Ultra-Fast, Low-Storage, Highly Effective Coarse-grained Selection in Retrieval-based Chatbot by Using Deep Semantic Hashing

Tian Lan\textsuperscript{1}, Xian-Ling Mao\textsuperscript{1}, Xiaoyan Gao\textsuperscript{1}, Wei Wei\textsuperscript{2}, and Heyan Huang\textsuperscript{1}

\textsuperscript{1}Beijing Institute of Technology
lantiangmftby@gmail.com,\{maoxl,xygao,hhy63\}@bit.edu.cn
\textsuperscript{2}Huazhong University of Science and Technology
Weiw@hust.edu.cn

Abstract

We study the coarse-grained selection module in retrieval-based chatbot. Coarse-grained selection is a basic module in a retrieval-based chatbot, which constructs a rough candidate set from the whole database to speed up the interaction with customers. So far, there are two kinds of approaches for coarse-grained selection module: (1) sparse representation; (2) dense representation. To the best of our knowledge, there is no systematic comparison between these two approaches in retrieval-based chatbots, and which kind of method is better in real scenarios is still an open question. In this paper, we first systematically compare these two methods from four aspects: (1) effectiveness; (2) index storage; (3) search time cost; (4) human evaluation. Extensive experiment results demonstrate that dense representation method significantly outperforms the sparse representation, but costs more time and storage occupation. In order to overcome these fatal weaknesses of dense representation method, we propose an ultra-fast, low-storage, and highly effective Deep Semantic Hashing Coarse-grained selection method, called DSHC model. Specifically, in our proposed DSHC model, a hashing optimizing module that consists of two autoencoder models is stacked on a trained dense representation model, and three loss functions are designed to optimize it. The hash codes provided by hashing optimizing module effectively preserve the rich semantic and similarity information in dense vectors. Extensive experiment results prove that, our proposed DSHC model can achieve much faster speed and lower storage than sparse representation, with limited performance loss compared with dense representation. Besides, our source codes have been publicly released for future research\textsuperscript{1}.

1 Introduction

Retrieval technique or response selection is a very popular and elegant approach to framing a chatbot i.e. open-domain dialog system. Given the conversation context, a retrieval-based chatbot aims to select the most appropriate utterance as a response from a pre-constructed database. In order to balance the effectiveness and efficiency, most of the retrieval-based chatbots (Fu et al., 2020) employ coarse-grained selection module to recall a set of candidate that are semantic coherent with the conversation context to speed up processing.

To the best of our knowledge, there are two kinds of approaches to build a coarse-grained selection module in retrieval-based chatbots: (1) sparse representation: TF-IDF or BM25 (Robertson and Zaragoza, 2009) is a widely used method. It matches keywords with an inverted index and can be seen as representing utterances in high-dimensional sparse vectors (Karpukhin et al., 2020); (2) dense representation: Large scale pre-trained language models (PLMs), e.g. BERT (Devlin et al., 2019) are commonly used to obtain the semantic representation of utterances, which could be used to recall semantic coherent candidates by using cosine similarity (Karpukhin et al., 2020).

So far, there is no systematic comparison between these two kinds of approaches in retrieval-based chatbots, and which kind of method is most appropriate in real scenarios is still an open question that confuses researchers in dialog system community. Thus, in this paper, we first conduct extensive experiment to compare these two approaches from four important aspects: (1) effectiveness; (2) search time cost; (3) index storage occupation; (4) human evaluation. Extensive experiment results on four popular response selection datasets demonstrate that the dense representation significantly outperforms the sparse representation at the expense of

\textsuperscript{1}https://github.com/gmftbyGMFTBY/HashRetrieval
the lower speed and bigger storage than sparse representation, which is unsufferable in real scenarios. Then, in order to overcome the fatal weaknesses of dense representation methods, we propose an ultra-fast, low-storage and highly effective Deep Semantic Hashing Coarse-grained selection module (DSHC) which effectively balances the effectiveness and efficiency. Specifically, we first stack a novel hashing optimizing module that consists of two autoencoders on a given dense representation method. Then, three well designed loss functions are used to optimize these two autoencoders in hashing optimizing module: (1) preserved loss; (2) hash loss; (3) quantization loss. After training, the autoencoders could effectively preserve rich semantic and similarity information of the dense vectors into the hash codes, which are very computational and storage efficient (Wang et al., 2018). Extensive experiment results on four popular response selection datasets demonstrate that our proposed DSHC model can achieve much faster search speed and lower storage occupation than sparse representation method, and very limited performance loss compared with the given dense representation method.

In this paper, our contributions are three-fold:

- We systematically compare current two kinds of coarse-grained selection methods in open-domain retrieval-based dialog systems from four important aspects: (1) effectiveness; (2) search time cost; (3) storage occupation; (4) human evaluation.

- We propose an ultra-fast, low-storage, and highly effective deep semantic hashing coarse-grained selection method, called DSHC, which overcomes the fatal weaknesses of the dense representation method.

- We have publicly released our source codes for future search.

