Conversational Question Answering over Knowledge Graphs
Magdalena Kaiser, Rishiraj Saha Roy and Gerhard Weikum
Max Planck Institute for Informatics, Germany

**SAMPLE CONVERSATION**

<table>
<thead>
<tr>
<th>Q1</th>
<th>When was Avengers: Endgame released in Germany?</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>24 April 2019</td>
</tr>
<tr>
<td>Q2</td>
<td>What was next from Marvel?</td>
</tr>
<tr>
<td>A2</td>
<td>Stan Lee</td>
</tr>
<tr>
<td>Q3</td>
<td>Release date?</td>
</tr>
<tr>
<td>A3</td>
<td>...</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Q1</th>
<th>When was Avengers: Endgame released in Germany?</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>24 April 2019</td>
</tr>
<tr>
<td>Q2</td>
<td>What was next from Marvel?</td>
</tr>
<tr>
<td>A2</td>
<td>Stan Lee</td>
</tr>
<tr>
<td>Q3</td>
<td>Release date?</td>
</tr>
<tr>
<td>A3</td>
<td>...</td>
</tr>
</tbody>
</table>

**CONVERSATIONAL QA IS CHALLENGING**

- Short, incomplete questions
- Implicit context

**IMPROVING CONVQA BY LEARNING FROM FEEDBACK**

- Current systems learn from gold QA pairs: unrealistic
- **CONQUER**: Reinforcement learning model for QA
  - Learns from conversational stream in the absence of gold answers
  - Rewards based on reformulations: +1 (new intent = correct previous answer), -1 (reformulation = wrong previous answer)
- Reformulation detector based on BERT
- **ConvRef**: Conversational QA benchmark with reformulations

**CONQUER WORKFLOW**

1. Detect context entities in conversation = start points for agents’ walk by scoring KG neighborhood
2. Predict path by applying a policy network trained with REINFORCE algorithm
3. Generate answers: follow sampled path (during training), take top scoring paths and aggregate answer (at answering time)
4. Predict if next question is a reformulation by using a fine-tuned BERT model and give reward accordingly

**EXPERIMENTAL VARIANTS**

- **Four variants** of CONQUER to model two sources of noise (reformulation predictor and user behavior):
  - Ideal Reformulation Predictor:
    - No wrong predictions
  - Noisy Reformulation Predictor:
    - Fine-tuned BERT model that can make wrong predictions
  - Ideal User Model:
    - User behaves as in our assumption: reformulates if answer was wrong, otherwise issues new question
  - Noisy User Model:
    - User can also ask new question even though previous answer was wrong

**CONQUER SUCCESSFULLY LEARNS FROM REFORMULATIONS IN THE PRESENCE OF NOISE**

- **CONQUER** outperforms SOTA baseline **CONVEX** on **ConvRef** and **ConvQuestions**
- Similar performance of **CONQUER** variants
- **CONQUER** answers more questions earlier: requires less reformulations

**ConvRef BENCHMARK**

- Builds upon conversational KG-QA dataset **ConvQuestions** (11k conversations from 5 different domains)
- User study to collect reformulations by interacting with baseline QA system
- Different from paraphrases: Reformulations based on conversation history and system-generated wrong answer

**Contact:** mkaiser@mpi-inf.mpg.de
**Complete Information:** conquer.mpi-inf.mpg.de