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Question Answering Using Deep Learning

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Abstract— Question answering (QA) is a well-researched problem in NLP. QA application are information retrieval and entity extraction. The paper propose long short-term memory (LSTM)model for text-based question answering where questions are based on a particular sentence. Given a sentences and a question to the model for predict the correct answer. Here question answering using memory network(MN). The memory network including 4 components are input,generalization,output,response. Memory network is the longterm memory is required to read a story and then answer the questions. Input is sentences,options and the questions. First passes the question and sentences to the memory model. Using score function assigns a score to each question-sentences pair and get more similar sentences. After the result is matched to the supporting factors using score function. To get the correct answer. Here used the facebook babi dataset.

Index Terms—Memory Network(MN), Long Short-Term Memory *(LSTM)*

INTRODUCTION

Answering questions based on a particular text requires a diverse skillset. Two challenges in artificial intelligence research have been to build models that can make multiple computational steps in the service of answering a question or completing a task, and models that can describe long term dependencies in sequential data. In this work it presentation novel long short-term memory (LSTM) architecture where the lstm reads from a possibly large external memory multiple times before outputting a symbol. Our model can be considered a continuous form of the Memory Network implemented in [1]. The model in that work was not easy to train via backpropagation and required supervision at each layer of the network. The continuity of the model present here means that it can be trained end-to-end from input-output pairs and so are applicable to more tasks. Tasks where such supervision is unavailable such as in language modeling or realistically supervised question answering tasks.Our model can also be seen as a version of lstm search with multiple computational steps (which term hops) per output symbol [2]. It will show experimentally that the multiple hops over the longterm memory are crucial to good performance of our model on these tasks, and that training the memory representation can be integrated in a scalable manner into our end-to-end neural network model. Long short-term memory(LSTM) is The example of question answering system are give above. The input is question and sentences are like "Mary moved to the bathroom.John went to the hallway".The options is" bathroom, hallway",Question is Where is Mary? passed through the system to get answer is bathroom.

Principles of multichoice question answering system is to provide a set of tasks, in a similar way to how software testing is built in computer science. Ideally each task is a leaf test case, as independent from others as possible and tests in the simplest way possible one aspect of intended behavior. Subsequent (non-leaf) tests can build on these by testing combinations as well. Each task provides a set of training and test data, with the intention that a successful model performs well on test data. Following [4] the supervision in the training set is given by the true answers to the questions and also set of relevant statements for answering a given question, which may or may not be used by the learner. We set up the tasks so that correct answers are limited to a single word (Q: Where is Mark? A: bathroom), or else a list of words (Q: What is Mark holding?) and options are also included as evaluation is then clear-cut, and is measured simply as right or wrong.

All the tasks are perform noiseles and a human able to read that language can potentially achieve 100 accuracy. We tried to choose tasks that are natural to a human: they are by simple usual situations and no background in areas such as formal semantics, machine learning, logic or knowledge representation is required for an adult to solve them. The data itself is produced using a simple simulation of characters and objects moving around and interacting in locations. The simulation allows us to generate data in many different scenarios where the true labels are known by grounding to the simulation. For each task, we describe it by giving a small sample of the dataset including statements, questions, options and the true labels. Single Supporting Fact consists of questions where a before given single supporting fact, potentially amongst a set of other irrelevant facts, provides the answer. The first test one of the simplest cases of this, by asking for the location of a person, example is Mary travelled to the office". Where is Mary?. This tasks was already employed . It can be considered the [3]. Two or Three Supporting facts A harder task is to answer questions where two supporting statements must be chained to answer the question.

II. RELATED WORKS

Question Answering system perform different methods for predicting the answer. HBCNN,DFN,CNN

Wenpeng Yin et. al. (2016)in this methodology the authors proposes Understanding open-domain text is one of the primary challenges in natural language processing (NLP)[4]. Machine comprehension benchmarks evaluate the systems ability to understand text based on the text content only. In this work, investigate machine comprehension on MCTest, a question answering (QA) benchmark. Prior work is mainly based on feature engineering approaches. It come up with a

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neural network framework, named hierarchical attention based convolutional neural network (HABCNN) to address this task without any manually designed features. The HABCNN for this task by two routes are one is through traditional joint modeling of passage, question and answer, one is through textual entailment. HABCNN employs an attention mechanism to detect key phrases, key.

