

# Auto-Join: Join Tables by Leveraging Transformations



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## 1. A Bird-Eye View

- Problem:** How to join these pairs of tables automatically **without any human inputs** (including rows/columns to join)?

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

Name	Title
Suhela Chowdhury	Principal
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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

Each pairs of tables have a clear syntactic transformation between the matching rows, such as *Split*, *Concatenation*, *Substring* and *Constant*. Applying the transformation to one table creates a *join column* that can be used to equi-join with a *key column* of the other table.

- Scenarios:** One-off, *ad hoc* data analysis often requires joining data from different sources whose data values are formatted differently. An automated solutions saves time and money on ETL.
- Fuzzy join?** Manual parameter tuning is required otherwise likely to produce unsatisfactory result.
- Our Solution:**

- Efficiently identifies promising row pairs that can potentially join using substring indexes
- Using the row pairs as examples to learn a *minimum-complexity* transformation whose execution can lead to equi-joins.

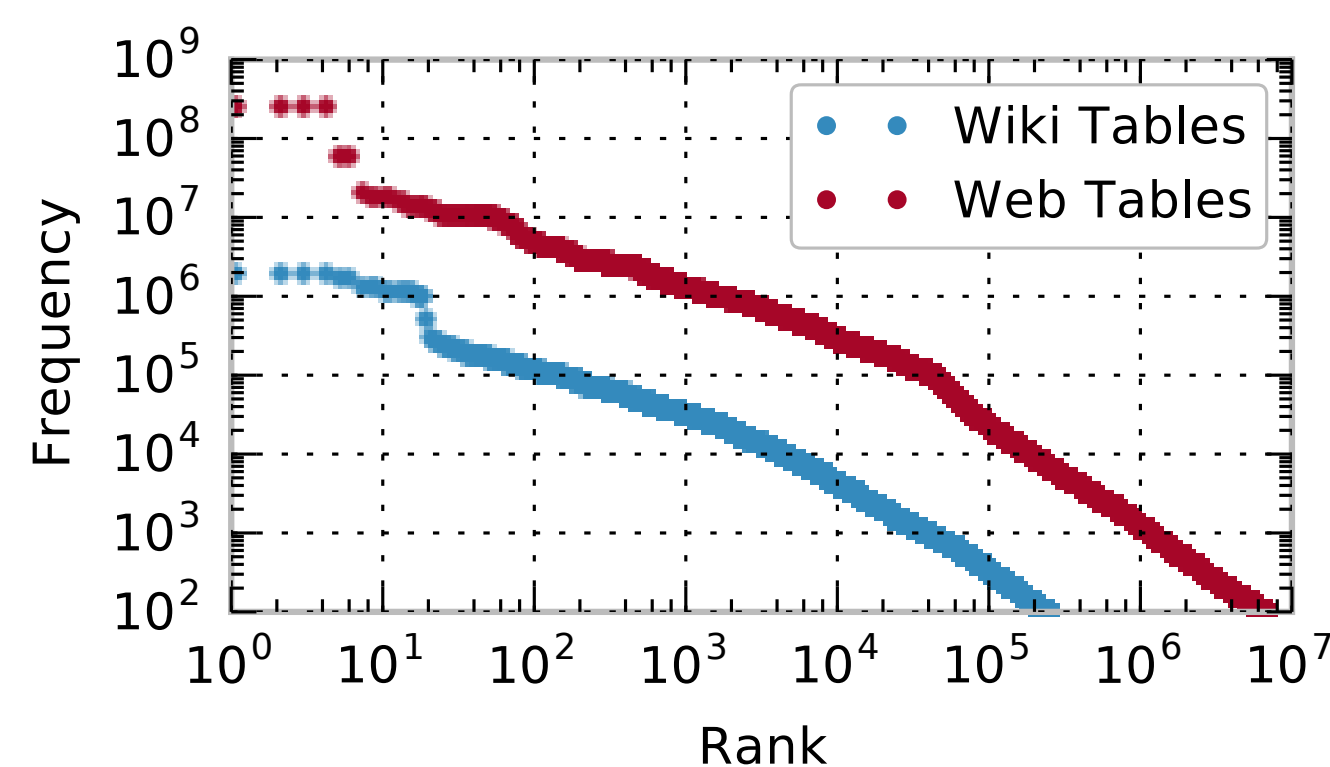
Source Column	...	Join Column	...
Obama, Barack(1961-)	...	Barack Obama	...
Bush, George W.(1946-)	...	George W. Bush	...
Clinton, Bill(1946-)	...	Bill Clinton	...
Bush, George H. W.(1924-)	...	George H. W. Bush	...

```
Concat(
  Select(Split(
    Select(Split(
      Select(Input, 0),
      ",", 1),
      " ", 0),
    Select(Split(
      Select(Input, 0),
      ",", 1),
      " ", 0))
```

