Building a Production Model for Retrieval-Based Chatbots

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Abstract

Response suggestion is an important task for building human-computer conversation systems. Recent approaches to conversation modeling have introduced new model architectures with impressive results, but relatively little attention has been paid to whether these models would be practical in a production setting. In this paper, we describe the unique challenges of building a production retrieval-based conversation system, which selects outputs from a whitelist of candidate responses. To address these challenges, we propose a dual encoder architecture which performs rapid inference and scales well with the size of the whitelist. We also introduce and compare two methods for generating whitelists, and we carry out a comprehensive analysis of the model and whitelists. Experimental results on a large, proprietary help desk chat dataset, including both offline metrics and a human evaluation, indicate production-quality performance and illustrate key lessons about conversation modeling in practice.

1 Introduction

Predicting a response given conversational context is a critical task for building open-domain chatbots and dialogue systems. Recently developed conversational systems typically use either a generative or a retrieval approach for producing responses (Wang et al., 2013; Ji et al., 2014; Vinyals and Le, 2015; Serban et al., 2015; Li et al., 2016; Xing et al., 2016; Deb et al., 2019). While both of these approaches have demonstrated strong performance in the literature, retrieval methods often enjoy better control over response quality than generative approaches. In particular, such methods select outputs from a whitelist of candidate responses, which can be pre-screened and revised for desired qualities such as sentence fluency and diversity.

Most previous work on retrieval models has concentrated on designing neural architectures to improve response selection. For instance, several works have improved model performance by encoding multi-turn conversation context instead of single-turn context (Serban et al., 2015; Zhou et al., 2016; Wu et al., 2017). More recent efforts (Zhou et al., 2018; Zhang et al., 2018) have explored using more advanced architectures, such as the Transformer (Vaswani et al., 2017), to better learn the mapping between the context and the candidate responses.

Relatively little effort, however, has been devoted to the practical considerations of using such models in a real-world production setting. For example, one critical consideration rarely discussed in the literature is the inference speed of the deployed model. While recent methods introduce rich computation, such as cross-attention (Zhou et al., 2018), to improve the modeling between the conversational context and candidate response, the model outputs must be re-computed for every pair of context and response. As a consequence, these models are not well-suited to a production setting where the size of the response whitelist can easily extend into the thousands.

Another critical concern is the whitelist selection process and the associated retrieval evaluation. Most prior work have reported Recall@\textit{k} on a small set of randomly selected responses which include the true response sent by the agent (Lowe et al., 2015; Zhou et al., 2016, 2018; Wu et al., 2017; Zhang et al., 2018). However, this oversimplified evaluation may not provide a useful indication of performance in production, where the whitelist is not randomly selected, is significantly larger, and may not contain the target response.

In this paper, we explore and evaluate model
and whitelist design choices for building retrieval-based conversation systems in production. We present a dual encoder architecture that is optimized to select among as many as 10,000 responses within a couple tens of milliseconds. The model makes use of a fast recurrent network implementation (Lei et al., 2018) and multi-headed attention (Lin et al., 2017) and achieves over a 4.1x inference speedup over traditional encoders such as LSTM (Hochreiter and Schmidhuber, 1997). The independent dual encoding allows pre-computing the embeddings of candidate responses, thereby making the approach highly scalable with the size of the whitelist. In addition, we compare two approaches for generating the response candidates, and we conduct a comprehensive analysis of our model and whitelists on a large, real-world help desk dataset, using human evaluation and metrics that are more relevant to use in a production setting.

2 Related Work

This paper extends the line of work on conversational retrieval models for multi-turn response selection (Lowe et al., 2015; Al-Rfou et al., 2016; Zhou et al., 2016, 2018; Wu et al., 2016, 2017; Yan et al., 2016; Lu et al., 2017; Zhang et al., 2018; Shalyminov et al., 2018; Deb et al., 2019; Yang et al., 2019). Our model is most similar to Lowe et al. (2015), who construct the context of the conversation by concatenating all previous utterances. They use an RNN to separately encode the context and each candidate response, and they then compute a matching score between the context and response representations to determine the best response for that context.

Other recent work has explored more complex methods of incorporating information from the context of a conversation. Serban et al. (2015) and Zhou et al. (2016) employ a hierarchical architecture in which they encode the context using RNNs at both the word level and the utterance level. In contrast to these models, which generate a single context encoding, Wu et al. (2017) designed a network that matches a response to each utterance in the context individually.

