Community-Based Question Answering via Asymmetric Multi-Faceted Ranking Network Learning

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Abstract

Nowadays the community-based question answering (CQA) sites become the popular Internet-based web service, which have accumulated millions of questions and their posted answers over time. Thus, question answering becomes an essential problem in CQA sites, which ranks the high-quality answers to the given question. Currently, most of the existing works study the problem of question answering based on the deep semantic matching model to rank the answers based on their semantic relevance, while ignoring the authority of answerers to the given question. In this paper, we consider the problem of community-based question answering from the viewpoint of asymmetric multi-faceted ranking network embedding. We propose a novel asymmetric multi-faceted ranking network learning framework for community-based question answering by jointly exploiting the deep semantic relevance between question-answer pairs and the answerers' authority to the given question. We then develop an asymmetric ranking network learning method with deep recurrent neural networks by integrating both answers' relative quality rank to the given question and the answerers' following relations in CQA sites. The extensive experiments on a large-scale dataset from a real world CQA site show that our method achieves better performance than other state-of-the-art solutions to the problem.

Introduction

Nowadays the community-based question answering (CQA) sites become the popular Internet-based web service, which have accumulated millions of questions and their posted answers over time (Zhao et al. 2016b). The benefits of CQA have been well-recognized today. We have witnessed the popular CQA sites such as Yahoo ! Answer and Quora. The community-based question answering has become an essential problem in CQA sites, which ranks the high-quality answers to the given questions.

Currently, the problem of community-based question answering has attracted considerable attention (Ji et al. 2012; Qiu and Huang 2015; Shen et al. 2015; Wang and Nyberg 2015; Dong et al. 2015; Fang et al. 2016). Most of the existing works consider the problem as text matching task, which learn the deep semantic matching model (Hu et al. 2014; Qiu and Huang 2015), and then rank the answers to the given

question based on their semantic relevance. Although existing question answering methods have achieved promising performance, they mainly focus on developing the deep semantic matching models for the problem, while ignoring the importance of answerers' authority on the given question.

Unlike the previous studies, we consider the problem of community-based question answering as high-quality answer ranking task, which is based on the answers' deep semantic relevance and the answerers' authority to the given question. Let us take the question "what are some recent and upcoming breakthrough in deep learning?" in Quora as an example. We notice that the answer provided by Yann-LeCun receives the most thumb-ups voted by the CQA community, due to its semantic relevance and the expertise authority of Yann-LeCun on the area of deep learning. It is also observed that the experts in CQA sites usually provide the high-quality answers (Zhao et al. 2015; Bouguessa, Dumoulin, and Wang 2008).

On the other hand, with the prevalence of online social networks in CQA sites (Zhao et al. 2015), we introduce the multi-faceted ranking network for community-based question answering by jointly exploiting the deep semantic relevance between question-answer pairs and the answerers' authority in CQA sites. Currently, most of the existing network learning works (Perozzi, Al-Rfou, and Skiena 2014; Tang et al. 2015; Wu et al. 2016a) follow the symmetric assumption that the user model learning will be symmetric for any two connected users in networks. However, the symmetry assumption will not be always beneficial for learning users' expertise authority model in the directed CQA networks. One user follows another user in CQA networks does not mean that their expertise authorities are similar. Thus, it is natural to develop the asymmetric multi-faceted ranking network learning for the problem.

In this paper, we formulate the problem of community-based question answering from the viewpoint of asymmetry multi-faceted ranking network learning. Specifically, we design the multi-faceted ranking function for question answering based on the deep semantic relevance of question-answer pairs and the users' expertise authority. We then integrate the multi-faceted ranking function and users' asymmetric following relations in CQA sites into a unified asymmetric multi-faceted ranking network learning framework, named as AMRNL. We then develop an asymmetric network learn-

ing method with recurrent neural networks for the proposed model. When a certain question is queried, AMRNL ranks the answers for it based on the trained asymmetric multi-faceted ranking network embedding. The main contributions of this paper are as follows:

- Unlike the previous studies, we formulate the problem of community-based question answering from the viewpoint of asymmetric multi-faceted ranking network learning. That is, we learn the multi-faceted ranking function based on both the deep semantic relevance of question-answer pairs and users' expertise authority in CQA sites.

- We propose an asymmetric ranking network learning method with deep recurrent neural networks for the proposed model, which is optimized by the back-propagation method.

- We evaluate the performance of our method on the well-known question answering site Quora. The extensive experiments show that our method can outperform several state-of-the-art solutions to the problem.

Question Answering via Asymmetric CQA Network Learning

In this section, we first present the problem of community-based question answering from the viewpoint of multi-faceted ranking function learning and then introduce the asymmetric multi-faceted ranking network learning framework. Finally, we propose an asymmetric ranking network learning method with deep recurrent neural networks for the problem.

