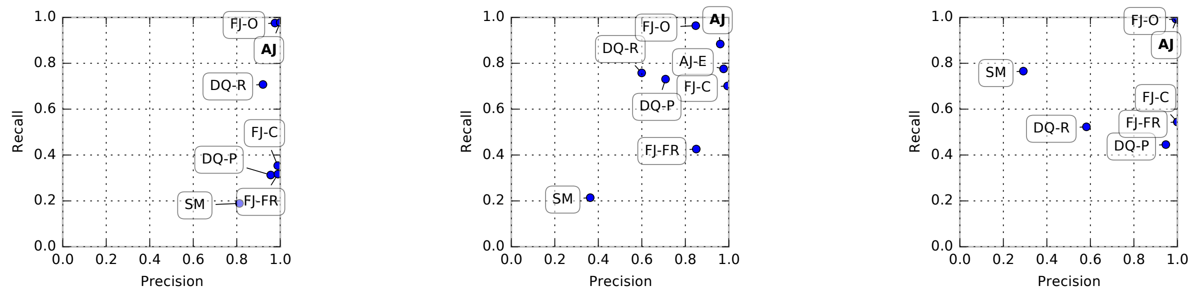
Note that this method acts much like an "Oracle" – it has access to not only the columns that join, but also the ground truth join result to "fine tune" its configuration for the best performance. These optimizations are not feasible in practice, so this provides an upper bound on what fuzzy join like methods can achieve.

Fuzzy Join - Column (`FJ-C`). In this method, we perform fuzzy join on columns that participate in joins in the ground truth as if these are known, but without using detailed row-level ground truth of which rows should join with which for configuration optimization. We use techniques discussed in Section 5 to determine the best parameter configuration.

Fuzzy Join - Full Row (`FJ-FR`). This fuzzy join variant is similar to `FJ-C`, but we do not provide the information on which columns are used in join in the ground truth. As a result, this approach considers full rows in each table. This represents a realistic scenario of how fuzzy join would be used without ground truth.

Dynamic q-gram - Precision (`DQ-P`). Since q-grams already identify some joinable row-pairs (from which we gen-

[4]`https://www.microsoft.com/en-us/research/publication/auto-join-joining-tables-leveraging-transformations/`



(a) Enterprise Benchmark **(b) Web Table Benchmark** **(c) Synthetic Benchmark**

Figure 5: Average precision/recall comparison for all methods on three benchmarks.

erate transformations), one may wonder if it is sufficient to perform join using q-gram matches alone. In this method we use matches produced in Section 3.1, and only allow 1-to-1 q-gram matches to ensure high precision. Joinable row pairs are used directly as join result.

Dynamic q-gram - Recall (DQ-R). This algorithm is similar to DQ-P, except that we allow n-to-1 q-gram matches as join results. This produces results of higher recall but can also lead to lower precision compared to DQ-P.

Auto-Join (AJ). This is our Auto-Join algorithm. We create a variant **Auto-Join - Equality** (shorten as AJ-E) that only uses equality join without the fuzzy join described in Section 5.

6.3 Quality Comparison

In this section we discuss the experimental results on three benchmarks. Figure 5 shows the average precisions and recalls comparison on all three benchmarks. Table 2, Figure 6 and 7 show the F-scores on all the benchmark datasets.

6.3.1 *Enterprise Benchmark*

Enterprise contains data that are mostly clean and well structured – values are consistently encoded with few typos or inconsistencies as they are likely dumped from sources like relational databases (e.g., Figure 3 and Figure 4). Unlike other benchmarks, a significant fraction of joins are N:1 join through hierarchically relationships (e.g., Figure 3).

The precision and recall results are show in Figure 5a. First, Auto-Join (AJ) achieves near-perfect precision (0.9997) and recall (0.9781) on average. In comparison, the oracle baseline FJ-O has precision at 0.9756 and recall at 0.9755, which is inferior to Auto-Join. Recall that FJ-O is the Oracle version of fuzzy join that uses ground truth to find the best possible configuration, which provides an upper-bound for fuzzy join and not feasible in practice. This demonstrates the advantage of transformation-based join over fuzzy join when consistent transformations exist. We note that in this test case using equality-join only AJ-E (with no optimized fuzzy join) produces virtually the same quality results, because values in this benchmark are clean and well structured.