The rest of this paper is organized as follows: we introduce the important concepts and background covered in our paper in Section 2. The experiment settings is presented in Section 3. In Section 4, we systematically compare the current two kinds of methods in coarse-grained selection module: (1) sparse representation; (2) dense representation. In Section 5, we introduce our proposed DSHC model, and detailed experiment results are elaborated. In Section 6, we conduct the case study. Finally, we conclude our work in Section 7. Due to the page limitation, more details and extra analysis can be found in Appendix.

2 Preliminary

2.1 Retrieval-based Chatbot

Retrieval-based chatbots, or retrieval-based open-domain dialog systems, which are widely used in the real scenarios, have gained great progress over the past few years. So far, most of the retrieval-based chatbots contain two modules (Fu et al., 2020; Luan et al., 2020): coarse-grained selection module and fine-grained selection module.

2.1.1 Coarse-grained Selection Module

Coarse-grained selection module recalls a set of candidate responses that are semantic coherent with the conversation context from the pre-constructed database. As described before, there are two kinds of approaches to construct a coarse-grained selection module: sparse and dense representation.

Sparse representation: Due to the simply implementation and effective performance, sparse representation methods, represented by TF-IDF and BM25 (Robertson and Zaragoza, 2009), have been widely used in lots of real applications. Because the utterance that has the keywords overlap with the conversation context is likely to be an appropriate candidate response, sparse representation could effectively recall appropriate candidates for the fine-grained selection module.

The advantage of this method is that it runs very quickly. As shown in Table 6, with the help of the well designed data structure, such as inverted index and skiplist, it can achieve the best computational complexity $O(\log n)$. However, there are still lots of appropriate candidate responses that don’t have the word overlap with the conversation context, but have very high semantic correlation with the context. Sparse representation cannot effectively find these cases in the pre-constructed database, which may lead to the bad performance. For example, as shown in Table 1, it can be found that, the ratio of the ground-truths that can be retrieved by considering word-overlap is low.

Dense representation: Recently, dense representation methods, represented by dual-encoder architecture, (Lowe et al., 2015; Tahami et al., 2020; Humeau et al., 2020; Karpukhin et al., 2020), have attracted increasing attention of researchers, because the rich semantic information could be effec-
tively leveraged. Besides, large scale pre-trained language models (PLMs) significantly boost the performance of dense representation methods. As shown in Figure 1, it can be found that, a dense representation method that leverages the dual-encoder architecture contains two modules: (1) semantic encoders (Humeau et al., 2020; Tahami et al., 2020; Karpukhin et al., 2020) are used to obtain the semantic representations of context and candidate responses. It should be noted that, context semantic encoder and candidate semantic encoder don’t share the parameters, and are optimized separately during training; (2) matching degree is calculated by using dot production or cosine similarity, and utterances that have Top-K matching degrees will be selected as the candidates.

However, due to the high computational burden of similarity calculating, dense representation method runs very slowly. As shown in Table 6, it can be found that its computational complexity is much bigger than sparse representation methods.

2.1.2 Fine-grained Selection Module

Based on the candidate responses provided by the coarse-grained selection module, fine-grained selection module selects the most appropriate one as the final response to the given conversation context. Over the past few years, there are numerous works proposed to improve the performance of fine-grained selection module in retrieval-based chatbots (Wu et al., 2017; Zhang et al., 2018; Zhou et al., 2018; Tao et al., 2019b; Gu et al., 2019; Tao et al., 2019a; Yuan et al., 2019). Especially, recent works (Whang et al., 2019; Gu et al., 2020) achieve the state-of-the-art results for fine-grained selection by using large scale pre-trained language models (PLMs), e.g. BERT (Devlin et al., 2019). However, because of the diminishing returns (Bisk et al., 2020), it becomes more and more difficult to improve the open-domain dialog systems by updating the fine-grained selection module. Compared with the fine-grained selection module, there are very few works to study the coarse-grained selection module, which is a potential breakthrough to improve the retrieval-based open-domain dialog systems further, and ignored by most of works.

In this paper, a fine-grained selection module serves two purposes: (1) Construct a reliable metric that measures the average correlation between the conversation context and candidates; (2) Build retrieval-based chatbots with different coarse-grained selection modules to measure their whole performances.

2.2 Deep Semantic Hashing

Due to computational and storage efficiencies of the compact binary hash codes, hashing methods has been widely used for large-scale similarity search (Xu et al., 2015). The main methodology of deep hashing is similarity preserving, i.e., minimizing the gap between the similarities computed in the original space and the similarities in the hashing code space (Wang et al., 2018). After optimizing, the hashing codes could save the rich semantic information and similarity information in original dense vectors.

3 Experiment Settings

3.1 Datasets

In this paper, we select four popular chinese open-domain dialog datasets:

- **E-Commerce Corpus** (Zhang et al., 2018) is collected from the real world conversations between the customers and the service staff from the largest ecommerce platform Taobao\(^2\). It is commonly used to test the multi-turn response selection models (Zhang et al., 2018; Yuan et al., 2019).

