EndCold: An End-to-End Framework for Cold Question Routing in Community Question Answering Sites

Jiankai Sun, Jie Zhao, Huan Sun, and Srinivasan Parthasarathy
Department of Computer Science and Engineering, The Ohio State University, USA
{sun.1306,zhao.1359,sun.397}.osu.edu,srini@cse.ohio-state.edu

Abstract
Routing newly posted questions (a.k.a cold questions) to potential answerers with the suitable expertise in Community Question Answering sites (CQAs) is an important and challenging task. The existing methods either focus only on embedding the graph structural information and are less effective for newly posted questions, or adopt manually engineered feature vectors that are not as representative as the graph embedding methods. Therefore, we propose to address the challenge of leveraging heterogeneous graph and textual information for cold question routing by designing an end-to-end framework that jointly learns CQA node embeddings and finds best answerers for cold questions. We conducted extensive experiments to confirm the usefulness of incorporating the textual information from question tags and demonstrate that an end-2-end framework can achieve promising performances on routing newly posted questions asked by both existing users and newly registered users.

Introduction
Community Question Answering services (CQAs) such as Stack Exchange and Yahoo! Answers are examples of social media sites, with their usage being examples of an important type of computer supported cooperative work in practice. In recent years, the usage of CQAs has seen a dramatic increase in both the frequency of questions posted and general user activity. This, in turn, has given rise to several interesting problems ranging from expertise estimation to question difficulty estimation, and from automated question routing to incentive mechanism design on such CQAs (Yang et al. 2013; Fang et al. 2016; Sun et al. 2018a).

In this work, we focus on the problem of routing newly posted questions to suitable experts before answers are written (item cold-start). Usually, there are two types of questions in CQAs – resolved (questions with answers) and newly posted questions (questions that have not received any answers). The newly posted questions may themselves be posted by new askers (such as newly registered users who have not asked a question earlier) or existing askers (such as users who have asked several questions previously). We refer to these newly posted questions as cold questions. The majority of approaches have focused on evaluating content quality after the fact (after questions have been resolved) (Yang et al. 2013). Yet, as the CQAs continue to grow, routing the cold questions to matching experts before answers have been provided has become a critical problem. For example, in Stack Overflow, about 5.22 million questions have not been answered ¹.

Recently, the usage of graphs has seen an increase in solving the question routing problem. For example, Sun et al. (Sun et al. 2018a) proposed QDEE to leverage Expertise Gain Assumption (EGA) to build the competition graph and then applied social agony (Tatti 2014; 2015) to infer graph hierarchy and assign each node a scalar value to represent where it stands in the competition graph. The assigned scalar value of question nodes are question difficulty scores, and the assigned scalar value of user nodes are user expertise scores. QDEE then routed cold questions to users with matching expertise based on the corresponding questions’ difficulty level. It’s worth mentioning that both question difficulty and user expertise follow the characteristic of asymmetric transitivity. For example, given a question q₁ is easier than q₂ and q₂ is easier than q₃, we can infer that q₁ is easier than q₃ conveniently. Sun et al. (Sun et al. 2019) proposed ATP to tackle the challenge of directed graph embedding with asymmetric transitivity preservation and then they leveraged the proposed embedding results to appropriately route and assign newly posted questions to users with the suitable expertise and interest in CQAs. However, a multiple pipeline including directed graph embedding generation and experts finding is required where each step has to be optimized separately. Another drawback is that ATP can only leverage graph structure information, while other information (such as textual information) that does not follow the asymmetric transitivity can not be incorporated. It limits ATP in inferring the embedding of cold questions asked by new askers who have no activities in CQAs and hence ATP cannot work well for routing such questions to suitable answerers.

In Stack Exchange sites, voting is central for providing quality questions and answers ². The more that people vote on a post, the more certain future visitors can be confident of the quality of information contained within the post. Voting

¹https://stackexchange.com/sites#
²https://stackoverflow.com/help/why-vote
indicates a CQA community’s long-term review for a given user’s expertise level under a specific topic. ColdRoute (Sun et al. 2018b) views the problem of identification of best answerers as a regression problem (finding the answerers who have the highest predicted voting scores). The input features of ColdRoute are users’ past asking and answering activities in CQAs, and ColdRoute can leverage Factorization Machines (FMs) (Rendle 2010; 2012) to model pairwise interactions among different objects (questions, askers, answerers, and question tags). While in theory FMs can model high-order interactions, in practice it only models order-2 feature interactions due to the high complexity (Guo et al. 2017).

