Interlinking: Performance Assessment of User Evaluation vs. Supervised Learning Approaches

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Why Link Discovery?

1. **Fourth Linked Data principle**
2. **Links are central for**
   - Cross-ontology QA
   - Data Integration
   - Reasoning
   - Federated Queries
   - ...
3. **Linked Data on the Web:**
   - 10+ thousand datasets
   - 89+ billion triples
   - $\approx 500+$ million links
Why is it difficult?

Definition (Link Discovery)

- Given sets $S$ and $T$ of resources and relation $\mathcal{R}$
- Task: Find $M = \{(s, t) \in S \times T : \mathcal{R}(s, t)\}$
- Common approaches:
  - Find $M' = \{(s, t) \in S \times T : \sigma(s, t) \geq \theta\}$
  - Find $M' = \{(s, t) \in S \times T : \delta(s, t) \leq \theta\}$

Time complexity

- Large number of triples
- Quadratic a-priori runtime
- 69 days for mapping cities from DBpedia to Geonames (1ms per comparison)
- Decades for linking DBpedia and LGD ...
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1. **Time complexity**

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2 Complexity of specifications

- Combination of several attributes required for high precision
- Adequate atomic similarity functions difficult to detect
- Tedious discovery of most adequate mapping
Introduction

- Interlinking tools LIMES, SILK, RDFAI,...

- Interlinking tools differ in many factors such as:
  1. Automation and user involvement
  2. Domain dependency
  3. Matching techniques

- Manual links validation as a user involvement:
  1. Benchmarks
  2. Active learning positive and negative examples
Introduction

- Commonly used
  - String distance/similarity measures
    - Edit distance
    - Q-Gram similarity
    - Jaro-Winkler
    - ...
  - Metrics
    - Minkowski distance
    - Orthodromic distance
    - Symmetric Hausdorff distance
    - ...

Idea

- Learning distance/similarity measures from data can lead to better accuracy while linking.
Introduction

- Commonly used
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Problem

- Edit distance does not differentiate between different types of edits.

Source labels
- Generalised epidermolysis
- Diabetes I
- Diabetes II

Target labels
- Generalized epidermolysis
- Diabetes I
- Diabetes II
## Problem
- Edit distance does not differentiate between different types of edits.

<table>
<thead>
<tr>
<th>Source labels</th>
<th>Target labels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generalised epidermolysis</td>
<td>Generalized epidermolysis</td>
</tr>
<tr>
<td>Diabetes I</td>
<td>Diabetes I</td>
</tr>
<tr>
<td>Diabetes II</td>
<td>Diabetes II</td>
</tr>
</tbody>
</table>
Motivation/2

- Choosing $\theta \in [0, 1)$

- Choosing $\theta \in [1, 2)$

Solution: Weighted edit distance

- Assign weight to each operation: substitution, insertion, deletion.
Motivation/2

Choosing $\theta \in [0, 1)$

Choosing $\theta \in [1, 2)$

Solution: Weighted edit distance

Assign weight to each operation: substitution, insertion, deletion.
Motivation/3

Cost matrix

- Costs are arranged in a quadratic matrix $M$
- Cell $m_{i,j}$ contains the cost of transforming character associated to row $i$ into character associated with column $j$
- Characters are from an alphabet
  \{'A',..., 'Z', 'a',..., 'z', '0',..., '9', '$\epsilon$'\}
- Main diagonal values are zeros

\[
\begin{array}{ccccccc}
A & B & C & D & \cdots & \varepsilon \\
\hline
A & 0 & 1 & 1 & 1 & \cdots & 1 \\
B & 1 & 0 & 1 & 1 & \cdots & 1 \\
C & 1 & 1 & 0 & 1 & \cdots & 1 \\
D & 1 & 1 & 1 & 0 & \cdots & 1 \\
& \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\
& \vdots & \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\
& \varepsilon & \cdots & \cdots & \cdots & \cdots & 1 \\
\end{array}
\]
Motivation/4

■ Pros
  ■ Can differentiate between edit operations.
  ■ Better F-measure in some cases.

■ Cons
  ■ No dedicated scalable algorithm for weighted edit distances
  ■ Difficult to use for link discovery.
### F-measure Results

<table>
<thead>
<tr>
<th></th>
<th>DBLP–Scholar</th>
<th>ABT–Buy</th>
<th>DBLP–ACM</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>F-measure (%)</strong></td>
<td>87.85</td>
<td>0.60</td>
<td>97.92</td>
</tr>
<tr>
<td><strong>Without REEDED (s)</strong></td>
<td>30,096</td>
<td>43,236</td>
<td>26,316</td>
</tr>
<tr>
<td><strong>With REEDED (s)</strong></td>
<td>668.62</td>
<td>65.21</td>
<td>14.24</td>
</tr>
</tbody>
</table>

![Bar chart showing F-measure comparison with and without REEDED for DBLP–Scholar, ABT–Buy, and DBLP–ACM datasets.](chart.png)
Extension of existing algorithms