- **Douban Corpus** (Wu et al., 2017) is another popular response selection dataset, which contains dyadic dialogs crawle from the Douban Group\(^3\). It should be noted that, in the original test dataset, each conversation context may

\(^2\)https://www.taobao.com
\(^3\)https://www.douban.com/group
have multiple ground-truths, and we ignore these cases in this paper.

- **Zh50w Corpus**\(^4\) is a Chinese open-domain dialog corpus. It is crawled from the Weibo social network platform, which has more casual conversations than Douban Corpus and E-Commerce Corpus.

- **LCCC Corpus** (Wang et al., 2020) is a large-scale cleaned Chinese open-domain conversation dataset. The quality of LCCC Corpus is ensured by a rigorous data cleaning pipeline, which is built based on a set of rules and a classifier. The size of the original LCCC Corpus is very huge, and we randomly sample 2 million conversations in this paper.

For each corpus, we save all of the responses in train and test datasets into corresponding pre-constructed database, which is used by coarse-grained selection module. The details of these datasets are shown in Table 1.

| Datasets     | Train | Test | Retrieval Ratio | Database Size |
|--------------|-------|------|-----------------|---------------|
| E-Commerce   | 1M    | 1,000| 46.81%          | 109,105       |
| Douban       | 1M    | 667  | 54.57%          | 442,280       |
| Zh50w        | 1M    | 3,000| 28.5%           | 388,614       |
| LCCC         | 4M    | 10,000| 33.59%         | 1,651,899     |

Table 1: Data statistic of four popular datasets. **Retrieval Ratio** is the proportion of samples that can be retrieved by sparse representation methods. **Database Size** is the number of the utterances saved in pre-constructed database.

### 3.2 Methods

In this paper, three coarse-grained selection methods are measured: (1) **BM25** (Robertson and Zaragoza, 2009): following the previous works (Karpukhin et al., 2020; Xiong et al., 2020; Luan et al., 2020), we select BM25 sparse representation method, which is widely used in real scenarios; (2) **Dense** (Karpukhin et al., 2020): we select Dense as the dense representation method, which use the PLM-based dual-encoder architecture to construct the coarse-grained selection module (Karpukhin et al., 2020; Luan et al., 2020); (3) **DSHC**: our proposed deep semantic hashing based coarse-grained selection method. More details are shown in Section 5.

To implement BM25 method, Elasticsearch\(^5\) is used in this paper, which is a very powerful search engine based on the Lucene library. For Dense and DSHC methods, following the previous works (Xiong et al., 2020; Karpukhin et al., 2020), FAISS\(^6\) (Johnson et al., 2017; Karpukhin et al., 2020) toolkit is used in this paper. Besides, GPU devices (GeForce GTX 1080 Ti) are used to accelerate the searching process.

### 3.3 Evaluation Metrics

To measure the performance of these coarse-grained selection modules in real scenarios, we select four important evaluation metrics:

- **Effectiveness**: Following previous work (Xiong et al., 2020; Karpukhin et al., 2020), Coverage@20/100 (Top-20/100) metric is used to evaluate whether Top-20/100 retrieved candidates include the ground-truth response. However, during the testing, we find that this metric is not appropriate to measure the effectiveness of the coarse-grained selection module. The reasons are as follows: The Top-20/100 metric only demonstrates whether only one ground-truth response can be retrieved. It cannot reflect the quality of all of the retrieved candidates. A good coarse-grained selection module should recalls candidates that are all semantic coherent with the given conversation context, not only one candidate. Thus, in this paper, we propose a Correlation@20/100 (Correlation-20/100) as a more reliable metric to measure the effectiveness. Specifically, we leverage a state-of-the-art fine-grained selection module (Whang et al., 2019) that fine-tunes on BERT model, to provide average correlation scores of the retrieved candidates.

- **Search Time Cost**: Search time cost is a core metric in a real application, which directly influences the interaction speed between chatbots and customers. In this paper, we records the average time cost (milliseconds) that the coarse-grained selection module searches the \(b\) candidate responses for each conversation context in test dataset, where \(b = 16\).

- **Index Storage**: For every coarse-grained selection module, it will construct a index that is calculated off-line to search the candidates. For sparse representation method, the index is a inverted index storing a mapping from keywords to its locations.

\(^4\)https://github.com/yangjianxin1/GPT2-chitchat
\(^5\)https://www.elastic.co
\(^6\)https://github.com/facebookresearch/faiss
in a candidate response. For dense representation method, the index is a huge matrix $M \in \mathbb{R}^{n \times d}$ that saves the dense vectors of all candidate responses, where $n$ is the number of the utterances in the pre-constructed database, and $d$ is the length of vectors.

**Human Evaluation:** In dialog system research community, human evaluation is the most reliable metric to measure the performance of dialog systems (Liu et al., 2016; Tao et al., 2018). In this paper, for each corpus, three crowd-sourced annotators are employed to evaluate the quality of generated responses for 200 randomly sampled conversation context. It should be noted that, the responses are generated by a whole retrieval-based chatbot, which consists of one coarse-grained selection module (BM25 or Dense or DSHC) and a state-of-the-art fine-grained selection module (Whang et al., 2019). During the evaluation, the annotators are requested to select a preferred response, or vote a tie from two responses that are generated by two retrieval-based chatbots. Besides, Cohen’s kappa scores (Cohen, 1960) are used to measure the intra-rater reliability.