Therefore, we propose to solve the cold question routing problem by marrying the merits of the above two types of methods. On one hand, we use graph embedding techniques to encode useful high-order graph structure information, and on the other hand, we enable the incorporation of heterogeneous information (e.g. textual) in the node embedding as well. Specifically, users (including both askers and answerers), questions, and question tags are represented as three different types of nodes, which are connected by their historical interactions into an undirected CQA graph. We then employ a Graph Convolutional Network (GCN) (Kipf and Welling 2016) to generate deeper and neighbor-aware node representations in the undirected graph. Our proposed method allows more flexible node interactions and can enrich the question/user node embeddings with the textual information from question tags. And question tags can bridge the gap between cold questions and exiting nodes in the CQA graph. This overall end-to-end framework can be optimized directly with the cold question routing objective, which enables the learning of task-specific embeddings for heterogeneous nodes in the CQA graph, and a better cold question routing performance.

In summary, we made the following contributions:

- Encode users’ past asking and answering activities and textual information by using an undirected heterogeneous graph, of which nodes are questions, tags, and users (askers and answerers) and edges are interactions among them.
- Build an end-to-end framework which can route cold questions in CQAs effectively.
- Demonstrate the effectiveness of our proposed framework on various Stack Exchange sites.

**Related Work**

Recently, Sun et al. (Sun et al. 2018a) observed that users typically gain expertise across multiple interactions with the CQA and tend to ask more difficult questions within the same domain over time, which is referred to as Expertise Gain Assumption (EGA). They leveraged EGA and added additional edges between questions asked by the same user to the previous competition graph (Liu, Song, and Lin 2011; Liu et al. 2013; Wang, Jing Liu, and Guo 2014) to combat the sparseness problem. They then proposed QDEE to lever social agony (Tatti 2014; 2015) to infer graph hierarchy and assign each node a scalar value to represent where it stands in the competition graph. The assigned scalar value of question nodes are question difficulty scores, and the assigned scalar value of user nodes are user expertise scores. There is some work which can model the users’ past asking and answering activities by using a graph and then some graph embedding methods (Fang et al. 2016; Zhao et al. 2016; 2017) are proposed to address the above limitation. The problem of graph embedding seeks to represent vertices of a graph in a low-dimensional vector space in which meaningful semantic, relational and structural information conveyed by the graph can be accurately captured (Ma et al. 2018). Recently, one has seen a surge of interest in developing such methods including ones for learning such representations for directed graphs while preserving important properties such as asymmetric transitivity (Ou et al. 2016; Sun et al. 2019). Question difficulty and user expertise follow the characteristic of asymmetric transitivity. For example, given a question $q_1$ is easier than $q_2$ and $q_2$ is easier than $q_3$, we can infer that $q_1$ is easier than $q_3$ easily. It happens to estimate user expertise too. We can infer that $u_1$ has more expertise than $u_3$ based on the fact that $u_1$ has more expertise than $u_2$ and $u_2$ has more expertise than $u_3$ in a specific domain. Sun et al. (Sun et al. 2019) proposed ATP to tackle the challenge of directed graph embedding with asymmetric transitivity preservation and then they leveraged the proposed embedding results to appropriately route and assign newly posted questions to users with the suitable expertise and interest in CQAs. However, a multiple pipeline including directed graph embedding generation and experts finding is required where each step has to be optimized separately. Another drawback is that ATP can only leverage graph structural information while cannot leverage textual information (such as question tags) since these textual information cannot be naturally leveraged to construct the input directed graph. It indicates that ATP has some limitation on inferring the embedding of cold questions asked by new askers who have no activities in CQAs and hence cannot work well for routing cold question asked by new askers to suitable answerers.

Question difficulty and user expertise can vary in different topics. In Stack Exchange sites, users are required to use tags (a tag is a word or phrase) to describe the topic(s) of the question. Each question can be assigned multi-tags to represent its most relevant topics. Hence tags are important user-generated category information that achieves fine-grained and dynamic topic representation. Users who use a particular tag when posting questions or answers might prefer topic summaries most relevant to that tag (Ramage and Hall 2009). In our experiments, the average number of tags per question is 2.82 and 2.96 in Stack Exchange site Apple and Physics respectively. Hence a solely scalar value to represent question difficulty level or user expertise is not thorough. By iteratively introducing questions tags and textual descriptions (question title and body), ColdRoute (Sun et al. 2018b) demonstrated that question tags play a more important role than question title and body in terms of experts finding. ColdRoute views the problem
of identification of best answerers as finding the answerers who have the highest predicted voting scores. Given a cold question \(q\) and a set of potential answerers \(C_q\), \textit{ColdRoute} predicts each candidate \(u\)'s voting score for \(q\), where \(u \in C_q\) and then selects the user who achieves the highest predicted voting score as the best answerer for \(q\). In Stack Exchange sites, voting is central for providing quality questions and answers. Voting up a post signals to the rest of the community that the post is interesting, well-researched, and useful. A highly voted post reflects the quality of the post – which may be viewed by the future visitors. The more that people vote on a post, the more certain future visitors can be confident of the quality of information contained within the post. Voting indicates a CQA community’s long-term review for a given user’s expertise level under a specific topic. Each voting score is an integer, which is calculated based on the difference between the corresponding answer’s up-votes and down-votes which are assigned to it by users who viewed the question or provided answers in the CQAs. The input features of \textit{ColdRoute} are users’ past asking and answering activities in CQAs, and \textit{ColdRoute} can leverage Factorization Machines (FMs) (Rendle 2010; 2012) to model the interactions among different objects (questions, askers, answerers, and question tags).