While many of the models cited above implement their RNNs with an LSTM (Hochreiter and Schmidhuber, 1997), we instead use an SRU (Lei et al., 2018). SRU uses light recurrence, which makes it highly parallelizable, and Lei et al. (2018) showed that it trains 5-9x faster than cuDNN LSTM. SRU also exhibits a significant speedup in inference time compared to LSTM (by a factor of 4.1x in our experiments), which is particularly relevant in a production setting. Furthermore, Lei et al. (2018) showed that SRU matches or exceeds the performance of models using LSTMs or the Transformer architecture (Vaswani et al., 2017) on a number of NLP tasks, meaning significant speed gains can be achieved without a drop in performance.

Despite the abundance of prior work on retrieval models for dialogue, whitelist selection has received relatively little attention. Since practical use of conversational models has typically not been addressed, most models are evaluated on their ability to select the correct response from a small list of randomly sampled responses (Lowe et al., 2015). Another option, from Wu et al. (2017), is to use Apache Lucene\(^1\) to select a list of response candidates relevant to each context. However, neither method produces a single whitelist that can be used for every context and reviewed for quality. The closest work to ours is Lu et al. (2017), who build a whitelist using a k-means clustering of responses. We extend this work by doing a more comprehensive analysis of different whitelist selection methods, and we further analyze the effect of whitelist size on performance.

3 Model Architecture

Next we describe the architecture of our retrieval model. The two inputs to the model are a context \(c\), which is a concatenation of all utterances in the conversation, and a candidate response \(r\). In the context, we use special tokens to indicate whether each utterance comes from the customer or the agent. The model outputs a score \(s(c, r)\) indicating the relevance of the response to the context. The model architecture is described in detail below and is illustrated in Figure 1.

3.1 Dual Encoders

At the core of our model are two neural encoders \(f_c\) and \(f_r\) to encode the context and the response, respectively. These encoders have identical architectures but learn separate weights.

Each encoder takes a sequence of tokens \(w = \{w_1, w_2, \ldots, w_n\}\) as input, which is either a con-

\(^1\)http://lucene.apache.org/
text or a response. Due to the prevalence of typos in both user and agent utterances in real chats, we use fastText (Bojanowski et al., 2016) as the word embedding method. fastText learns both word-level and character-level features and is therefore more robust to misspellings. We pre-trained fastText embeddings on a corpus of 15M utterances from help desk conversations and then fixed the embeddings while training the neural encoders.

Each encoder consists of a recurrent neural network followed by a multi-headed attention layer (Lin et al., 2017) to perform pooling. We use multi-layer, bidirectional SRUs as the recurrent network. Each layer of the SRU involves the following computation:

\[
\begin{align*}
    f_t &= \sigma(W_f x_t + v_f \odot c_{t-1} + b_f) \\
    c_t &= f_t \odot c_{t-1} + (1 - f_t) \odot (W_c x_t) \\
    r_t &= \sigma(W_r x_t + v_r \odot c_{t-1} + b_r) \\
    h_t &= r_t \odot c_t + (1 - r_t) \odot x_t,
\end{align*}
\]

where \( \sigma \) is the sigmoid activation function, \( W_f, W_c, W_r \in \mathbb{R}^{d_h \times d_e} \) are learned parameter matrices, and \( v_f, v_r, b_f, b_r \in \mathbb{R}^{d_h} \) are learned parameter vectors.

The multi-headed attention layer compresses the encoded sequence \( h = \{h_1, h_2, \ldots, h_n\} \) into a single vector. For each attention head \( i \), attention weights are generating with the following computation:

\[
\alpha^{(i)} = \text{softmax}(\sigma(h^T W_a^{(i)} v_a^{(i)})),
\]

where \( \sigma \) is a non-linear activation function, \( W_a^{(i)} \in \mathbb{R}^{d_h \times d_a} \) is a learned parameter matrix, and \( v_a^{(i)} \in \mathbb{R}^{d_a} \) is a learned parameter vector.