Second, the SM algorithm achieves lower precision and recall then other baselines methods. This shows that their approach in building the translation formula using fixed substring indexes, as mentioned earlier in Section 6.2, is not expressive enough to handle transformations needed in real join scenarios we encountered.

Third, fuzzy join algorithms (FJ-FR and FJ-C) produced good precision due to our conservative fuzzy-join optimization. However, their recall is low, because in certain cases where the join values are hierarchical, non-joinable row pairs may also have low syntactic distance (e.g., Figure 3), which makes it difficult to differentiate between joinable and non-joinable row pairs using distance functions alone.

Lastly, DQ-P produces joins based on 1-to-1 q-gram matches, which has high precision but low recall. This is consistent with our analysis that 1-to-1 q-gram matches are often good joinable row pairs for transformation learning. On the other hand, DQ-R relaxes the matching constraints, and as expected produces better recall but lower precision.

Figure 6 shows the F-scores on individual cases. It is clear that in most datasets, AJ achieved higher scores than the baselines, demonstrating that AJ is more resilient to complications such as N:1 joins and common substrings between joinable and non-joinable row pairs. In the test cases **uk ad sector** and **region atu 1**, AJ did worse than DQ methods. A close inspection reveals that it finds an alternative transformation that only covers a subset of the joinable results.

6.3.2 *Web Benchmark*

Unlike Enterprise that have a significant number of N:1 joins, in Web most join cases are 1:1, entity-to-entity joins (e.g., Figure 1 and Figure 2), and are considerably more dirty with ad-hoc inconsistencies.

Figure 5b gives the quality comparisons. First, AJ has a considerably higher average precision than the oracle fuzzy join FJ-O, but a lower average recall. This is not surprising because FJ-O uses ground truth to optimizing its configuration parameters, which is not feasible in practice. We do notice that because FJ-O always joins a row with its top-1 match by score as long as the score is above a certain threshold, which leads to many false positives and thus lower precision. The problem is the most apparent for cases where most rows from one table do not actually participate in join. This is an inherent shortcoming of top-1 fuzzy join methods that AJ can overcome.

We see in Figure 5b that Auto-Join (AJ) has a higher average recall than its equality join version, AJ-E (0.8840 vs. 0.7757), but slightly lower precision (0.9504 vs. 0.9758). This is because inconsistencies exist in certain cases, where one correct transformation alone does apply to all rows that should join. In such cases, optimized fuzzy join brings significant gain in recall (≈ 0.11), with a small loss in precision (≈ 0.025).

SM does not perform well compared to other methods. Transformations required in Web benchmark are often too more complex for SM that relies on fixed substring indexes.

We analyze individual cases for which FJ-C produces higher F-scores than AJ, as shown in Figure 7. For cases like **uk pms**, we found that although AJ learnt the correct transformation and achieved a perfect precision, the fuzzy join step was not able to cover the rest of joinable row pairs that have inconsistencies in entities' naming. For complex

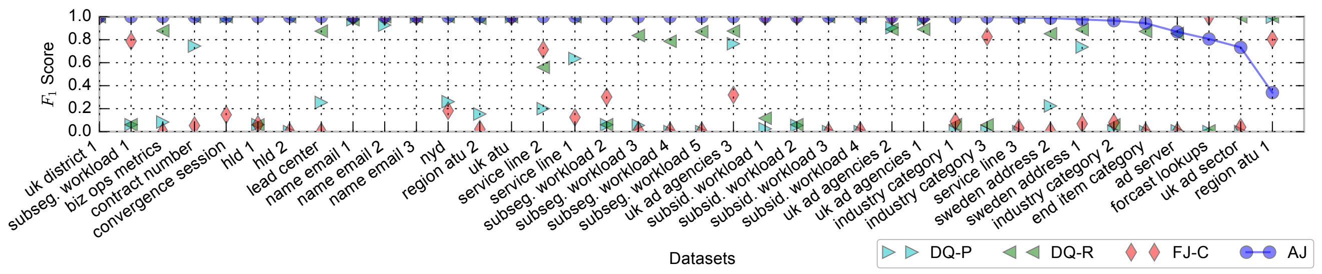


Figure 6: F-Scores on Enterprise Benchmark.