The Problem

Before presenting the problem, we first introduce some basic notions and terminologies. Since the questions and answers in CQA sites are always the sequential data with variant length, we then encode their contents into fixed length feature vectors for semantic representation using recurrent neural networks. Given a set of input questions $X = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$ and answers $Y = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_m\}$, we take the last hidden layer of neural networks as the semantic embedding of the questions by $Q = \{\mathbf{q}_1, \mathbf{q}_2, \ldots, \mathbf{q}_n\}$ and that of the answers by $A = \{\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_m\}$. We then denote the set of user expertise authority embeddings by $U = \{\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_l\}$ where $\mathbf{u}_i$ is the embedding vector for the latent expertise of the i-th user. The quality of answers to the given questions is voted through thumb-ups/downs, which indicates the community's long term review (Zhao et al. 2015).

We propose the multi-faceted ranking function based on the semantic relevance of question-answer pairs and the answerers' expertise authority for community-based question answering by $f_{\mathbf{M}}(\mathbf{q}_i, \mathbf{u}_j, \mathbf{a}_k) = s_{\mathbf{M}}(\mathbf{q}_i, \mathbf{a}_k) s(\mathbf{q}_i, \mathbf{u}_j)$, where $s_{\mathbf{M}}(\mathbf{q}_i, \mathbf{a}_k)$ is the semantic matching function, and $s(\mathbf{q}_i, \mathbf{u}_j)$ is the expertise authority function of answerers to the given question $\mathbf{q}_i$. We then define the semantic matching function by $s_{\mathbf{M}}(\mathbf{q}_i, \mathbf{a}_k) = \mathbf{q}_i^T \mathbf{M} \mathbf{a}_k$, where $\mathbf{M} \in R^{d \times d}$ is the ranking metric matrix to calculate the semantic relevance between the i-th question $\mathbf{q}_i$ and the k-th answer $\mathbf{a}_k$.
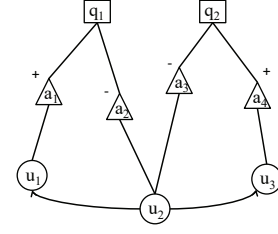

Figure 1: Heterogeneous Asymmetric CQA Network

The parameter d is the size of embedding dimensions for both questions and answers in CQA sites. We next define the expertise authority function by $s(\mathbf{q}_i, \mathbf{u}_j) = \mathbf{q}_i^T \mathbf{u}_j$, which is compute the expertise authority of the j-th user to the i-th question.

Given the collected community votes of the answers for the given questions, we introduce the relative quality rank to model the multi-faceted ranking function, which is in the form of ordered tuple (i, j, k, o, p), meaning that "the j-th answer provided by the k-th user, obtains more thumb-ups than the o-th answer provided by the p-th user for the i-th question" . Let $R = \{(i, j, k, o, p)\}$ denote the set of ranking pair constraints derived from the community votes. More formally, we aim to learn the multi-faceted ranking metric function that for any $(i, j, k, o, p) \in R$, the inequality holds:

$$f_{\mathbf{M}}(\mathbf{q}_i, \mathbf{u}_j, \mathbf{a}_k) > f_{\mathbf{M}}(\mathbf{q}_i, \mathbf{u}_o, \mathbf{a}_p). \tag{1}$$

We then utilize the users' asymmetric following relations in CQA sites to further improve the performance of multi-faceted ranking function learning. We denote the asymmetric following relations between users by $\mathbf{S}^{l \times l}$. The entry $s_{ij} = 1$ if the i-th user follows the j-th user in CQA site, otherwise $s_{ij} = 0$. We then propose the heterogeneous asymmetric multi-faceted ranking network by integrating both users' asymmetric following relations and the relative quality rank of question-answer pairs for community-based question answering. We next denote the heterogeneous asymmetric multi-faceted ranking network by $G = (V, E)$ where the set of nodes V is composed of questions X, answers Y and users U, and the set of edges consists of pairwise ranking R and users' asymmetric following relations S in CQA sites. We illustrate a simple example of heterogeneous asymmetric multi-faceted ranking network in Figure 1. We show the relative quality ranking of the question-answer pairs as follows. The answer $\mathbf{a}_2$ provided by user $\mathbf{u}_2$ (i.e., marked with $+$ on the answering relation), receives more thumb-ups than the answer $\mathbf{a}_1$ provided by user $\mathbf{u}_1$ (i.e., marked with $-$ on the answering relation) for question $\mathbf{q}_1$. We also illustrate the asymmetric following relation between users $\mathbf{u}_1$ and $\mathbf{u}_2$ (i.e., $s_{21} = 1$) in Figure 1.

