A KNOWLEDGE BASED TWO-STAGE CASCADE MODEL FOR TEST-QUESTION/ANSWER RETRIEVAL

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ABSTRACT

Test-question/answer retrieval task has raised higher requirements in terms of accuracy, coverage and semantic understanding. We design a cascade model with two-stage training processes: The first stage uses 41,532 user test-question click records and 207,660 unclick records, which are collected from a designed test-question-answer experimental platform, to generate 200,000 pairwise training dataset to train a deep learning model, which could improve generalization ability. The second stage combines the output of the first stage with structural knowledge as new features to train a logistic regression for selecting the results from the candidates with higher accuracy, the training dataset is generated by manually annotating 20,000 test-question samples. The structural knowledge is also manually extracted from the samples for generating a small knowledge graph, and on this condition, we design knowledge features. Experimental results show that the proposed model outperforms the state-of-the-art algorithms, among which the cascading model contributes 3% improvement and the knowledge features contribute 1% improvement.

KEYWORDS

Deep Learning, Test-Question/Answer Retrieval, Knowledge Feature, Cascade Model

1. INTRODUCTION

In recent years, vertical domain search services have become more and more popular in China. One of the most popular domains is education. China has 200 million primary, secondary and college students who create strong demand for educational resources. Various search applications have been developed to address the students' needs for knowledge and answers. For example, Zuoyebang (<https://www.zybang.com/>) allows students of all disciplines to search for test-questions. Students can input their questions in the form of text, voice or images, and the system provides answers. Unlike traditional information retrieval tasks or relevance models, test-question searching has unique requirements, which are described below:

- Strong generalizability: Test-questions are often expressed in a diverse and complex manner. Some results have the same meaning as the target query, but are expressed in a different manner, so traditional term-matching based relevance models (Salton et al. 1975) do not work.
- Semantic understanding for high accuracy: A relevance model without semantic understanding may lead to serious misinterpretations (Gómez-Adorno et al. 2013). For example, "Length and width are known. How should area be calculated" versus "Length and width are known. How should perimeter be calculated" are very different, but it is hard to distinguish them without semantic understanding.
- Interpretable model: Deep Learning is hard to interpret, thus increasing the incidence of errors and bad cases. For test-question/answer tasks, errors are usually unacceptable because minor differences may lead to irrelevant answers. Proper understanding arising from correct interpretations is particularly important for test-question retrieval.

Much research has focused on improving the generalizability of existing relevance models, and improving their capacity for semantic understanding (Xiao et al. 2018, P. S. Huang et al. 2013). However, researchers have seldom conducted specific domain optimization using procedures such as combining users' behavior records with domain structural knowledge to design an interpretable model. Not only is it hard to design a complete model for accurate semantic understanding, it is also hard to generalize it to handle lots of complex semantic representations in reality. To achieve this, we designed a knowledge-based two-stage cascading model, the main innovations of which are listed as below:

- The framework was designed to take into account both generalizability and accuracy. In the first stage, generalizability was improved by using a large-scale users' online behavior log. In the second stage, structural knowledge was used to obtain results that are more accurate.
- The first stage was achieved by use of a deep learning framework with pairwise strategy (Timur et al. 2019) which detected users' preference patterns from a training dataset based on 200,000 pairwise data. A multi-layer deep neural network was designed on the framework. We selected word embedding (Danchen et al. 2018) to vectorize the input so that we could obtain the maximum fuzzy matching segment of title towards query.
- We designed knowledge features and used pointwise strategy to improve the capability of semantic understanding and to acquire results that are more accurate.

2. THE FRAMEWORK OF THE PROPOSED MODEL.

We designed a two-stage cascading model to handle the test-question/answer retrieval task. The framework is shown in Figure 1:

Figure 1. Framework of the two-stage cascading model

2.1 Stage 1: Deep Neural Network Model with Pairwise Learning Strategy

According to previous studies (Sunil et al. 2017, Jun et al. 2015), users' preferences and clicking behaviors show a strong semantic correlation. In this case, the dataset contains 200,000 pairwise training data, and we adopted a pairwise strategy. When different users entered the same query, we selected two candidate results, labelled Title 1 and Title 2. If the number of clicks on Title 1 was greater than that on Title 2 we classed Title 1 as a good title and Title 2 as a poor title, and a pairwise based partial order is generated. To eliminate the influence of ranking position COEC (Click Over Expected Clicks) was used (Zhang et al. 2007).

