A Multi-Granularity Matching Attention Network for Query Intent Classification in E-commerce Retrieval

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ABSTRACT

Query intent classification, which aims at assisting customers to find desired products, has become an essential component of the e-commerce search. Existing query intent classification models either design more exquisite models to enhance the representation learning of queries or explore label-graph and multi-task to facilitate models to learn external information. However, these models cannot capture multi-granularity matching features from queries and categories, which makes them hard to mitigate the gap in the expression between informal queries and categories.

This paper proposes a Multi-granularity Matching Attention Network (MMAN), which contains three modules: a self-matching module, a char-level matching module, and a semantic-level matching module to comprehensively extract features from the query and a query-category interaction matrix. In this way, the model can eliminate the difference in expression between queries and categories for query intent classification. We conduct extensive offline and online A/B experiments, and the results show that the MMAN significantly outperforms the strong baselines, which shows the superiority and effectiveness of MMAN. MMAN has been deployed in production and brings great commercial value for our company.

CCS CONCEPTS

 Information systems → Query intent; • Computing methodologies → Natural language processing.

KEYWORDS

Query intent classification; multi-granularity matching attention network; multi-label text classification; e-commerce retrieval

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1 INTRODUCTION

Online shopping has become a way of life for people in the last few decades. More and more e-commerce platforms (e.g., eBay, Amazon, Taobao, and JD) provide consumers with hundreds of millions of products. Due to the diversity of user needs and commodity types, e-commerce search systems need to have the ability to identify the intention of the search query.

Query intent classification has attracted increasing attention from both academic and industrial areas. Multi-label classification models such as XML-CNN [7], LSAN [14], and HiAGM [21] have been proposed to learn the contextual information of documents to enhance the representation learning of queries. However, different from the general search engine, the queries of e-commerce applications are usually very short and lack enough contextual signals, and are even insensitive to the word order. These problems make these models cannot capture the most important information of the query. Moreover, a query may have different meanings. For example, the query "book hotel" expects the service about getting accommodation. However, the character "book" may mislead the model to predict the paper book. These polysemous queries increase the difficulty of precisely classifying the user's intent.

Some recent query intent classification models, such as CNN [3, 16, 17], LSTM [11, 13, 15], and attention-based models [1, 2, 10, 18], explore using the correlation between query intent and textual similarity or label-graph to facilitate models to learn external information. Unfortunately, these models are heavily dependent on the training data. It makes these models hard to generalize for the long tail queries that lack enough supervision signal from users.

To concurrently address the above challenges, we proposed a Multi-granularity Matching Attention Network (MMAN), which contains three modules: self-matching module, char-level matching module, and semantic-level matching module to comprehensively extract features from the query itself and query-category interaction matrix for mitigating the gap in expression between queries and categories for long-tail query intent classification.

The contributions of this paper can be summarized as follows:

- We propose a novel strategy that explicitly extends category information to reduce the expression gap between queries and categories.
- We design an effective model MMAN that contains three major components: self-matching module, char-level matching module, and semantic-level matching module, which focus on query representation learning, long-tail query enhancement, and semantic disambiguation respectively.
- We conduct extensive offline experiments on two large-scale real-world datasets and online A/B test experiments. Experimental results show that our model achieves significant improvement over state-of-the-art models.

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2 MODEL

Figure 1 illustrates the components of the proposed model, which is mainly composed of four major modules: (1) query and category representation learning module; (2) self-matching module; (3) charlevel matching module; and (4) semantic-level matching module.



2.1 Query and Category Representation

The query and category representation is the basis of aligning both into the same semantic space. Pre-trained language models [4, 8, 19] have been widely applied in industrial applications, so we use BERT as the encoder for both the query and categories.

To better learn the semantics of the product categories, the category character sequence is composed of two parts: (1) category name $n = [n_1, n_2, ..., n_{L_n}]$ where L_n denotes the number of categories; (2) the selected core product words $m = [m_1, m_2, ..., m_{L_m}]$ where L_m denotes the number of product words.

