Learning to Rank Question-Answer Pairs using Hierarchical Recurrent Encoder with Latent Topic Clustering

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Abstract

In this paper, we propose a novel end-to-end neural architecture for ranking answers from candidates that adapts a hierarchical recurrent neural network and a latent topic clustering module. With our proposed model, a text is encoded to a vector representation from an word-level to a chunk-level to effectively capture the entire meaning. In particular, by adapting the hierarchical structure, our model prevents performance degradations in longer text comprehension while other recurrent neural networks suffer from it. Additionally, the latent topic clustering module extracts semantic information from target samples. This clustering module is useful for any text related tasks by allowing each data sample to find its nearest topic cluster, thus helping the neural network model analyze the entire data. We evaluate our models on the Ubuntu Dialogue Corpus and consumer electronic domain question answering dataset, which is related to Samsung products. The proposed model shows better performances than conventional architectures, resulting in state-of-the-art results for ranking question-answer pairs.

Introduction

Recently neural network architectures have shown great success in many machine learning fields such as image classification, speech recognition, machine translation, chat-bot, question answering, and other task-oriented areas. Among these, the automatic question answering (QA) task has long been considered a primary objective of artificial intelligence.

In the commercial sphere, the QA task is usually tackled by using pre-organized knowledge bases and/or by using information retrieval (IR) based methods, which are applied in popular intelligent voice agents such as Siri, Alexa, and Google Assistant (from Apple, Amazon, and Google, respectively). Furthermore, on-line QA service systems like Wolframalpha respond to user requests. Another type of advanced QA systems is IBM’s Watson who builds knowledge bases from unstructured data. These raw data are also indexed in search clusters to support user queries (Fan et al. 2012; Chu-Carroll et al. 2012).

In academic literature, researchers have recently studied reading comprehension (RC) style QA tasks. With the release of sufficient datasets in terms of both large quantities and human validated qualities (Rajpurkar et al. 2016; Nguyen et al. 2016; Weston et al. 2015), researchers have proposed neural network architectures with end-to-end learning. Wang et al. (2017) proposed another network that encodes information in a given passage with the questions into representational vectors. They matched one another to select the best answer from the passage (Wang et al. 2017). This RC task is also tackled by putting additional episodic memory blocks in the neural network architecture to focus attention on the relevant word in the passage iteratively (Sukhbaatar et al. 2015; Kumar et al. 2016).

Both QA systems in the commercial sphere and academic literature utilize the QA pair ranking as a primary object that has been extensively investigated among researchers (Liu and others 2009; Lowe et al. 2015; Baudiš et al. 2016; Zhang et al. 2017). The ranking task selects the best answer among candidate answers retrieved from knowledge bases or IR based modules. Many neural network architectures with end-to-end learning methods are proposed to address this text ranking task.

In this paper, we focus on developing a novel neural network architecture and additional data clustering module to improve the performance in ranking answer candidates with end-to-end learning. This work can be used not only for the QA ranking task, but also to evaluate the relevance of next utterance with given dialogue generated from the dialogue model. The key contributions of our work are as follows:

First, we introduce a Hierarchical Recurrent Dual Encoder (HRDE) model to effectively calculate the affinity among question-answer pairs to determine the ranking. Empirical results show that the HRDE prevents performance degradations in understanding longer texts while other recurrent neural networks suffer.

Second, we propose a Latent Topic Clustering (LTC) module to extract latent information from the target dataset, and apply these additional information in end-to-end training. This module allows each data sample to find its nearest topic cluster, thus helping the neural network model analyze the entire data. The LTC module can be combined to any neural network as a source of additional information. This is a novel approach using latent topic cluster information for the QA task, especially by applying the combined model of HRDE and LTC to the QA pair ranking task.

Lastly, extensive experiments are conducted to investigate efficacy and properties of the proposed model. Our proposed model outperforms previous state-of-the-art methods in the Ubuntu Dialogue Corpus, which is one of the largest text datasets.
pair scoring datasets. We also evaluate the model on real world QA data crawled from crowd-QA web pages and from Samsung’s official web pages. Our model also shows the best results for the QA data when compared to previous neural network models.

Related Work

Researchers have released question and answer datasets for research purposes and have proposed various models to solve these datasets. (Wang, Smith, and Mitamura 2007) introduced small dataset to rank sentences that have higher probabilities of answering questions. Additional datasets (Yang, Yih, and Meek 2015; Tan et al. 2015) were introduced for WikiQA and insuranceQA, although they are license issues. To alleviate the difficulty in aggregating sentence similarity rankings (Baudí et al. 2016; Lowe et al. 2015). As of now, the Ubuntu Dialogue dataset is one of the largest corpus openly available for text ranking.

