Generating Fine-Grained Open Vocabulary Entity Type Descriptions

Rajarshi Bhowmik and Gerard de Melo
• **Knowledge Graph**
  – Vast repository of structured facts

• **Why short textual description?**
  – Can succinctly characterize an entity and its type

• **Goal:** Generate succinct textual description from factual data
Motivating Problem

- Fixed inventory of ontological types (e.g. Person)
Motivating Problem

- Abstract ontological types can be misleading

About: Star Wars

An Entity of Type: sports team, from Named Graph: http://dbpedia.org,

- Missing short textual descriptions for many entities
Hey Siri who is Roger Federer

Here is what I found:

Roger Federer
Swiss tennis player

Roger Federer is a Swiss professional tennis player who is currently ranked world No. 2 in men's singles tennis by the Association of Tennis Professionals. Federer has won 20 Grand Slam singles titles and has held the world No.

See More on Wikipedia

<table>
<thead>
<tr>
<th>Mass</th>
<th>187 lb</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height</td>
<td>6 ft 1 in</td>
</tr>
</tbody>
</table>
More Applications: Named Entity Disambiguation
• **Discerning most relevant facts**
  – Nationality and occupation for a person
    • E.g. “Swiss tennis player”, “American scientist”
  – Genre, regions and release year for a movie
    • E.g. “1942 American comedy film”

• Open vocabulary: applicable any kind of entity

• Generated text is *coherent*, *succinct* and *non-redundant*

• *Sufficiently concise* to be grasped at a single glance
Key Contributions

• Dynamic memory-based generative model
  – jointly leverages *fact embeddings* + *context of the generated sequence*

• Benchmark dataset
  – 10K entities with large variety of types
  – Sampled from Wikidata
Model Architecture

• 3 key modules:
  – Input Module
  – Dynamic Memory Module
  – Output Module
Input Module

- **Input**
  - set of $N$ facts $\{f_1, f_2, ..., f_N\}$

- **Output**
  - concatenation of Fact Embeddings $[f_1, f_2, ..., f_N]$

- Learn Fact Embeddings using **Word Embeddings** + **Positional Encoder**

- Positional Encoder:
  $$f_i = \sum_{j=1}^{J} l_j \circ w_{ij}$$
Dynamic Memory Module

- **Current context**
  - Attention weighted sum of fact embeddings
    \[ c^t = \sum_{i=1}^{N} a^t_i f_i \]
- **Attentions weights** depends on two factors:
  - How much information from a particular fact is used by the previous memory state
  - How much information of a particular fact is invoked in the current context of the output sequence
- **Update memory state with**
  - current context
  - previous memory state
  - current output context

Number of memory updates = Length of output sequence
Output Module

- Decode the current memory state to generate the next word

- Decoder GRU input:
  - current memory state $m_t$,
  - previous hidden state $h^{(t-1)}$
  - previous word $w^{(t-1)}$
    - During Training: ground truth
    - During evaluation: predicted word

- Concatenate output of GRU with the current context vector $c_t$

- Pass through a fully connected layer followed by a Softmax
Sampled from Wikidata RDF dump and transformed to a suitable format

Sampled 10K entities with a English description and at least 5 facts

\[ \text{fact} = (\text{property name}, \text{property value}). \]

Transformed into a phrasal form by concatenating the words of the property name and its value

- E.g. \((\text{Roger Federer, occupation, tennis player}) \rightarrow \text{‘occupation tennis player’}\)
Evaluation: Baselines

• Fact-to-sequence Encoder-Decoder Model
  – Sequence-to-sequence model (Sutskever et al.) is tweaked to work on the fact embeddings generated by positional encoder

• Fact-to-sequence Model with Attention Decoder
  – Decoder module uses an attention mechanism

• Static Memory
  – Ablation study: *No memory update* using the dynamic context of the output sequence

• Dynamic Memory Networks (DMN+)
  – Xiong et al.’s model with minor modifications
  – A question module gets an input question such as “Who is Roger Federer?” or “What is Star Wars?”
### Evaluation: Results

<table>
<thead>
<tr>
<th>Model</th>
<th>B-1</th>
<th>B-2</th>
<th>B-3</th>
<th>B-4</th>
<th>ROUGE-L</th>
<th>METEOR</th>
<th>CIDEr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Facts-to-seq</td>
<td>0.404</td>
<td>0.324</td>
<td>0.274</td>
<td>0.242</td>
<td>0.433</td>
<td>0.214</td>
<td>1.627</td>
</tr>
<tr>
<td>Facts-to-seq w. Attention</td>
<td>0.491</td>
<td>0.414</td>
<td>0.366</td>
<td>0.335</td>
<td>0.512</td>
<td>0.257</td>
<td>2.207</td>
</tr>
<tr>
<td>Static Memory</td>
<td>0.374</td>
<td>0.298</td>
<td>0.255</td>
<td>0.223</td>
<td>0.383</td>
<td>0.185</td>
<td>1.328</td>
</tr>
<tr>
<td>DMN+</td>
<td>0.281</td>
<td>0.234</td>
<td>0.236</td>
<td>0.234</td>
<td>0.275</td>
<td>0.139</td>
<td>0.912</td>
</tr>
<tr>
<td>Our Model</td>
<td>0.611</td>
<td>0.535</td>
<td>0.485</td>
<td>0.461</td>
<td>0.641</td>
<td>0.353</td>
<td>3.295</td>
</tr>
</tbody>
</table>
## Evaluation: Examples

<table>
<thead>
<tr>
<th></th>
<th>Wikidata Item</th>
<th>Ground Truth Description</th>
<th>Generated Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Matches</strong></td>
<td>Q669081</td>
<td>municipality in Austria</td>
<td>Municipality in Austria</td>
</tr>
<tr>
<td></td>
<td>Q23588047</td>
<td>microbial protein found in Mycobacterium Abscessus</td>
<td>microbial protein found in Mycobacterium Abscessus</td>
</tr>
<tr>
<td><strong>More specific</strong></td>
<td>Q1865706</td>
<td>footballer</td>
<td>Finnish footballer</td>
</tr>
<tr>
<td></td>
<td>Q19261036</td>
<td>number</td>
<td>natural number</td>
</tr>
<tr>
<td><strong>More general</strong></td>
<td>Q7815530</td>
<td>South Carolina politician</td>
<td>American politician</td>
</tr>
<tr>
<td></td>
<td>Q4801958</td>
<td>2011 Hindi film</td>
<td>Indian film</td>
</tr>
<tr>
<td><strong>Semantic drift</strong></td>
<td>Q16164685</td>
<td>polo player</td>
<td>water polo player</td>
</tr>
<tr>
<td></td>
<td>Q1434610</td>
<td>1928 film</td>
<td>filmmaker</td>
</tr>
<tr>
<td><strong>Alternative</strong></td>
<td>Q7364988</td>
<td>Dean of York</td>
<td>British academic</td>
</tr>
<tr>
<td></td>
<td>Q1165984</td>
<td>cyclist</td>
<td>German bicycle racer</td>
</tr>
</tbody>
</table>
Evaluation: Attention Visualization
Conclusion

• Short textual descriptions facilitate instantaneous grasping of key information about entities and their types

• Discerning crucial facts and compressing it to a succinct description

• Dynamic memory-based generative architecture achieves this

• Introduced a benchmark dataset with 10K entities
Thank you!

https://github.com/kingsaint/Open-vocabulary-entity-type-description
Questions?