After obtaining the above high-quality product words, we concatenate them with category names and then feed them into BERT to encode category representation. To map queries and categories into the same semantic space, query and category share the same BERT model, which can be formulated as follows:

$$Q_i = \text{BERT}_{\text{Token}}([x_1, x_2, \dots, x_{L_q}]),$$

$$C_j = \text{BERT}_{\text{Token}}([n_1, n_2, \dots, n_{L_n}, m_1, m_2, \dots, m_{L_m}]),$$
(1)

where BERT_{Token} is the final layer of BERT without "CLS"; $\mathbf{Q}_i \in \mathbb{R}^{L_q \times d}$ and $\mathbf{C}_j \in \mathbb{R}^{L_c \times d}$ denote the token embedding matrix of query and category, respectively.

2.2 Self-matching module

A typical text classification model is usually built on pure query text. Thus we leverage this advantage in self-attention style.

Since query words contribute to the query representation differently, we apply the attention mechanism to summarize the query embedding matrix to extract intent-related words that are important to represent the query:

$$\mathbf{u}_{i} = \mathbf{v}_{i} \tanh\left(\mathbf{W}_{q}\mathbf{Q}_{i}^{T}\right),$$

$$\mathbf{q}_{i} = \sum_{t=1}^{L_{q}} \mathbf{Q}_{i,t} \operatorname{softmax}(\mathbf{u}_{i,t}),$$
(2)

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where $\mathbf{v}_i \in \mathbb{R}^{1 \times d}$, $\mathbf{W}_q \in \mathbb{R}^{d \times d}$ and $\alpha = \operatorname{softmax}(\mathbf{u}_{i,t})$ is a score function which determines the importance of words for composing sentence representation about the current query.

2.3 Char-level matching module

For long-tail queries, it lacks enough training samples for the model to precisely predict the user's intent. In this situation, auxiliary knowledge such as category names and core product words are a necessary complement to facilitate the model's decision.

In order to extract the fine-grained interactive features between the query and all categories, we perform dot-product between query representation Q_i and category representations C_j , and then stack each query-category interaction matrix on channel dimension, which can be formulated as follows:

$$\mathbf{M}_{j} = \mathbf{Q}_{i} \mathbf{W}_{qc} \mathbf{C}_{j}^{I},$$

$$\mathbf{M} = [\mathbf{M}_{1}, \mathbf{M}_{2}, \dots, \mathbf{M}_{C}],$$

(3)

where $W_{qc} \in \mathbb{R}^{d \times d}$ is a trainable weight, $\mathbf{M}_j \in \mathbb{R}^{L_q \times L_c}$ is the interaction matrix between query and category, and $\mathbf{M} \in \mathbb{R}^{|C| \times L_q \times L_c}$ is the feature map on the character level interaction between query and each category.

Then, to extract the fine-grained matching features from the feature map **M**, we employ a 2D convolution module with a window size $r_w \times r_h$ as follows:

$$\mathbf{s}_{i,j}^{(k)} = ReLU\left(\sum_{a=0}^{r_{\mathbf{w}}} \sum_{b=0}^{r_{h}} \mathbf{W}_{a,b} \mathbf{M}_{i+a,j+b}^{(k)} + \mathbf{b}\right),\tag{4}$$

where *k* denotes the *k*-th channel of feature map \mathbf{M} , $\mathbf{W}_{a,b}$ is a convolutional kernel, **b** is a bias vector. We conduct convolution operation on each channel of the feature map \mathbf{M} .

Next, a 2D max pooling layer is applied to distill most import features from the feature map **s** and can be formulated as follow:

$$\widetilde{\mathbf{s}}_{i,j}^{(k)} = \max_{0 \le c \le p_w} \max_{0 \le d \le p_h} \mathbf{s}_{i+c,j+d}^{(k)},$$
(5)

where p_w and p_h are the width and height of the 2D max pooling.