### 4 Comparison of Sparse and Dense Representation Methods

In this section, we measure the performance of two kinds of coarse-grained selection module. The experiment results are shown in Table 2 and Table 3, and we can make the following conclusions:

**Effectiveness:** As shown in Table 3, it can be observed that, dense representation method show the worse performance than BM25 method on Top-20/100 metrics. As described before, the Top-20/100 metrics are questionable to measure the quality of the retrieved candidates, because Top-20/100 metrics cannot consider the average coherence between the candidates and the given conversation context. As for the Correlation-20/100 metrics, it can be found that the dense representation significantly outperforms the BM25 method. For example, compared with BM25 method, dense representation method achieves average 19.89% absolute improvement on Correlation-20 metric, which demonstrates that the candidates retrieved by dense representation method are more semantic coherent with the conversation context.

**Index Storage:** Referring to the results in sixth columns in Table 3, it can be observed that the dense representation method has more than 200 times the average index storage occupation of the BM25 method. As shown in Figure 3 (b), it can also be observed that, the index storage is even much bigger than the pre-constructed database. The index storage becomes too big to use in real scenarios as more and more utterances are saved in pre-constructed database.

**Search Time Cost:** Referring to the results in the seventh column in Table 3, although the computational complexity of Dense method is much bigger than BM25 method, Dense achieves the smaller searching time cost than BM25 method on E-Commerce Corpus and Douban Corpus, with the help of the parallel computing provided by GPU devices. However, if the size of the pre-constructed database becomes huge, the dense representation method still cost more time than BM25 method, for example, LCCC Corpus.

**Human Evaluation:** As shown in Table 2, it can be found that dense representation method brings more preferable responses compared with BM25 method on these four datasets, which indicates that rich semantic information captured by dense representation does improve the response quality.

| Dense vs. BM25 | Win   | Loss  | Tie   | Kappa |
|----------------|-------|-------|-------|-------|
| E-Commerce     | 0.5917| 0.2117| 0.1967| 0.7679|
| Douban         | 0.4783| 0.1883| 0.3333| 0.8240|
| Zh50w          | 0.5017| 0.2683| 0.23   | 0.7143|
| LCCC           | 0.5233| 0.305  | 0.1717| 0.5558|

Table 2: Human evaluation of Dense vs. BM25 on four datasets. Very high Cohen’s kappa scores prove the high consistency among the annotators.

Compared with BM25 method, dense representation method could achieve better performance but cost more time and index storage occupation, which is unsatisfied in real scenarios. In order to overcome these fatal weaknesses, in next section, we propose a novel deep semantic hashing based coarse-grained selection module, called DSHC.

### 5 Deep Semantic Hashing

#### Coarse-grained Selection Method (DSHC)

5.1 Methodology

5.1.1 The Architecture of DSHC

The overview of our proposed DSHC model is shown in Figure 2, which contains two parts: conversation embedding and hashing optimizing.

For conversation embedding part, we leverage a trained dense representation coarse-grained selec-
Table 3: The comparison between the BM25 method and Dense method. Dense method significantly outperforms BM25 method, but cost more time and index storage occupation.

(a) Experiment results on E-Commerce Corpus.

| Methods | Top-20 | Top-100 | Correlation-20 | Correlation-100 | Index Storage | Search Time Cost (20/100) |
|---------|--------|---------|----------------|----------------|---------------|---------------------------|
| BM25    | 0.025  | 0.085  | 0.618          | 0.5122         | 2.9 Mb        | 89.5 ms/129.4 ms          |
| Dense (gpu) | 0.204  | 0.413  | 0.9537         | 0.9203         | 320 Mb        | 40.6 ms/39.8 ms           |

(b) Experiment results on Douban Corpus.

| Methods | Top-20 | Top-100 | Correlation-20 | Correlation-100 | Index Storage | Search Time Cost (20/100) |
|---------|--------|---------|----------------|----------------|---------------|---------------------------|
| BM25    | 0.063  | 0.096  | 0.6957         | 0.6057         | 21.4 Mb       | 448.7 ms/499.7 ms         |
| Dense (gpu) | 0.054  | 0.1049 | 0.9403         | 0.9067         | 1.3 Gb        | 200 ms/177.1 ms           |

(c) Experiment results on Zh50w Corpus.

| Methods | Top-20 | Top-100 | Correlation-20 | Correlation-100 | Index Storage | Search Time Cost (20/100) |
|---------|--------|---------|----------------|----------------|---------------|---------------------------|
| BM25    | 0.0627 | 0.1031 | 0.84           | 0.7341         | 10.8 Mb       | 91.5 ms/122.8 ms          |
| Dense (gpu) | 0.044  | 0.0824 | 0.9655         | 0.9424         | 1.2 Gb        | 122.4 ms/128.3 ms         |

