Can LMs Learn New Entities from Descriptions? Challenges in Propagating Injected Knowledge

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Motivation

Prior work has investigated knowledge editing in pre-trained LMs, updating model parameters to alter outputs to match what users want. We focus specifically on injecting new entities into models.

RQ1: Can LMs make inferences based on updated knowledge?

- We propose a new task called Entity Knowledge Propagation (EKP).

RQ2: How do SOTA knowledge editing methods perform on EKP?

- We compare fine-tuning, MEND, ROME, and in-context use of the definition on two datasets.

Entity Knowledge Propagation: when we teach an LM about a new entity, can the model make inferences about it?

We update an LM on a definition sentence of a new entity using any KE method such as finetuning, MEND, or ROME.

The updated LM is evaluated on a probe sentence. This could be a cloze-style task such as ECBD.

Experiments

Datasets

1. Entity Inferences (new in this work)
   - Manually crafted probe sentences using templates
     - Definition: Hurricane Nana was a minimal Category 1 hurricane that caused moderate damage across Belize in early September 2020.
     - Entity: Hurricane Nana
     - Options: acted, brewed, built, destroyed,...
     - Label: destroyed

2. Entity Cloze By Date (ECBD, Onoe et al., 2022)
   - Derived from Wikipedia sentences
     - Definition: An mRNA vaccine uses a copy of a molecule called messenger RNA to produce an immune response.
     - Sentence: mRNA vaccines do not affect or reprogram [MASK].
     - Entity: mRNA vaccine
     - Year: 2020
     - Label: DNA inside the cell

Knowledge Editing Methods

- Standard Finetuning
- MEND (Mitchell et al., 2022)
- ROME (Meng et al., 2022)
- (Baseline) Prepending a definition sentence

Results

<table>
<thead>
<tr>
<th>Entity Inferences / GPT2-XL (1.5B)</th>
<th>Pre-Edit</th>
<th>Finetune</th>
<th>ROME</th>
<th>Prepend-def</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>82.9</td>
<td>62.2</td>
<td>64.1</td>
<td>62.9</td>
</tr>
<tr>
<td>Edit Performance (↑)</td>
<td>38.0</td>
<td>16.7</td>
<td>18.7</td>
<td>22.5</td>
</tr>
<tr>
<td>Specificity (→)</td>
<td>36.1</td>
<td>26.1</td>
<td>27.7</td>
<td>26.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ECBD / GPT-Neo (1.3B)</th>
<th>Pre-Edit</th>
<th>Finetune</th>
<th>MEND</th>
<th>Prepend-def</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perplexity</td>
<td>38.6</td>
<td>26.1</td>
<td>27.7</td>
<td>26.1</td>
</tr>
<tr>
<td>Edit Performance (↑)</td>
<td>36.1</td>
<td>26.1</td>
<td>27.7</td>
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Takeaways

- Existing knowledge editing techniques can modify facts but struggle to make inferences based on those facts.
- Prompting baseline (prepending definition) is hard to beat, suggesting that more future research is needed.
- Follow up work that achieves better performance: Propagating Knowledge Updates to LMs Through Distillation (Padmanabhan et al., 2023)

Data is available at github.com/yasumasaonoe/entity_knowledge_propagation