Finally, the output of the final feature maps is flattened and mapped into a low dimensional space by a linear transformation layer, denoted as $\mathbf{Z}_1 \in \mathbb{R}^{|C| \times d}$, which contains fine-grained matching features between query and each category.

2.4 Semantic-level matching module

Literal matching features may not enough to fully capture the user's real intent since the word in the query may be polysemous. For example, both "apple watch" and "apple juice" has high relevance score with "apple" on character level, however, semantically different from each other. Therefore, it is also necessary to capture the relevance between query and category on the semantic level.

To that end, we first obtain the category representation on the semantic level. In this phase, we employ a mean pooling on the time step of the character sequence of category representation C_i , and stack each category representation together:

$$\mathbf{c}_{i} = \operatorname{mean}(\mathbf{C}_{i}), \mathbf{C} = [\mathbf{c}_{1}, \mathbf{c}_{2}, \dots, \mathbf{c}_{|C|}],$$
(6)

where $\mathbf{C} \in \mathbb{R}^{|C| \times d}$ is the representation of all categories.

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Then, a cross-attention layer is applied to integrate the query with all categories' representations:

$$\mathbf{Z}_2 = \mathbf{Q}_i^T \operatorname{softmax}(\mathbf{C}\mathbf{W}_{qs}\mathbf{Q}_i^T), \tag{7}$$

where $\mathbf{W}_{qs} \in \mathbb{R}^{d \times d}$ is a trainable weight, and $\mathbf{Z}_2 \in \mathbb{R}^{|C| \times d}$ is the matching features between query and labels at the semantic level.

2.5 Training and Inference

After the above process, we have obtained query self-representation \mathbf{q}_i , fine-grained query-category matching features \mathbf{Z}_1 and coarsegrained matching features \mathbf{Z}_2 . All of these representations contribute to predicting the user's intent, and thus we employ matrix multiplication to fuse them together. Specifically, we introduce the nonlinear transformation layer which is defined as:

$$\widehat{y} = \mathbf{W}_{x}^{T} ReLU \left(\mathbf{q}_{i} \mathbf{W}_{qf} + [\mathbf{Z}_{1}, \mathbf{Z}_{2}] \mathbf{W}_{z} \right), \qquad (8)$$

where $\mathbf{W}_{qf} \in \mathbb{R}^{d \times |C|}$, $\mathbf{W}_z \in \mathbb{R}^{2d}$, and $\mathbf{W}_x \in \mathbb{R}^{|C| \times |C|}$ are linear transformation matrices.

In this paper, we use $y \in \mathcal{R}^{|C|}$ to represent the ground-truth label of a query, where $y_i = 0, 1$ denotes whether the query belongs to the category *i*. The whole framework is trained with the multi-label cross-entropy loss which can be formulated as follows:

$$\mathcal{L} = -\sum_{c=1}^{C} y^{c} \log\left(\sigma\left(\widehat{y}^{c}\right)\right) + \left(1 - y^{c}\right) \log\left(1 - \sigma\left(\widehat{y}^{c}\right)\right) , \qquad (9)$$

where σ is the sigmoid function.

3 EXPERIMENT

3.1 Dataset

In order to verify the effectiveness and generality of the MMAN, we conduct experiments on two large-scale real-world datasets collected from users' click logs of the JD application. The statistics of the datasets are listed in Table 1.

- **Category Data**: To evaluate the performance of MMAN, we randomly sample queries and corresponding clicked products from search logs over a period of one month. The product's category is treated as the query's intent. To filter unreliable categories, we normalized the click frequency of the category and compute the cumulative distribution function (CDF) of the category's probability. When *CDF* > 0.9, the rest with low probabilities are removed.
- Scene Data: We divide the collected categories into eight different domains, such as "travel", "hotel booking", "medical consultation", "car service", etc. The categories of the query are mapped into domains, which form the Scene data. Different from the training data, the test dataset is annotated by experts in each domain. It is worth noting that the experts not only annotate the domain of the query but also annotate all categories to which the query belongs.