Yin, Wenpeng this work focuses on answering singlerelation factoid questions over Freebase. Each question can acquire the answer from a single fact of form (subject, predicate, object) in Freebase[5]. This task, simple question answering (SimpleQA), can be addressed via a two-step pipeline: entity linking and fact selection. In fact selection, we match the subject entity in a fact candidate with the entity mention in the question by a character-level convolutional neural network (char-CNN), and match the predicate in that fact with the question by a word-level CNN (word-CNN). sentences and key snippets that are relevant to answering the question. Experiments show that HABCNN outperforms prior deep learning approaches by a big margin. The document in two different ways, one based on question-attention, one based on answer-attention and then compare the two projected document representations to determine whether the answer matches the question. In the second one, every question answer pair is reformatted into a statement, then the whole task is treated through textual entailment. In both roadmaps, convolutional neural network (CNN) is explored to model all types of text. As human beings usually do for such a QA task, our model is expected to be able to detect the key snip- pets, key sentences, and key words or phrases in the document. In order to detect those informative parts required by questions, it explore an attention mechanism to model the document so that its representation contains required information intensively.

Danqi Chen et. al.(2016)Enabling a computer to understand a document so that it can answer comprehension questions is a central, yet unsolved goal of NLP. A key factor impeding its solution by machine learned systems is the limited availability of human-annotated data. seek to solve this problem by creating over a million training examples by pairing CNN and Daily Mail news articles with their summarized bullet points, and show that a neural network can then be trained to give good performance on this task. This paper, conduct a thorough examination of this new reading comprehension task. The primary aim is to understand what depth of language understanding is required to do well on this task. System to understand a document so that it can answer comprehension questions. Given the (passage, question, answer) triple. The RC introduce CNN and Daily Mail dataset. Dataset do not help solve more complex RC reasoning task. CNN/Daily Maildatasets are valuable datasets, which provide a promising avenue for training effective statistical models for reading comprehension tasks. Nevertheless, argue that: (i) this dataset is still quite noisy due to its method of data creation and coreference errors; (ii) current neural networks have almost reached a performance ceiling on this dataset; and (iii) the required reasoning and inference level of this dataset is still quite simple.

Yichong Xu et. al.(2018)the paper presents a novel neural model Dynamic Fusion Network (DFN), for machine reading comprehension (MRC). DFNs differ from most state-of-theart models in their use of a dynamic multi-strategy attention process, in which passages, questions and answer candidates are jointly fused into attention vectors, along with a dynamic multi-step reasoning module for generating answers. With the use of reinforcement learning, for each input sample that consists of a question, a passage and a list of candidate answers, an instance of DFN with a sample-specific network architecture can be dynamically constructed by determining what attention strategy to apply and how many reasoning steps to take. Experiments show that DFNs achieve the best result reported on RACE, a challenging MRC dataset that contains real human reading questions in a wide variety of types. A detailed empirical analysis also demonstrates that DFNs can produce attention vectors that summarize information from questions, passages and answer candidates more effectively than other popular MRC models. It consists of a standard Lexicon Encoding Layer and a Context Encoding Layer. Other two layer is Dynamic Fusion Layer and a Memory Generation Layer. The Dynamic Fusion Layer applies different attention. Strategies to different question types. The Memory Genertion Layer encodes question-related information in the passage for answer prediction. The problem of passages of a wide variety of styles and answering questions of different complexity.

III. QUESTION ANSWERING USING LSTM

The system architecture of the question answering system. Answering the questions are explain it. The designing and implementation of the proposed system are discussed along with the data. A memory network is composed of a memory m (in the form of a collection of vectors or strings, indexed individually as mi), and four possibly learned functions I, G, O, and R.