Using the notations above, we define the problem of community-based question answering from the viewpoint of asymmetric multi-faceted ranking network learning as follows. Given the input question X, answers Y, the pairwise ranking constraints R derived from community vote, and the heterogeneous ranking network G, our goal is to learn the

multi-faceted ranking function based on the ranking metric matrix $\mathbf{M}$ and all the embedding users U, and rank the answers to the given question. The best answer $\mathbf{a}$ qualifying for the question $\mathbf{q}$ is selected according to $f_{\mathbf{M}}(\mathbf{q}, \mathbf{a}, U)$.

Heterogeneous Asymmetric Ranking Network Learning with Recurrent Neural Networks

In this section, we first present the heterogenous asymmetric multi-faceted ranking network learning framework for community-based question answering, and then present the learning process in Figures 2(a) and 2(b).

We first introduce the proper semantic representation method for both questions and answers in CQA sites. Given a sequence of words for question $\mathbf{x}_i$, we represent the t-th word by pre-training word embedding (Mikolov et al. 2013) as x_{it} and then use the sequence $(x_{i1}, x_{i2}, \ldots, x_{ik})$ as the input of the corresponding recurrent neural networks. In this work, we choose the variant recurrent neural networks called long-short term memory (LSTM) (Hochreiter and Schmidhuber 1997) to learn the question representations by:

$$
\begin{aligned}
\mathbf{i}_t &= \delta(\mathbf{W}_i \mathbf{x}_t + \mathbf{G}_i \mathbf{h}_{t-1} + \mathbf{b}_i), \\
\hat{\mathbf{C}}_t &= tanh(\mathbf{W}_c \mathbf{x}_t + \mathbf{G}_f \mathbf{h}_{t-1} + \mathbf{b}_f), \\
\mathbf{f}_t &= \delta(\mathbf{W}_f \mathbf{x}_t + \mathbf{G}_f \mathbf{h}_{t-1} + \mathbf{b}_f), \\
\mathbf{C}_t &= \mathbf{i}_t \cdot \hat{\mathbf{C}}_t + \mathbf{f}_t \cdot \mathbf{C}_t, \\
\mathbf{o}_t &= \delta(\mathbf{W}_o \mathbf{x}_t + \mathbf{G}_o \mathbf{h}_{t-1} + \mathbf{V}_o \mathbf{C}_t + \mathbf{b}_o) \\
\mathbf{h}_t &= \mathbf{o}_t \cdot tanh(\mathbf{C}_t), \quad (2)
\end{aligned}
$$

where δ represents the sigmoid activation function; $\mathbf{W}$s, $\mathbf{G}$s and $\mathbf{V}_o$ are the weight matrices, and $\mathbf{b}$s are the bias vectors. We train the LSTM networks and then take the output of the last LSTM cell, $\mathbf{h}_k$, as the semantic representation of question, denoted by $\mathbf{q}$. Similarly, we learn the sematic representation of answers using LSTM networks, denoted by $\mathbf{a}$. Considering the fact that the answers may be in the paragraph with several sentences in CQA sites, we split them into sentences for learning the semantic representations and then merge the representations by an additional max-pooling layer.

We then present the multi-faceted ranking function learning method for high-quality answer ranking in community-based question answering. Given the representations of question-answers, and their relative quality rank in CQA sites, we now design its multi-faceted ranking loss function $\mathcal{L}_r$ as follows:

$$
\mathcal{L}_r = \sum_{(i,j,k,o,p) \in R} \max(0, c + f_{\mathbf{M}}^-(\mathbf{q}_i, \mathbf{u}_o, \mathbf{a}_p) - f_{\mathbf{M}}^+(\mathbf{q}_i, \mathbf{u}_j, \mathbf{a}_k)),
$$

(3)

where the superscript $f_{\mathbf{M}}^+(\cdot)$ denotes the high-quality answers (with higher votes) and $f_{\mathbf{M}}^-(\cdot)$ denotes the low-quality answers (with lower votes) for question answering. We denote the hyper-parameter c ($0 < c < 1$) controls the margin in the loss function and R is the set of pairwise relative quality rankings.