Idea

- $edit(x, y) = \theta \rightarrow$ Need $\theta$ operations to transform $x$ into $y$
- $\delta(x, y) \geq \theta \cdot \min_{i \neq j} m_{ij}$

Extension

1. Run existing algorithm with threshold $\frac{\theta}{\min_{i \neq j} m_{ij}}$
2. Filter results by using $\delta(x, y) \geq \theta$

Problem

Does not scale.
Extension of existing algorithms

**Idea**

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Extension

1. Run existing algorithm with threshold $\frac{\theta}{\min_{i \neq j} m_{ij}}$
2. Filter results by using $\delta(x, y) \geq \theta$

Problem

Does not scale.
- Series of filters.
- Both **complete** and **correct**.
Length-Aware Filter

- **Input**: a pair \((s, t) \in S \times T\) and a threshold \(\theta\)
- **Output**: the pair itself or null

**Insight**
Given two strings \(s\) and \(t\) with lengths \(|s|\) resp. \(|t|\), we need at least \(||s| - |t||\) edit operations to transform \(s\) into \(t\).

**Examples**

A. \(\langle s, t, \theta \rangle = \langle "realize", "realise", 1 \rangle\)
\[||s| - |t|| = 0, \quad \Rightarrow \text{pass}\]

B. \(\langle s, t, \theta \rangle = \langle "realize", "real", 1 \rangle\)
\[||s| - |t|| = 3, \quad \Rightarrow \text{discard}\]
Character-Aware Filter

- **Input**: a pair \((s, t) \in \mathcal{L}\) and a threshold \(\theta\)
- **Output**: the pair itself or null

**Insight**

Given two strings \(s\) and \(t\), if \(|C|\) is the number of characters that do not belong to both strings, we need at least \(\frac{|C|}{2}\) operations to transform \(s\) into \(t\).

**Examples**

A. \(\langle s, t, \theta \rangle = \langle “realize“, “realise“, 1 \rangle\)

\[ C = \{s, z\}, \quad \left\lfloor \frac{|C|}{2} \right\rfloor \cdot \min_{i \neq j} (m_{ij}) = 0.5, \quad \Rightarrow \text{pass} \]

B. \(\langle s, t, \theta \rangle = \langle “realize“, “concept“, 1 \rangle\)

\[ C = \{r, c, a, l, i, z, o, n, p, t\}, \quad \left\lfloor \frac{|C|}{2} \right\rfloor \cdot \min_{i \neq j} (m_{ij}) > 1, \quad \Rightarrow \text{discard} \]
Verification Filter

- **Input**: a pair \((s, t) \in C\) and a threshold \(\theta\)
- **Output**: the pair itself or null

**Insight**

**Definition of Weighted Edit Distance.** Two strings \(s\) and \(t\) are similar iff the sum of the operation costs to transform \(s\) into \(t\) is less than or equal to \(\theta\).

**Examples**

A. \(\langle s, t, \theta \rangle = \langle \text{“realize“}, \text{“realise“}, 1 \rangle\)

\[\delta(s, t) = m_{z,s} = 0.6, \quad \Rightarrow \text{pass}\]
## Datasets

<table>
<thead>
<tr>
<th>dataset.property</th>
<th>domain</th>
<th># of pairs</th>
<th>avg length</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBLP.title</td>
<td>bibliographic</td>
<td>6,843,456</td>
<td>56.359</td>
</tr>
<tr>
<td>ACM.authors</td>
<td>bibliographic</td>
<td>5,262,436</td>
<td>46.619</td>
</tr>
<tr>
<td>GoogleProducts.name</td>
<td>e-commerce</td>
<td>10,407,076</td>
<td>57.024</td>
</tr>
<tr>
<td>ABT.description</td>
<td>e-commerce</td>
<td>1,168,561</td>
<td>248.183</td>
</tr>
</tbody>
</table>
Weight configuration

Given an edit operation, the higher the probability of error, the lower its weight.

1. Load typographical error frequencies
2. For insertion and deletion, calculate total frequency for each character
3. Normalize values on max frequency
### Evaluation/1

DBLP.title — bibliographic domain — 6,843,456 pairs

<table>
<thead>
<tr>
<th>$\theta$</th>
<th>PassJoin* average (± st.dev.)</th>
<th>REEDED average (± st.dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10.75 (± 0.92)</td>
<td>10.38 (± 0.35)</td>
</tr>
<tr>
<td>2</td>
<td>30.74 (± 5.00)</td>
<td>15.27 (± 0.76)</td>
</tr>
<tr>
<td>3</td>
<td>89.60 (± 1.16)</td>
<td>19.84 (± 0.14)</td>
</tr>
<tr>
<td>4</td>
<td>246.93 (± 3.08)</td>
<td>25.91 (± 0.29)</td>
</tr>
<tr>
<td>5</td>
<td>585.08 (± 5.47)</td>
<td>37.59 (± 0.43)</td>
</tr>
</tbody>
</table>

* Extended to deal with weighted edit distances.
ACM.authors — bibliographic domain — 5,262,436 pairs