**Problem Statement**

Assume we are given four relational sets of data in terms of Questions \(Q = \{q_1, q_2, \ldots, q_n\}\), Askers \(A = \{a_1, a_2, \ldots, a_m\}\), Answerers \(U = \{u_1, u_2, \ldots, u_k\}\), and Question Tags \(T = \{t_1, t_2, \ldots, t_l\}\). For each question \(q_i \in Q\), we have a tuple of the form \((\text{Asker}_i, \text{Answerers}_i, \text{BestAnswerer}_i, \text{Tags}_i, \text{Scores}_i)\), where \(\text{Asker}_i \in A\), \(\text{Answerers}_i \subset U\), \(\text{BestAnswerer}_i \in U\), and \(\text{Tags}_i \subset T\). Each voting score \(\text{Scores}_i\) is an integer, which is calculated based on the difference between \(\text{Answerer}_i\)'s up-votes and down-votes which are assigned to it by users who viewed the question or provided answers for that in the CQA environment. Note that the \textit{BestAnswerer} for a question may not be specified by \textit{Asker}.

Given the preliminaries (above), in this work, we focus on the problem of routing newly posted questions to suitable experts before answers are written (item cold-start). Each quadruple case \((q, u, a, t)\), where \(q \in Q\), \(u \in U\), \(a \in A\), and \(t \in T\) has a voting score \(y \in \mathbb{R}\), which is equal to the difference between times of up-voting and down-voting. Given the testing question set \(Q_t\), the predicted ranking list of all potential answerers for a test question \(q^*\) is \(\mathbb{R}^m\) for all \(q^* \in Q_t\). The answerer who’s ranked top 1 among all candidates in \(\mathbb{R}^m\) for the corresponding target question \(q^*\) will be selected as the best answerer for \(q^*\).

**Methodology**

In this section, we talk about the design of our proposed framework (both sequential and end-2-end). The key steps of the sequential and end-2-end model for routing newly posted questions are shown in Figure 1. We refer the sequential model as \textit{Seq} and the end-2-end model as \textit{EndCold}. The key steps of \textit{Seq} are:

1. Build the undirected heterogeneous CQA graph which incorporates users past asking and answering activities and their corresponding textual information in CQAs.
2. Apply suitable graph embedding methods to learn representations for each node (including question, user, and tag) in the corresponding input CQA graph.
3. Model the question routing problem as a regression problem, and concatenate the embeddings of question, asker, answerer, and tag as feature vectors and use corresponding voting scores as targets to train a suitable regression model \(f\).
4. Apply \(f\) to predict the voting score a candidate user can achieve on a given cold question \(q^*\).
5. Routing \(q^*\) to its corresponding predicted best answerer, identified by selecting the user who’s predicted to achieve the highest voting score among all candidate answerers.

The biggest difference between our sequential model \textit{Seq} and end-2-end framework \textit{EndCold} is that \textit{EndCold} optimizes the graph embedding module (step 2 in \textit{Seq}) and regression module (step 3 in \textit{Seq}) simultaneously as shown in Figure 1.

**Build the undirected CQA graph**

Figure 2 illustrates how we build the corresponding heterogeneous CQA graph of which nodes are questions, tags, and users (including askers and answerers) and edges represent the interactions among questions, askers, answerers, and question tags. User 1 asked a question 1 which has tags 1 and 2. User 2, 3, and 4 answered question 1. User 4 asked a question 2 with tag 2 and 3. Question 2 was answered by user 3, 5 and 6. Edges are interactions among all questions, tags, askers and answerers.

Both users’ past asking and answering activities and their corresponding textual information (question tags) are incorporated in the above CQA graph, which can help us bridge the gap between cold question nodes and existing nodes in the CQA graph. Cold questions can be connected with the existing CQA graph via the common question tag nodes they have and existing asker node (not applicable for cold questions asked by new askers).