To tackle the Ubuntu dataset, (Lowe et al. 2015) adopted the “term frequency-inverse document frequency” approach to capture important words among context and next utterances (Ramos and others 2003). (Bordes, Weston, and Usunier 2014; Yu et al. 2014) proposed deep neural network architecture for embedding sentences and measuring similarities to select answer sentence for a given question. (Kadlec, Schmid, and Kleindienst 2015) used convolution neural network (CNN) architecture to embed the sentence while a final output vector was compared to the target text to calculate the matching score. They also tried using long short-term memory (LSTM) (Hochreiter and Schmidhuber 1999), bi-directional LSTM and ensemble method with all of those neural network architectures and achieved the best results on the Ubuntu Dialogues Corpus dataset. Another type of neural architecture is the RNN-CNN model, which encodes each token with a recurrent neural network (RNN) and then feeds them to the CNN (Baudí et al. 2016). (Tan et al. 2015) used an attention based model as an extension of the RNN-CNN model.

Recently, the hierarchical recurrent encoder-decoder model was proposed to embed contextual information in user query prediction and dialogue generation tasks (Sordoni et al. 2015; Serban et al. 2016). A lower-level RNN embedded sentence level information from sequence inputs of the words in each sentence while an upper-level RNN embedded sentence turns level information from sequence inputs of the lower-level RNN output vector. This shows improvement in the dialogue generation model where the context for the utterance is important. As another type of neural network architecture, memory network was proposed by (Sukhbaatar et al. 2015). Several researchers adopted this architecture for the RC task, because it can extract contextual information from each sentence and use it in finding the answer (Xiong, Merity, and Socher 2016; Kumar et al. 2016).

However, none of this research is applied to the QA pair ranking task directly.

Model

In this section, we depict a previously released neural text ranking model, and then introduce our proposed neural network model.

Recurrent Dual Encoder (RDE)

Recurrent neural network (RNN) is a variant of neural network which is designed to learn sequential or time-varying patterns (Medsker and Jain 1999). A subset of sequential data is fed into the RNN which leads to the formation of the network’s internal hidden state. To model the time series patterns. This internal hidden state is updated at each time step with the input data $w_t$ and the hidden state of the previous time step $h_{t-1}$ as follows:

$$h_t = f_\theta(h_{t-1}, w_t),$$

(1)

where $f_\theta$ is the RNN function with weight parameter $\theta$, $h_t$ is hidden state at $t^{th}$ word input, $w_t$ is $t^{th}$ word in a target question $w^Q = \{w_{1:t,q}\}$ or an answer text $w^A = \{w_{1:t,a}\}$.

When we consider the best answer from text candidates for a given question, the previous RDE model uses two RNNs to calculate affinity among texts (Lowe et al. 2015). Among these RNNs, one corresponds to encode question text while the other corresponds to encode answer text.

After encoding each part of the data, the affinity among the text pairs is calculated by using the final hidden state value of each question and answer RNNs. The whole network is trained end-to-end to minimize the loss among matching probability and ground-truth label. The matching probability between question text $w^Q$ and answer text $w^A$ with the training objective are as follows:

$$p(\text{label}) = \sigma((h^Q_{t_{q}})^T M h^A_{t_{a}} + b),$$

$$\mathcal{L} = -\log \prod_{n=1}^{N} p(\text{label}_n | h^Q_{n,t_{q}}, h^A_{n,t_{a}}),$$

(2)

where $h^Q_{t_{q}}$ and $h^A_{t_{a}}$ are last hidden state of each question and answer RNN with the dimensionality $h \in \mathbb{R}^d$. The $M \in \mathbb{R}^{d \times d}$ and bias $b$ are learned model parameters. The $N$ is total number of samples used in training and $\sigma$ is the sigmoid function. The matching probability also can be calculated by using another feed-forward neural network model as in (Tai, Socher, and Manning 2015), however we uses the dot-product method for simplicity.

Hierarchical Recurrent Dual Encoder (HRDE)

From now we explain our proposed model. The previous RDE model tries to encode the text in question or in answer with RNN architecture. It would be less effective as the length of the word sequences in the text increases because RNN’s natural characteristic of forgetting information from long ranging data. To address this phenomenon, (Bahdanau, Cho, and Bengio 2014) proposed attention mechanism to address this RNN’s forgetting mechanism, however, it still shows a limitation when we consider very large sequential length data such as 162 steps average in the Ubuntu Dialogue Corpus dataset. To overcome this limitation, we
The word-level RNN part is responsible for encoding the words sequence by using two hierarchical level of RNN architecture.

The HRDE model divides long sequential text data into small chunks such as sentences, and encodes the whole text from word-level to chunk-level by using two hierarchical level of RNN architecture.