The encoded sequence representation is then pooled to a single vector for each attention head \( i \) by summing the attended representations:

\[
\tilde{h}^{(i)} = \sum_{j=1}^{n} \alpha^{(i)}(j) h_j.
\]

Finally, the pooled encodings are averaged across the \( n_h \) attention heads:

\[
\tilde{h} = \frac{1}{n_h} \sum_{i=1}^{n_h} \tilde{h}^{(i)}.
\]

The output of the encoder is the vector \( f(w) = \tilde{h} \).

### 3.2 Scoring

To determine the relevance of a response \( r \) to a context \( c \), our model computes a matching score between the context encoding \( f_c(c) \) and the response encoding \( f_r(r) \). This score is simply the dot product of the encodings:

\[
s(c, r) = f_c(c) \cdot f_r(r).
\]

### 3.3 Training

We optimize the model to maximize the score between the context \( c \) and the response \( r^+ \) actually sent by the agent while minimizing the score between the context and each of \( k \) random (“negative”) responses \( r_1^-, \ldots, r_k^- \). This is accomplished by training the model to minimize the cross-entropy loss:

\[
\mathcal{L} = -s(c, r^+) + \log \sum_{r \in R} e^{s(c, r)},
\]

where \( R = \{r^+, r_1^-, \ldots, r_k^-\} \).

Although negative responses could be sampled separately for each context-response pair,
we instead use a method inspired by Logeswaran and Lee (2018) and share a set of negative responses across all examples in a batch. Specifically, for each batch, we sample $k$ responses from the set of all agent responses (weighted according to response frequency), and we use those $k$ responses as the negative responses for every context-response pair in the batch. This has the benefit of reducing the number of responses that need to be encoded in each batch of size $b$ from $O(bk)$ to $O(b + k)$, thereby significantly accelerating training.

3.4 Whitelist Generation

After training, we experimented with two methods of creating the whitelist from which our model selects responses at inference time. For each method, we created both a 1,000 response whitelist and a 10,000 response whitelist. Having a whitelist with any more than 10,000 responses would likely make a manual review infeasible.

Frequency-Based Method. Responses that are sent frequently are more likely to be relevant in multiple conversations and are less likely to contain errors. Therefore, one method of building a high-quality whitelist is simply to collect messages that are sent often. We created frequency-based whitelists by selecting the 1,000 or 10,000 most common agent responses, after accounting for minor variations in capitalization, punctuation, and whitespace.

Clustering-Based Method. Although selecting responses based on frequency may help guarantee quality, manual examination of the frequency whitelists showed that they contained many redundant responses. Therefore, we experimented with a clustering-based whitelist selection method in the hope of reducing redundancy and increasing response diversity. Specifically, we encoded all agent responses using our response encoder $f_r$ and then used $k$-means clustering with $k = 1,000$ or $k = 10,000$ to cluster the responses. We then selected the most common response from each cluster to create the whitelists.

4 Experiments and Results

We evaluated our model and whitelists on a large, proprietary help desk chat dataset using several offline metrics and a human evaluation. We particularly emphasize metrics relevant to production, such as inference speed and Recall@$k$ from a large candidate set. The human evaluation illustrates how our model and whitelists compare to each other and to the responses sent by a real human agent.

4.1 Data

The help desk chat dataset used in our experiments consists of 15M utterances from 595K conversations. We randomly split the conversations into train, validation, and test sets with 80%, 10%, and 10% of the conversations, respectively. Since each conversation includes several agent responses, each of which produces a context-response example, our dataset consists of 6.6M training examples, 828K validation examples, and 828K test examples. Additional dataset statistics are provided in Table 1. An example chat conversation can be seen in Table 2.

4.2 Model Details

We implemented the dual encoder model using PyTorch (Paszke et al., 2017). We use pre-trained fastText embeddings of dimension $d_e = 300$, a 4-layer bidirectional SRU3 with hidden size $d_h = 300$, and multi-headed attention with 16 heads and a hidden size of $d_a = 64$. The batch size was 200 and we used $k = 200$ negative responses for each positive response. To ensure quick encoding even for long inputs, contexts were restricted to the 500 most recent tokens and responses were restricted to the 100 most recent tokens4. The model was optimized using Adam (Kingma and Ba, 2014) with the Noam learning rate schedule from Vaswani et al. (2017). The model was trained for 30 epochs, with each epoch limited to 10,000 training batches (2M training examples). Training took about 32 hours on a single Tesla V100 GPU.

