Strong Baselines for Simple Question Answering over Knowledge Graphs with and without Neural Networks

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(<https://www.aclweb.org/anthology/N18-2047.pdf>)

1. *General problem/task definition*: Baseline for Q&A with knowledge graph has not been explored adequately and unclear how much Neural Networks techniques actually help. The authors seek to establish strong baseline to objectively quantify the contribution of various DL techniques to many steps of Q&A problem which include entity detection, entity linking, relation prediction and evidence combination
2. *Concise summaries of the articles*: On SIMPLEQUESTION dataset, the authors find simple LSTMs and GRUs with few common heuristics yield accuracies that comparable with state-of-the-art techniques. They also show non deep learning techniques such as CRF and Logistic Regression perform reasonably well on entity detection and relation prediction. They conclude that some state-of-the-art NN architectures only improve modestly at the cost of significant complexity and heavy technical debt
3. TODO
4. *Future work*: Benefits of neural networks could be obtained with more “complex” systems, therefore isolating their advantages in a controlled manner is desirable. For the task of  
   simple QA over knowledge graphs, the authors suggest to start with simple strong baselines of simple neural network or classical technique then move to more complexed system after adequately examine the baseline

Personalizing Dialogue Agents: I have a dog, do you have pets too?

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Artificial Intelligence (cs.AI); Computation and Language (cs.CL)

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1. *General problem/task definition*: Chatbots for social dialogue tend to have several problems: their responses are too generic and irrelevant while lacking context and consistent persona. The authors propose using models condition on profile information and interlocutors’ information to make the dialogue more human like.
2. *Concise summaries of the articles*: The paper introduces the PERSONACHAT dataset which consists of crowd-sourced dialogues where each participant plays the part of an assigned persona; while each persona has a word-distinct paraphrase. The authors test various ranking and generative models on the PERSONACHAT dataset, and show that models that have access to their own personas in addition to the state of the dialogue are scored as more consistent by annotators but not as more engaging. They also show that models trained on PERSONACHAT (with or without personas) are more engaging than models trained on dialogue from other resources (movies, Twitter). Therefore, the PERSONACHAT dataset is an useful training set for open ended conversation system.
3. TODO
4. *Future work*: Predicting the profiles from a conversation moves chitchat tasks in the direction of goal-directed dialogue, which has metrics for success. Because we collect paraphrases of the profiles, they cannot be trivially matched; indeed, we believe the original and rephrased profiles are interesting as a semantic similarity dataset in their own right. We hope that the data will aid training agents that can ask questions about users’ profiles, remember the answers, and use them naturally in conversation

HHH: An Online Medical Chatbot System based on Knowledge Graph and Hierarchical Bi Directional Attention

[Qiming Bao](https://arxiv.org/search/cs?searchtype=author&query=Bao%2C+Q), [Lin Ni](https://arxiv.org/search/cs?searchtype=author&query=Ni%2C+L), [Jiamou Liu](https://arxiv.org/search/cs?searchtype=author&query=Liu%2C+J) (Submitted on 8 Feb 2020)

Proceedings of the Australasian Computer Science Week Multiconference (ACSW 2020)

(<https://arxiv.org/pdf/2002.03140.pdf>)

1. *General problem/task definition*: A knowledge-based system holds clear advantages  
   in providing targeted responses to well-defined questions and thus is a convenient and reliable approach in implementing a question answering system in knowledge centric domains such as medical fields. However, a knowledge-based system can sometimes be too rigid in a conversational context. The paper’s authors propose a neural network model which provides a more flexible way for various situations where questions are not matched in knowledge-based system.
2. *Concise summaries of the articles*: The authors propose an online question and answer system for medical application. The hybrid system consists of a knowledge graph and a text similarity model to find the most similar question from a large QA dataset using hierarchical BiLSTM attention architecture. The text-similarity model is found to outperform MaLSTM and BERT due to the benefit of its attention layer and its embedding on the domain specific data.
3. *Compare and contrast*: Point out the similarities and differences of the papers. Do they agree with each other? Are results seemingly in conflict? If the papers address different subtasks, how are they related? (If they are not related, then you may have made poor choices for a lit review...). This section is probably the most valuable for the final project, as it can become the basis for [a related work section](https://github.com/cgpotts/cs224u/blob/master/projects.md#Related-work).
4. *Future work*: The paper only considered the single-turn question-and-answer mechanism. An important future direction is to add user profiles into the system and provide a more  
   precise and tailored medical assistant to each specific user.
5. *References section*: The entries should appear alphabetically and give at least full author name(s), year of publication, title, and outlet if applicable (e.g., journal name or proceedings name). Beyond that, we are not picky about the format. Electronic references are fine but need to include the above information in addition to the link.