Figure 1 shows a diagram of the HRDE model. The word-level RNN part is responsible for encoding the words sequence \( w_{c,t} = \{ w_{c,1:t} \} \) in each chunk. The chunk can be sentences in paragraph, paragraphs in essay, turns in dialogue or any kinds of smaller meaningful sub-set from the text. Then the final hidden states of each chunk will be fed into chunk-level RNN with its original sequence order kept. Therefore the chunk-level RNN can deal with pre-encoded chunk data with less sequential steps. The hidden states of the hierarchical RNNs are as follows:

\[
\begin{align*}
    h_{c,t} &= f_\theta(h_{c,t-1}, w_{c,t}), \\
    u_c &= g_\theta(u_{c-1}, h_c),
\end{align*}
\]

where \( f_\theta \) and \( g_\theta \) are the RNN function in hierarchical architecture with weight parameters \( \theta \), \( h_{c,t} \) is word-level RNN’s hidden status at \( t \)th word in \( c \)th chunk. The \( w_{c,t} \) is \( t \)th word in \( c \)th chunk of target question or answer text. The \( u_c \) is chunk-level RNN’s hidden state at \( c \)th chunk sequence, and \( h_c \) is word-level RNN’s last hidden state of each chunk \( h_c \in \{ h_{1:c,t} \} \). For the choice of RNN function, we use the Gated Recurrent Unit (GRU) because it shows comparable performance to the LSTM while requiring less weight parameters (Chung et al. 2014).

We use the same training objective as the RDE model, and the final matching probability between question and answer text is calculated using chunk-level RNN as follows:

\[
p(\text{label}) = \sigma((u^Q_{c,a})^T M u^A_{c,a} + b),
\]

where \( u^Q_{c,a} \) and \( u^A_{c,a} \) are chunk-level RNN’s last hidden state of each question and answer text with the dimensionality \( u_c \in \mathbb{R}^{d_u} \), which involves the \( M \in \mathbb{R}^{d_u \times d_e} \).

The final matching probability between question and answer is retrieved by using dot-product calculation.

The HRDE-LTC model divides long sequential text data into small chunks such as sentences, and encodes the whole text from word-level to chunk-level by using two hierarchical level of RNN architecture.

Figure 2: Diagram of the HRDE-LTC. Input vector is compared to each latent topic memory \( m_k \). The output is normalized to calculate the cluster assigning probability \( p_k \). Cluster-info contained vector is retrieved by summing over \( m_k \) weighted by the \( p_k \). The final encoding vector is retrieved by concatenating original input vector and cluster-info contained vector.

**Latent Topic Clustering (LTC)**

To learn how to rank QA pairs, a neural network should be trained to find the proper feature that represents the information within the data and fits the model parameter that can approximate the true-hypothesis. For this type of problem, we propose the LTC module for grouping the target data to help the neural network find the true-hypothesis with more information from the topic cluster in end-to-end training.

The blue-dotted box on the right-side of Figure 2 shows LTC structure diagram. To assign topic information, we build internal latent topic memory \( m \in \mathbb{R}^{d_m \times K} \), which is only model parameter to be learned, where \( d_m \) is vector dimension of each latent topic and \( K \) is number of latent topic cluster. For a given input sequence \( x = \{ x_{1:t} \} \) with these \( K \) vectors, we construct LTC process as follows:

\[
p_k = \text{softmax}(<(x)^T m_k>),
\]

\[
x_k = \sum_{k=1}^K p_k m_k,
\]

\[
e = \text{concat}(x, x_k).
\]

First, the similarity between the \( x \) and each latent topic vector is calculated by dot-product. Then the resulting \( K \) values are normalized by the softmax function \( \text{softmax}(z_k) = e^{z_k}/\sum e^{z_i} \) to produce a similarity probability \( p_k \). After calculating the latent topic probability \( p_k \), \( x_k \) is retrieved from summing over \( m_k \) weighted by the \( p_k \). Then we concatenate this result with the original encoding vector to generate the final encoding vector \( e \) with the LTC information added.

Note that the input sequence of the LTC could be any type of neural network based encoding function \( x = \text{enc}(w) \) such as RNN, CNN and multilayer perceptron model (MLP). In addition, if the dimension size of \( x \) is dif-
ferent dimension size from memory vector dimension, addi-
tional output projection layer should be placed after \( x \) before 
applying dot-product to the memory for vector dimension transformation.

**Combined Model of (H)RDE and LTC**

As the LTC module extracts additional topic cluster information from the input data, we can combine this module with any neural network in their end-to-end training flow. In our experiments, we combine the LTC module with the RDE and HRDE models.

**RDE with LTC** The RDE model encodes question and answer texts to \( h^Q_{i_t} \) and \( h^A_{i_t} \), respectively. Hence, the LTC module could take these vectors as the input to generate latent cluster information with added vector \( e \). With this vector, we calculate the affinity among question and answer texts as well as additional cluster information. The following equation shows our RDE-LTC process:

\[
p(label) = \sigma((h^Q_{i_t})^T M e^A + b).
\]

In this case, we applied the LTC module only for the answer side, assuming that the answer text is longer than the question. Thus, it needs to be clustered. To train the network, we use the same training objective, to minimize cross-entropy loss, as in equation (2).

