Entity-Duet Neural Ranking: Understanding the Role of Knowledge Graph Semantics in Neural Information Retrieval
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Motivation and Background
- Queries and documents often match based on knowledge
  - Query: “Meituxiuixiu web version”
  - Document: “Meituxiuixiu web version: An online picture processing program”
- Meituxiuixiu web version: Meituxiuixiu is the most popular Chinese image processing software, launched by the Meitu company
- Our motivation is to study the effectiveness of knowledge graph semantics in state-of-the-art neural ranking models

Entity-Duet Neural Ranking Model (EDRM)
- Enriched-entity Embedding
  - Integration of knowledge graph semantics
- Neural Entity-Duet Framework
  - Multi-level soft matches in the embedding space
- Integration with Kernel based Neural Ranking (K-NRM)
  - K-NRM and Conv-KNRM are state-of-the-arts, which calculate n-gram and entity cross matches with Gaussian Kernels
  - K-NRM -> EDRM-KNRM
  - Conv-KNRM -> EDRM-CKNRM

Experimental Methodology
- Dataset:
  - Sogou query log
  - About 100K training queries and 1K testing queries
- Knowledge Graph:
  - CN-DPedia, a Chinese knowledge graph
  - Entities in both queries and documents are linked with CMNS
- End-to-end Training:
  - Train on relevance labels estimated by a click model (DCTR), about 850K training pairs
  - Test on two click model labels (DCTR->Testing-SAME and TACM->Testing-DIFF) and raw user clicks (Testing-RAW)

Experimental Results

<table>
<thead>
<tr>
<th>Method</th>
<th>Testing-SAME</th>
<th>Testing-DIFF</th>
<th>Testing-RAW</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NDCG@1</td>
<td>NDCG@10</td>
<td>NDCG@1</td>
</tr>
<tr>
<td>BM25</td>
<td>0.142 -46%</td>
<td>0.287 -32%</td>
<td>0.163 -46%</td>
</tr>
<tr>
<td>RankSVM</td>
<td>0.146 -45%</td>
<td>0.309 -24%</td>
<td>0.170 -43%</td>
</tr>
<tr>
<td>Coor-Ascent</td>
<td>0.159 -40%</td>
<td>0.355 -15%</td>
<td>0.209 -30%</td>
</tr>
<tr>
<td>DRRM</td>
<td>0.137 -48%</td>
<td>0.313 -29%</td>
<td>0.213 -29%</td>
</tr>
<tr>
<td>CDSSM</td>
<td>0.144 -46%</td>
<td>0.333 -21%</td>
<td>0.183 -39%</td>
</tr>
<tr>
<td>MP</td>
<td>0.218 -17%</td>
<td>0.379 -10%</td>
<td>0.197 -34%</td>
</tr>
<tr>
<td>K-NRM</td>
<td>0.265</td>
<td>0.420</td>
<td>0.300</td>
</tr>
<tr>
<td>Conv-KNRM</td>
<td>0.336 27%</td>
<td>0.481 15%</td>
<td>0.338 13%</td>
</tr>
<tr>
<td>EDRM-KNRM</td>
<td>0.310 17%</td>
<td>0.455 8%</td>
<td>0.333 11%</td>
</tr>
<tr>
<td>EDRM-CKNRM</td>
<td>0.340 28%</td>
<td>0.482 15%</td>
<td>0.371 24%</td>
</tr>
</tbody>
</table>

On Testing-SAME
- Significant improvement compared to K-NRM
- Little improvement compared to Conv-KNRM
- Conv-KNRM is able to learn phrases matches (entity) from data

On Testing-DIFF and Testing-RAW
- Significant improvement compared to K-NRM and Conv-KNRM
- EDRM shows generalization ability

Knowledge based Neural Ranking Model:
- Integrate knowledge graph semantics in state-of-the-art neural ranking models
- Entity types and descriptions are external embeddings to match entities and n-grams

End-to-end Training with User Clicks:
- A data-driven combination of entity-oriented search and neural information retrieval

Effectiveness and Generalization ability:
- Show greater advantage on hard and short queries
- Improve performances on more difficult testing scenarios

Conclusion

Dataset:
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- About 100K training queries and 1K testing queries

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Paper
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Performance on Different Scenarios
- Query Difficulty Scenario
- Query Length Scenario

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Ranking contribution for EDRM-CKNRM
- Overall kernel weight
  - Most of the weight goes to soft match
  - Entity related matches play an important role
  - Cross-space matches are more important

Individual kernel weight
- N-grams and entities are important components which share almost uniformly distributed weight