---

4https://stackoverflow.com/help/why-vote
In this section, we talk about the sequential model named as Seq-TA (By default, Seq is referred to Seq-TA in our paper) which takes the undirected CQA Graph with question tags as the input and leverages any suitable graph embedding algorithms to generate embeddings for the question, user, and tag nodes. Take our experiments for example, we use node2vec (Grover and Leskovec 2016) to generate corresponding embeddings. Each answering thread between a question and an answerer can be represented as a quadruple of the target question, its asker, the corresponding answerer, and question tags. The corresponding quadruple case \langle q, u, a, t \rangle \in \langle Q, U, A, T \rangle can be represented as a concatenated feature vector \langle \tilde{q}, \tilde{u}, \tilde{a}, \tilde{t} \rangle, where \tilde{q}, \tilde{u}, and \tilde{a} are the embedding vectors of question q, answerer u, and asker a respectively. \tilde{t} is the average embedding of tags in set t. The voting score of u achieved on q is an integer. A regression model \textit{f} is trained based on the above feature vectors as inputs and corresponding voting scores as the targets.

This design gives us the flexibility to explore the different features’ relative importance in cold question routing. For example, information of asker and question tags can be iteratively introduced to our model to explore their relative importance as follows:

- **Seq-A**: explore the importance of question asker by using triples of \langle Q, U, A \rangle on routing cold questions asked by existing askers. Other settings are as same as Seq-TA.
- **Seq-T**: explore the importance of question tags by using triples of \langle Q, U, T \rangle on routing cold questions either from existing askers or new askers. Other settings are as same as Seq-TA.
- **Seq-Un**: explore the importance of question asker and tags by using triples of \langle Q, U \rangle on routing cold questions. Other settings are as same as Seq-TA.

Regarding the regression module, we examined two types of SVM based regressors implemented by scikit-learn. One is a Epsilon-Support Vector Regression (SVM)\textsuperscript{6} with the polynomial kernel (degree is set as 2). Another is the LinearSVR\textsuperscript{7} with the kernel type as a linear function. A neural network based regressor which is implemented based on Keras\textsuperscript{8} has also been taken into examination.

### The End-2-End Module for Cold Question Routing

The end-2-end module consists of two layers: embedding layer and regression layer. The embedding layer is built based on the Graph Convolutional Networks (GCNs) (Kipf and Welling 2016). The core idea behind GCNs is to learn how to iteratively aggregate feature information from local graph neighborhoods using neural networks (Ying et al. 2018). A single convolution operation transforms and aggregates feature information from a nodes one-hop neighborhod, and by stacking multiple such convolutions information can be propagated across far reaches of a graph (Ying et al. 2018). The embedding layer is followed by a multilayer perceptron (MLP) to do the regression. In our experiments, we use 2 layers in GCNs and 3 hidden layers in MLP. We evaluate the mean squared error for all the training examples.

### Experts Finding for Cold Questions

The final step of both Seq and EndCold is to identify the best answerers for cold questions, which works as follows:

1. Given a cold question \( q^* \) and a set of potential answerers \( C_q^* \), predict each candidate u’s voting score for \( q^* \), where \( u \in C_q^* \).
2. Select the user who achieves the highest voting score as the best answerer for \( q^* \).

Given a newly posted question \( q^* \) asked by an asker a using tags t and a potential answerer u, the prediction function \( f_{Seq} \) in Seq can treat the new question as a missing value by \( f_{Seq}(\tilde{q}, \tilde{u}, \tilde{a}, \tilde{t}) \). The user u who achieves the highest value of \( f_{Seq}(\tilde{q}, \tilde{u}, \tilde{a}, \tilde{t}) \) will be selected as the best answerer for question \( q^* \). It’s possible that the newly posted question \( q^* \) can be asked by a new asker who has no information to learn the corresponding embedding vector. Then the prediction function \( f_{EndCold} \) can treat the new asker as a missing value by \( f_{EndCold}(\tilde{q}, \tilde{u}, \tilde{a}, \tilde{t}) \).

Instead of using missing value \( \tilde{q} \) to represent the feature vector of \( q^* \) in Seq, EndCold can leverage GCNs to propagate information from existing tag nodes and asker nodes (if applicable) to \( q^* \). \( q^* \) can accumulate these information and get its corresponding embedding vector as \( \tilde{q}^* \). The regression function \( f_{EndCold} \) in EndCold can predict the voting score u can achieve on \( q^* \) as \( f_{EndCold}(\tilde{q}^*, \tilde{u}, \tilde{a}, \tilde{t}) \).

