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Hybrid CNN-LSTM Model for Answer Identification

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Abstract: ***User quest for information has led to development of Question Answer (QA) system to provide relevant answers to user questions. The QA task are different than normal NLP tasks as they heavily depend to semantics and context of given data. Retrieving and predicting answers to verity of questions require understanding of question, relevance with context and identifying and retrieving of suitable answers. Deep learning helps to produce impressive performance as it employs deep neural network with automatic feature extraction methods. The paper proposes a hybrid model to identify suitable answer for posed question. The proposes power exploits the power of CNN for extracting features and ability of LSTM for considering long term dependencies and semantic of context and question. Paper provides a comparative analysis on deep learning methods useful for predicting answer with the proposed method .The model is implemented on twenty tasks of babI dataset of Facebook .***

Keywords ***: Deep neural network, LSTM, Question Answer system, recurrent neural network***

I. INTRODUCTION

RESEARCHES on Question Answering (QA) [1] [2] systems have attained progressive consideration in current years with the unpredictable advances on machine learning and development of data. Answer assortment from community question answering (CQA) (i.e. Yahoo! Answers1) is a significant task for establishing automatic QA systems [3]. It intends at deriving constructive QA pairs [4] [5] from various CQA outfits. The major complexity relies in how to link the semantic gaps among QA [6] [7] pairs. Supervised machine learning is a typical one in dealing with certain problems namely, deep learning and statistical learning. End-to-end (e2e) Deep Neural Networks (DNN) could evade multifaceted characteristics of engineering and it includes improved learning ability when compared with previous learning approaches, therefore it has turn out to be a major flow in mining QA matching [8] [9]. Consequently, owing to the growing recognition of social Q&A [10] [11], a mixture of diverse questions is often required on Social Network Sites (SNSs).

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Certain users search for objective and subjective knowledge or accurate truth, like, "How do I setup a xxx software ?" Some users ask for more subjective knowledge, like, personal recommendations or opinions on definite subjects, like, "What should I eat for increasing stamina?"

Objective questions are concerned for the accurateness of the answer and are predicted to be answered by further consistent sources, while subjective questions necessitate additional varied replies, which depend on personal perspective and *opinion [12] [13] [14]. Expert discovery for QA [15] [16] is a challenging issue in CQA systems; taking place in numerous real appliances namely, recognition of most excellent answers and question routing. So as to offer high quality experts, several traditional techniques learn the user representation from their previous QA [17] activities in CQA systems. On the other hand, the previous performances of users in the majority of CQA [18] [19] systems are quite limited, and therefore the user representation might was not properly modelled. Answer assortment in CQA [20] is to identify relevant or good answers for producing constructive QA [21] pairs that are important to develop the knowledge base of numerous intelligent systems, such as, chatbot or automatic QA. Although certain works on matching question with answer have revealed the efficiency in identifying first-rate answers from probable candidate answer series, answer assortment in CQA [22] is still a complicated one for two reasons: Initial one is that response posts generally includes ill-syntax, informal or even partial sentences. The subsequent one is that there are obscure associations between response posts, for example, it might include the posts, which are comments for preceding reply of a question rather than answers of the question.

II. LITERATURE REVIEW

In 2018, Zhou et al. [1] have suggested a recurrent convolutional neural network (RCNN) scheme for selecting answers in community question answering (CQA). Initially, the demonstrations of QA were discovered independently by means of CNNs. Subsequently, a entirely associated NN was exploited to generatea fixed length depiction for every question answer pair. At last, for recognizing the matching feature of answers for a specified question, softmax classifier was deployed. The outcomes demonstrate the efficiency of the established scheme on the performance of answer assortment in CQA. In 2015, Zhao et al. [2] have illustrated the issue of expert discovery from the point of view of "missing value estimation". Users' social network was then utilized for deducing user representation, and therefore develops the performance of expert discovery in CQA systems.

Moreover, a new graph-regularized matrix completion model was developed for deducing user representation.

Two proficient iterative measures, Graph Regularized Matrix Completion Extended Gradient Method (GRMC-EGM), and Graph Regularized Matrix Completion Accelerated proximal Gradient search Method (GRMC-AGM) [2] was developed to resolve the optimization issue. The adopted technique was simulated and experimental analysis demonstrates the efficiency of the introduced schemes in evaluation with the conventional expert discovery approaches.