**HRDE with LTC** The LTC can be combined with the HRDE model, in the same way it is applied to the RDE-LTC model by modifying equation 6 as follows:

\[
p(label) = \sigma((u^Q_{c_q})^T M e^{n-A} + b),
\]

where \( u^Q_{c_q} \) is the final network hidden state vector of the chunk-level RNN for a question input sequence. The \( e^{n-A} \) is the LTC information added vector from equation (5), where the LTC module takes the input \( x = u^A \) from the HRDE model equation (3). The HRDE-LTC model also use the same training objective, minimizing cross-entropy loss, as in equation (2). Figure 2 shows a diagram of the combined model with the HRDE and the LTC.

**Experimental Setup and Dataset**

**The Ubuntu Dialogue Corpus**

The Ubuntu Dialogue Corpus has been developed by expanding and preprocessing the Ubuntu Chat Logs\(^1\), which refer to a collection of logs from the Ubuntu-related chat room for solving problem in using the Ubuntu system by (Lowe et al. 2015). Among the utterances in the dialogues, they consider each utterance, starting from the third one, as a potential \{response\} while the previous utterance is considered as a \{context\}. The data was processed extracting \{\{context\}, \{response\}, flag\} tuples from the dialogues.

These tuples are used as ground-truth data, and applied negative sampling to the response to generate false-label data for training. We called this original Ubuntu dataset as Ubuntu-v1 dataset. After releasing the Ubuntu-v1 dataset, researchers published v2 version of this dataset\(^2\). Main updates are separating train/valid/test dataset by time so that mimics real life implementation, where we are training a model on past data to predict future data, changing sampling procedure to increase average turns in the \{context\}.

We consider this Ubuntu dataset is one of the best dataset in terms of its quality, quantity and availability for evaluating the performance of the text ranking model. In our experiments with the Ubuntu-v1 dataset, we use the same preprocessing, i.e. tokenization and named entities replacement, and vocabulary size for fair comparison. For the Ubuntu-v2 dataset, we use standard preprocessing of the data using the python-based natural language toolkit NLTK (Bird, Klein, and Loper 2009). We perform tokenization only to see the model performance clearly.

To encode the text with the HRDE and HRDE-LTC model, a text needs to be divided into several chunk sequences with predefined criteria. For the Ubuntu-v1 dataset case, we divide the \{context\} part by splitting with end-of-sentence delimiter “.eos.”, and we do not split the \{response\} part since it is normally short and does not contain “.eos.” information. For the Ubuntu-v2 dataset case, we split the \{context\} part in the same way as we do in the Ubuntu-v1 dataset while only using end-of-turn delimiter “.eot.”. Table 1 shows properties of the Ubuntu dataset.

**Consumer Product Question Answering Corpus**

To test the robustness of the proposed model, we introduce an additional question and answer pair dataset related to an actual user’s interaction with the consumer electronic product domain. We crawled data from various sources like the Samsung Electronics’ official web site\(^3\) and crowd QA web sites\(^4\). On the official web page, we can retrieve data consisting of user questions and matched answers like frequently asked questions and troubleshooting. From the crowd QA sites, there are many answers from various users for each question. Among these answers, we choose answers from company certificated users to keep the reliability of the answers high. If there are no such answers, we skip that question-answer pair. In addition, we crawl hierarchical product category information related to QA pairs. In particular, mobile, office, photo, tv/video, accessories, home appliance as top-level categories, and specific categories like galaxy s7, tablet, led tv and others are used. We collected these meta-information for further use. The total size of the Samsung QA data is over 100,000 pairs and we split the data into approximately 80,000/10,000/10,000 samples to create train/valid/test sets, respectively (see Table 1 for further information). To create the train set, we use a QA pair sample as a ground-truth and perform negative sampling for answers among training sets to create false-label datasets. In this way, we generated \{\{question\}, \{answer\}, flag\} triples. We do the same procedure to create valid and test sets by only differentiating more negative sampling within each dataset to gen-

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1These logs are available from 2004 to 2017 at http://irclogs.ubuntu.com

2https://github.com/rkadlec/ubuntu-ranking-dataset-creator

3http://www.samsung.com/us

4https://answers.yahoo.com, http://answers.us.samsung.com
| Dataset   | # Samples | Message (Avg.) | Response (Avg.) |
|-----------|-----------|----------------|-----------------|
|           | Train     | Val. | Test   | # tokens | # groups | # tokens | # groups | # tokens /group |
| Ubuntu-v1 | 1M        | 35,609 | 35,517 | 162.47 ±12.47 | 8.43 ±6.32 | 20.14 ±18.41 | 14.44 ±13.93 | I               |
|           |           |       |        |          |          |          |          |               |
| Ubuntu-v2 | 1M        | 19,560 | 18,920 | 85.92 ±71.71 | 4.95 ±2.98 | 20.73 ±20.19 | 17.01 ±16.41 | I               |
|           |           |       |        |          |          |          |          |               |
| Samsung QA| 81,808    | 10,000 | 10,000 | 12.84 ±6.42 | 4          |          | 173.48 ±192.12 | 6.09 ±5.58 | 29.28 ±9.12    |

Table 1: Properties of the Ubuntu and Samsung QA datasets. The message and response are {context}, {response} in Ubuntu and {question}, {answer} in the Samsung QA dataset. Standard deviations are shown below each average value.