4.3 Results and Analysis

AUC and AUC@$p$. To determine the model’s ability to use context to distinguish between true responses and negative responses, we use the metrics AUC and AUC@$p$. AUC is the area under the receiver operating characteristic curve when using the score $s(c, r)$ to determine whether each re-

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3SRU code available at https://github.com/taolei87/sru/tree/master/sru

4A context with 500 tokens contains 39 utterances on average, which is typically more than enough to understand the topic of conversation. Almost all responses are shorter than 100 tokens.
Table 1: Summary statistics for the propriety help desk dataset.

|                          | Value       |
|--------------------------|-------------|
| Conversations            | 594,555     |
| Utterances               | 15,217,773  |
| Customer utterances      | 6,943,940   |
| Agent utterances         | 8,273,833   |
| Mean conversation length (# utterances) | 25.60       |
| Mean utterance length (# tokens) | 12.70       |
| Mean customer utterance length (# tokens) | 7.53       |
| Mean agent utterance length (# tokens) | 17.15      |

Table 2: A sample conversation from the propriety help desk chat dataset. The sample has been lightly edited to remove proprietary information.

**Example Conversation**

**Customer:** I would like to pay my bill can you help me?

**Agent:** I can definitely help you to pay your bill. Are we going to work with the account logged in now?

**Customer:** Yes it still says there is no money on my account.

**Agent:** I understand that. I have reviewed your account and it shows here that the payment has been posted and you’re all good until next month service.

**Customer:** Oh ok thank you for all your help.

**Agent:** You’re welcome. Anything for a valued customer like you!

Table 3: AUC and AUC@p of our model on the propriety help desk dataset.

| Metric     | Validation | Test  |
|------------|------------|-------|
| AUC        | 0.991      | 0.977 |
| AUC@0.1    | 0.925      | 0.885 |
| AUC@0.05   | 0.871      | 0.816 |
| AUC@0.01   | 0.677      | 0.630 |

Table 4: Recall@k from n response candidates for different values of n using random whitelists. Each random whitelist includes the correct response along with n−1 randomly selected responses.

| Candidates | R@1 | R@3 | R@5 | R@10 |
|------------|-----|-----|-----|------|
| 10         | 0.892 | 0.979 | 0.987 | 1    |
| 100        | 0.686 | 0.842 | 0.894 | 0.948 |
| 1,000      | 0.449 | 0.611 | 0.677 | 0.760 |
| 10,000     | 0.234 | 0.360 | 0.421 | 0.505 |

Recall and Whitelist Size. In order to determine our model’s ability to select the correct response from a whitelist, we use recall at k from n (R_n@k), which is the proportion of times that the true response is ranked as one of the top k responses in a whitelist containing n candidate responses.

Table 4 shows R_n@k on the test set for different values of n and k when using a random whitelist, meaning a whitelist which contains the true response and n−1 randomly sampled responses\(^5\). As discussed in the introduction, most prior work evaluate their models using a random whitelist with n = 10 candidates. However, a production whitelist needs to contain hundreds or thousands of response candidates in order to provide relevant responses in a variety of contexts. Therefore, a more meaningful metric for production purposes is R_n@k for n ≥ 100. Table 4 shows that recall drops significantly as n grows, meaning that the R_{10}@k evaluation performed by prior work may significantly overstate model performance in a production setting.

Comparison Between Whitelists. An interesting question we would like to address is whether

\(^5\)To be precise, we sampled responses without replacement weighted according to the frequency with which the response was sent by agents.
Table 5: Recall@$k$ for random, frequency, and clustering whitelists of different sizes. The “+” indicates that the true response is added to the whitelist.

| Whitelist       | R@1   | R@3   | R@5   | R@10  | BLEU  |
|-----------------|-------|-------|-------|-------|-------|
| Random 10K+     | 0.252 | 0.400 | 0.472 | 0.560 | 37.71 |
| Frequency 10K+  | 0.257 | 0.389 | 0.455 | 0.544 | 41.34 |
| Clustering 10K+ | 0.230 | 0.376 | 0.447 | 0.541 | 37.59 |
| Random 1K+      | 0.496 | 0.663 | 0.728 | 0.805 | 59.28 |
| Frequency 1K+   | 0.513 | 0.666 | 0.726 | 0.794 | 67.05 |
| Clustering 1K+  | 0.481 | 0.667 | 0.745 | 0.835 | 61.88 |
| Frequency 1K    | 0.273 | 0.465 | 0.550 | 0.658 | 47.13 |
| Clustering 1K   | 0.331 | 0.542 | 0.650 | 0.782 | 49.26 |