\textsuperscript{6}http://scikit-learn.org/stable/modules/generated/sklearn.svm.SVR.html
\textsuperscript{7}http://scikit-learn.org/stable/modules/generated/sklearn.svm.LinearSVR.html
\textsuperscript{8}https://keras.io
It is possible that the potential answerer $u$ is a newly registered user who has not provided any answer before in CQAs (user cold-start). In this scenario, the prediction function can be simplified as $f(q^*, 0, \vec{a}, \vec{t})$. All new registered users will receive the same predicted voting score for the same target question. More efforts will be spent to make accurate predictions for the user cold-start problem in our future work.

**Experiments and Analyses**

We conducted our cold question routing experiments following the same settings as ColdRoute on 8 large Stack Exchange sites (Sun et al. 2018b). We compare our proposed models with state-of-the-art methods based on two popular evaluation criteria (Precision\(^6\)) (Zhu et al. 2014; Zhao et al. 2016; Fang et al. 2016; Zhao et al. 2017; Sun et al. 2018b; 2019) and Accuracy (Zhou et al. 2016; Fang et al. 2016; Zhao et al. 2017; Sun et al. 2018b; 2019))\(^9\).

**Performance of Different Sequential Models**

In this section, we compare the routing performance of different sequential models with different embedding methods (such as node2vec and ATP) on various input graphs (such as directed competition graph used by QDEE and undirected CQA graph with question tags proposed in this work) with our proposed models. The key steps of each method in this section follow the same sequential framework as we discussed in Methodology section. The differences fall in how to build the input graph and get the embedding vector for each node in the corresponding input graph. The details of all comparison partners are as follows:

- **Seq-Dir-ATP**: The input graph of Seq-Dir-ATP is the same directed competition graph used in QDEE. Embeddings of nodes (questions and users) are generated by ATP. Given a newly posted question $q^*$, Seq-Dir-ATP applies Expertise Gain Assumption (EGA) (Sun et al. 2018a) to use the source and target embedding of the question which has the highest difficulty level among all questions asked by the same asker to approximate $q^*$’s source and target embedding respectively. Given a candidate user $u$, the number of votes $v$ can achieve on $q^*$ can be predicted by feeding the concatenated source and target feature vectors of $q^*$ and $u$ to a regression model $f$, which can be represented as $f(\vec{q}^*, \vec{u}^*, \vec{a}, \vec{t})$, where $\vec{q}^*$ and $\vec{u}^*$ represent corresponding node’s source and target feature vector respectively. The dimension of both source and target feature vector is tuned to set as 128. Hence the dimension of concatenated feature for $f$ is 512.

- **Seq-Dir**: It uses the same directed competition graph as Seq-Dir-ATP. However, Seq-Dir leverages node2vec (Grover and Leskovec 2016) to generate embeddings for question and user nodes. Like Seq-Dir-ATP, EGA is applied to generate embeddings for newly posted questions. Feature vector representations of $q^*$ and $u$ are concatenated as inputs of the regression model. Parameters are tuned to set as $p = q = 1, d = 128^{10}$. Hence the dimension of concatenated feature for $f$ is 256.

It’s worth mentioning Seq-Dir-ATP and Seq-Dir cannot handle the scenario of cold questions asked by new askers since EGA can only be applied to questions asked by existing askers to infer the embedding vector of the newly posted question. Hence, we only show their corresponding performance on routing cold questions asked by existing askers. The experiment results are summarized in Figure 3, where we can make the following observations:

- The best overall performance is achieved by Seq-AT, which concatenates the embedding of all four nodes in the $(\vec{q}, \vec{u}, \vec{a}, \vec{t})$ quadruple as input features and feeds them to the regression model. The fact that Seq-AT consistently outperforms its feature-ablated variants Seq-A, Seq-T and Seq-Un gives us some guideline that it is necessary to incorporate both user past activities (asking and answering) and textual information when designing question routing algorithms.

- For all the CQA sites and under all metrics, the four methods using the undirected CQA graph with question tags as input perform significantly better than Seq-Dir and Seq-Dir-ATP which use the directed competition graph. It demonstrates the advantage of using our proposed undirected CQA Graph with question tags in comparison with using the directed competition graph leveraged by QDEE (Sun et al. 2018a) and ATP (Sun et al. 2019) on the task of cold question routing.

- Note that despite Seq-Un does not explicitly use the embedding of question tag nodes, it still significantly outperforms Seq-Dir. This is because the graph embedding algorithm (node2vec (Grover and Leskovec 2016)) in our experiments allows neighboring nodes to share information, so the question node embeddings are regulated by their assigned tags as well.

