**Motivation and Background**

- Queries and documents often match based on knowledge
  - **Query:** “Meituxiuxiu web version”
  - **Document:** “Meituxiuxiu web version: An online picture processing tool”
- **Meituxiuxiu web version:** Meituxiuxiu 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 8500K training pairs
  - Test on two click model labels (DCTR→Testing-SAME and TACM→Testing-DIFF) and raw user clicks (Testing-RAW)

**Conclusion**

- **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

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**Experimental Results**

**Overall Performance**

<table>
<thead>
<tr>
<th>Method</th>
<th>Testing-SAME</th>
<th>Testing-DIFF</th>
<th>Testing-RAW</th>
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<tr>
<td>EDRM-CKNRM</td>
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<td>0.482</td>
<td>0.451</td>
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</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

**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

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**Performance on Different Scenarios**

- **Query Difficulty Scenario**
  - Greatest improvement on short and hard queries
  - Knowledge are more crucial for the limited query text

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**References**

Zhenghao Liu, Chenyan Xiong, Maosong Sun, Zhiyuan Liu

1. Tsinghua University
2. Carnegie Mellon University

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