- Maintains interactive speed even on large tables (10K rows) with a novel sampling scheme.
- Precision 98% and recall 93% on a benchmark of 73 real-world cases.

## 2. Identify Promising Row Pairs

- Q-Gram Distribution** in real-world tables is Zipfian, this makes the probability that a Q-Gram appears **exactly once** in each of two columns **by chance** is very small.
- 1-to-1 Q-Grams** can be used to identify promising row pairs.



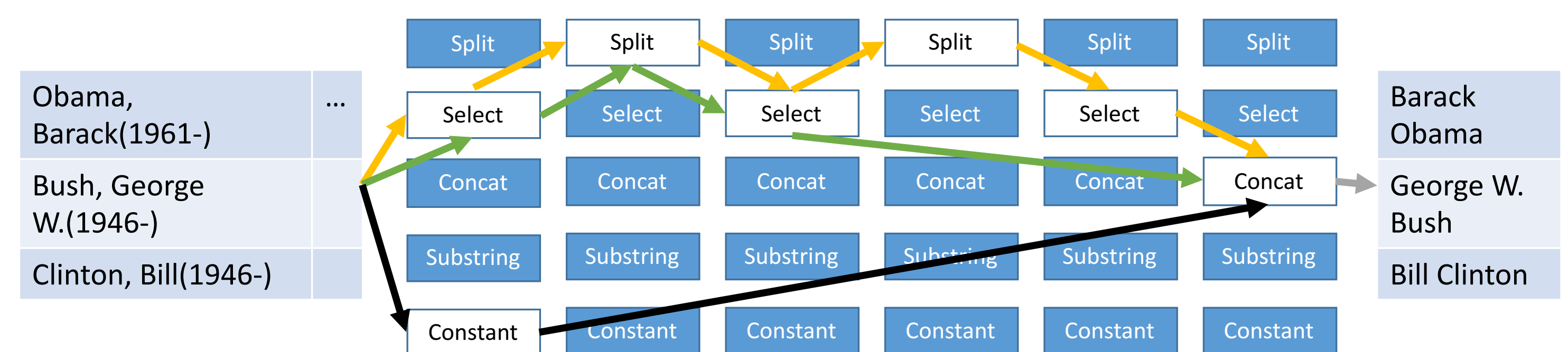
Source Column	...	Target Key Column	...
...	...	...	...
Bush, George W.(1946-)	...	George W. Bush	...