We now propose the heterogeneous asymmetric multi-faceted ranking network learning method for community-based question answering by integrating both the multi-faceted ranking function learning and users' asymmetric following relations in CQA sites. For each user in matrix $\mathbf{S}$, we

(a) Heterogeneous Asymmetric CQA Network

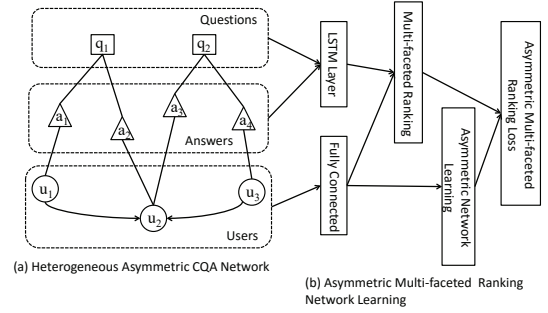(b) Asymmetric Multi-faceted Ranking Network Learning

Figure 2: The Overview of Heterogeneous Asymmetric Multi-faceted Ranking Network Learning for Community-based Question Answering. (a) The heterogeneous asymmetric CQA network is constructed by integrating the question-answer pairs and users' asymmetric following relations in CQA sites. (b) The questions, answers and users are encoded into fixed embedding vectors based on asymmetric multi-faceted network ranking loss.

first perform the row-normalization of their asymmetric following relations. That is, if the entry $s_{ij} = 1$ in matrix $\mathbf{S}$, then the entry is normalized by $w_{ij} = \frac{1}{|F_i|}$, where $|F_i|$ is the number of following users by the i-th user in $\mathbf{S}$. If there is no following relation between two users, then the normalized entry between them is set to 0. We denote the diagonal matrix by $\mathbf{F} = diag(|F_1|, |F_2|, \ldots, |F_l|)$ and the normalized relation matrix is given by $\mathbf{W} = \mathbf{F}^{-1}\mathbf{S}$. Following the simplest social influence assumption (Ellison and others 2007; Zhao et al. 2016a), we consider that the user's expertise authority model parameter can be represented by the linear combination of the following users' expertise model parameters. That is, for all $\mathbf{u}_i \in U$, the expertise $\mathbf{u}_i$ can be approximately reconstructed by $\mathbf{u}_i \approx \sum_{w_{ij} \in W, w_{ij} > 0} w_{ij} \mathbf{u}_j$, where w_{ij} is the positive weight of expertise basis $\mathbf{u}_j$ in representing $\mathbf{u}_i$, and $\mathbf{W}$ is the $l \times l$ normalized asymmetric relation matrix. Through minimizing the reconstruction error $\|\mathbf{u}_i - \sum_{w_{ij} > 0} w_{ij} \mathbf{u}_j\|_F^2$ and the proposed multi-faceted ranking function loss, we can enable the asymmetric multi-faceted ranking network learning based on the relative quality rank of question-answer pairs and the users' asymmetric following relations in CQA sites. Therefore, the problem of asymmetric multi-faceted ranking network learning can be mathematically formulated by

$$
\mathcal{L} = \mathcal{L}_r + \lambda \sum_{\mathbf{u}_i \in U} \|\mathbf{u}_i - \sum_{w_{ij} > 0} w_{ij} \mathbf{u}_j\|_F^2, \quad (4)
$$

where $\mathcal{L}_r$ is the multi-faceted ranking function loss and $\|\cdot\|_F^2$ is the Frobenius norm. The parameter λ is the trade-off parameter to balance the weight between the multi-faceted ranking function loss and the asymmetric network learning loss.

We now present the details of our proposed asymmetric multi-faceted ranking network learning. We denote all the model coefficients including neural network parameter, the result representations, and ranking metric matrix by Θ.

Table 1: Experimental results on nDCG with different proportions of data for training.

Methods	nDCG		
	60%	70%	80%
BOW	0.7001	0.7242	0.7325
QATM	0.7706	0.7805	0.7999
GRMC	0.608	0.6211	0.6435
Doc2Vec	0.7686	0.7930	0.8568
DeepWalk	0.8002	0.8287	0.8348
S-matrix	0.8296	0.8610	0.8942
CNTN	0.8322	0.8678	0.8967
HSNL	0.8704	0.8871	0.9080
AMRNL	**0.8884**	**0.9111**	**0.9234**

Table 2: Experimental results on Precision@1 with different proportions of data for training.

Methods	Precision@1		
	60%	70%	80%
BOW	0.4067	0.4092	0.4199
QATM	0.4095	0.4217	0.4284
GRMC	0.3321	0.3415	0.3500
Doc2Vec	0.3658	0.3705	0.3828
DeepWalk	0.3671	0.3737	0.3937
S-matrix	0.4849	0.5186	0.5462
CNTN	0.4325	0.4566	0.4831
HSNL	0.4896	0.5260	0.5275
AMRNL	**0.5025**	**0.5336**	**0.5681**

Therefore, the objective function in our learning process is given by

$$\min_{\Theta} \mathcal{L}(\Theta) = \mathcal{L}_c + \lambda \sum_{\mathbf{u}_i \in U} \|\mathbf{u}_i - \sum_{w_{ij} > 0} w_{ij} \mathbf{u}_j\|_F^2 + \alpha \|\Theta\|^2, \quad (5)$$

where α is the trade-off parameter between the training loss and regularization. To optimize the objective, we employ the stochastic gradient descent (SGD) with diagonal variant of AdaGrad in (Qiu and Huang 2015). At the t-th step, the parameters Θ is updated by:

$$\Theta_t \leftarrow \Theta_{t-1} - \frac{\rho}{\sqrt{\sum_{i=1}^t g_i^2}} g_t \quad (6)$$

where ρ is the initial learning rate and g_t is the subgradient at time t.