Score 1 is the relevance score between the query and Title 1, while Score 2 is the relevance score between the query and Title 2. A loss function is used to determine whether Score 1 is greater than Score 2. If $\text{Score 1} > \text{Score 2}$, then we consider that the DNN model has a correct understanding of relevance; If $\text{Score 1} \leq \text{Score 2}$, the learned model has biases in understanding the relevance, and needs to be optimized through a back-propagation algorithm. The DNN model consists of 5 layers which are described in Figure 2.

Figure 2. Framework of DNN with pairwise strategy

2.1.1 Input Format and Embedding Layer

For pairwise strategy, assume the input query = {q_term₁, q_term₂, q_term₃, ... q_term_q}, the positive title is posTitle = {p_term₁, p_term₂, p_term₃, ... p_term_p}, the negative title is negTitle = {n_term₁, n_term₂, n_term₃, ... n_term_n}. In the embedding layer, we use word2vec to vectorize each term of query, posTitle and negTitle, which can be seen in formulas (1), (2), and (3):

$$q_term_i \xrightarrow{\text{Embedding}} Vq_i = \{q_{i1}, q_{i2}, \dots, q_{ik}\} \quad (1)$$

$$p_term_i \xrightarrow{\text{Embedding}} Vp_i = \{p_{i1}, p_{i2}, \dots, p_{ik}\} \quad (2)$$

$$n_term_i \xrightarrow{\text{Embedding}} Vn_i = \{n_{i1}, n_{i2}, \dots, n_{ik}\} \quad (3)$$

where i is the i th term of query, posTitle or negTitle. q_{ij} , p_{ij} , n_{ij} are the value of j th dimension. k is the dimension of vector (which is set to 200 here). The configuration of the embedding layer can be seen below:

embedding_layer = {**type**: “embedding”,
learn strategy: “word2vec”,
parameter: “embedding param”,
input: [query, posTitle, negTitle],
output: [query embedding, posTitle embedding, negTitle embedding]}

2.1.2 Vector Sum Layer

In Vector Sum Layer, we use formulas (4), (5), and (6) to obtain vector representation of query and title, which are listed below:

$$q_v = \sum_{i=1}^q Vq_i = \{ \sum_{i=1}^q q_{i1}, \sum_{i=1}^q q_{i2}, \sum_{i=1}^q q_{i3}, \dots, \sum_{i=1}^q q_{ik} \} \quad (4)$$

$$p_v = \sum_{i=1}^p Vp_i = \{ \sum_{i=1}^p p_{i1}, \sum_{i=1}^p p_{i2}, \sum_{i=1}^p p_{i3}, \dots, \sum_{i=1}^p p_{ik} \} \quad (5)$$

$$n_v = \sum_{i=1}^n Vn_i = \{ \sum_{i=1}^n n_{i1}, \sum_{i=1}^n n_{i2}, \sum_{i=1}^n n_{i3}, \dots, \sum_{i=1}^n n_{ik} \} \quad (6)$$

where q_v represents the sum of query term vector, p_v represents the sum of posTitle term vector and n_v represents the sum of negTitle term vector. The configuration of Vector Sum Layer can be seen as below:

vector_sum_layer = {**type**: “vector sum”,
parameter: “vector_sum param”,
input: [query embedding, posTitle embedding, negTitle embedding],
output: [query emb sum, posTitle emb sum, negTitle emb sum]}

In addition, we designed a maximum sequence-matching algorithm to find the most related pattern of title towards query. The algorithm is displayed below:

```

Main:
  For each term q_termi in a query:
    PairSet < String t_patterni, Double scorei, >= Func(q_termi, query, title);
  End
  Assign variable New_title as the t_pattern with maximum score.
  //New_title is a segment of the title, and it has the highest similarity with the query.

PairSet < String t_pattern, Double score> Func(q_term, query, title):
  //Find all possible sequence matching patterns and their scores between query and title.
  Find all indexes that q_term appears in title as index = [ind(1), ind(2), ind(3)];
  Array<PairSet<String, Double>> arr = null;
  If no index is found, return <null, 0.0>
  Else:
    For i in index:
      score = 1;
      t_pattern = "q_term";
      For j in `seq indexOf(q_term, query) + 1 -> query.length`:
        If (indexOf(query[j], title) begin from indexOf(q_term, title) is not null):
          score += Dis_score(indexOf(query[j], title) - indexOf(q_term, title));
          //function Dis_score considers that if the distance between two adjacent terms of a query in the
          title is big, the score will be small.
          t_pattern += " " + query[j];
        fi
      End
      Arr.append(t_pattern, score);
    End
  End
  Find PairSet from arr with maximum score, and return the PairSet.

