The Need for String Joins

- Substantial amounts of data in existing RDBMSs are strings
- There is a need to correlate data stored in different tables
  - Applications: data cleaning, data integration
- Example: Find common customers across different services

<table>
<thead>
<tr>
<th>Service A</th>
<th>Service B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Divesh Srivastava</td>
<td>Eurodraft Corp.</td>
</tr>
<tr>
<td>John Paul McDougal</td>
<td>Hatronic Corp.</td>
</tr>
<tr>
<td>KIA International</td>
<td>Euroaft</td>
</tr>
<tr>
<td>Euroaft Corp.</td>
<td>Divesh Shrivastava</td>
</tr>
<tr>
<td>Hatronic Inc.</td>
<td>John P. McDougal</td>
</tr>
<tr>
<td>Comp. Sci. Dept.</td>
<td>Dept. of Comp. Sci.</td>
</tr>
<tr>
<td>...</td>
<td>KIA</td>
</tr>
</tbody>
</table>
Problems with Exact String Joins

- Typing mistakes, abbreviations, different conventions
- Standard equality joins do not "forgive such mistakes"

```
Service A
- Divesh Srivastava
- John Paul McDougal
- KIA International
- Euroaft Corp.
- Hatronic Inc.
- Comp. Sci. Dept.
- ...

Service B
- Euroraft Corp.
- Hatronic Corp.
- Euroaft
- Divesh Shrivastava
- John P. McDougal
- Dept. of Comp. Sci.
- KIA
```

Matching String Attributes

Need for a similarity metric!

- Match entries with **typing mistakes**
  - Divesh Srivastava vs. Divesh Shrivastava

- Match entries with **abbreviations**
  - Euroaft Corporation vs. Euroaft Corp.

- Match entries with **different conventions**
  - Comp. Sci. Dept. vs. Dept. of Comp. Sci.
Using String Edit Distance

String Edit Distance: Number of single character insertions, deletions, and modifications to transform one string to the other

<table>
<thead>
<tr>
<th>String 1</th>
<th>String 2</th>
<th>Ed. Dist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Divesh Srivastava</td>
<td>Divesh Shrivastava</td>
<td>1</td>
</tr>
<tr>
<td>Dept. Comp. Sci.</td>
<td>Dept. of Comp. Sci.</td>
<td>3</td>
</tr>
<tr>
<td>Euroaft Corporation</td>
<td>Euroaft</td>
<td>12</td>
</tr>
</tbody>
</table>

- **Good for** spelling errors, short word inserts/deletes
- **Problems with** word order variations, long word inserts/deletes

Using Cosine Similarity

Similar string pairs should share “infrequent” tokens (tokens can be words, groups of characters, ...)

<table>
<thead>
<tr>
<th>String 1</th>
<th>String 2</th>
<th>Ed. Dist</th>
</tr>
</thead>
<tbody>
<tr>
<td>EUROAFT CORPORATION</td>
<td>EUROAFT</td>
<td>12</td>
</tr>
<tr>
<td>EUROAFT CORPORATION</td>
<td>HATRONIC CORPORATION</td>
<td>6</td>
</tr>
</tbody>
</table>

**Similarity** = \( \sum_{\text{all tokens}} \text{weight}(\text{token, } t_1) \times \text{weight}(\text{token, } t_2) \)

- **Good for** common token inserts/deletes, token order variations
- **Problems with** rare token inserts/deletes, rare misspellings
Approximate String Joins

No native support for approximate string joins in RDBMSs

Two existing (straightforward) solutions:
- Join data outside of DBMS
- Join data via user-defined functions (UDFs) inside DBMS

AS Joins Outside DBMS

1. Export data
2. Join outside of DBMS
3. Import the result

Main advantage:
Can exploit specialized tools (e.g., address matching) and business rules, without restrictions from DBMS functionality

Disadvantages:
- Substantial amounts of data to be exported/imported
- Cannot be easily integrated with other DBMS processing steps
AS Joins Using UDFs

1. Write a UDF to check if two strings match within distance $K$
2. Write an SQL statement that applies the UDF to the string pairs

```sql
SELECT R.sA, S.sA
FROM R, S
WHERE approx_string_match(R.sA, S.sA, K)
```

Main advantage:
Easily integrated with other DBMS processing steps

Main disadvantage:
Inefficient: UDF applied to entire cross-product of relations

Our Approach: Use Q-grams

Intuition
- Similar strings have many common substrings (q-grams)
- Preprocess string data, generate auxiliary tables of substrings
- Perform "approximate string join", exploiting RDBMS capabilities of exact joins and aggregations

Advantages
- No modification of underlying RDBMS needed.
- Can leverage the RDBMS query optimizer.
- Much more efficient than the approach based on naive UDFs
What is a Q-gram?