3.2 Baseline Models

We compare MMAN with several strong baselines, including widelyused multi-label classification methods. The detailed introductions are listed as follows:

Statistic	Scene I	Data	Category Data		
Statistic	Train	Test	Train	Test	
Queries	4,459,214	9,877	4,593,037	9,877	
Total Labels	8	8	90	90	
Avg. chars	7.63	5.00	7.69	5.00	
Avg. # of labels	1.04	1.67	1.19	1.77	
Min. # of labels	1	1	1	1	
Max. # of labels	7	3	26	21	

(1) Multi-label text classification baselines: **RCNN** [6]: It captures contextual information with the recurrent and convolutional structure for text classification. **XML-CNN** [7]: It is a CNN-based model, which combines the strengths of CNN models and goes beyond the multi-label co-occurrence patterns. **LEAM** [12]: It is a label-embedding attentive model, which embeds the words and labels in the same space, and measures the compatibility of wordlabel pairs. **LSAN** [14]: It is a label-specific attention network to use document and label text to learn the label-specific document representation with the aid of self- and label-attention mechanisms.

(2) Query intent classification baselines: **PHC** [17]: It investigates the correlation between query intent classification and textual similarity and proposes a multi-task framework to optimize both tasks. **DPHA** [20]: It contains a label-graph-based neural network and a soft training mechanism with correlation-based label representation. **BERT** [4]: We use the pre-trained BERT-base ¹ delivered by google, and finetune it on the training set to predict the user's intent. **SSA-AC** [18]: It is an across-context attention model to extract external information from variant queries for intent classification.

3.3 Experiment Settings

Following the settings of previous work [18, 20], we report the micro and macro precision, recall, and F1-score of the models as the metrics of query intent classification.

We implement the models based on Tensorflow 2.4. Word embeddings were initialized by pre-trained word2vec [9], and whose dimensionality is 768. We use two convolution layers to extract char-level feature maps. The convolution layer has 8 [3,3] filters with [1,1] stride, and its max-pooling size is [2,2] with [2,2] stride. We use Adam algorithm [5] with learning rate as $5e^{-5}$. The max length of the query is set to 16. The threshold of labels is set to 0.5.

3.4 Experimental Results and Analysis

The experimental results are shown in Table 2. The results indicate that MMAN outperforms all baselines on two large-scale real-world datasets. Specifically, we have the following observations:

(1) MMAN significantly outperforms the multi-label classification baselines. A similar phenomenon can be observed in the comparison between query intent classification and multi-label classification models. Actually, most of these models are more suitable for contextual modeling of long texts. For queries typed by users on e-commerce, most of them are very short and lack contextual information, and are even insensitive to word order. These problems make them hard to capture the most important information for users' real intent.

¹https://tfhub.dev/tensorflow/bert_zh_L-12_H-768_A-12/4

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Table 2: The experimental results that compared with multi-label classification and query intent classification models.

	Scene Data				Category Data							
Models		Micro			Macro			Micro	-		Macro	
	Prec.	Recall	F1	Prec.	Recall	F1	Prec.	Recall	F1	Prec.	Recall	F1
RCNN [6]	94.14	77.67	85.11	83.09	86.01	83.69	69.76	54.03	60.89	70.51	62.42	62.15
XML-CNN [7]	94.73	76.00	84.34	80.87	86.47	81.91	66.73	56.36	61.11	68.08	64.15	62.12
LEAM [12]	94.19	68.46	79.29	88.84	78.60	82.84	72.67	49.91	59.18	69.96	47.56	52.15
LSAN [14]	94.73	74.14	83.18	80.31	86.05	81.48	68.33	51.36	58.64	71.64	61.00	61.93
PHC [17]	94.63	77.93	85.47	83.17	86.62	83.74	60.12	59.41	59.76	64.08	64.90	60.67
DPHA [20]	95.23	77.43	85.41	82.01	84.35	82.06	71.55	54.06	61.58	75.39	54.99	61.83
SSA-AC [18]	94.82	78.15	85.68	84.15	84.26	83.92	72.36	53.20	61.32	74.38	62.19	63.38
MMAN	95.52	82.26	88.39	87.26	86.15	85.93	75.64	55.07	63.74	75.77	64.56	66.47
w/o self-matching	96.03	81.24	88.02	88.14	85.72	84.86	75.25	54.35	63.11	73.26	64.08	65.68
w/o char matching	95.16	80.28	87.09	82.12	89.38	83.74	68.72	57.13	62.39	72.16	62.58	65.12
w/o semantic matching	95.86	81.14	87.89	84.36	87.62	84.15	72.18	56.16	63.17	73.61	63.27	65.05
BERT [4]	95.39	79.22	86.56	81.20	88.48	83.00	65.88	56.23	60.67	68.47	67.28	64.53

