CommSense: A Common Sense Questions Answering bot

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Abstract

This document provides the design of the project to be taken under the guidance of Dr. Cynthia Matuszek for a graduate class, CMSC 671 - Principles of Artificial Intelligence. It outlines the description and motivation for the project, artificial intelligence techniques planned to be used, details of phased implementation, relevant literature and evaluation strategy.

Project Description and Motivation

One critical aspect when thinking of artificial intelligence is Common Sense. It is what makes us truly intelligent. We expect a human is able to answer these type of questions using the observation and previous background knowledge. For example, it is common sense for us that fire is always warm. We hold intrinsic knowledge that is hard to replicate in artificial beings.

For a machine, which does not know or understand warmth, the concept of fire being warm is not a common knowledge. This is the premise for the motivation of our project. We want to develop a chat bot which can answer these common sense questions accurately. We will provide our bot a CommensenseQA corpus (Talmor et al. 2018) of multiple choice common sense questions as an input. This is a standard data set for common sense question answering tasks and consists of approximately **12K** questions with five choices each, one correct and four distracting. The input will be utilized by our bot to learn so that when it encounters such new questions it can answer them accurately.

Relevant AI Techniques

There are various AI techniques currently being used in the task of linguistically understanding common sense questions and matching the question with the correct answer, given a set of candidate answers. The natural language processing based models like BERT, GPT, and Knowledge Graphs make use of semantics and schema graphs to solve such types of problems.

The aim while implementing various AI techniques in our project will be to compare different models based on their accuracy and loss functions, trying out different versions of the models and then finalizing the efficient one. The actual model to be used while implementing the project is yet to be finalized since we will be exploring different types of natural language models for this.

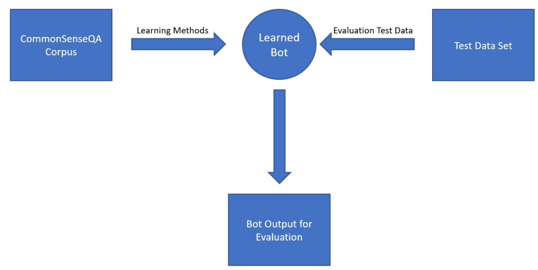

Figure 1: The overall project idea
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Knowledge Graphs use abstraction for various domains where the relations between edges, paths and variables of the domain are captured through graph-based data models. These data models capture, maintain, integrate and extract data values from a large data set (Hogan et al. 2021).

GPT-3(Generative Pre-trained Transformer) language model uses deep learning in order to produce textual data like sequences of letters, words and codes from the input sent to the computational system. The GPT-3 language model is trained on unlabeled data sets made up of mainly English words. To get accurate and relevant output, we need to train a large set of unlabeled data for the model to be able to predict the word sequences statistically and predict answers for the questions asked (Floridi and Chiriatti 2020).

BERT(Bidirectional Encoder Representations from Transformers) uses masked language modeling, where the model randomly masks some of the input tokens. The main aim is to predict the vocabulary id of the masked data based on its context. BERT is designed to pre-train bidirectional representations from unlabeled text by jointly conditioning on both left and right context. Hence, the model can be fine tuned with an additional output layer to create models for question answering and language inference, without any task specific architecture modifications (Devlin et al. 2019).

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Implementation Phases Details

The project will be implemented in the following three phases:

- **Phase 1**: We plan to further extend our literature review to understand more about the existing research. This phase includes a basic implementation of our commonsense questions answering bot using a subset of data (development data). At this stage, the bot will not have any observable intelligence yet but will be able to answer few questions (although with low accuracy). The code base for the chat bot will comprise of a model that trains, tests, and validates on data with labels to determine the accuracy of our chat bots response. The model itself will be relatively basic at this stage.
- **Phase 2**: During this phase, we will focus on creating different models to improve our basic bots' accuracy. We will train our bot using the whole training data set and will try to minimize the loss and maximize the accuracy. The final testing or evaluation will be performed on test data based on the loss and accuracy values obtained.
- **Phase 3**: This phase is dedicated to summarizing the results and conclusions of the project implementation in the form of a project report following AAAI formatting.

Relevant AI Literature

The current AI literature provides lots of relevant implementations and research using this data set. Given a natural language question, based on commonsense logic and a set of candidate answers to select from, the task is to select one answer from the set of options. We can select it from an external knowledge graph (Lin et al. 2019). The knowledge graph(G) can be defined from the available data as a fixed set of natural language concepts(V), with semantic relations between these concepts described by edges(E). Another work involved using the language models utilizing knowledge through pre-trained word vectors like Word2ec or contextualized word vectors using general encoded representations. Since there are only a few parameters for the model to learn from, the language models can be trained from scratch and fine-tuned later on (Mikolov et al. 2013). A semantic classifier can be trained for classification of the noisy labeled data, to create explanations for it and predict the output (Hancock et al. 2018). Language Modeling based techniques such as the GPT and BERT models can also be used for this task(Radford et al. 2018; Devlin et al. 2019).

Evaluation Strategy

Our evaluation strategy will be comprised of several components. We will compare the chat bots responses to our acceptable responses. During the training and testing sets our model will produce loss and accuracy evaluations. By plotting those figures we can create accuracy and loss graphs like the one shown in Figure 2. Our goal will be to create a model with high accuracy, low loss, and produce acceptable responses when prompted. Our goal will be to create a model with high accuracy, low loss, and produce acceptable responses when prompted.

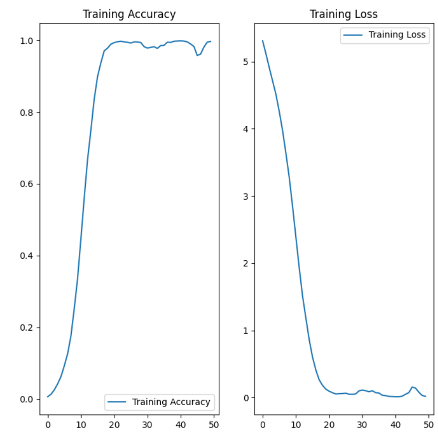

Figure 2: Model accuracy and loss

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