**LEMON: Explainable Entity Matching**

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**Entity Matching**

The task of deciding which records refer to the same real-world entities.

<table>
<thead>
<tr>
<th>Title</th>
<th>Belkin shield cable for phone touch touch tint</th>
<th>Title</th>
<th>Belkin spoof touch shirt</th>
<th>Brand</th>
<th>Belkin</th>
<th>Model</th>
<th>F8Z646T202</th>
<th>Price</th>
<th>$47.98</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category</td>
<td>mp3 accessories</td>
<td>Category</td>
<td>cases</td>
<td>Brand</td>
<td>Belkin</td>
<td>Model</td>
<td>F8Z646T202</td>
<td>Price</td>
<td>$47.98</td>
</tr>
</tbody>
</table>

**Table 1:** Example of two records that need to be classified as either a match or a non-match. In this case, from the Walmart-Amazon dataset.

**LEMON**

State-of-the-art entity matching models [2, 3] are hard to interpret, and popular explainability methods [5, 4, 6] do not work satisfactorily out of the box for this problem. Therefore, we propose LEMON:

**Figure 1:** Overview of LEMON. The method is based on LIME [5]. Please ask me to explain or check the paper* for details.

LEMON addresses three different challenges of applying feature attribution methods to entity matching using three distinct, but coherent, techniques:

**Challenges:**
1. Cross-record interactions  
2. Non-match explanations  
3. Variation in sensitivity

**Proposed techniques:**
1. Dual explanations  
2. Attribution potential  
3. Counterfactual granularity

**Figure 2:** Example of an explanation from LEMON. In this case for a Bert-based matcher on the example from Table 1.


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**Results**

We compare against state-of-the-art for explainable entity matching [1] and popular general-purpose explainability methods [5, 4, 6] on 13 popular datasets using both a state-of-the-art classical model (results not included in poster) and a deep learning model.

**Counterfactual Interpretation**

- To what degree explanations communicate how the matchers decision could have been different.

**Figure 3:** The counterfactual \( F_1 \) score for all evaluated explainability methods across 13 datasets using a Bert-based matcher. Higher is better.

**Explanation Faithfulness**

- To what degree explanations (do not) reflect the actual behavior of the matcher.

**Figure 4:** The perturbation error for all evaluated explainability methods across 13 datasets using a Bert-based matcher. Lower is better.

**User Study**

- To what degree explanations help (laymen) users successfully manipulate a record pair to flip the matchers decision. After showing the users an explanation, we ask them “What do you think is the smallest change to the records that would convince the matcher otherwise?”

**Figure 5:** The counterfactual precision of real users for LIME and LEMON across 13 datasets using a Bert-based matcher. Higher is better.