- **Q-gram**: A sequence of q characters of the original string
- Split each string into all overlapping q-grams
  - string with length $L \rightarrow L + q - 1$ q-grams
- Example: $q=3$
  - srivastava = ##s, #sr, sri, riv, iva, vas, ast, tav, ava, va$, a$$

Q-grams and String Edit Distance

- Each edit distance operation affects at most $q$ q-grams
- Two strings $S1$ and $S2$ with string edit distance $\leq K$ have at least $\max(S1.len, S2.len) + q - 1 - Kq$ q-grams in common
- Example:
  - srivastava = ##s, #sr, sri, riv, iva, vas, ast, tav, ava, va$, a$$
  - shrivastava = ##s, #sh, shr, hri, riv, iva, vas, ast, tav, ava, va$, a$$
- Useful filter: eliminate all string pairs without "enough" common q-grams (no false dismissals!)
Words and Cosine Similarity

Using *words* as tokens:

- Split each entry into words
- Similar entries share infrequent words

- **Problems with** misspellings, abbreviations
  
  Euroaft Corporation ≠ Eurodraft Corp.

"WHIRL" – W. Cohen, SIGMOD’98

Q-grams and Cosine Similarity

Use *q-grams* as tokens:

- Similar entries share many, infrequent q-grams

  Euroaft Corporation

  "#, #Eu, Eur, uro, roa, oaf, aft, …, Cor, orp, rpo, por, …

  "#, #Eu, Eur, urô, rod, odr, dra, raf, aft, …, Cor, orp, rp, …

  Eurodraft Corp.

- **Good for** common misspellings, abbreviations
Matching Strings Efficiently in SQL

- Problem 1:
  Find all pairs of strings $t_1, t_2$ with **string edit distance $\leq K$**

- Problem 2:
  Find all pairs of strings $t_1, t_2$ with **cosine similarity $\geq \varphi$** where
  \[
  \text{cosine similarity} = \sum_{\text{token}} \text{weight}(\text{token}, t_1) \times \text{weight}(\text{token}, t_2)
  \]

- SQL-only solution desirable:
  - Scalability
  - Robustness
  - Ease of deployment

Problem 1: Edit Distance in DBMS

- LENGTH FILTER: two strings $S1$ and $S2$ with **edit distance $\leq K$** cannot differ in length by $> K$

- COUNT FILTER: two strings $S1$ and $S2$ with **edit distance $\leq K$** have $\geq [\max(S1.len, S2.len) + q - 1] - Kq$ q-grams in common
  - Create auxiliary DBMS tables with tuples of the form:
    \(<\text{sid}, \text{qgram}>\), join and aggregate these tables

- POSITION FILTER: corresponding q-grams of $S1$ and $S2$ cannot differ in their positions by more than $K$
  - Create auxiliary DBMS tables with tuples of the form:
    \(<\text{sid}, \text{qgram}, \text{pos}>\), join and aggregate these tables
Problem 1: The SQL Statement

```
SELECT R1.sid, R2.sid
FROM R1, R1Q, R2, R2Q
WHERE R1.sid = R1Q.sid AND R2.sid = R2Q.sid AND
    R1Q.qgram = R2Q.qgram AND
    abs(R1Q.pos - R2Q.pos) <= k AND
    abs(LEN(R1.str) - LEN(R2.str)) <= k AND
    (LEN(R1.str)+q-1 > k*q OR LEN(R2.str)+q-1 > k*q)
GROUP BY R1.sid, R2.sid, R1.str, R2.str
HAVING COUNT(*) >= max(LEN(R1.str), LEN(R2.str))+q-1 - k*q AND
    edit_distance(R1.str, R2.str, k)
UNION ALL
```

```
SELECT R1.sid, R2.sid
FROM R1, R2
WHERE LEN(R1.str)+q-1 <= k*q AND LEN(R2.str)+q-1 <= k*q AND
    abs(LEN(R1.str) - LEN(R2.str)) <= k AND
    edit_distance(R1.str, R2.str, k)
```

Problem 1: Experimental Data

- Three customer data sets from AT&T Worldnet service
  - (a) set 1 with about 40K strings
  - (b) set 2 and (c) set 3 with about 30K strings each
Problem 1: DBMS Setup