1-to-1 Q-Gram

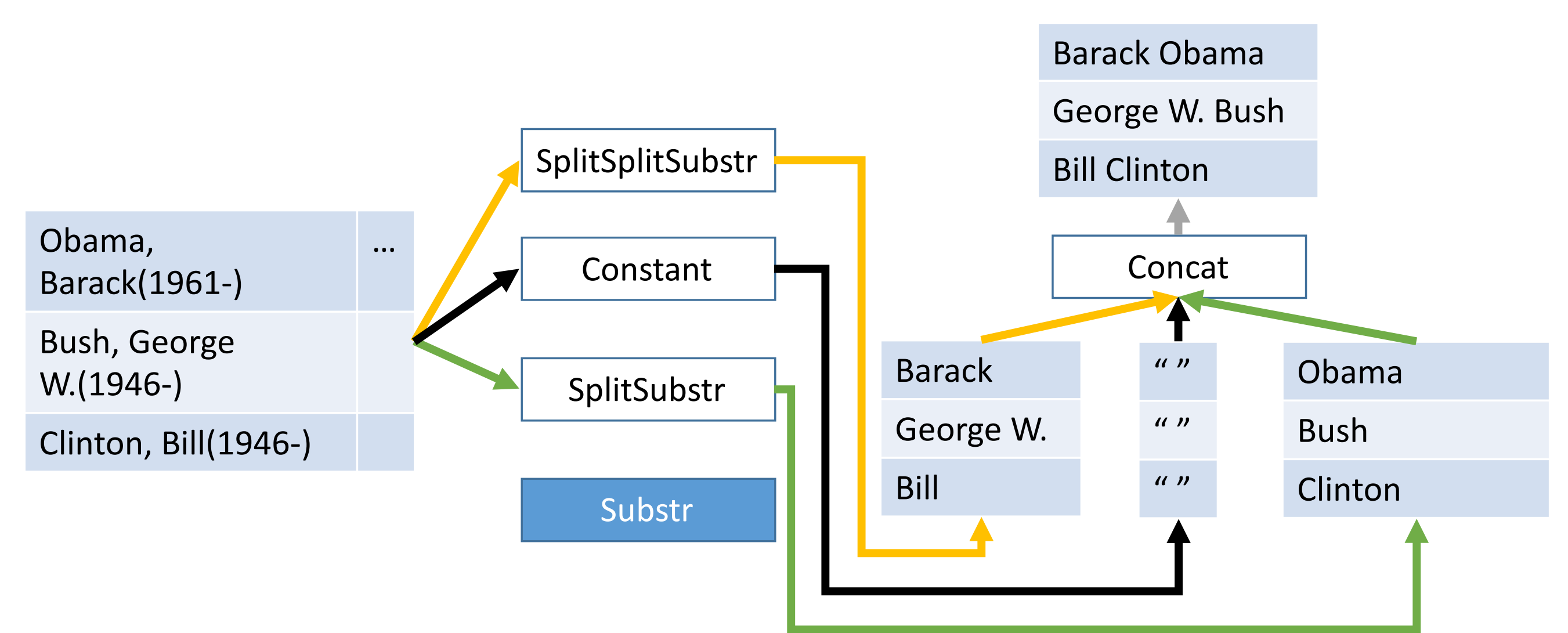
- Q-Gram Scoring:** Since 1-to-1 Q-Grams may not be sampled, target key column may contains a few duplicates, and a transformation may not result in 1-to-1 Q-Grams (e.g., N:1). We also use *n-to-m* Q-Grams, and quantify their “goodness” as  $\frac{1}{nm}$ .
- Q-Gram Search:** Our Q-Gram search algorithm uses a combination of suffix indexes and binary search to efficiently identify the optimal Q for every sampled data values and produce a ranked list of n-to-m Q-Grams for learning transformation.

## 3. Learning Transformation

- Learning as a search** over a graph of all possible syntactic operators and their parameters, and the transformation is the set of paths from the input to output.



- Search space shrinks** exponentially with respect to the number of examples.
- Logical operators** are easier for human to rationalize (e.g., “extract the first component”) and reduces search space.



- Algorithm:** Greedily construct a *minimum-complexity* transformation (the one with the least number of operators) by iteratively expanding an existing partial transformation with the most progress-yielding logical operator.