(d) Experiment results on LCCC Corpus.

| Methods | Top-20 | Top-100 | Correlation-20 | Correlation-100 | Index Storage | Search Time Cost (20/100) |
|---------|--------|---------|----------------|----------------|---------------|---------------------------|
| BM25    | 0.0376 | 0.07    | 0.8966         | 0.8253         | 44 Mb         | 190.1 ms/247 ms           |
| Dense (gpu) | 0.0351 | 0.0778 | 0.9832         | 0.9726         | 4.8 Gb        | 458.6 ms/572.2 ms         |

For hashing optimizing part, DSHC model optimizes two deep autoencoders to generate the hash codes $h_{ctx}$ and $h_{can}$ for $e_{ctx}$ and $e_{can}$ by minimizing the objective function that consists of three loss functions: quantization loss, hash loss, and preserved loss. Specifically, the hashing optimizing part first encodes the dense embeddings into the output vectors $o_{ctx}$, $o_{can}$:

\begin{equation}
\begin{aligned}
    o_{ctx} &= \text{Encoder}_{ctx}(e_{ctx}), o_{ctx} \in \mathbb{R}^{h} \\
    o_{can} &= \text{Encoder}_{can}(e_{can}), o_{can} \in \mathbb{R}^{h} \\
    h_{ctx} &= \text{sign}(o_{ctx}), \{-1, 1\}^{h} \\
    h_{can} &= \text{sign}(o_{can}), \{-1, 1\}^{h}
\end{aligned}
\end{equation}

, where $h$ is the hash code size. During inference, $\text{sign}(\cdot)$ function is used to convert $o_{ctx}$ and $o_{can}$ into the hash codes $h_{ctx}$ and $h_{can}$. Then, hashing optimizing part reconstructs the dense embeddings from $o_{ctx}$ and $o_{can}$:

\begin{equation}
\begin{aligned}
    E_{ctx} &= \text{Decoder}_{ctx}(o_{ctx}), E_{ctx} \in \mathbb{R}^{768} \\
    E_{can} &= \text{Decoder}_{can}(o_{can}), E_{can} \in \mathbb{R}^{768}
\end{aligned}
\end{equation}

Figure 2: The overview of our proposed DSHC model for retrieval-based chatbots. DSHC model contains two parts: conversation embedding and hashing optimizing.

5.1.2 Objective Function

Our proposed DSHC model aims to compressed the dense vectors $e_{ctx}$ and $e_{can}$ into semantic similarity-preserving hash codes $h_{ctx}$ and $h_{can}$ that
can be efficiently computed in real scenarios. Besides, the hash code of an appropriate response $h_{can}$ should be very similar to the hash code of the conversation context $h_{ctx}$, otherwise it is not. In order to achieve this goal, we design three loss functions to optimize the hashing optimizing part: (1) preserved loss; (2) hash loss; (3) quantization loss.

**Preserved loss:** To preserve rich semantic information in dense vectors into hash codes, the reconstructed dense embeddings $E_{ctx}$ and $E_{can}$ should be similar to $e_{ctx}$ and $e_{can}$. Thus, we design the preserved loss to measure the difference between $e_{ctx}$ and $E_{ctx}$, and between $e_{can}$ and $E_{can}$, which are the L2 norm (Euclidean norm) losses:

$$L_p = \|e_{ctx} - E_{ctx}\|^2 + \|e_{can} - E_{can}\|^2 \quad (3)$$

**Hash loss:** Although preserved loss ensures that the $e_{ctx}$ and $o_{can}$ contains the rich semantic information in $e_{ctx}$ and $e_{can}$, there is still no way to measure the similarity between the conversation context hash codes and candidate hash codes. In order to ensure that hash codes could preserve the semantic similarity between the conversation context and the candidate response, the hash loss is designed. For hash codes in Hamming space, if the similarity $S(o_{ctx}, o_{can}) = 1$, i.e., the candidate is appropriate to the context, the Hamming distance $\|o_{ctx} - o_{can}\|_H = 0.5(h - o_{ctx}^T o_{can})$ between $o_{ctx}$ and $o_{can}$ should be equal to 0, which indicates that $o_{ctx}^T o_{can}$ should be equal to $h$, where $h$ is the dimension of the hash codes; if the similarity $S(o_{ctx}, o_{can}) = 0$, i.e., the candidate is inappropriate to the context, the Hamming distance $\|o_{ctx} - o_{can}\|_H$ should be equal to $\frac{1}{2}$, which indicates that $o_{ctx}^T o_{can}$ should be equal to 0. Therefore, the hash loss is designed as following:

$$L_h = \|o_{ctx}^T o_{can} - hS(o_{ctx}, o_{can})\|^2 \quad (4)$$

s.t. $S(o_{ctx}, o_{can}) \in \{0, 1\}$

**Quantization loss:** So far, preserved loss and hash loss ensure that $o_{ctx}$ and $o_{can}$ preserve the semantic information and the similarity between them. However, during inference, the hash codes $h_{ctx}$ and $h_{can}$ are used to search the candidates, which are roughly converted by using $\text{sign}(\cdot)$ function. In order to narrow the gap between $h_{ctx}$ and $o_{ctx}$, and $h_{can}$ and $o_{can}$, the quantization loss (Wang et al., 2018) is used to ensure that each element of $o_{ctx}$ and $o_{can}$ can be close to “+1” or “-1”:

$$L_q = \|h_{ctx} - o_{ctx}\|^2 + \|h_{can} - o_{can}\|^2 \quad (5)$$

Finally, the overall objective function is obtained as follows:

$$L = L_p + L_h + \gamma_t \cdot L_q \quad (6)$$

s.t. $\gamma_t = \gamma_{min} + \frac{\gamma_{max} - \gamma_{min}}{T} \cdot t$

where $\gamma_t$ is a hyperparameter that dynamically balances the processing of optimizing hash loss and quantization loss. In this paper, $\gamma_{min} = 1e^{-4}$, $\gamma_{max} = 1e^{-1}$. $T$ is the number of the mini-batch in one epoch, and $t \in \{0, 1, 2..., T - 1\}$ is the current running step.

### 5.2 Overall Comparison

In this section, we carefully compare three coarse-grained selection methods: (1) BM25; (2) Dense; (3) our proposed DSHC model.

**Effectiveness:** As shown in Table 4, it can be observed that, our proposed DSHC model significantly outperforms the BM25 method. Besides, the performance of DSHC model is very close to the Dense representation method, which indicates that our proposed DSHC model effectively preserves the rich semantic information and the similarity information between the conversation context and candidate response. For example, there is only 2.6% absolute average decline on correlation-20 metric for DSHC-512 model. In view of that compressed binary hash codes lost lots of information, the results are pretty good.

**Index Storage:** Furthermore, as shown in sixth column in Table 4, it can also be found that, the index storage occupation of our proposed DSHC model is much smaller than the Dense method, even smaller than BM25 method if the dimension of the hash codes is 128.

**Search Time Cost:** Moreover, although the computational complexity of computing hamming distance is worse than BM25, with the help of very high computational efficiencies of hash codes, and parallel computing provided by GPU devices, our proposed DSHC model still achieves the smallest search time cost i.e. the fastest search speed, than BM25 methods. For example, DSHC-128 model is nearly 15x faster than the widely used BM25 method.

**Human Evaluation:** Finally, we also conduct the human evaluation to measure the performane
more accurately. As shown in Table 5 (a), it can be found that, the performance of DSHC and Dense methods are very close. Quite surprisingly, our proposed DSHC model is even better than Dense method on LCCC corpus. Besides, from Table 5 (b), it can also be found that, DSHC model significantly outperforms the widely used BM25 method, because DSHC model wins most of the time. The very high Cohen’s kappa scores demonstrate that the decision of the annotators are highly consistent.

(a) Human Evaluation of Dense vs. DSHC.

|        | Dense vs. DSHC | Win  | Loss | Tie  | Kappa  |
|--------|----------------|------|------|------|--------|
| E-Commerce | 0.3133 | 0.2683 | 0.4183 | 0.7025 |
| Douban  | 0.375 | 0.2217 | 0.4033 | 0.8251 |
| Zh50w   | 0.395 | 0.2833 | 0.3217 | 0.6679 |
| LCCC    | 0.3283 | 0.3733 | 0.2983 | 0.7716 |

(b) Human Evaluation of DSHC vs. BM25.

|        | DSHC vs. BM25 | Win  | Loss | Tie  | Kappa  |
|--------|---------------|------|------|------|--------|
| E-Commerce | 0.6017 | 0.1933 | 0.205 | 0.6733 |
| Douban  | 0.4767 | 0.2783 | 0.245 | 0.8506 |
| Zh50w   | 0.4733 | 0.335 | 0.1917 | 0.727 |
| LCCC    | 0.5317 | 0.27 | 0.1983 | 0.7115 |

Table 5: Human evaluation on four datasets. Very high Cohen’s kappa scores prove the high consistency among the annotators.

6 Case Study

Due to the page limitation, cases are shown in Table 8 in Appendix. Referring to these cases, it can be found that, the retrieval-based chatbots that use the dense representation and our proposed DSHC methods provide more semantic coherent responses to the given conversation context than BM25 method. Besides, the responses given by dense representation method and DSHC method are both very appropriate, which proves the effectiveness of our proposed DSHC model.

7 Conclusion

In this paper, we first systematically compare the dense and sparse representation method in retrieval-based chatbot from four important aspects: (1) effectiveness; (2) search time cost; (3) index storage; (4) human evaluation. Extensive experiment results demonstrate that dense representation method could achieve better performance at the expense of more time cost and higher storage occupation. In order to overcome these fatal weaknesses, we propose a deep semantic hashing based coarse-grained (DSHC) selection method. Extensive experiment results prove the effectiveness and the efficiency of DSHC model.