**Pointwise v.s. Pairwise**

In this section, we would like to compare the performance difference between pointwise and pairwise based sequential models on cold question routing in CQAs, with hoping that the corresponding results can guide our future design of the question routing system in CQAs. The difference between pointwise and pairwise based sequential models are listed as follows:

- **Pointwise**: its goal is to learn a regression function $f : \langle q, u, a, t \rangle \rightarrow \mathbb{R}$. The user $u \in U$ who achieves the highest value of $f(q, u, a, t)$ will be selected as the best answerer for question $q$.

- **Pairwise**: We introduce the relative quality rank to model users’ past answering activities in CQAs, which is in the

---

\(^6\)Other evaluation criteria such as Precision\(^0\)1 and MRR (Zhu et al. 2014) used in ColdRoute (Sun et al. 2018b) follow the same performance pattern as Precision\(^6\) and Accuracy. To save space, we don’t report their results here.

\(^9\)https://github.com/snap-stanford/snap/tree/master/examples/node2vec

\(^{10}\)
form of \((q, a, t, u_+, u_-)\), meaning that the answer provided by answerer \(u_+\), obtains more voting scores than the answer provided by the answerer \(u_-\) for question \(q\) asked by asker \(a\) with tag set \(t\). Let \(C = \{(q, a, t, u_+, u_-)\}\) denote the set of ranking pair constraints derived from the community votes. More formally, we aim to learn a ranking function \(f\) that for any \((q, a, t, u_+, u_-) \in C\), the inequality holds: \(f(q, a, t, u_+) > f(q, a, t, u_-) + \epsilon\). The user \(u_+ \in U\) who satisfies the most number of above constraints will be selected as the best answerer for question \(q\). Given the representations of question and answerers, and the relative quality rank in CQA sites, the loss function \(L_r\) in Pairwise is designed as follows:

\[
L_r = \sum_{(q, a, t, u_+, u_-) \in C} \max(0, \epsilon + f(q, a, t, u_-) - f^+(q, a, t, u_+))
\]

where \(f^+()\) denotes the voting score achieved by high-quality answerers and \(f()\) represents the voting score of low-quality answerers for question routing. The hyper-parameter \(\epsilon (\epsilon > 0)\) controls the margin in the loss function and \(C\) is the set of pairwise relative ranking constraints.

In our experiments, the pairwise based model \(Seq\) (pairwise) leveraged \(SVM_{Rank}\) (Joachims 2006) to learn the partial order of two potential answerers given a newly posted question. As shown in Table 1 (cold questions asked by existing askers) and 2 (cold questions asked by new askers), \(Seq\) (pairwise) does not show significant improvement over the pointwise model \(Seq\) (pointwise) consistently. The reason is that \(Seq\) (pairwise) suffers from the data sparseness problem. Table 3 shows the statistical information of 8 Stack Exchange sites used in our experiments. The average number of answers per question among the 8 Stack Exchange sites is 1.79, and 57.19% of questions have only answer, which indicate that \(Seq\) (pairwise) cannot extract enough valid question-answerer pairs for training. With CQAs growing and information of answers becoming dense, \(Seq\) (pairwise) can have more valid relative ranking constraints in \(C\) to train and then be more robust and effective.

### Sequential Model v.s. End-2-End Model

In this section, we aim to compare the difference between our sequential model and end-2-end model. As shown

![P@3 of Different Sequential Models](image1.png)

(a) Precision@3

![Acc. of Different Sequential Models](image2.png)

(b) Accuracy

Table 1: Performance on newly posted questions asked by existing askers in 8 different Stack Exchange sites

| Site         | Apple | AskUbuntu | Gaming | Physics | Scifi | Serverfault | Tex | Unix |
|--------------|-------|-----------|--------|---------|-------|-------------|-----|------|
| Doc2Vec      | 0.3889 | 0.4133    | 0.2971 | 0.3571  | 0.276 | 0.3979      | 0.5029 | 0.4175 |
| ColdRoute-T  | 0.6581 | 0.6274    | 0.7796 | 0.7194  | 0.7742 | 0.6074      | 0.6343 | 0.6869 |
| ColdRoute-A  | 0.6026 | 0.5889    | 0.7157 | 0.6582  | 0.6846 | 0.5799      | 0.5657 | 0.5690 |
| ColdRoute-TA | 0.5641 | 0.5717    | 0.6805 | 0.6939  | 0.7599 | 0.5778      | 0.6114 | 0.6667 |
| Seq (pointwise) | 0.7607 | 0.668    | 0.8019 | 0.6837  | 0.8172 | 0.6     | **0.7029** | 0.6902 |
| Seq (pairwise) | **0.7692** | 0.7345 | 0.8147 | 0.6786  | **0.8208** | 0.6117 | 0.6286 | **0.7003** |
| EndCold      | 0.7607 | **0.743** | **0.8339** | 0.7041  | 0.8208 | 0.6222      | 0.6914 | 0.6902 |