```

Algorithm 1. Maximum sequence-matching algorithm for finding the most suitable title segment for the target query

2.1.3 Fully Connected Layer

We assign a 128-dimension vector of neurons in a fully connected layer, and map the 200-dimension embedding vector into the 128-dimension vector (Hinton et al. 2006). In the fully connected layer, all queries share the same parameter distributions and all titles share the same parameter distributions. In the embedding layer, we use a pre-training strategy to obtain the vectored representation of each term. The configuration of fully connected layer can be seen below:

```

full_connect_layer = {type: "full connect",
                      learning strategy: "full connection",
                      parameter: "full connect param",
                      input: [query emb sum, posTitle emb sum, negTitle emb sum],
                      output: [query fc, posTitle fc, negTitle fc]}

```

2.1.4 Cosine and Loss Function Layer

In the cosine layer, we use a cosine function to calculate the cosine similarity (Metzler et al. 2005) between query and posTitle, and between query and negTitle. In the loss function layer, we select Hinge Loss function. The detail of the network design is shown below:

```

cos_sim_layer = {type: "cosine sim",
                 input: [{query fc, posTitle fc}, {query fc, negTitle fc}]
                 output: [pos_cos_sim_score, neg_cos_sim_score]}
loss_layer = {type: "HingeLoss",
              input: [pos_cos_sim_score, neg_cos_sim_score, label]
              output: loss}
network = {embedding layer, vector sum layer, full connect layer, cos_sim_layer, loss_layer}

```

2.2 Stage 2: Knowledge Feature Design for Accurate Semantic Understanding

Scores obtained from Stage 1 were used to improve generalizability. In addition, we added features to improve the model's capacity for semantic understanding. Added features included entity-attribute (which was extracted

from the condition description of a question), and the target solution of the question. We manually extracted entity-attribute and entity-action from the samples to generate a small knowledge graph that covers 7 disciplines (Chinese, math, chemistry, physics, biology, history and geography). The knowledge graph contains 2,582 entities, 6,336 attributes and 1,213 actions. For math related questions, we defined three patterns to identify different target solutions. These are summarized below:

Pattern 1: “求” (request) + [entity][attribute] | [entity] | [attribute] + “?” | “”

Pattern 2: [entity][attribute] | [entity] | [attribute] + “怎么求” (how to find out) | “?” | “”

Pattern 3: [entity][attribute] | [entity] | [attribute] + “是” | “重” | “有” (is | has) | “” + “多少” (how much) + [unit] | “” + “?” | “”

We use the extracted entity-attribute-action to build the knowledge graph, then use the knowledge graph to generate knowledge features. The main principle is that we use the knowledge graph and a NLP parse method to extract entities, attributes, attribute values and actions for both query and title. We then analyze whether query and title describe the same entity with the same attribute or action, for the same attribute, and whether they have the same value. The comparison results can be seen as knowledge features, and gets assigned to a sequence of feature slots. Details of the knowledge feature generation can be seen below in Figure3.

Figure 3. Examples of knowledge extraction features.

3. DATA

Table 1. Data Format of test-question/answer searching records

Userid	Query	Title	Answer	Rank	Click
1	using 30 stamps with a length of 3cm and a width of 2.5cm	Use 30 stamps that have a length of 3cm and a width of 2.5cm to form a square. What is the length of the square' s sides?	Using 30 stamps with a length of 3cm and a width of 2.5cm to form a square without gaps, the area of every stamp is calculated first, and then the total area of the square. After that, the square root of the area is just the length of sides.	2	1
2	Oxygen production equation with hydrogen peroxide	How to write equation for oxygen production from hydrogen peroxide	$2\text{H}_2\text{O}_2 = \text{MnO}_2 = 2\text{H}_2\text{O} + \text{O}_2 \uparrow$	3	1
3	When a car suddenly starts, passengers will move backward, because they are under the force of inertia	“When a car suddenly starts, passengers will move backward, because they are under the force of inertia” . Why is this sentence wrong?	It should not be “under the force of inertia” , because inertia is an inherent property of objects. The original sentence should be changed to: when a car suddenly starts, passengers will move back because they have inertia.	1	1

The experimental dataset, which mainly comprises records relating to users' searching and clicking behavior in the test-question/answer domain, is collected from a vertical domain experimental platform. We crawled 325,415 questions from websites, which cover 7 disciplines, and then built the test-question-answer platform by using a term-matching cosine algorithm. Participants were invited to use the platform and provided clicking data, allowing us to collect 41,532 records relating to user searching and clicking, and 20,7660 unclicked records for pairwise comparison. The format of each record is described in Table 1.