References

Yonatan Bisk, Ari Holtzman, Jesse Thomason, Jacob Andreas, Yoshua Bengio, Joyce Chai, M. Lapata, A. Lazaridou, Jonathan May, Aleksandr Nisnevich, Nicolas Pinto, and Joseph P. Turian. 2020. Experience grounds language. In EMNLP.

J. Cohen. 1960. A coefficient of agreement for nominal scales. Educational and Psychological Measurement, 20:37 – 46.

J. Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In NAACL-HLT.

Zhenxin Fu, Shaobo Cui, Mingyue Shang, Feng Ji, Dongyan Zhao, H. Chen, and R. Yan. 2020. Context-to-session matching: Utilizing whole session for response selection in information-seeking dialogue systems. Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining.

Jia-Chen Gu, Tianda Li, Q. Liu, Xiao-Dan Zhu, Zhenhua Ling, Zhiming Su, and Si Wei. 2020. Speaker-aware bert for multi-turn response selection in retrieval-based chatbots. Proceedings of the 29th ACM International Conference on Information & Knowledge Management.

Jia-Chen Gu, Z. Ling, and Q. Liu. 2019. Interactive matching network for multi-turn response selection in retrieval-based chatbots. Proceedings of the 28th ACM International Conference on Information and Knowledge Management.

Samuel Humeau, Kurt Shuster, Marie-Anne Lachaux, and J. Weston. 2020. Poly-encoders: Architectures and pre-training strategies for fast and accurate multi-sentence scoring. In ICLR.

Jeff Johnson, Matthijs Douze, and Hervé Jégou. 2017. Billion-scale similarity search with gpus. arXiv preprint arXiv:1702.08734.

V. Karpukhin, Barlas Oğuz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen tau Yih. 2020. Dense passage retrieval for open-domain question answering. In EMNLP.

C. Liu, Ryan Lowe, I. Serban, Michael Noseworthy, Laurent Charlin, and Joëlle Pineau. 2016. How not to evaluate your dialogue system: An empirical study of unsupervised evaluation metrics for dialogue response generation. ArXiv, abs/1603.08023.

Ryan Lowe, Nissan Pow, I. Serban, and Joëlle Pineau. 2015. The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. ArXiv, abs/1506.08909.
### (a) Experiment results on E-Commerce Corpus.

| Methods       | Top-20 | Top-100 | Correlation-20 | Correlation-100 | Index Storage | Search Time Cost (20/100) |
|---------------|--------|---------|----------------|-----------------|---------------|---------------------------|
| BM25          | 0.025  | 0.035   | 0.615          | 0.5122          | 2.9 Mb        | 89.5ms/129.4ms            |
| Dense (gpu)   | 0.204  | 0.413   | 0.9537         | 0.9203          | 320 Mb        | 389.3ms/401.5ms           |
| DSHC-128 (gpu)| 0.183  | 0.366   | 0.9252         | 0.8808          | 1.7 Mb        | 4ms/6.3ms                 |
| DSHC-512 (gpu)| 0.214  | 0.382   | 0.944          | 0.9065          | 6.7 Mb        | 9.3ms/18.7ms              |

### (b) Experiment results on Douban Corpus.

| Methods       | Top-20 | Top-100 | Correlation-20 | Correlation-100 | Index Storage | Search Time Cost (20/100) |
|---------------|--------|---------|----------------|-----------------|---------------|---------------------------|
| BM25          | 0.063  | 0.096   | 0.6957         | 0.6057          | 21.4 Mb       | 448.7ms/499.7ms           |
| Dense (gpu)   | 0.054  | 0.1049  | 0.9403         | 0.9203          | 1.3 Gb        | 200ms/177.1ms             |
| DSHC-128 (gpu)| 0.012  | 0.0465  | 0.8375         | 0.8016          | 6.8 Mb        | 20.9ms/19.6ms             |
| DSHC-512 (gpu)| 0.0225 | 0.066   | 0.8838         | 0.8474          | 27 Mb         | 52.3ms/45.2ms             |

### (c) Experiment results on Zh50w Corpus.

| Methods       | Top-20 | Top-100 | Correlation-20 | Correlation-100 | Index Storage | Search Time Cost (20/100) |
|---------------|--------|---------|----------------|-----------------|---------------|---------------------------|
| BM25          | 0.0627 | 0.1031  | 0.84           | 0.7341          | 10.8 Mb       | 91.5ms/122.8ms            |
| Dense (gpu)   | 0.044  | 0.0824  | 0.9655         | 0.9424          | 1.2 Gb        | 122.4ms/128.3ms           |
| DSHC-128 (gpu)| 0.027  | 0.0724  | 0.9108         | 0.8835          | 6.0 Mb        | 20.3ms/28ms               |
| DSHC-512 (gpu)| 0.0377 | 0.0934  | 0.944          | 0.9223          | 24.3         |                           |

### (d) Experiment results on LCCC Corpus.

| Methods       | Top-20 | Top-100 | Correlation-20 | Correlation-100 | Index Storage | Search Time Cost (20/100) |
|---------------|--------|---------|----------------|-----------------|---------------|---------------------------|
| BM25          | 0.0376 | 0.07    | 0.8966         | 0.8253          | 44 Mb         | 190.1ms/247ms             |
| Dense (gpu)   | 0.0351 | 0.0778  | 0.9832         | 0.9726          | 4.8 Gb        | 458.6ms/572.2ms           |
| DSHC-128 (gpu)| 0.014  | 0.0348  | 0.9369         | 0.9187          | 26 Mb         | 20.4ms/24.4ms             |
| DSHC-512 (gpu)| 0.0204 | 0.0494  | 0.9663         | 0.9526          | 101 Mb        | 76.4ms/94ms               |

Table 4: Parameters 128 and 512 are the dimension of the hash codes $h$ in our proposed DSHC model.