<table>
<thead>
<tr>
<th>PassJoin*</th>
<th>REEDED</th>
</tr>
</thead>
<tbody>
<tr>
<td>θ</td>
<td>average</td>
</tr>
<tr>
<td>1</td>
<td>9.07 ± 1.05</td>
</tr>
<tr>
<td>2</td>
<td>18.53 ± 0.22</td>
</tr>
<tr>
<td>3</td>
<td>42.97 ± 1.02</td>
</tr>
<tr>
<td>4</td>
<td>98.86 ± 1.98</td>
</tr>
<tr>
<td>5</td>
<td>231.11 ± 2.03</td>
</tr>
</tbody>
</table>

* Extended to deal with weighted edit distances.
GoogleProducts.name — e-commerce domain — 10,407,076 pairs

<table>
<thead>
<tr>
<th>θ</th>
<th>PassJoin* average</th>
<th>st. dev.</th>
<th>REEDED average</th>
<th>st. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>17.86 ± 0.22</td>
<td></td>
<td>15.08 ± 2.50</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>62.31 ± 6.30</td>
<td></td>
<td>20.43 ± 0.10</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>172.93 ± 1.59</td>
<td></td>
<td>27.99 ± 0.19</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>475.97 ± 5.34</td>
<td></td>
<td>42.46 ± 0.32</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>914.60 ± 10.47</td>
<td></td>
<td>83.71 ± 0.97</td>
<td></td>
</tr>
</tbody>
</table>

* Extended to deal with weighted edit distances.
ABT.description — e-commerce domain — 1,168,561 pairs

<table>
<thead>
<tr>
<th>$\theta$</th>
<th>PassJoin*</th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>average</td>
<td>st.dev.</td>
<td>average</td>
<td>st.dev.</td>
</tr>
<tr>
<td>1</td>
<td>74.41</td>
<td>± 1.80</td>
<td>24.48</td>
<td>± 0.41</td>
</tr>
<tr>
<td>2</td>
<td>140.73</td>
<td>± 1.40</td>
<td>27.71</td>
<td>± 0.29</td>
</tr>
<tr>
<td>3</td>
<td>217.55</td>
<td>± 7.72</td>
<td>30.61</td>
<td>± 0.34</td>
</tr>
<tr>
<td>4</td>
<td>305.08</td>
<td>± 4.78</td>
<td>34.13</td>
<td>± 0.30</td>
</tr>
<tr>
<td>5</td>
<td>410.72</td>
<td>± 3.36</td>
<td>38.73</td>
<td>± 0.44</td>
</tr>
</tbody>
</table>

* Extended to deal with weighted edit distances.
## Effect of filters

<table>
<thead>
<tr>
<th>GooglePr.name</th>
<th>$\theta = 1$</th>
<th>$\theta = 2$</th>
<th>$\theta = 3$</th>
<th>$\theta = 4$</th>
<th>$\theta = 5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$</td>
<td>L</td>
<td>$</td>
<td>616,968</td>
<td>1,104,644</td>
<td>1,583,148</td>
</tr>
<tr>
<td>$</td>
<td>N</td>
<td>$</td>
<td>4,196</td>
<td>4,720</td>
<td>9,278</td>
</tr>
<tr>
<td>$</td>
<td>A</td>
<td>$</td>
<td>4,092</td>
<td>4,153</td>
<td>4,215</td>
</tr>
<tr>
<td>$RR(%)$</td>
<td>99.96</td>
<td>99.95</td>
<td>99.91</td>
<td>99.63</td>
<td>95.53</td>
</tr>
</tbody>
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<thead>
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<th>ABT.description</th>
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</tr>
</thead>
<tbody>
<tr>
<td>$</td>
<td>S \times T</td>
<td>$</td>
<td>1,168,561</td>
<td>1,168,561</td>
<td>1,168,561</td>
</tr>
<tr>
<td>$</td>
<td>L</td>
<td>$</td>
<td>22,145</td>
<td>38,879</td>
<td>55,297</td>
</tr>
<tr>
<td>$</td>
<td>N</td>
<td>$</td>
<td>1,131</td>
<td>1,193</td>
<td>1,247</td>
</tr>
<tr>
<td>$</td>
<td>A</td>
<td>$</td>
<td>1,087</td>
<td>1,125</td>
<td>1,135</td>
</tr>
<tr>
<td>$RR(%)$</td>
<td>99.90</td>
<td>99.90</td>
<td>99.89</td>
<td>99.88</td>
<td>99.87</td>
</tr>
</tbody>
</table>
Conclusion and Future Work

- Presented REEDED, a **time-efficient, correct and complete** LD approach for weighted edit distances.
- Showed that REEDED scales better than simple extension of existing.
- Future work includes:
  - Develop similar approach for weighted $n$-gram similarities.
  - Combine REEDED with specification learning approaches:
    - RAVEN, using Linear SVMs;
    - EAGLE, COALA using genetic programming.
  - Devise unsupervised learning approach for weights.
Thank you!

Questions?

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