We implement the same model ourselves, because we need a baseline model to compare with other proposed models such as the RDE-LTC, HRDE and HRDE-LTC.

**Implementation Details**

**Ubuntu dataset case** To implement the RDE model, we use two single layer GRU with 300 hidden units. Each GRU is used to encode {context} and {response}, respectively. The weight for the two GRU are shared. The hidden units weight matrix of the GRU are initialized using orthogonal weights (Saxe, McClelland, and Ganguli 2013), while input embedding weight matrix is initialized using a pretrained embedding vector, the Glove (Pennington, Socher, and Manning 2014), with 300 dimension. The vocabulary size is 144,953 and 183,045 for the Ubuntu-v1/v2 case, respectively. We use the Adam optimizer (Kingma and Ba 2014), with gradients clipped with norm value 1. The maximum time step for calculating gradient of the RNN is determined according to the input data statistics in Table 1.

For the HRDE model, we use two single layer GRU with 300 hidden units for word-level RNN part, and another two single layer GRU with 300 hidden units for chunk-level RNN part. The weight of the GRU is shared within the same hierarchical part, word-level and chunk-level. The other settings are the same with the RDE model case. As for the combined model with the (H)RDE and the LTC, we choose the latent topic memory dimensions as 256 in both ubuntu-v1/v2 experiment case. The number of the clusters in LTC module is decided to 3 for both the RDE-LTC and the HRDE-LTC cases. In HRDE-LTC case, we applied LTC module to the {context} part because we think it is longer having enough information to be clustered with. All of these hyper-parameters are selected from additional parameter searching experiments.

The dropout (Srivastava et al. 2014) is applied for the purpose of regularization with the ratio of: 0.2 for the RNN in the RDE and the RDE-LTC, 0.3 for the word-level RNN part in the HRDE and the HRDE-LTC, 0.8 for the latent topic memory in the RDE-LTC and the HRDE-LTC.

We need to mention that our implementation of the RDE module has the same architecture as the LSTM model (Kadlec, Schmid, and Kleindienst 2015) in ubuntu-v1/v2 experiments case. It is also the same architecture with the RNN model (Baudiš et al. 2016) in ubuntu-v2 experiment case.

We apply the same method in such a way that the Ubuntu dataset is generated from the Ubuntu Dialogue Corpus to maintain the consistency. We will make the Samsung QA dataset available on request.

**Empirical Results**

**Evaluation Metrics**

We regards all the tasks as selecting the best answer among text candidates for the given question. Following the previous work (Lowe et al. 2015), we report model performance as recall at $k$ (R@$k$) relevant texts among given 2 or 10 candidates (e.g., 1 in 2 R@1). Though this metric is useful for ranking task, R@1 metric is also meaningful for classifying the best relevant text.

Each model we implement is trained multiple times (10 and 15 times for Ubuntu and the Samsung QA datasets in our experiments, respectively) with random weight initialization, which largely influences performance of neural network model. Hence we report model performance as mean and standard derivation values (Mean±Std).

**Performance Evaluation**

**Comparison with state-of-the-art methods** As Table 2 shows, our proposed HRDE and HRDE-LTC models achieve the best performance for the Ubuntu-v1 dataset. We also find that the RDE-LTC model shows improvements from the baseline.

For the ubuntu-v2 dataset case, Table 3 reveals that the HRDE-LTC model is best for three cases (1 in 2 R@1, 1 in 10 R@2 and 1 in 10 R@5). Comparing the same model with

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3The access information of the code repository will be placed here after review process.
In the Samsung QA case, Table 4 indicates that the proposed RDE-LTC, HRDE, and the HRDE-LTC model show performance improvements when compared to the baseline model, RDE. The average accuracy statistics are higher in the Ubuntu QA case when compared to the Ubuntu case. We think this is due to the smaller vocabulary size and context variety. The Ubuntu QA dataset deals with narrower topics than in the Ubuntu dataset case. We are certain that our proposed model shows robustness in several datasets and different vocabulary size environments.