In 2017, Shen et al. [3] have established a scheme for enhancing the Q&A system performance by dynamically forwarding questions to clients who were able to respond the questions. As a result, Social Q&A, an online based Q&A approach was modelled and executed. The established scheme was moreover developed with efficiency and security improvements by defending user identify and privacies and recovering answers for frequent questions automatically. The algorithms and architecture were described, and wide-ranging extensive simulation was performed to evaluate Social Q&A in evaluation with erstwhile schemes.

In 2018, Lao et al. [4] have adopted a new co-attention method by merging Sentence-guide Word Attention (SWA) and Question-guide Image Attention (GIA) in an integrated model. Accordingly, for multi-modal fusion, a "Cross-modal Multistep Fusion (CMF)" network was introduced to produce multistep characteristics and accomplish numerous interactions for two modalities, instead of concerning on designing multifaceted interactions among two models similar to the majority of present feature fusion schemes. To evade the linear raise of the cost, the constraints were shared for every phase in the CMF. Wide-ranging experimentations were revealed that the adopted technique can accomplish reasonable or improved performance than the conventional schemes.

In 2018, Wu et al. [5] have suggested a technique for integrating high-level conceptions into the successful CNN-RNN scheme, and demonstrate that it attains a considerable development over the conventional schemes. It was known that the similar method could be exploited to integrate exterior knowledge that was significantly imperative for answering sophisticated visual questions. Particularly, a visual Q&A scheme was modelled, which merges an interior depiction of the image content with data extracted from a common knowledge. It mainly permits questions to be enquired where the image does not include the data necessary to choose the suitable answer. The last representation accomplishes the most excellent outcomes for visual Q&A on numerous foremost standard datasets.

In 2017, Xiang et al. [6] have introduced a Deep NN (DNN) structural design in order to discover the deterministic data regarding answer selection. The suggested scheme could sustain diverse input systems via the organization of CNN and other certain schemes. Experimentations were performed on "SemEval-2015 cQA dataset". From the results, 58.35% on macroaveraged F1was accomplished that performs better than the Top-1 system in the shared task by 1.16% and enhances the conventional DNN-dependent technique by 2.21%.

In 2016, Liu and Jansen [7] have designed a scheme based on intent detection as a binary classification issue, and therefore for every question, subjective and objective classes were portrayed. A wide-ranging set of lexical, contextual, and syntactical features were exploited to construct the classifier and the investigational outcomes demonstrate reasonable classification behavior. On deploying the classifier, depth analysis was performed to evaluate objective and subjective questions, with respect to the way they were questioned and answered. It was discovered that the two types of questions demonstrated much diverse features, and further confirm the advantages of discriminating questions based on its subjectivity orientation.

In 2017, Yue et al. [8] have developed the dynamic memory networks to carry out "Textual QA" in which the inputs were processed to take out hierarchical and global salient features simultaneously. Consequently, they were deployed to formulate numerous feature sets at every interpretation phases. Experimentations were performed on a public Textual Q&A dataset in two approaches: without and with supervision from labels of constructive details. Finally, when distinguished with preceding works, the developed technique demonstrates improved stability and accuracy.

III. PROPOSED MODEL

Our model uses a hierarchical 6-layer multistage process for generating appropriate answer for a question given the context.Word embedding Layeremploys word2vec model to convert context, query and expected answer to vector. A distributed representation of token is obtained by word embedding. A 300 dimensionality ofword vectors are created and trained using continuous bag-of-words architecture for story, question and answer. The dataset is converted to a triplet (story, question, answer).LSTM is a recurrent neural network which has the capability to remember long-distance sequences and the immediate previous hidden vector. LSTM also helps to improve the problem of vanishing or exploding gradient.After a Story Embedding Layer,2-layerof LSTM mechanism is employed for story. Similarly, a 2-layer LSTM mechanism is deployed for question.

Given an input sentence sequence

$s = \{ s(1) , s(2) , \cdots , s(n) \}$

s(t) is the E dimension word vector in t time. The hidden vector h(t) at the time step t is updated as follows.

$$it = \sigma(Wi[h(t-1), s(t)] + bi)$$
$$ft = \sigma(Wf\,[h(t-1)\,, s(t)\,] + bf)$$
$$ot = \sigma(Wo\,[h(t-1)\,, s(t)\,] + bo)$$
$$t = \tanh(Wc\,[h(t-1)\,, s(t)\,] + bc)$$
$$ct = ft * ct - 1 + it * t$$
$$ht = ot * \tanh(Ct)$$

Convolution helps to identify prominent features from the question and story context. One dimensional convolution layer with a maxpooling layer of size 2 helps to highlight the important terms in story and question. Convolutional structure uses a filter of size 3. Every window with size of 3captures information in LSTM output matrix of size 3. A Max pooling layer of size is 2 follows the convolution. The pooling operation combines the several values into one thereby preventing the overfitting problem and reducing the computation cost of the model. Attention layercombines the context of query to the relative story to identify the solution.