| Site         | Acc   |
|--------------|-------|
| Doc2Vec      | 0.3076 | 0.4333 |
| ColdRoute-T  | 0.6324 | 0.6054 |
| ColdRoute-A  | 0.5822 | 0.5814 |
| ColdRoute-TA | 0.5573 | 0.5671 |
| Seq (pointwise) | 0.6836 | 0.6572 |
| Seq (pairwise) | **0.7079** | 0.7092 |
| EndCold      | 0.7022 | **0.7189** |

Figure 3: Performance of Different Sequential Models on Routing Cold Questions Posted by Existing Askers
in Table 1 and 2, the overall performance of end-2-end model EndCold is better than the performance of sequential models (both pointwise and pairwise). For example, EndCold improves upon the evaluation metrics (Accuracy and Precision) over Seq (pointwise) by 3.37% and 3.33% respectively on routing cold questions asked by new askers. Above results demonstrate the effectiveness of our end-2-end framework in comparing with the sequential models.

Comparison with the State-of-the-art on Cold Question Routing

In this section, we compared our proposed model with ColdRoute (Sun et al. 2018b), a state-of-the-art model on routing cold questions posted by both new and existing askers to suitable experts. ColdRoute encodes users’ past asking and answering activities by using one-hot encoding, which can cause sparsity problem. Instead of using one-hot encoding and then suffering from the sparsity problem, our proposed model leverages the dense embedding vectors of question, asker, answerer and question tags (average) to build the input feature vector for training. It’s worth mentioning that ColdRoute fails to take the higher-order interactions among questions, askers, answerers, and question tags into consideration due to the high complexity. ColdRoute-A, ColdRoute-T, and ColdRoute-TA are three variants of ColdRoute and they were designed to explore the importance of asker information, question tags, and both respectively.

We also compare our model with some semantic matching based approaches (Srba and Bielikova 2016; Li and King 2010; Li, King, and Lyu 2011; Dong et al. 2015; Yang and Manandhar 2014; Szpektor, Maarek, and Pellegr 2013; Yang et al. 2013; Sun et al. 2018b). These matching models have demonstrated their power on finding suitable experts recently (Srba and Bielikova 2016). Due to space limitation \(^1\), we only show the performance of Doc2Vec (Le and Mikolov 2014; Dong et al. 2015) The Doc2Vec used in our paper is implemented by gensim \(^2\). The dimension of the feature vector is tuned to set as 80.

As shown in Table 1 and 2, our proposed models perform better than ColdRoute (ColdRoute-A, ColdRoute-T, and ColdRoute-TA) and Doc2Vec on routing cold questions asked by both existing askers and new askers, which demonstrates the effectiveness of our proposed framework.

Conclusion and Future Work

In this paper, we proposed an end-to-end framework for cold question routing in CQAs. The input of the framework is an undirected heterogeneous CQA graph with encodes users’ past asking and answering activities and textual information of questions. Our proposed model can leverage the higher-order graph structure and content information to embed nodes in the input graph, and do the question routing simultaneously. Extensive experiments show that our model performs better than the state-of-the-art models on routing cold questions (asked by both existing askers and new askers).

As a future work, we plan to test our models on other CQAs with different settings (such as having more dense askers and answerers). In order to increase the expertise of the entire community, we plan to address the problem of routing newly posted questions (item cold-start) to newly registered users (user cold-start) in CQAs.

---

\(^1\) Other semantic matching models such as Bag of Words (Figueroa and Neumann 2013; Zhou et al. 2013) and Latent Dirichlet Allocation (Guo et al. 2008; Ji et al. 2012), and Word2Vec (Mikolov et al. 2013) follow the same pattern as Doc2Vec.

\(^2\) https://radimrehurek.com/gensim/models/doc2vec.html
Acknowledgments This work is supported by NSF grants EAR-1520870, CCF-1645599, CCF-1629548, IIS-1550302, and CNS-1513120, and a grant from the Ohio Supercomputer Center (PAS0166). All content represents the opinion of the authors, which is not necessarily shared or endorsed by their sponsors.