| Model               | 1 in 2 | 1 in 10 | 1 in 10 | 1 in 10 | 1 in 10 |
|---------------------|--------|---------|---------|---------|---------|
|                     | R@1    | R@2     | R@5     | R@1    | R@2     | R@5     |
| TF-IDF[1]           | 0.659  | 0.410   | 0.545   | 0.708   |         |         |
| CNN[2]              | 0.848  | 0.549   | 0.684   | 0.896   |         |         |
| LSTM[2]             | 0.901  | 0.638   | 0.784   | 0.949   |         |         |
| RDE                 | 0.898  | ±0.002  | ±0.009  | ±0.007  | ±0.002  | ±0.001  |
| RDE-LTC             | 0.903  | ±0.001  | ±0.003  | ±0.003  | ±0.003  | ±0.001  |
| HRDE                | 0.915  | ±0.001  | ±0.001  | ±0.001  | ±0.001  | ±0.001  |
| HRDE-LTC            | 0.916  | ±0.001  | ±0.001  | ±0.001  | ±0.001  | ±0.001  |

Table 2: Model performance results for the Ubuntu-v1 dataset. Models [1,2] are from (Lowe et al. 2015; Kadelic, Schmid, and Kleindienst 2015), respectively.

| Model | 1 in 2 | 1 in 10 | 1 in 10 | 1 in 10 | 1 in 10 |
|-------|--------|---------|---------|---------|---------|
|       | R@1    | R@2     | R@5     | R@1    | R@2     | R@5     |
| LSTM[3]| 0.869  | 0.552   | 0.721   | 0.924   |         |         |
| RNN[4]           | 0.907  | ±0.002  | ±0.004  | ±0.004  | ±0.003  | ±0.003  |
| CNN[4]           | 0.863  | ±0.003  | ±0.004  | ±0.005  | ±0.003  | ±0.003  |
| RNN-CNN[4]       | 0.911  | ±0.001  | ±0.002  | ±0.002  | ±0.003  | ±0.003  |
| Attention[5]     | 0.903  | ±0.002  | ±0.005  | ±0.005  | ±0.002  | ±0.002  |
| RDE               | 0.894  | ±0.002  | ±0.008  | ±0.006  | ±0.002  | ±0.002  |
| RDE-LTC          | 0.899  | ±0.002  | ±0.004  | ±0.004  | ±0.004  | ±0.004  |
| HRDE             | 0.914  | ±0.001  | ±0.001  | ±0.001  | ±0.001  | ±0.001  |
| HRDE-LTC         | 0.915  | ±0.002  | ±0.003  | ±0.003  | ±0.003  | ±0.003  |

Table 3: Model performance results for the Ubuntu-v2 dataset. Models [3,4,5] are from (Lowe et al. 2015; Baudiš et al. 2016; Tan et al. 2015), respectively.

Our implementation (RDE) and (Baudiš et al. 2016)’s implementation (RNN), there is a large gap in the accuracy (0.610 and 0.664 of 1 in 10 R@1 for RDE and RNN, receptively). We think this is largely influenced by the data preprocessing method, because the only differences between these models is the data preprocessing, which is (Baudiš et al. 2016)’s contribution to the research. We are certain that our model performs better with the exquisite datasets, because we see improvements from the RDE model to the HRDE model and additional improvements with the LTC module in all test cases (the Ubuntu-v1/v2 and the Samsung QA).

In the Samsung QA case, Table 4 indicates that the proposed RDE-LTC, HRDE, and the HRDE-LTC model show performance improvements when compared to the baseline model, RDE. The average accuracy statistics are higher in the Samsung QA case when compared to the Ubuntu case. We think this is due to the smaller vocabulary size and context variety. The Samsung QA dataset deals with narrower topics than in the Ubuntu dataset case. We are certain that our proposed model shows robustness in several datasets and different vocabulary size environments.

| Model               | 1 in 2 | 1 in 10 | 1 in 10 | 1 in 10 | 1 in 10 |
|---------------------|--------|---------|---------|---------|---------|
|                     | R@1    | R@2     | R@5     | R@1    | R@2     | R@5     |
| RDE                 | 0.978  | ±0.002  | ±0.009  | ±0.003  | ±0.001  | ±0.001  |
| RDE-LTC             | 0.981  | ±0.002  | ±0.009  | ±0.003  | ±0.001  | ±0.001  |
| HRDE                | 0.981  | ±0.002  | ±0.011  | ±0.004  | ±0.001  | ±0.001  |
| HRDE-LTC            | 0.983  | ±0.002  | ±0.010  | ±0.003  | ±0.001  | ±0.001  |

Table 4: Model performance results for the Samsung QA dataset.

| # clusters | Accuracy (1 in 10 R@1) |
|------------|------------------------|
| 1          | Ubuntu-v1              | Ubuntu-v2              | Samsung QA             |
|            | 0.643±0.009            | 0.610±0.008            | 0.869±0.009            |
| 2          | 0.655±0.005            | 0.616±0.006            | 0.870±0.011            |
| 3          | 0.656±0.003            | 0.625±0.004            | 0.877±0.010            |
| 4          | 0.651±0.005            | 0.622±0.005            | 0.880±0.009            |

Table 5: The RDE-LTC model results with different numbers of latent clusters. “Cluster 1” is the baseline model, RDE.