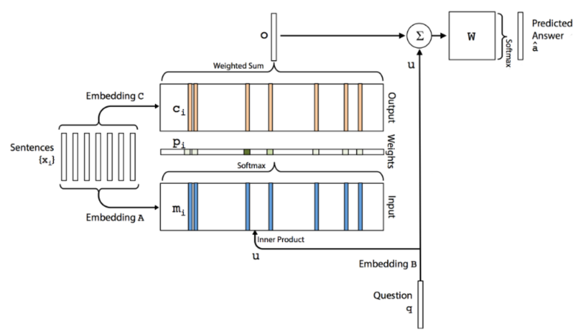

Fig. 2. Question Answering System

A. SYSTEM DESIGN

The system design consist of mainly three phase. The first is the input representation, second is the output representation and third is the generating the final prediction. The detail description is shown below.
1) Input representation: The given an input set x1, .., xi to be stored in memory. The entire set of xi are converted into memory vectors mi of dimension d computed by embedding each xi in a continuous space, in the simplest case, using an embedding matrix A . The query q is also embedded (again, in the simplest case via another embedding matrix B with the same dimensions as A) to obtain an internal state u. In the

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embedding space, we compute the match between u and each memory mi by taking the inner product followed by a softmax. pi = Softmax(UTmi mi). (1) where Softmax defined in this way p is a probability vector over the inputs.

B. Output memory representation

The options are embedded. Each xi has a corresponding output vector ci (given in the simplest case by another embedding matrix C). The response vector from the memory o is then a sum over the transformed inputs ci , weighted by the probability vector from the input.
Because the function from input to output is smooth, we can easily compute gradients and backpropagate through it. Other recently proposed forms of memory or attention take this approach.
1) Generating the final prediction: In the single layer case, the sum of the output vector o and the input embedding u is then passed through a final weight matrix W and a softmax to produce the predicted label:
a = Softmax(W(o + u))
The overall model is shown in Fig. 1(a). During training, all three embedding matrices A, B and C, as well as W are jointly learned by minimizing a standard cross-entropy loss between a and the true label a. Training is performed using stochastic gradient descent.

C. EVALUATION AND RESULTS

This section talks about the experimental setup, evaluation and results obtained for the proposed question answering system. The experiment perform diiferent methods. The methods are CNN,HBCNN,DFN AND LSTM. The LSTM is more accuracy compared to other methods.

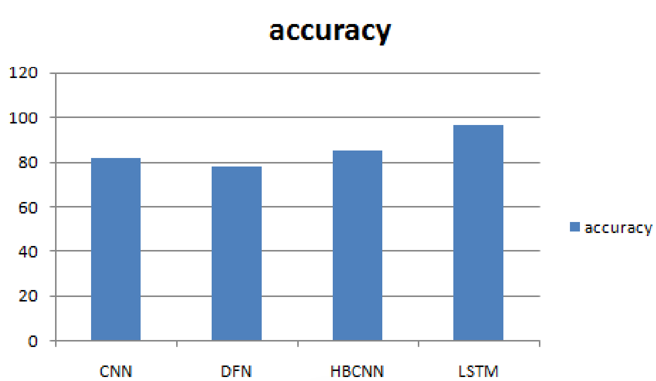

Fig. 3. Performance comparison of models in terms of accuracy

D. Dataset
The facebook bAbI dataset is including sentences, question, answer and also mark the supporting factors (which sentences are more relate to the answer). The dataset split the data into two . They are 10,000 for training and 1000 for testing questions. It emphasize that the goal is still to use as little data as possible to do well on the task and without resorting to engineering task-specific tricks that will not generalize to other tasks, as they may not be of much use subsequently. Note that the aim during evaluation is to use the same learner across all tasks to evaluate its skills and capabilities. The datasets are including sentences,questions,options and answers.

E. RESULT

The Question Answering system input is sentences,question and options. The LSTM method using for finding the correct answer and then get high accuracy. The LSTM layer is better method in question answering system. The accuracy is increasing using the options.

IV. CONCLUSION AND FUTURE WORK

In this paper used a LSTM based model for multiple choice question answering. Using sentences option tuple as input gave significant advantage to the model. However, there is a lot of scope for future work. The question answering system also used the options. That options used to increase the answer accuracy. Question answering using the LSTM model. The proposed system generates single support factor for question answering system extend two and three support factor for question answering system. The feature scope of question answering system is the proposed system generates single support factor for question answering system. It extend two and three support factor for question answering system. The bAbI dataset is a small, closed and synthetic data set. Further experimentation should be run using larger non-synthetic data sets.

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