Table 3: Online improvements of the MMAN. Improvements are statistically significant with p < 0.05 on paired t-test.

	GMV	UV value	UCVR
Online model (BERT)	-	-	-
MMAN	+0.351%	+0.401%	+0.113%

(2) Compared with recent intent classification methods, MMAN achieves better performance on both datasets. Although these models also utilize the interaction information between query and labels, all of them only consider the matching features at the semantic level, which makes the models unable to mitigate the gap between informal query expression and formal category information and hard to capture the fine-grained clues for long tail classification.

(3) After removing these three modules of MMAN, we can see that the micro and macro F1 decay about 3% compared with the complete model. This result further shows that all of these components in MMAN provide complementary information to each other, and are requisite for intent classification.

In conclusion, MMAN achieves significant improvement over these strong baselines on the metrics of micro-F1 and macro-F1, which further confirms the effectiveness of learning multi-granularity matching features from query and category interaction, which facilitates the model to mitigate the gap of expressions between query and category and learns the most significant features for capturing the user's real intent.

3.5 Online Evaluation

Before being launched in production, we routinely deploy the MMAN on the JD search engine and make it randomly serve 10% traffic as the test group. During the A/B testing period, we monitor the performance of MMAN and compare it with the previously deployed model. This period conventionally lasts for at least a week. For online evaluation, we use some business metrics: Page Views (PV), Product Clicks (Click), Gross Merchandise Volume (GMV), UV value, and Conversion Rate of Users (UCVR).

The online experimental results are shown in Table 4 and Table 3. Referring to the table, we can observe that the PV and Click metrics Table 4: Online performance of the MMAN compared with the online BERT model. Improvements of MMAN are statistically significant with p < 0.01 on paired t-test.

Scene	PV	Click
hotel booking	+74.85%	+36.49%
travel and vacation	+9.94%	+1.75%
checkup service	+5.95%	+4.89%
aesthetic medicine	+44.42%	+26.30%
medical consultation	+22.76%	+5.66%
car service	+20.17%	+9.38%
furniture customization	+10.07%	+6.60%
Overall	+19.62%	+7.78%

of the above scenes get a dramatic improvement compared with the base group, which means (1) the incremental categories recalled by the new model MMAN are indeed the category the users required; (2) by increasing the recall rate of related categories, users tend to view and click more products. With the increase in product selection, the conversion rate of users has increased a lot, leading to more GMV and UCVR improvement (+0.351%).

4 CONCLUSION AND FUTURE WORK

In this paper, we propose a multi-granularity matching attention network to comprehensively extract features from the char-level and semantic-level of a query-category interaction matrix. In this way, the model can overcome the problem of a lack of training samples for long-tail queries and eliminate the difference in expression between queries and categories. The offline and online A/B experiments achieve significant improvements over the state of the art. Furthermore, MMAN has already been deployed in production at the JD application and brings great commercial value, which confirms that MMAN is a practical and robust solution for large-scale query intent classification services.

In future work, we plan to explore utilizing external knowledge such as the taxonomic hierarchy of categories and product information to completely model the category representations for further enhancing the model's performance. A Multi-Granularity Matching Attention Network for Query Intent Classification in E-commerce Retrieval

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