Degradation Comparison for Longer Texts To verify the HRDE model’s ability compared to the baseline model RDE, we split the testset of the Ubuntu-v1/v2 datasets based on the “number of chunks” in the { context}. Then, we measured the top-1 recall (same case as 1 in 10 R@1 in Table 2, and 3) for each group. Figure 3 demonstrates that the HRDE models, in darker blue and red colors, shows better performance than the RDE models, in lighter colors, for every “number of chunk” evaluations. In particular, the HRDE models are consistent when the “number-of-chunks” increased, while the RDE models degrade as the “number-of-chunks” increased.

Effects of the Latent Topic Cluster Numbers We analyze the RDE-LTC model for different numbers of latent clusters. Table 5 indicates that the model performances increase as the number of latent clusters increase (until 3 for the Ubuntu and 4 for the Samsung QA case). This is probably a major reason for the different number of subjects in each dataset. The Samsung QA dataset has an internal category related to the type of consumer electronic products (6 top-level categories), so that the LTC module makes clusters these categories. The Ubuntu dataset, however, has diverse contents related to issues in using the Ubuntu system. Thus, the LTC module has fewer clusters with the sparse topic compared to the Samsung QA dataset.

Comprehensive Analysis of Latent Topic Clustering We conduct quantitative and qualitative analysis on the HRDE-LTC model for four latent topic clusters. The Samsung QA dataset has category information; hence, latent topic clustering results can be compared with real categories. We randomly choose 20k samples containing real category information and evaluate each sample with the
Figure 3: The HRDE and RDE model performance comparisons for the number-of-chunk in the Ubuntu dataset. Each boxplot shows average accuracy with standard deviation. The HRDE models, in darker blue and red colors, show consistent performances as the number-of-chunks increased. Meanwhile, the RDE models in lighter colors show performance degradation as the number-of-chunks increased. Furthermore, 13+ indicates all data over 13-chunks.

Figure 4: Examples of the cluster proportions for four real categories from 20k evaluated samples. Each color corresponds to each cluster.

HRDE-LTC model. The cluster with the highest similarity among the latent topic clusters is considered a representative cluster of each sample.

Figure 4 shows proportion of four latent clusters among these samples according to real category information. Even though the HRDE-LTC model is trained without any ground-truth category labels, we observed that the latent cluster is formed accordingly. For instance, cluster 2 is shown mostly in “Mobile” category samples while “clusters 2 and 4” are rarely shown in “Home Appliance” category samples.

Additionally, we explore sentences with higher similarity score from the HRDE-LTC module for each four cluster. As can be seen in Table 6, “cluster 1” contains “screen” related sentences (e.g., brightness, pixel, display type) while “cluster 2” contains sentences with exclusive information related to the “Mobile” category (e.g., call rejection, voice level). This qualitative analysis explains why “cluster 2” is shown mostly in the “Mobile” category in Figure 2. We also discover that “cluster 3” has the largest portion of samples. As “cluster 3” contains “security” and “maintenance” related sentences (e.g., password, security, log-on, maintain), we assume that this is one of the frequently asked issues in the Samsung QA dataset. Table 6 shows example sentences with high scores from each cluster.

Table 6: Example sentences for each cluster.

| Cluster | Example |
|---------|---------|
| 1       | How to adjust the brightness on the s**d300 series monitors |
| 2       | How do I reject an incoming call on my Samsung Galaxy Note 3? |
| 3       | How should I clean and maintain the microwave? |
| 4       | How do I connect my surround sound to this TV and what type of cables do I need |

Conclusion

In this paper, we proposed the HRDE model and LTC module. HRDE showed higher performances in ranking answer candidates and less performance degradations when dealing with longer texts compared to conventional models. The LTC module provided additional performance improvements when combined with both RDE and HRDE models, as it added latent topic cluster information according to dataset properties. With this proposed model, we achieved state-of-the-art performances in Ubuntu datasets. We also evaluated our model in real world question answering dataset, Samsung QA. This demonstrated the robustness of the proposed model with the best results.
References

Bahdanau, D.; Cho, K.; and Bengio, Y. 2014. Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473.

Baudiš, P.; Pichl, J.; Vyskočil, T.; and Šedivý, J. 2016. Sentence pair scoring: Towards unified framework for text comprehension. arXiv preprint arXiv:1603.06127.

Bird, S.; Klein, E.; and Loper, E. 2009. Natural language processing with Python: analyzing text with the natural language toolkit. ” O’Reilly Media, Inc.”.

Bordes, A.; Weston, J.; and Usunier, N. 2014. Open question answering with weakly supervised embedding models. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases, 165–180. Springer.

Chu-Carroll, J.; Fan, J.; Boguraev, B.; Carmel, D.; Sheinwald, D.; and Welty, C. 2012. Finding needles in the haystack: Search and candidate generation. IBM Journal of Research and Development 56(3.4):6–1.

Chung, J.; Gulcehre, C.; Cho, K.; and Bengio, Y. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.