Experiments

Data Preparation

We evaluate the performance of our method using the Quora dataset in (Zhao et al. 2015), which is obtained from a popular question answering site, Quora. The dataset contains 444,138 questions, 95,915 users and 887,771 answers from Quora, and users' following relationship in Twitter's social network. The quality of users on answering the question is indicated through thumbs-up/down voted by the community. Following the experimental setting in (Yang et al. 2013; Zhao et al. 2015), we sort the questions based on their posted timestamp. We use the first 60%, 70% and 80% posted questions as training set, other 10% for validation and the remaining 10% for testing. So the training and testing data do not have overlap. For the ground truth, we consider all the corresponding answers as the candidate answer set and and their received thumbs-up/down as the ground truth ranking scores. The better answers tend to obtain higher ratings. Note that our task is to predict the relative quality rank of answers to the given question, instead of the exact thumbs-up/down values. Given the testing question set $\mathcal{Q}$, we denote the predicted ranking of all the answers for testing question q by R^q, and the ranked answer at the i-th position by r_i.

Performance Comparison

We evaluate the performance of our proposed method based on three widely-used ranking evaluation criteria for

Table 3: Experimental results on Accuracy with different proportions of data for training.

Methods	Accuracy		
	60%	70%	80%
BOW	0.3463	0.3107	0.3647
QATM	0.3145	0.3234	0.3673
GRMC	0.2466	0.251	0.2588
Doc2Vec	0.2991	0.337	0.3887
DeepWalk	0.3234	0.3318	0.3759
S-matrix	0.3658	0.4242	0.4588
CNTN	0.3723	0.4261	0.4577
HSNL	0.3897	0.4283	0.4720
AMRNL	**0.4025**	**0.4566**	**0.4951**

the problem of community-based question answering in CQA site, i.e., normalized discounted cumulative gain (nDCG) (Shen et al. 2015), Precision@1 (Qiu and Huang 2015) and Accuracy (Zhao et al. 2015). The relevance score in nDCG is based on the received thumbs-up/down of the answers. Precision@1 computes the average number of times that the best answer is ranked on top by a certain algorithm. The Accuracy is the normalized criteria of accessing the ranking quality of the best answer, where $Accuracy = 1$ (best) means that the best answer returned by a certain algorithm always ranks on top while $Accuracy = 0$ means the opposite. We compare our method with other seven state-of-the-art methods for the problem as follows:

- **BOW** method is an answer ranking algorithm based on the bag-of-words representation of both questions and answers for computing the relevant score.
- **QATM** method (Ji et al. 2012) is a question-answer topic model that learns the latent topics aligned across the question-answer pairs for question answering.
- **GRMC** method (Zhao et al. 2015) is the graph regularized matrix completion model, which provides the answer ranking based on the answerers' expertise authority.
- **Doc2Vec** method (Le and Mikolov 2014) is an question answering algorithm based on the distributed bag-of-words representation that encodes both questions and answers into a low-dimensional continuous feature space for answer ranking model.
- **CNTN** method (Qiu and Huang 2015) is a convolutional neural tensor network architecture that encodes the sentences in semantic space and model their interactions with
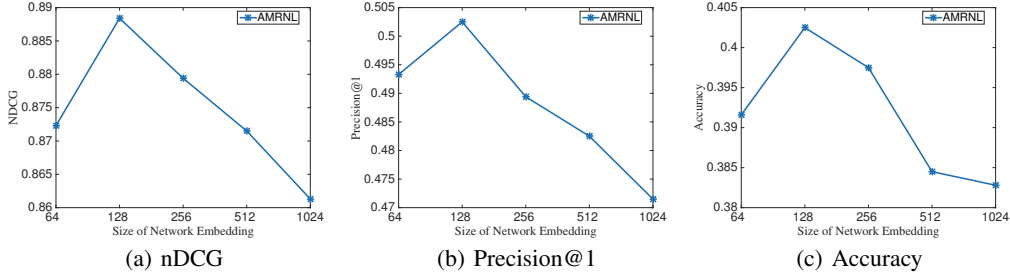
(a) nDCG   (b) Precision@1   (c) Accuracy

Figure 3: Effect of Embedding Dimension on nDCG, Precision@1 and Accuracy using 60% of data for training.

