Improving Search Results Ranking Using a Knowledge Graph

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Motivation

- Augmenting machine learned models with knowledge graphs (KGs) can help add domain-specific knowledge to models.
- Tasks such as question-answering, named entity recognition have benefitted from this augmentation.
- KGs have been successfully used in search as well for ranking.
Task

Improve the quality of search results using a KG
How can we use a KG to improve our model?

- KG-aware learning methods can be classified into two categories:
  - Embedding-based methods
  - Regularization-based methods

- Baseline model is a neural network that takes features derived from query, entity, and query-entity as inputs.
- Incorporated KG-based embeddings of the entity (and also query in case of KEWER) to make the model KG-aware
How can we use a KG to improve our model?

- We experimented with the following approaches to learn the embeddings:
  - TransE embeddings
  - Knowledge Graph Attention Network for Recommendation (KGAT)
  - Knowledge graph Entity and Word Embedding for Retrieval (KEWER)
TransE

View relations as translations performed on entity embeddings.

Translating Embeddings for Modeling Multi-relational Data, Antoine Bordes et. al., NeuRIPS 2013
KEWER

Entity search model which embeds words and entities in the same space.
Experiments

- Training data: 996,332 examples of query-entity features and binary relevance label tuples.
- Knowledge Graph:
  - 508,725 entities
  - 7,887,096 head-relation-tail triples
  - 20 entity types including Person, Video (i.e. movie or TV series), Genre (e.g. thriller).
  - 18 relations including acted_in, directed_by.
- Trained 64 dimensional embeddings of entities separately and added them as features into the baseline model.
- Evaluation based on Normalized Mean Reciprocal Rank (NMRR) metric.
## Results

<table>
<thead>
<tr>
<th>Model</th>
<th># Model Parameters</th>
<th>NMRR Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>870,401</td>
<td>-</td>
</tr>
<tr>
<td>Baseline + KGAT entity embeddings</td>
<td>878,593</td>
<td>0%</td>
</tr>
<tr>
<td>Baseline + KEWER entity embeddings</td>
<td>878,593</td>
<td>1.36%</td>
</tr>
<tr>
<td>Baseline + KEWER entity and query</td>
<td>886,785</td>
<td>1.36%</td>
</tr>
<tr>
<td>embeddings</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline + TransE entity embeddings</td>
<td>878,593</td>
<td>2.56%</td>
</tr>
</tbody>
</table>
Observations

- Incorporating transE embeddings of entities resulted in the largest NMRR improvement.
- KGAT did not scale well to large datasets.
- In case of KEWER, entity embeddings improved the NMRR compared to the baseline by 1.36%.
- Additionally incorporating query embeddings did not result in further improvement of the NMRR.
Future Work

- Scale up our experiments in terms of data and model training.
- Evaluate the improvements across different query classes.
- Explore jointly training the embedding model and the ranking model.
- Explore how to represent queries in KGs.