Social IQA: Social Interaction Question Answering

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Abstract

Question Answering has become a widely researched problem in Natural Language Processing (NLP). Prior benchmarks focused on physical and taxonomic knowledge. This work addresses the Social Interaction Question Answering (Social IQA) problem, the first large scale benchmark for commonsense reasoning about social situations. A major challenge in Social IQA is the matching of answers with respective questions. Textual entailment is a basic task in natural language processing. Most approaches for solving this problem use only the textual content present in training data. This work tackles the question answering with an external knowledge such as Wikipedia, which is extracted and a graph is created. We perform our experiments on the Social IQA Dataset (Sap et al., 2019), which has context, question and answers.

1. Introduction

Human language offers a unique unconstrained approach to probe through questions and reason through answers about social situations. Social IQA requires a commonsense reasoning for such social situations. The ability to make sense out of the actions of others is critical to people's daily functioning. Humans are social experts, they understand that people's actions are directed at goals and are driven by intentions (Ganaie and Mudasir, 2015). Social intelligence is an aggregated measure of self and social awareness, evolved social beliefs and attitudes, and a capacity and appetite to manage complex social changes, i.e. it is the core nature of the people and how they act in the social system.

2. Dataset/Task Description

Social IQA contains 37,588 multiple choice questions with three answer choices per question. Questions and answers are gathered through three phases of crowdsourcing aimed to collect the context,the question,and set of positive and negative answers (Sap et al., 2019). An example of the Social IQA dataset is as follows:

Context: Bailey was tired of her husband beating her so she filed for divorce today.
Question: how will this make others feel?
Options: (a) happy (b) downhearted (c) frightened

In this example, as Bailey is getting hit by her husband, others have sympathy towards ba1iley. When she files divorce, others feel happy as she won't get hit by her husband again. This kind of interpretation is easy for humans as they know what marriage is and what does beating mean and what happens when people get divorce as they trivially acquire these social reasoning skills, but this can't be taught to a machine directly. Giving just the premise won't make the machine understand implicit meaning about the premise. So, we need to induce machines with common sense knowledge to make them understand marriage implies connection, beating implies sadness, divorce implies no connection, no connection implies no beating, therefore no beating implies happiness.

3. Methods/ Implementation

We can induce common sense logic into the system by using the following approaches (Pratyay and Baral, 2020)

- Use a pretrained model like BERT, RoBERTa and fine-tune the model with the dataset.

- Induce external knowledge into the model and classify based on that.
- Combine both the methods, i.e. first fine-tune the pretrained model with the dataset and then add external knowledge based on the problem domain into the model.

We need additional external knowledge even though the pretrained models such as BERT, RoBERTa are trained on huge common sense data because most of these models are trained on the data obtained from BookCorpus and English Wikipedia, which may not be sufficient to train the model to possess knowledge of social situations.

3.1 Proposed Approach

External Knowledge can be acquired by following approaches:

- Using the Knowledge Repository: There are many Knowledge Repositories present that are made using different sources. The knowledge repositories are further divided into two types,unstructured and structured knowledge repositories. Examples of some repositories are ATOMIC, ConceptNet.
- Using the web to scrap the required knowledge: We can also extract the required knowledge from the web using non-stop words and retrieving in a form which will be useful for models to analyse, Elastic search can be used for Web scraping.

3.2 Overview of Fine Tuning BERT with Social IQA dataset:

The Social IQA dataset is in the form of a Json file with context, question, answerA, answerB and answerC as its labels. The input dataset is tokenized to a format with which the BERT was pre trained by using “bert-large-uncased” and then CLS tokens are generated from the formatted input dataset. These CLS tokens are fine-tuned with the BERT model which will be used in classification.

4. Conclusion and FutureDirections

Social IQA is a common sense reasoning task for social situations. We have used a pretrained model bert-large-uncased for the classification, but using only this model is not completely efficient.
We will analyse the different approaches of implementing external knowledge into the system as discussed, based on the empirical results of the model performance on different kind of questions such as questions which have maximum similarity between the choices, questions which have emotional state as a choice etc and use the best source to optimize the model

References

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