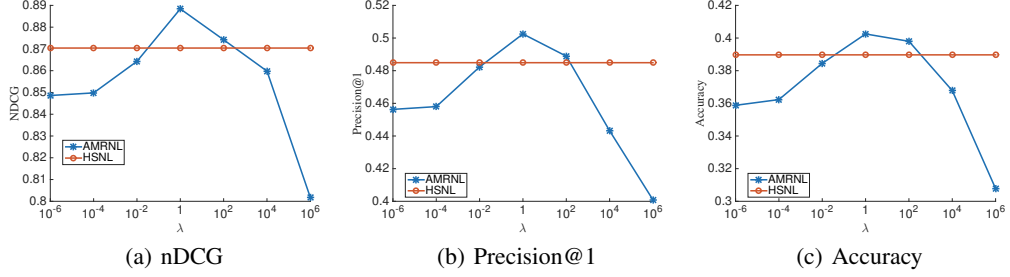(a) nDCG   (b) Precision@1   (c) Accuracy

Figure 4: Effect of Parameter λ on nDCG, Precision@1 and Accuracy using 60% of data for training.

a tensor layer.

- **HSNL** method (Fang et al. 2016) is a semantic matching model with recurrent neural networks that utilizes the random-walk methods for network sampling.
- **S-matrix** method (Shen et al. 2015) is the similarity matrix based architecture to model the complicated matching relations between questions and answers for answer retrieval.
- **DeepWalk** method (Perozzi, Al-Rfou, and Skiena 2014) learns the embedding of both questions and answers based on the network structure.

Among them, we use the code of the methods Doc2Vec, GRMC, HSNL and DeepWalk, and carefully implement the methods QATM, CNTN and S-matrix for comparison. Unlike these question answering methods (Ji et al. 2012; Le and Mikolov 2014; Qiu and Huang 2015; Fang et al. 2016; Shen et al. 2015; Perozzi, Al-Rfou, and Skiena 2014) based on semantic matching, our method AMRNL learns the multi-faceted ranking function for high-quality answer ranking.

Tables 1, 2 and 3 show the evaluation results on nDCG, Precision@1 and Accuracy, respectively. The evaluation were conducted with different ratio of the data from 60%, 70% to 80%. The hyperparameters and parameters which achieve the best performance on the validation set are chosen to conduct the testing evaluation. We report the average value of all the methods on the three evaluation criteria. The experimental results reveal a number of interesting points:

- The deep semantic matching methods Doc2Vec, CNTN, HSNL and S-matrix outperform the methods BOW and QATM based on the bag-of-words, which suggests that

the deep semantic matching model is critical for the problem.

- The authority-based methods GRMC and DeepWalk also achieve the comparable performance compared with BOW and QATM. This suggests that the authority model can also improve the performance of question answering.
- In all the cases, our AMRNL achieves the best performance, which shows that leveraging both deep semantic matching and the authority model via asymmetric network learning can further improve the performance of question answering.

There are two essential parameters, which are the size of network embedding and the trade-off parameter λ. We vary the size of network embedding from 32 to 1024, and the value of λ from 10^{-6} to 10^{6}. We use 60% of the data for training and then illustrate the performance of our method by varying λ on nDCG, Precision@1 and Accuracy in Figures 3(a), 3(b) and 3(c). We notice that the HSNL method consistently outperforms other methods in most of the evaluation criteria. Thus, we mainly compare our methods with HSNL by varying parameter λ in Figures 4(a), 4(b) and 4(c). We observe that our method achieves the best performance when the size of network embedding is set to 128 and the value of parameter λ is set to 1. The updating rules for minimizing the objective function of AMRNL method are essentially iterative. Figure 5(a) shows the convergence curve of AMRNL method and Figure 5(b) demonstrates its running time. The x-axis denotes the iteration number. The y-axis in Figure 5(a) is the value of the objective function and the y-axis in Figure 5(b) is the cost of running time. We can observe that the training of our method AMRNL is efficient.
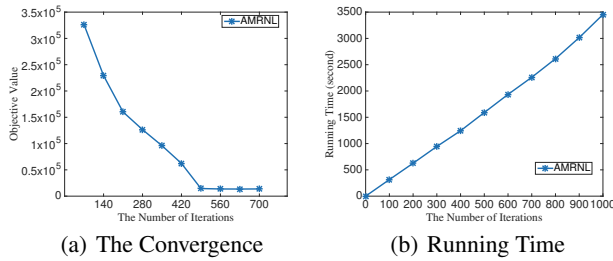
(a) The Convergence (b) Running Time

Figure 5: The convergence and running time of AMRNL.