## 4. Optimized Fuzzy Join

- Dirty Data:** Data may contain typos and errors, and different sources may have different namings. Applying transformation and equi-join may miss row pairs that are joinable.
- Fuzzy join constraints** for archiving high-quality join result:
  - Every row in the join column cannot be joined with more than one distinct row in target key column – similar to key-foreign-key constraint
  - Every row in the target key column cannot be joined with more than one distinct row in the join column – assume consistency within one column

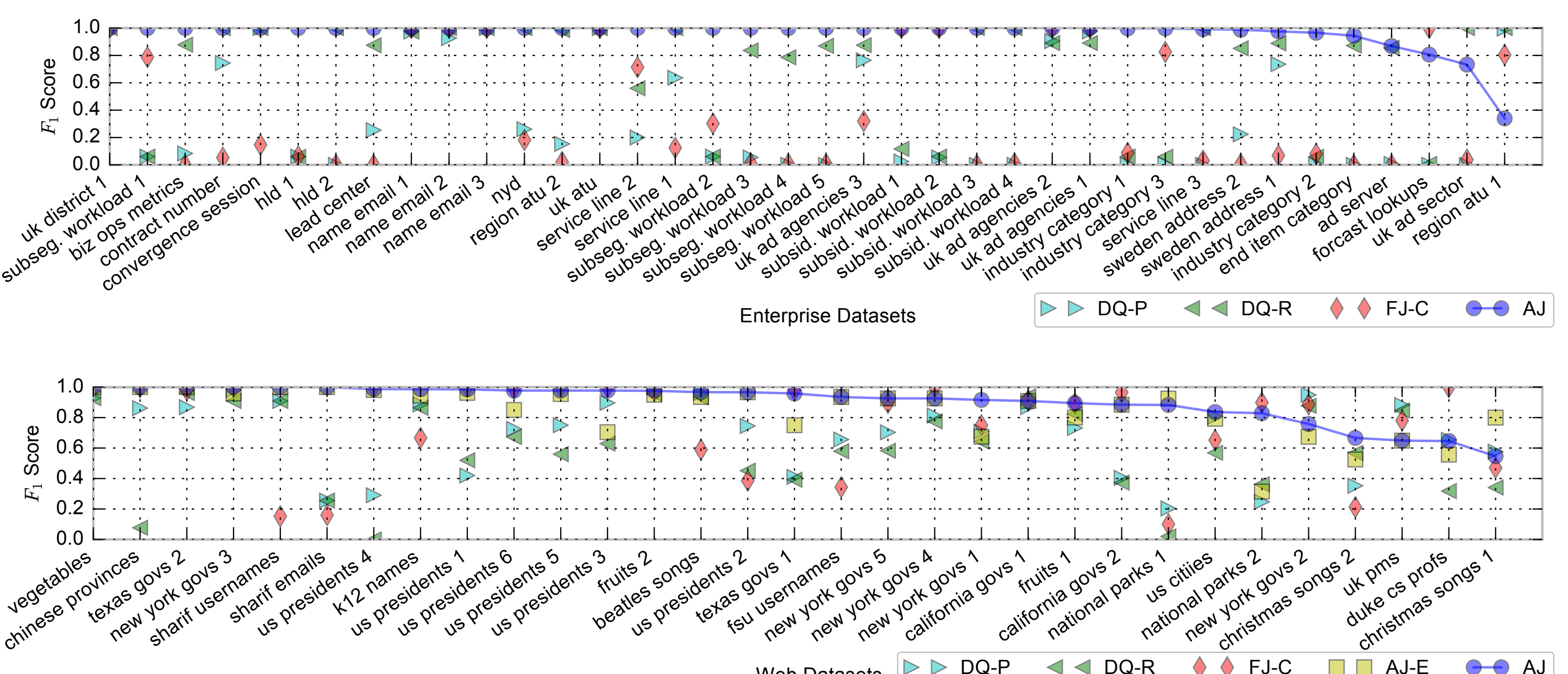
Join Column	Target Key Column	...
Bill Clinton	Will Clinton	...
George W. Bush	George W. Bush	...
...	George H. W. Bush	...
George H. W. Bush	...	...

Equi-Join  
Fuzzy-join

- Optimization:** We apply binary search and the above constraints to efficiently find the optimal tuning in the fuzzy join parameter space.

## 5. Evaluation

- Quality evaluation** uses tables from Microsoft enterprise spreadsheets and tables from the Web.



- Performance evaluation** uses DBLP dataset; Auto-Join runs less than 5 seconds at 10K rows and 14 seconds at 100K rows.