Fan, J.; Kalyanpur, A.; Gondek, D. C.; and Ferrucci, D. A. 2012. Automatic knowledge extraction from documents. IBM Journal of Research and Development 56(3.4):5–1.

Hochreiter, S., and Schmidhuber, J. 1997. Long short-term memory. Neural computation 9(8):1735–1780.

Kadlec, R.; Schmid, M.; and Kleindienst, J. 2015. Improved deep learning baselines for ubuntu corpus dialogs. arXiv preprint arXiv:1510.03753.

Kingma, D., and Ba, J. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.3556.

Kumar, A.; Irsoy, O.; Ondruska, P.; Iyyer, M.; Bradbury, J.; Gulrajani, I.; Zhong, V.; Paulus, R.; and Socher, R. 2016. Ask me anything: Dynamic memory networks for natural language processing. In International Conference on Machine Learning, 1378–1387.

Liu, T.-Y., et al. 2009. Learning to rank for information retrieval. Foundations and Trends® in Information Retrieval 3(3):225–331.

Lowe, R.; Pow, N.; Serban, I.; and Pineau, J. 2015. The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. arXiv preprint arXiv:1506.08909.

Medsker, L., and Jain, L. C. 1999. Recurrent neural networks: design and applications. CRC press.

Nguyen, T.; Rosenberg, M.; Song, X.; Gao, J.; Tiwary, S.; Majumder, R.; and Deng, L. 2016. Ms marco: A human generated machine reading comprehension dataset. arXiv preprint arXiv:1611.09268.

Pennington, J.; Socher, R.; and Manning, C. D. 2014. Glove: Global vectors for word representation. In EMNLP, volume 14, 1532–1543.

Rajpurkar, P.; Zhang, J.; Lopyrev, K.; and Liang, P. 2016. Squad: 100,000+ questions for machine comprehension of text. arXiv preprint arXiv:1606.05250.

Ramos, J., et al. 2003. Using tf-idf to determine word relevance in document queries. In Proceedings of the first instructional conference on machine learning, volume 242, 133–142.

Saxe, A. M.; McClelland, J. L.; and Ganguli, S. 2013. Exact solutions to the nonlinear dynamics of learning in deep linear neural networks. arXiv preprint arXiv:1312.6120.

Serban, I. V.; Sordoni, A.; Bengio, Y.; Courville, A. C.; and Pineau, J. 2016. Building end-to-end dialogue systems using generative hierarchical neural network models. In AAAI, 3776–3784.

Sordoni, A.; Bengio, Y.; Vahabi, H.; Lioma, C.; Grue Simonen, J.; and Nie, J.-Y. 2015. A hierarchical recurrent encoder-decoder for generative context-aware query suggestion. In Proceedings of the 24th ACM International on Conference on Information and Knowledge Management, 553–562. ACM.

Srivastava, N.; Hinton, G. E.; Krizhevsky, A.; Sutskever, I.; and Salakhutdinov, R. 2014. Dropout: a simple way to prevent neural networks from overfitting. Journal of machine learning research 15(1):1929–1958.

Sukhbaatar, S.; Weston, J.; Fergus, R.; et al. 2015. End-to-end memory networks. In Advances in neural information processing systems, 2440–2448.

Tai, K. S.; Socher, R.; and Manning, C. D. 2015. Improved semantic representations from tree-structured long short-term memory networks. arXiv preprint arXiv:1503.00075.

Tan, M.; Santos, C. d.; Xiang, B.; and Zhou, B. 2015. Lstm-based deep learning models for non-factoid answer selection. arXiv preprint arXiv:1511.04108.

Wang, W.; Yang, N.; Wei, F.; Chang, B.; and Zhou, M. 2017. Gated self-matching networks for reading comprehension and question answering. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, 189–198.

Wang, M.; Smith, N. A.; and Mitamura, T. 2007. What is the jeopardy model? a quasi-synchronous grammar for qa. In EMNLP-CoNLL, volume 7, 22–32.

Weston, J.; Bordes, A.; Chopra, S.; Rush, A. M.; van Merriënboer, B.; Joulin, A.; and Mikolov, T. 2015. Towards ai-complete question answering: A set of prerequisite toy tasks. arXiv preprint arXiv:1502.05698.

Xiong, C.; Merity, S.; and Socher, R. 2016. Dynamic memory networks for visual and textual question answering. In International Conference on Machine Learning, 2397–2406.

Yang, Y.; Yih, W.-t.; and Meek, C. 2015. Wikiqa: A challenge dataset for open-domain question answering. In EMNLP, 2013–2018.

Yu, L.; Hermann, K. M.; Blunsom, P.; and Pulman, S. 2014. Deep learning for answer sentence selection. arXiv preprint arXiv:1412.1632.

Zhang, X.; Li, S.; Sha, L.; and Wang, H. 2017. Attentive interactive neural networks for answer selection in community question answering. In AAAI, 3525–3531.