Related Work

In this section, we briefly review some related work on deep question answering and network learning.

Recently, deep learning models show great potential for question answering and deliver state-of-the-art performance in semantic matching. Hu et al. (Hu et al. 2014) introduce the convolutional neural network models for sentence matching in question answering. Iyyer et al. (Iyyer et al. 2014) propose a recursive neural network model that reason over factoid question answering by modeling textual compositionality. Shen et al. (Shen et al. 2015) introduce the similarity matrix based architecture to model the complicated matching relations between questions and answers. Sutskever et al. (Sutskever, Vinyals, and Le 2014) employ the multilayered LSTM to map the input sequence to a vector of a fixed dimensionality, and then another deep LSTM to decode the target sequence from the vector. Qiu et al. (Qiu and Huang 2015) propose a convolutional neural tensor network architecture to encode the sentences in semantic space and model their interactions with a tensor layer, which integrates sentence modeling and semantic matching into a single model. Wang et al. (Wang and Nyberg 2015) employ the LSTM model for answer selection in question answering. Dong et al. (Dong et al. 2015) introduce multi-column convolutional neural networks for question understanding. Zhou et al. (Zhou et al. 2015a) introduce the metadata powered word embedding method for question retrieval in CQA. Wu et al. (Wu et al. 2016b) propose the tag recommendation method for question answering. Zhou et al. (Zhou et al. 2015b) employ convolution neural networks to learn the joint representation of question-answer pair, and then uses the joint representation as input of the long short-term memory to learn the answer sequence of a question. Fang et al. (Fang et al. 2016) propose the max-margin LSTM architecture for semantic matching. Most of the existing approaches consider the problem as text matching task, which learn the semantic matching model. Unlike previous studies, we consider the problem as high-quality answer ranking task, which is based on the answers' semantic relevance and the answerers' authority to the given question.

On the other hand, the network learning approaches mainly exploit the network structure for vertex embedding (Dai, Dai, and Song 2016; Guan et al. 2016). Perozzi et al. (Perozzi, Al-Rfou, and Skiena 2014; Tang et al. 2015) propose the network structure embedding method. Chang et al. (Chang et al. 2015) propose the embedding method for heterogeneous networks. Yang et al. (Yang et al. 2015) develop the learning method for attributed networks. Tan et al. (Tan et al. 2014) propose the learning method to map users across networks. Wu et al. (Wu et al. 2016a) devise the embedding algorithm for multi-modal networks. Tang et al. (Tang, Qu, and Mei 2015) propose the predictive embedding method for heterogeneous networks. Ou et al. (Ou et al. 2016) develop the high-order proximity preserved network embedding method based on singular value decomposition. Grover et al. (Grover and Leskovec 2016) propose the node2vec framework for learning continuous feature representations for nodes in networks, which is based on the biased random walk procedure. However, the objective of multi-faceted ranking network learning in our problem is different from these deep network representation methods. Thus, these methods may not be suitable for our problem.

Conclusion

In this paper, we formulated the problem of community-based question answering from the viewpoint of multi-faceted ranking network embedding. We propose a novel asymmetric multi-faceted ranking network learning framework for the problem by jointly exploiting the deep semantic relevance between question-answer pairs and the answerers' authority to the given question. We then develop an asymmetric ranking network learning method with deep recurrent neural networks by integrating both answers' relative quality rank to the given question and the answerers' following relations in CQA sites. We evaluate the performance of our method using the dataset from the well-known question answering site Quora. The extensive experiments demonstrate that our method can achieve better performance than several state-of-the-art solutions to the problem.

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References

Bouguessa, M.; Dumoulin, B.; and Wang, S. 2008. Identifying authoritative actors in question-answering forums: the case of yahoo! answers. In *SIGKDD*, 866–874. ACM.

Chang, S.; Han, W.; Tang, J.; Qi, G.-J.; Aggarwal, C. C.; and Huang, T. S. 2015. Heterogeneous network embedding via deep architectures. In *SIGKDD*, 119–128. ACM.

Dai, H.; Dai, B.; and Song, L. 2016. Discriminative embeddings of latent variable models for structured data. In *ICML*, 2702–2711.

Dong, L.; Wei, F.; Zhou, M.; and Xu, K. 2015. Question answering over freebase with multi-column convolutional neural networks. In *ACL*, volume 1, 260–269.

Ellison, N. B., et al. 2007. Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication* 13(1):210–230.