Table 6: Recall@$1$ versus coverage for frequency and clustering whitelists.

| Whitelist       | R@1       | Coverage  |
|-----------------|-----------|-----------|
| Frequency 10K   | 0.136     | 45.04%    |
| Clustering 10K  | 0.164     | 38.38%    |
| Frequency 1K    | 0.273     | 33.38%    |
| Clustering 1K   | 0.331     | 23.28%    |

Recall versus Coverage. Although recall is a good measure of performance, recall alone is not a sufficient criterion for whitelist selection. The recall results in Table 5 seem to indicate that the clustering-based whitelists are strictly superior to the frequency-based whitelists in the realistic case when we only consider responses that are already contained in the whitelist, but this analysis fails to account for the frequency with which this is the case. For instance, a whitelist may have very high recall but may only include responses that were sent infrequently by agents, meaning the whitelist will perform well for a handful of conversations but will be irrelevant in most other cases.

To quantify this effect, we introduce the notion of coverage, which is the percent of all context-response pairs where the agent response appears in the whitelist, after accounting for minor deviations in capitalization, punctuation, and whitespace. A whitelist that contains responses that are sent more frequently by agents will therefore have a higher coverage.

Table 6 shows R@1 and coverage for the frequency and clustering whitelists. While the clustering whitelists have higher recall, the frequency whitelists have higher coverage. This is to be expected since the frequency whitelists were specifically chosen to maximize the frequency of the included responses. Since both recall and coverage are necessary to provide good responses for a wide range of conversations, these results indicate the importance of considering the trade-off between recall and coverage inherent in a given whitelist selection method.

It may be interesting in future work to further investigate these trade-offs in order to identify a whitelist selection method that can simultaneously optimize recall and coverage.
Human Evaluation. While offline metrics are indicative of model performance, the best measure of performance is a human evaluation of the model’s predictions. Therefore, we performed a small-scale human evaluation of our model and whitelists. We selected 322 contexts from the test set and used our model to generate responses from the Frequency 10K, Frequency 1K, Clustering 10K, and Clustering 1K whitelists. Three human annotators were shown each context followed by five responses: one from each of the four whitelists and the true response sent by the agent. The annotators were blinded to the source of each response. The annotators were asked to rate each response according to the following categories:

**Bad:** The response is not relevant to the context.
**Good:** The response is relevant to the context but is vague or generic.
**Great:** The response is relevant to the context and directly addresses the issue at hand.

For example, three such responses for the context “My phone is broken” would be:

**Bad response:** Goodbye!
**Good response:** I’m sorry to hear that.
**Great response:** I’m sorry to hear that your phone is broken.

The results of the human evaluation are in Table 7. Our proposed system works well, selecting acceptable (i.e. good or great) responses about 80% of the time and selecting great responses more than 50% of the time.

Interestingly, the size and type of whitelist seem to have little effect on performance, indicating that all the whitelists contain responses appropriate to a variety of conversational contexts. Since the frequency whitelists are simpler to generate than the clustering whitelists and since the 1K whitelists contain fewer responses to manually review than the 10K whitelists, the Frequency 1K whitelist is the preferred whitelist for our production system.

Inference Speed. A major constraint in a production system is the speed with which the system can respond to users. To demonstrate the benefit of using an SRU encoder instead of an LSTM encoder in production, we compared the speed with which they encode a random conversation context at inference time, averaged over 1,000 samples. We used a single core of Intel Core i9 2.9 GHz CPU. As seen in Table 8, an SRU encoder is over 4x faster than an LSTM encoder with a similar number of parameters, making it more suitable for production use.

Table 8 also highlights the scalability of using a dual encoder architecture. Since the embeddings of the candidate responses are independent from the conversation context, the embeddings of the whitelist responses can be pre-computed and stored as a matrix. Retrieving the best candidate once the context is encoded takes a negligible amount of time compared to the time to encode the context.

Ablation analysis. Finally, we performed an ablation analysis to identify the effect of different aspects of the model architecture and training regime. The results are shown in Table 9, and details of the model variants are available in the Appendix.