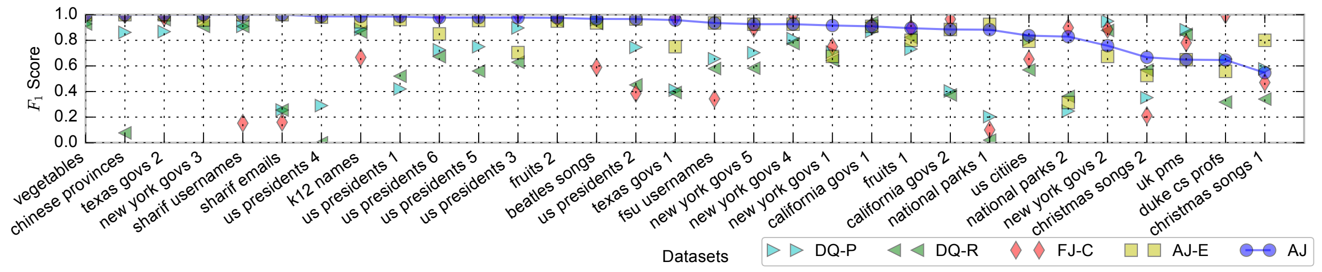


Figure 7: F-Scores on Web Table Benchmark.

Table 2: F-Scores on Synthetic Benchmark

	Citeseer	NameConcat	Time	UserID
DQ-P	0.9826	0.1264	0.0392	0.7572
DQ-R	0.9826	0.1356	0.2025	0.6638
FJ-C	0.4637	0.1651	1.0000	0.8795
SM	0.0291	0.1186	0.5464	0.7553
AJ	1.0000	1.0000	1.0000	1.0000

cases like `duke cs profs`, the correct join actually requires more than one transformations in order to join all rows. Although `AJ` learns one transformation with perfect precision, it falls short in recall as not all joinable rows are covered. For these two datasets, the fuzzy distances between the non-joinable row pairs using the original join-columns are larger than when using the derived column. So it is easier for `FJ-C`, which uses the original join-columns, to differentiate between joinable and non-joinable row pairs and achieve higher F-score, even though `FJ-C` and `AJ` uses the same fuzzy join method.

6.3.3 *Synthetic Benchmark*

`Synthetic` contains cases synthetically generated as described in prior work [23] using split or concatenation. The cases here are relatively simple and we use these as a validation test to complement with our previous benchmarks.

Figure 5c shows that `AJ` achieves perfect precision and recall, matching the oracle fuzzy join `FJ-O`. Other methods produce results similar to the previous benchmarks.

Table 2 shows the F-scores on individual cases. Both of `DQ-P` and `DQ-R` performs poorly on the `Time` dataset. `Time` is synthetically generated by concatenating three columns with second (0-59), minute (0-59), and hour (0-23) into a time column separated by ":". Due to the small space of numbers, there are many common substrings and few 1-to-1 or n-to-1 q-gram matches, thus the low scores of `DQ-P` and `DQ-R`. These two approaches work well on `Citeseer`, which has many 1-to-1 q-gram matches due to unique author names and publication titles. `AJ` achieved perfect F-scores on all datasets, since it just needs a few examples to produce the generalized transformations needed.

We found that `SM` achieved good recall in this benchmark, however, its average precision is relatively low (see Figure 5c). This result is not as well as what is reported in the original work [23]. This is likely because the method is data-sensitive, and it tends to fall into a local optimum with its use of greedy strategy in finding a translation formula. Since the translation formula is constructed incrementally by inspecting one source column at a time with no reverse-back, the addition of a single incorrect partial formula stops the whole algorithm from finding the globally optimal formula. This step is quite sensitive to the variance in the lengths of the substrings that matches with the target column. This is evident in Table 2, as `SM` did relatively better in `Time` and `UserID`, which has smaller variances (`Time` has zero variance, and `UserID` uses a fixed-length substring in the translation formula), while the scores in `Citeseer` and `NameConcat` are much lower.