- Used Oracle 8i (supports UDFs), on Sun 20 Enterprise Server
- Materialized the q-gram tables with entries <sid, qgram, pos> (less than 2 minutes per table)
- Tested configurations with and without indexes on the auxiliary q-gram tables (less than 5 minutes to generate each index)

The generation time for the auxiliary q-gram tables and indexes is small: even on-the-fly materialization is feasible

Problem 1: RDBMS Query Plans

- Naive approach with UDFs: nested-loops joins (prohibitively slow even for small data sets)
- Q-gram approach: usually sort-merge joins
- In our prototype implementation, sort-merge joins is the fastest too
Problem 1: Naïve UDFs vs. Q-grams

For a subset of set1, our technique was 20 to 30 times faster than the naïve use of UDFs.

LENGTH FILTER: 40-70% reduction for set1 (small length deviation)
90-98% reductions for set2, set3 (big length deviation)
+COUNT FILTER: > 99% reduction
+POSITION FILTER: ~ additional 50% reduction
Problem 1: Effect of Q-gram Size

- For the given data sets, q=2 worked best
- q=2 is small enough to avoid, as much as possible, the space overhead for the auxiliary tables

Problem 2: Cosine Similarity in DBMS

- Create in SQL relations $R_i$Weights (token weights from $R_i$)
- Compute similarity of each tuple pair

<table>
<thead>
<tr>
<th>$R_i$</th>
<th>Name</th>
<th>$R_i$Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>EUROAFT CORP</td>
<td>0.98</td>
</tr>
<tr>
<td>2</td>
<td>HATRONIC INC</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>INC</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>0.14</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$R_j$</th>
<th>Name</th>
<th>$R_j$Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>HATRONIC CORP</td>
<td>0.98</td>
</tr>
<tr>
<td>2</td>
<td>CORP</td>
<td>0.25</td>
</tr>
<tr>
<td>3</td>
<td>EUROAFT CORP</td>
<td>0.95</td>
</tr>
<tr>
<td>4</td>
<td>INC</td>
<td>0.30</td>
</tr>
<tr>
<td>5</td>
<td>EUROAFT</td>
<td>0.97</td>
</tr>
<tr>
<td>6</td>
<td>CORP</td>
<td>0.25</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$R_i$</th>
<th>$R_j$</th>
<th>Similarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>EUROAFT CORP</td>
<td>EUROAFT INC</td>
<td>0.98</td>
</tr>
<tr>
<td>EUROAFT CORP</td>
<td>EUROAFT CORP</td>
<td>1.00</td>
</tr>
<tr>
<td>EUROAFT CORP</td>
<td>HATRONIC CORP</td>
<td>0.05</td>
</tr>
<tr>
<td>HATRONIC INC</td>
<td>HATRONIC INC</td>
<td>0.99</td>
</tr>
<tr>
<td>HATRONIC INC</td>
<td>EUROAFT INC</td>
<td>0.04</td>
</tr>
</tbody>
</table>
Problem 2: Naïve SQL

Computes similarity for many useless pairs

```
SELECT r1w.tid AS tid1, r2w.tid AS tid2
FROM R1Weights r1w, R2Weights r2w
WHERE r1w.token = r2w.token
GROUP BY r1w.tid, r2w.tid
HAVING SUM(r1w.weight*r2w.weight) \geq \phi
```

Expensive operation!

Problem 2: Sampling Step

- Cosine similarity = \( \sum \text{weight(token, } t_1) \times \text{weight(token, } t_2) \)
- Products cannot be high when weight is small
- Can (safely) drop low weights from R1Weights (adapted from [Cohen & Lewis, SODA97] for efficient execution in an RDBMS)

```
R1Weights

<table>
<thead>
<tr>
<th>Token</th>
<th>W</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.9144</td>
</tr>
<tr>
<td>2</td>
<td>0.8419</td>
</tr>
<tr>
<td>...</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.01247</td>
</tr>
<tr>
<td>1</td>
<td>0.00504</td>
</tr>
</tbody>
</table>
```

R2Sample

```

<table>
<thead>
<tr>
<th>Token</th>
<th>TIMES SAMPLED</th>
</tr>
</thead>
<tbody>
<tr>
<td>EUROAFT</td>
<td>18 (18/20=0.90)</td>
</tr>
<tr>
<td>HATRONIC</td>
<td>17 (17/20=0.85)</td>
</tr>
</tbody>
</table>
```

Eliminates low similarity pairs
(e.g., "EUROAFT INC" with "HATRONIC INC")
Problem 2: Sampling-Based Joins