---

Yi Luan, Jacob Eisenstein, Kristina Toutanova, and M. Collins. 2020. Sparse, dense, and attentional representations for text retrieval. *ArXiv*, abs/2005.00181.

S. Robertson and H. Zaragoza. 2009. The probabilistic relevance framework: Bm25 and beyond. *Found. Trends Inf. Retr.*, 3:333–389.

Amir Vakili Tahami, Kamyar Ghajar, and A. Shakery. 2020. Distilling knowledge for fast retrieval-based chatbots. *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*.

Chongyang Tao, Lili Mou, Dongyan Zhao, and R. Yan. 2018. Ruber: An unsupervised method for automatic evaluation of open-domain dialog systems. In *AAAI*.

Chongyang Tao, Wei Wu, Can Xu, Wenpeng Hu, Dongyan Zhao, and R. Yan. 2019a. One time of interaction may not be enough: Go deep with an interaction-over-interaction network for response selection in dialogues. In *ACL*.

Chongyang Tao, Wei Wu, Can Xu, Wenpeng Hu, Dongyan Zhao, and R. Yan. 2019b. Multi-representation fusion network for multi-turn response selection in retrieval-based chatbots. *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*.

Jingdong Wang, T. Zhang, Jingkuan Song, N. Sebe, and H. Shen. 2018. A survey on learning to hash. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40:769–790.

Yida Wang, Pei Ke, Yinhe Zheng, Kaili Huang, Y. Jiang, X. Zhu, and Minlie Huang. 2020. A large-scale chinese short-text conversation dataset. *ArXiv*, abs/2008.03946.

T. Whang, Dongyub Lee, Chanhee Lee, Kisu Yang, Dongsuk Oh, and Heuiseok Lim. 2019. Domain adaptive training bert for response selection. *ArXiv*, abs/1908.04812.

Yu Wu, Wei Yu Wu, M. Zhou, and Zhoujun Li. 2017. Sequential match network: A new architecture for multi-turn response selection in retrieval-based chatbots. In *ACL*.

Lee Xiong, Chenyan Xiong, Ye Li, Kwok-Fung Tang, J. Liu, P. Bennett, Junaid Ahmed, and Arnold Overwijk. 2020. Approximate nearest neighbor negative contrastive learning for dense text retrieval. *ArXiv*, abs/2007.00808.

Jiaming Xu, P. Wang, Guanhua Tian, Bo Xu, Jun Zhao, Fangyuwan Wang, and Hongwei Hao. 2015. Convolutional neural networks for text hashing. In *IJCAI*.

Chunyuan Yuan, W. Zhou, M. Li, Shangwen Lv, F. Zhu, Jizhong Han, and Songlin Hu. 2019. Multi-hop selector network for multi-turn response selection in retrieval-based chatbots. In *EMNLP/IJCNLP*.
Although BM25 method achieves the best computational complexity of three coarse-grained selection methods are shown in Table 6. Although BM25 method achieves the best computational complexity by using well designed data structure, such as inverted index and skiplist, it cannot be accelerated by using GPU devices. In real scenarios, with the help of the parallel computing provided by GPU devices, DSHC method could achieve much faster searching speed.

It should be noted that, lots of works have been proposed to optimize the computational complexity of computing the dot production and Hamming distance, such as product quantizer and inverted index, and the computational complexities of Dense and DSHC methods shown in Table 6 are the worst cases. In this paper, we don’t consider to leverage these techniques to search candidates in Dense and DSHC methods. Brute-force search i.e. linear scan is used to find the Top-K (20/100) candidates in coarse-grained selection module, which directly scans all of the utterances in the pre-constructed database.

### A.2 Hyperparameters Analysis

In this section, we analyze the hyperparameter $h$ i.e. the dimension of the hash codes, in our proposed DSHC model. For our proposed DSHC model, we separately test the 16,32,48,64,128,256,512,1024 dimensions of the hash codes. The results are shown in Table 7.

### A.4 Storage Occupation Visualization

The storage occupation of the pre-constructed database and index are shown in Figure 3.
Figure 3: The index and pre-constructed database storage occupation in four datasets. It should be noted that the scale is nonlinear.
I have seen it before. No, you did it on purpose. Lol, it’s really close. Very good, very creamy. Okay. Yes. Now, please check the delivery address. We can send it in your today. We need goods by EMS.

Table 8: Utterances are already translated from Chinese to English.