As Table 9 shows, the training set size and the number of negative responses for each positive response are the most important factors in model performance. The model performs significantly worse when trained with hinge loss instead of cross-entropy loss, indicating the importance of the loss function. We also experimented with a hierarchical encoder, where two different recurrent neural networks are used to encode contexts, one at the word level and one at the utterance level. We observed no advantage to using a hierarchical encoder, despite its complexity and popularity for encoding conversations (Serban et al., 2015; Zhou et al., 2016). Finally, we see that a 2 layer LSTM performs similarly to either a 4 layer or a 2 layer SRU with a comparable number of parameters. Since the SRU is more than 4x faster at inference time with the same level of performance, it is the
| Model                        | Parameters | Validation AUC@0.05 | Test AUC@0.05 |
|------------------------------|------------|--------------------|---------------|
| Base                         | 8.0M       | 0.871              | 0.816         |
| 4L SRU → 2L LSTM             | 7.3M       | 0.864              | 0.829         |
| 4L SRU → 2L SRU              | 7.8M       | 0.856              | 0.829         |
| Flat → hierarchical          | 12.4M      | 0.825              | 0.559         |
| Cross entropy → hinge loss   | 8.0M       | 0.765              | 0.693         |
| 6.6M → 1M examples           | 8.0M       | 0.835              | 0.694         |
| 6.6M → 100K examples         | 8.0M       | 0.565              | 0.417         |
| 200 → 100 negatives          | 8.0M       | 0.864              | 0.647         |
| 200 → 10 negatives           | 8.0M       | 0.720              | 0.412         |

Table 9: An ablation study showing the effect of different model architectures and training regimes on performance on the proprietary help desk dataset.

5 Conclusion

In this paper, we present a fast dual encoder neural model for retrieval-based human-computer conversations. We address technical considerations specific to the production setting, and we evaluate our model and two whitelist generation methods on a large help desk chat dataset. We observe that traditional offline evaluation metrics significantly overestimate model performance, indicating the importance of using evaluation metrics more relevant to a production setting. Furthermore, we find that our proposed model performs well, both on offline metrics and on a human evaluation. Due to its strong performance and its speed at inference time, we conclude that our proposed model is suitable for use in a production conversational system.

One important direction for future work is a deeper analysis of the whitelist selection process. Although our analysis found similar performance across whitelists according to a human evaluation, our offline metrics indicate underlying trade-offs between different characteristics of the whitelists such as recall and coverage. A better understanding of the implications of these trade-offs may lead to improved whitelist generation methods, thereby further improving the performance of retrieval-based models.

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A Appendix

A.1 Ablation Study

Table 9 shows the results of an ablation study we performed to identify the most important components of our model architecture and training regime. Each variant is described below.

Base. This is the model architecture described in Section 3.

4L SRU $\rightarrow$ 2L LSTM. We replace the 4 layer SRU encoder with a 2 layer LSTM encoder, which has a comparable number of parameters when using the same hidden sizes.

4L SRU $\rightarrow$ 2L SRU. We use an SRU with 2 layers instead of 4 layers. In order to match parameters, we use a hidden size of $d_h = 475$ instead of $d_h = 300$ in the model with 2 layers.

Flat $\rightarrow$ hierarchical. We replace the SRU encoder with two SRU encoders, one which operates at the word level and one which operates at the utterance level, following the architectures of Serban et al. (2015); Wu et al. (2017).

Cross entropy $\rightarrow$ hinge loss. Instead of using the cross-entropy loss defined in Equation 6, we use the hinge loss, which is defined as:

$$
\mathcal{L} = \sum_{i=1}^{k} |s(c, r^+) - s(c, r^-_i) + m| \quad (7)
$$

where the margin $m = 0.25$ encourages separation between the score of the correct response and the score of each negative response.

6.6M $\rightarrow$ 1M examples. We train on a dataset with 1 million examples instead of the full 6.6 million training examples.

6.6M $\rightarrow$ 100K examples. We trained on a dataset with 100 thousand examples instead of the full 6.6 million training examples.

200 $\rightarrow$ 100 negatives. During training, we sample 100 negatives for each context-response pair instead of 200 negatives.

200 $\rightarrow$ 10 negatives. During training, we sample 10 negatives for each context-response pair instead of 200 negatives.