**Knowledge Diffusion for Neural Dialogue Generation**

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### Introduction

Previous neural dialogue systems based on knowledge base are capable of answering facts related inquiries, WH questions in particular. However, it is still far behind a natural knowledge grounded dialogue system, which should be able to understand the facts involved in current dialogue session (so-called facts matching, i.e.: Item 1, 2), as well as diffuse them to other similar entities for knowledge-based chit-chats (namely entity diffusion, i.e.: Item 3, 4):

- **Knowledge Retriever**
- **Decoder**

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### Model Architecture

- **Overview**
- **Knowledge Retriever**
- **Decoder**

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### Dataset

We collect a multi-turn conversation corpus which includes not only facts related inquiries but also knowledge-based chit-chats. The data is publicly available at [https://github.com/liushuman/neural-knowledge-diffusion](https://github.com/liushuman/neural-knowledge-diffusion).

We obtain the element information of each movie from [https://movie.douban.com/](https://movie.douban.com/) and build the knowledge base K. The question-answering dialogues and knowledge related chit-chat are crawled from [https://zhidao.baidu.com/](https://zhidao.baidu.com/) and [https://www.douban.com/group/](https://www.douban.com/group/).

The conversations are grounded on the knowledge using NER, string match, and artificial scoring and filtering rules. The total 32977 conversations consisting of 104567 utterances are divided into training (32177) and testing set (800).

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### Experiments and Conclusion

In this work, we propose a neural knowledge diffusion (NKD) model to introduce knowledge into dialogue generation.

- **We identify the problem of incorporating knowledge bases and dialogue systems as facts matching and entity diffusion.**

- **We manage both facts matching and entity diffusion by introducing a novel knowledge diffusion mechanism and generate the responses with the retrieved knowledge items, which enable the convergent and divergent thinking over the knowledge base.**

- **The experimental results show that the proposed model effectively generate more diverse and meaningful responses involving more accurate relevant entities compared with the state-of-the-art baselines.**

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<table>
<thead>
<tr>
<th>Model</th>
<th>Factoid QA</th>
<th>Entire Dataset</th>
<th>Human Evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSTM</td>
<td>7.8</td>
<td>2.6</td>
<td>1.65</td>
</tr>
<tr>
<td>HRED</td>
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<td>70.3</td>
<td>20.9</td>
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<tr>
<td>NKD-ori</td>
<td>67.0</td>
<td>22.9</td>
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<td>24.8</td>
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<tr>
<td>NKD-atte</td>
<td>55.1</td>
<td>18.4</td>
<td>16.0</td>
</tr>
</tbody>
</table>

Demo Conversation:

X₁: It's a bit boring recently. Any good horror movies, guys?  
X₂: I've watched a lot.  
X₃: Have seen it before, really great.  
X₄: It is well worth watching.  
X₅: What type do you like?  
X₆: I like thrilling movies.  
X₇: Recommended some thrilling movies.  
X₈: I'm new to this genre.  
X₉: I'm new to this genre.  
X₁₀: I want to watch something new.  
X₁₁: Recommended a few new movies.  
X₁₂: What's the rating like?  
X₁₃: The rating is high.  
X₁₄: That's a great choice!  
X₁₅: Thanks, I'll watch it.  

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