References
Dong, H.; Wang, J.; Lin, H.; Xu, B.; and Yang, Z. 2015. Predicting best answerers for new questions: An approach leveraging distributed representations of words in community question answering. In FCST.
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.
Figueroa, A., and Neumann, G. 2013. Learning to rank effective paraphrases from query logs for community question answering. In AAAI.
Grover, A., and Leskovec, J. 2016. Node2vec: Scalable feature learning for networks. In KDD.
Guo, J.; Xu, S.; Bao, S.; and Yu, Y. 2008. Tapping on the potential of qa community by recommending answer providers. In CIKM.
Guo, H.; TANG, R.; Ye, Y.; Li, Z.; and He, X. 2017. Deepfm: A factorization-machine based neural network for cfr prediction. In IJCAI.
Ji, Z.; Xu, F.; Wang, B.; and He, B. 2012. Question-answer topic model for question retrieval in community question answering. In CIKM.
Joachims, T. 2006. Training linear svms in linear time. In KDD.
Kipf, T. N., and Welling, M. 2016. Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907.
Le, Q., and Mikolov, T. 2014. Distributed representations of sentences and documents. In ICML.
Li, B., and King, I. 2010. Routing questions to appropriate answerers in community question answering services. In CIKM.
Li, B.; King, I.; and Lyu, M. R. 2011. Question routing in community question answering: Putting category in its place. In CIKM.
Liu, J.; Wang, Q.; Lin, C.; and Hon, H. 2013. Question difficulty estimation in community question answering services. In EMNLP.
Liu, J.; Song, Y.-I.; and Lin, C.-Y. 2011. Competition-based user expertise score estimation. In SIGIR.
Ma, Y.; Ren, Z.; Jiang, Z.; Tang, J.; and Yin, D. 2018. Multi-dimensional network embedding with hierarchical structure. In WSDM.
Mikolov, T.; Sutskever, I.; Chen, K.; Corrada, G.; and Dean, J. 2013. Distributed representations of words and phrases and their compositionality. In NIPS.
Ou, M.; Cui, P.; Pei, J.; Zhang, Z.; and Zhu, W. 2016. Asymmetric transitivity preserving graph embedding. In KDD.
Ramage, D., and Hall, D. e. a. 2009. Labeled lda: A supervised topic model for credit attribution in multi-labeled corpora. In EMNLP.
Rendle, S. 2010. Factorization machines. In ICDM.
Rendle, S. 2012. Factorization machines with libfm. In ACM Trans. Intell. Syst. Technol.
Rendle, S., and Bielikova, M. 2016. A comprehensive survey and classification of approaches for community question answering. ACM Trans. Web.
Sun, J.; Moosavi, S.; Ramnath, R.; and Parthasarathy, S. 2018a. QDEE: Question Difficulty and Expertise Estimation in Community Question Answering Sites. In ICWSM.
Sun, J.; Vishnu, A.; Chakrabarti, A.; Siegel, C.; and Parthasarathy, S. 2018b. Coldroute: effective routing of cold questions in stack exchange sites. In ECML PKDD.
Sun, J.; Bandyopadhyay, B.; Bashizade, A.; Liang, J.; Sadayappan, P.; and Parthasarathy, S. 2019. Atp: Directed graph embedding with asymmetric transitivity preservation. In AAAI.
Szpektor, I.; Maarek, Y.; and Pelleg, D. 2013. When relevance is not enough: Promoting diversity and freshness in personalized question recommendation. In WWW.
Tatti, N. 2014. Faster way to agony discovering hierarchies in directed graphs. In ECML PKDD.
Tatti, N. 2015. Hierarchies in directed networks. In ICDM.
Wang, Q.; Jing Liu, B. W.; and Guo, L. 2014. A regularized competition model for question difficulty estimation in community question answering services. In EMNLP.
Yang, B., and Manandhar, S. 2014. Exploring user expertise and descriptive ability in community question answering. In ASONAM.
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.
Yang, R.; He, R.; Chen, K.; Eksombatchai, P.; Hamilton, W. L.; and Leskovec, J. 2018. Graph convolutional neural networks for web-scale recommender systems. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery &#38; Data Mining, KDD ’18, 974–983.
Zhao, Z.; Yang, Q.; Cai, D.; He, X.; and Zhuang, Y. 2016. Expert finding for community-based question answering via ranking metric network learning. In IJCAI.
Zhao, Z.; Lu, H.; Zheng, V. W.; Cai, D.; He, X.; and Zhuang, Y. 2017. Community-based question answering via asymmetric multi-faceted ranking network learning. In AAAI.
Zhou, G.; Liu, Y.; Liu, F.; Zeng, D.; and Zhao, J. 2013. Improving question retrieval in community question answering using world knowledge. In IJCAI.
Zhu, H.; Chen, E.; Xiong, H.; Cao, H.; and Tian, J. 2014. Ranking user authority with relevant knowledge categories for expert finding. In WWW.