The format used to label the 20,000 samples from the 41,532 records is shown in Table 2. For each sample, the following were manually extracted: entity-attribute; entity-action; target from query; result. Queries and titles were then compared from two perspectives: target matching (same/not same/unknown) and relevance (Rel). Relevance is on a scale from 0 to 2, where 2 is the most relevant. We also used patterns defined above to formalize the math-related solution target.

Table 2. Manual labeling format of the selected records

id	Query	Target	Title	Entity -Attribute -Action	Target	Target matching (same/not same/unknown)	Rel
1	using 30 stamps with a length of 3cm and a width of 2.5cm	NULL	Use 30 stamps that have a length of 3cm and a width of 2.5cm to form a square. What is the length of the square's sides?	Entity: square Attribute: length, width Unit: [cm]	How much is the length of the side? [Pattern 3]	Unknown	2
2	Oxygen production equation with hydrogen peroxide	Oxygen production equation	How to write the equation for oxygen production from hydrogen peroxide	Entity: hydrogen peroxide Action: oxygen production Entity: oxygen	equation for oxygen production	Yes	2
3	When a car suddenly starts, passengers will move backward, because they are under the force of inertia	NULL	"When a car suddenly starts, passengers will move backward, because they are under the force of inertia". Why is the sentence wrong?	Entity: inertia Action: move backward	Why is the sentence wrong?	Unknown	2

4. RESULTS AND DISCUSSION

We selected 80% of the 41,532 data as a training dataset. The remaining 20% were used as test data. Two baselines were selected: LR (Logistic Regression) with pointwise strategy and LR + DNN with point-pairwise strategy. Neither baseline considers knowledge features. The experimental results are shown in Figure 4:

Figure 4. Experimental results of the proposed model

In the graphs shown in Figure 4, the abscissa represents Recall, and the ordinate represents Precision. The Area Under Curve (AUC) of LR + pointwise strategy is 86.6%. This is improved upon by both LR + DNN (AUC=89.14%), and LR + DNN with knowledge features (AUC=90.02%). Another important benefit of the proposed model is that it fluctuates less than the other models, making it a more useful predictor.

When we set a threshold of 30% on recall, the precision of the three models was 92%, 94% and 97% respectively. We also selected several cases to further illustrate the performance of the proposed model, as shown in Table 3.

Table 3. Case Studies of the proposed model with recall at 30%

Query	LR	LR + DNN	LR + DNN + Knowledge Features
How many usages does “Ji” have?	How many usages does “De” have?	How many usages does “De” have?	What is the specific usage of “Ji” in Chinese?
Why should diazo reaction be carried out at low temperatures?	Why should diazo reaction be carried out at low temperatures?	Why does diazo reaction not need to be carried out under strong acid conditions?	What is diazo reaction? Why should it be carried out at low temperatures?
In a circle with a diameter of 4cm, draw the largest square.	Draw the largest circle in a square with a length of 4cm.	Draw the largest square in a circle.	Here is a circle with a diameter of 4cm. Please draw the largest square in the circle and calculate its area.

As can be seen in Table 3, the proposed model performs better on cases where query and title have the same meaning but are expressed in different ways. By taking into consideration entities related to knowledge points, the model can identify important differences and make correct judgement, while other state-of-art algorithms still depend on term matching similarity. Currently, knowledge features can only contribute a 1% improvement, because the construction of the knowledge graph is still at an early stage. With continuous construction of the knowledge graph, the model will be improved significantly.

For parameter assignment, we set learning rate at 0.02, batch at 128, margin of hinge-loss at 0.1, and sampling-rate of shuffle at 0.1. The training curve can be seen below in Figure 5.

Figure 5. Accuracy statistics of training process

5. CONCLUSION

In this research, we used a two-stage cascading model with knowledge features to optimize a test-question/answer search task. In Stage 1, we used a log of 41,532 clicked records and 207,660 unclicked records to generate a 200,000 pairwise dataset. This was used to train a DNN model to recognize semantic correlation through users' preference patterns, thus further improving generalizability. In stage 2, we designed and incorporated knowledge features to improve semantic understanding by the model, of different questions. The combination of Stages 1 and 2 could not only accurately interpret semantic information relating to the

questions, but also improved generalizability using the large-scale user log. One challenge in information retrieval is generalizing from a precise semantic model. The proposed model helps to address that challenge.

In future, we would like to design more complete and accurate knowledge features, and create a domain knowledge graph for test-questions/answers. In addition, we are seeking to incorporate LR and DNN into a unified framework to realize collaborative learning, which can achieve a dynamic balance between generalizability and accurate semantic understanding.

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