Fang, H.; Wu, F.; Zhao, Z.; Duan, X.; Zhuang, Y.; and Ester, M. 2016. Community-based question answering via heterogeneous social network learning. In *AAAI*.

Grover, A., and Leskovec, J. 2016. node2vec: Scalable feature learning for networks. In *KDD*, 855–864.

Guan, Z.; Chen, L.; Zhao, W.; Zheng, Y.; Tan, S.; and Cai, D. 2016. Weakly-supervised deep learning for customer review sentiment classification. In *IJCAI*, 3719–3725.

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

Hu, B.; Lu, Z.; Li, H.; and Chen, Q. 2014. Convolutional neural network architectures for matching natural language sentences. In *NIPS*, 2042–2050.

Iyyer, M.; Boyd-Graber, J. L.; Claudino, L. M. B.; Socher, R.; and Daumé III, H. 2014. A neural network for factoid question answering over paragraphs. In *EMNLP*, 633–644.

Ji, Z.; Xu, F.; Wang, B.; and He, B. 2012. Question-answer topic model for question retrieval in community question answering. In *CIKM*, 2471–2474. ACM.

Le, Q. V., and Mikolov, T. 2014. Distributed representations of sentences and documents. *arXiv preprint arXiv:1405.4053*.

Mikolov, T.; Chen, K.; Corrado, G.; and Dean, J. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.

Ou, M.; Cui, P.; Pei, J.; Zhang, Z.; and Zhu, W. 2016. Asymmetric transitivity preserving graph embedding. In *KDD*, 1105–1114.

Perozzi, B.; Al-Rfou, R.; and Skiena, S. 2014. Deepwalk: Online learning of social representations. In *SIGKDD*, 701–710. ACM.

Qiu, X., and Huang, X. 2015. Convolutional neural tensor network architecture for community-based question answering. In *IJCAI*, 1305–1311.

Shen, Y.; Rong, W.; Sun, Z.; Ouyang, Y.; and Xiong, Z. 2015. Question/answer matching for cqa system via combining lexical and sequential information. In *AAAI*.

Sutskever, I.; Vinyals, O.; and Le, Q. V. 2014. Sequence to sequence learning with neural networks. In *NIPS*, 3104–3112.

Tan, S.; Guan, Z.; Cai, D.; Qin, X.; Bu, J.; and Chen, C. 2014. Mapping users across networks by manifold alignment on hypergraph. In *AAAI*, 159–165.

Tang, J.; Qu, M.; Wang, M.; Zhang, M.; Yan, J.; and Mei, Q. 2015. Line: Large-scale information network embedding. In *WWW*, 1067–1077. WWW.

Tang, J.; Qu, M.; and Mei, Q. 2015. Pte: Predictive text embedding through large-scale heterogeneous text networks. In *SIGKDD*, 1165–1174. ACM.

Wang, D., and Nyberg, E. 2015. A long short-term memory model for answer sentence selection in question answering. *ACL*.

Wu, F.; Lu, X.; Song, J.; Yan, S.; Zhang, Z.; Rui, Y.; and Zhuang, Y. 2016a. Learning of multimodal representations with random walks on the click graph.

Wu, Y.; Wu, W.; Li, Z.; and Zhou, M. 2016b. Improving recommendation of tail tags for questions in community question answering. In *AAAI*.

Yang, L.; Qiu, M.; Gottipati, S.; Zhu, F.; Jiang, J.; Sun, H.; and Chen, Z. 2013. Cqarank: jointly model topics and expertise in community question answering. In *CIKM*, 99–108. ACM.

Yang, C.; Liu, Z.; Zhao, D.; Sun, M.; and Chang, E. Y. 2015. Network representation learning with rich text information. In *IJCAI*, 2111–2117.

Zhao, Z.; Zhang, L.; He, X.; and Ng, W. 2015. Expert finding for question answering via graph regularized matrix completion. *TKDE* 27(4):993–1004.

Zhao, Z.; Lu, H.; Cai, D.; He, X.; and Zhuang, Y. 2016a. User preference learning for online social recommendation. *IEEE Trans. Knowl. Data Eng.* 28(9):2522–2534.

Zhao, Z.; Yang, Q.; Cai, D.; He, X.; and Zhuang, Y. 2016b. Expert finding for community-based question answering via ranking metric network learning. In *IJCAI*, 3000–3006.

Zhou, G.; He, T.; Zhao, J.; and Hu, P. 2015a. Learning continuous word embedding with metadata for question retrieval in community question answering. In *ACL*, 250–259.

Zhou, X.; Hu, B.; Chen, Q.; Tang, B.; and Wang, X. 2015b. Answer sequence learning with neural networks for answer selection in community question answering. *arXiv preprint arXiv:1506.06490*.