6.4 Scalability Evaluation

We used the DBLP datasets [1] to evaluate the scalability of `SM`, `FJ-O`, `FJ-C`, and `AJ-E`. In the DBLP data set, each record has three fields: authors, title, and year of publication. For the purpose of scalability evaluation, we create a synthetic target table that is the concatenation of these three fields. We sample N records from the source table and the target table where N = {100, 1K, 10K, 100K, 1M}, and measure the corresponding end-to-end execution time. Some existing methods are very slow on large data sets so we set a timeout at 2 hours. Note that we omit results for `FJ-FR` since it is identical to `FJ-C` for this data set. We also do not compare with `DQ-R` and `DQ-P` since these are sub-components from the proposed `AJ` method.

Figure 8 shows the end-to-end running times. `AJ-E` is 2-3 orders of magnitude faster than existing methods. In particular, `SM` and `FJ-O` time out at 10K rows, and `FJ-C` times out at 100K rows; the runtime of these methods grow quickly with the table sizes.

For `AJ-E`, we break down the time into three stages – indexing, transformation-generation, and equi-join. We find that equi-join is efficient and accounts for less than 5% of

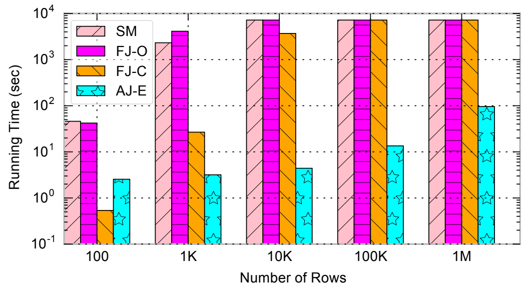


Figure 8: End-to-end running time comparison

overall execution time. The cost of transformation learning increases slowly, from 2.5 seconds at 100 rows to 6.4 seconds at 1M rows, as the number of attempts for transformations learning does not increase with the table size. The indexing time becomes a dominant factor as the number of rows grows over 100K.

In addition, we experimented Auto-Join without the optimized row sampling (Section 4) to see its impact on efficiency. Without sampling the algorithm reaches timeout on the data set with 1M rows, which shows the importance of sampling-based optimization for scaling to large data sets.

7. RELATED WORKS

Warren and Tompa proposed a schema translation technique in the context of data integration [23], which is closely related to Auto-Join. Their technique is based on string alignment that produces a transformation given two tables as input. However, the set of transformations they consider is limited to only concatenation, which is not sufficient to handle transformations required to join real tables as our experiment results show. Our approach, in comparison, supports much more expressive transformations that can handle almost all real join cases encountered, provides probabilistic guarantee of its success, and maintain an interactive speed even for large tables.

There is a long and fruitful line of research on schema matching that identifies column correspondence between tables, where certain types of transformations have been considered. For example, *iMap* [11] was developed to handle transformations such as numerical conversion and string concatenation. Similarly *Bellman* [10] can also find column correspondence when the underlying transformation is simple string concatenations.

Compared to Auto-Join, in schema matching one only needs to identify column-level correspondence for humans to judge, where no precise correspondence is produced at the row-level. In Auto-Join we need to reproduce the underlying transformation at the row-level in a generative process. Furthermore in schema matching transformations considered are limited since q-gram match and fuzzy matching is often sufficient to identify column correspondence. Techniques we develop for Auto-Join can precisely identify complex relationships between columns with high confidence, which can in fact be used for schema matching.

Program-by-example [19] is a programming paradigm studied in the programming language community to facilitate program generation based on examples, which is closely related to our transformation learning component. Systems such as FlashFill [15], BlinkFill [22] and Foofah [18] perform transformations when given input/output examples. In comparison, our system automatically identifies such examples. Our program generation algorithm is also considerably different from existing techniques that requires efficient enumeration of all feasible programs.

A related problem to Auto-Join is to automatically join tables with semantic relationships. Techniques are developed using corpus-driven co-occurrence statistics [17], which is orthogonal to joining tables using syntactic string transformations studied in this work.

8. CONCLUSION

We developed Auto-Join, a system for automatically join tables with transformation programs, which is currently being integrated into a Microsoft data preparation system. Interesting future directions include automatically joining tables with semantic relationships, as well as complex domain-specific functions.

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