<table>
<thead>
<tr>
<th>Name</th>
<th>Token</th>
<th>W</th>
</tr>
</thead>
<tbody>
<tr>
<td>1abrpeaf</td>
<td>HATRONIC</td>
<td>0.98</td>
</tr>
<tr>
<td>2abrpeaf</td>
<td>CORP</td>
<td>0.02</td>
</tr>
<tr>
<td>2abrpeaf</td>
<td>HATRONIC</td>
<td>0.98</td>
</tr>
<tr>
<td>2abrpeaf</td>
<td>INC</td>
<td>0.01</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Token</th>
<th>W</th>
</tr>
</thead>
<tbody>
<tr>
<td>1abrpeaf</td>
<td>HATRONIC</td>
</tr>
<tr>
<td>2abrpeaf</td>
<td>CORP</td>
</tr>
<tr>
<td>2abrpeaf</td>
<td>HATRONIC</td>
</tr>
<tr>
<td>2abrpeaf</td>
<td>INC</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>R1</th>
<th>R2</th>
<th>Similarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>EUROAFT CORP</td>
<td>EUROAFT INC</td>
<td>0.98</td>
</tr>
<tr>
<td>EUROAFT CORP</td>
<td>EUROAFT CORP</td>
<td>0.9</td>
</tr>
<tr>
<td>HATRONIC INC</td>
<td>HATRONIC CORP</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Problem 2: Sampling-Based SQL

```sql
SELECT r1w.tid AS tid1, r2s.tid AS tid2
FROM R1Weights r1w, R2Sample r2s, R2sum r2sum
WHERE r1w.token = r2s.token AND r1w.token = r2sum.token
GROUP BY r1w.tid, r2s.tid
HAVING SUM(r1w.weight*r2sum.total*r2s.c) ≥ S*φ
```

Fully implemented in pure SQL!
Problem 2: Experimental Setup

- 40,000 entries from AT&T customer database, split into $R_1$ (26,000 entries) and $R_2$ (14,000 entries)
- Tokenizations:
  - Words
  - Q-grams, $q=2$ & $q=3$
- Methods compared:
  - Variations of sample-based joins
  - Baseline in SQL
  - WHIRL [SIGMOD98], adapted for handling q-grams

Problem 2: Metrics

Execute the (approximate) join for similarity $\geq \phi$

- **Precision**: (measures accuracy)
  - Fraction of the pairs in the answer with real similarity $\geq \phi$

- **Recall**: (measures completeness)
  - Fraction of the pairs with real similarity $\geq \phi$ that are also in the answer

- Execution time
Problem 2: Comparing with WHIRL

- Sample-based Joins: Good recall across similarity thresholds. Retrieves many interesting matches (many good matches have similarity ~0.5)
- WHIRL: Low recall (memory problems) – Misses many good matches
- WHIRL: Perfect precision result of post-join step

Problem 2: Changing Sample Size

- Increased sample size → More accurate weight estimation → Better recall, precision
- Drawback: Increased execution time (more pairs found)

3-grams, S=128
Problem 2: Execution Time

3-grams
WHIRL and sample-based joins ‘break-even’ at $S \sim 64, 128$
Baseline in SQL >24hrs, never finished (out of disk space)

Problem 2: Evaluation Summary

- Sample-based joins preferable when recall is important. WHIRL good for very high thresholds (“a few good matches”)

- Cosine similarity with q-grams gives better results (semantically). Higher execution time compared to word-based cosine similarity

- Sample-based joins more adaptable and flexible:
  - …easier to tune
  - …more scalable
  - …more robust
  - …easy to deploy in any environment
Related Work

- Tejada, Knoblock & Minton. Learning domain-independent string ... KDD 2002.

Conclusions

- We introduced techniques for mapping approximate string joins into “vanilla” SQL expressions, each with its own advantages:
  - String edit distance: no false positives
  - Cosine similarity: tradeoff between recall and efficiency
- Our techniques do not require modifying the underlying RDBMS
  - Significantly outperform existing approaches
- Other applications?
Acknowledgements

- Joint work with:
  - Luis Gravano (Columbia University)
  - Panagiotis G. Ipeirotis (Columbia University)
  - H. V. Jagadish (University of Michigan)
  - Nick Koudas (AT&T Labs-Research)
  - S. Muthukrishnan (Rutgers University, AT&T Labs-Research)

- Based on papers in VLDB’01 and WWW’03, and poster in ICDE’03