It merges the question and story vectors and produces a set of question aware feature vectors for each word in the context. Attention layer helps to retain information from long input sentence.

Finally, we merge the two models for question and context to attention layer to find prominent layers. A fully connected dense layer is used for sequences. Finally, fully connected dense layer helps to identify appropriate answer to the posed question.

IV. EXPERIMENTAL SETUP

The models were implemented on Nvidia GPU based system in python with keras 1.2.2 layer and Theano. All models were trained, validated and tested on single supporting facts data of bAbi dataset.Word2Vec was used for creating the word vector. The batch size was maintained to 32 with 120 epochs and dropout rate of 0.03 for each model. The models were tested on adam and RMSprop optimizers. The loss is calculated by categorical crossentropy method. The results of various model using adam optimizer are summarized in table 1.

Babi Dataset: Facebook AI Research presented the bAbi dataset for researchers working in field of question answering and text processing. It is a collection of set of contexts with MCQ pairs in English and Hindi. The dataset consists of 1000 questions for training and 1000 for testing. The dataset consists of triple {story, question, answer}. A sample entry in the dataset is as follows:

Story:
1 Mary moved to the bathroom.
2 Sandra journeyed to the bedroom.
3 Mary got the football there.
4 John went to the kitchen.
5 Mary went back to the kitchen.
6 Mary went back to the garden.
Q: Where is the football?
A: garden

The dataset needs to be pre-processed before using in model. The triple is separated to story which acts as context, question as query and answer. All sentences before the question tag are combined to make a story. Tokenization for separating words for embedding is done. Word2Vec model is employed for embedding. Answers are encoded using one hot vector method

V. RESULT AND DISCUSSION

The results discussed here are for single supporting facts for babi dataset. The question answer system is a multiclass classification problem. The systems implemented uses 40 epochs and categorical cross entropy loss function is optimized using Adam optimizer implementation of gradient descent.

Table 1: Results for various models

Model	**Training Accuracy**	**Validation Accuracy**	**Testing Accuracy**
bAbi LSTM model (27)	60.53	46	50.4
bAbi Memory network [29]	66.66	33.6	33.6
Dynamic memory network [30]	75.3	32.5	32.5
Bidirectional LSTM [33]	64.21	46	49.8
bAbi LSTM CNN [32]	95.56	94	95.4
Proposed Model	**97%**	**92%**	**97%**

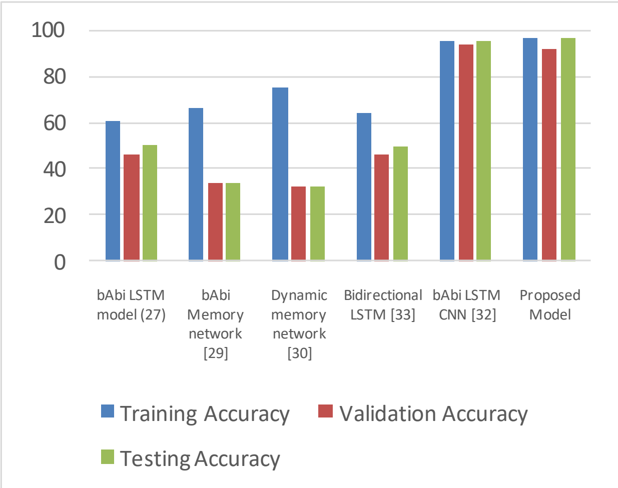

Figure 1 : Comparative Results

VI. CONCLUSION

Generation of proper answer is a significant task in natural language processing. Many deep learning architectures have been to solvethe answer generation task. This papertries to survey different deep learning architectures for answer generation on bAbi dataset. The proposed method shows promising accuracy of 97% as compared to other methods.There are several future research directions. Linguistic approach based on specific domain knowledge would provide a conclusive solution to predict answers. Identifying the question type and their automatic classification is one direction for research. .Different methods explored so far in this paper, show acceptable results for their respective application areas but fail to deliver when implemented beyond that. Transfer learning [31] can be applied to question answering and answer selection. Sentence modelling, paraphrase identification and semantic relatedness are few areas where deep learning methods can be used for answer selection/generation.Further the system can be implemented in open domain question answering, community question answering,answer selection, answer generation, summarization and has many other applications.

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