SUFFIX RETRIEVAL-AUGMENTED LANGUAGE MODELING

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ABSTRACT

Causal language modeling (LM) uses word history to predict the next word. BERT, on the other hand, makes use of bi-directional word information in a sentence to predict words at masked positions. While BERT is effective in sequence encoding, it is non-causal by nature and is not designed for sequence generation. In this paper, we propose a novel language model, Suffix Retrieval-Augmented LM (SUREALM), that simulates a bi-directional contextual effect in an autoregressive manner. SUREALM employs an embedding retriever to search for training sentences in a data store that share similar word history during sequence generation. In particular, the suffix portions of the retrieved sentences mimic the “future” context. We evaluated our proposed model on the DSTC9 spoken dialogue corpus and showed promising word perplexity reduction on the validation and test set compared to competitive baselines. Our source code is released on GitHub.

Index Terms — SUREALM, causal language modeling, suffix embedding retrieval, sentence transformers

1. INTRODUCTION

Causal language modeling possesses great flexibility among most natural language tasks due to its unsupervised and generative nature. Large-scale pre-training on Transformer architecture like GPT2 has resulted in powerful models capable of capturing general knowledge of natural language. However, unlike bidirectional language models such as BERT, RoBERTa, causal language modeling can only look at the word history to predict the next word. While this is mathematically sound, such left-hand contextual information may potentially hinder the language model from capturing semantic knowledge at its fullest. On the other hand, while BERT provides satisfactory performance for sequence encoding thanks to its bi-directional nature, it is designed for masked language modeling which predicts the word identity at a masked position in a sentence. BERT is non-causal and thus is not suitable for sequence generation.

Recent studies have shown that retrieving prefix contextual information from an external data store can further improve performance of a causal language model without increasing the number of model parameters [1]. However, the retrieved information are still uni-directional. In this paper, we propose a novel language model, Suffix Retrieval-Augmented LM (SUREALM), that employs an embedding retriever for suffix retrieval from a data store. During sequence generation, the current word history, referred as prefix in the rest of the paper, is submitted to an embedding retriever to search for similar prefixes in a data store. Then the corresponding suffixes of these training sentences are viewed as “future” context to guide sequence generation. The intuition is that sentences sharing a similar given prefix may probably have strong correlation on their suffixes. For example, “how may i” and “how can i” are similar prefixes. If the model also knows the complete reference sentence “how can i help you”, then the model would tend to predict “help you” given a novel prefix “how may i”. To exploit this assumption, we perform all possible splitting of each training sentence into a triple: a prefix, a word, and a suffix. We employ pre-trained sentence transformers [2] to encode the prefix and suffix of each training sentence to create an embedding data store. Then an embedding retriever such as FAISS [3] is employed for prefix-suffix embedding retrieval given an encoded prefix. The retrieved prefix-suffix embeddings are augmented into the word embedding inputs during sequence generation, achieving the causal language modeling with a simulated bi-directional effect. SUREALM is causal because it only uses word history for predicting the next word. SUREALM is simulated bi-directional because it exploits “future” context from other similar sentences.

Our contributions are two-folded: First, we propose SUREALM, a new causal language model enhanced by prefix-suffix embedding retrieval to simulate a bi-directional effect for sequence generation. Second, we perform extensive experiments and show effectiveness of our model on the DSTC9 dialogue corpus.

2. RELATED WORK

Improving language model using retrieval technique is not new. [4] employs document retrieval to retrieve relevant documents which are used to create an adaptive language model and interpolating it with the background statistical N-gram language model. [5] employs information retrieval to perform language model adaptation for statistical machine translation. Once the language models are adapted, they are kept fixed during sequence generation.

Memory Networks (MemNNs [6]) are a family of neural networks integrating a memory component which can be updated during training. To avoid large storage of external memory, MemNNs can be trained end-to-end [7] by computing a compatibility score between a query and memory items, similar to an attention mechanism. SUREALM resembles MemNNs as we utilize an external data store as “memory”. However, SUREALM’s “memory” contains precomputed embeddings and is retrieved with an embedding retriever for computational efficiency. Like E2E MemNNs [7], we also distinguish between memory and query. We further construct our memory as prefix-suffix pairs enabling a more effective retrieval scheme by matching input query with prefixes.

Most recent development in language modeling is based on transformers [8]. BERT-based Masked language modeling [9,10] exploits bi-directional information of a sentence to predict the word identity of the masked tokens. While BERT is effective in encoding sequences, it is not suitable for sequence generation due to its
non-causal nature. Causal language modeling such as GPT2 [11] is uni-directional. Our proposed model attempts to retain the best of the two worlds as autoregressive and simulated bi-directional via augmentation of suffix embeddings during sequence generation.

One noticeable work for language modeling using embedding retrieval is nearest neighbor language model (KNN-LM) [12]. Their approach store dynamic information in an external knowledge base. During sequence generation, KNN-LM uses the current prefix to retrieve similar prefixes in the data store using embedding retrieval. The output probability distribution is estimated by looking at the corresponding next words in the retrieved prefixes. Such word probability distribution is linearly interpolated with the output word distribution from the causal transformer LM. While it has shown effectiveness in reducing word perplexity, their approach is uni-directional in terms of utilization of information for word prediction. Our proposed model enjoys the simulated bi-directional effect of utilizing “future” contextual information to guide sequence generation.

Another work is retrieval-augmented generation for question and answering [13]. Their approach employs an embedding retrieval over the encoded document embeddings. Then the top-k retrieved document embeddings are viewed as latent variables for answer generation. These latent variables are marginalized in the generator within a sequence-to-sequence generation framework. Related work of using retrieval technique for language modeling pre-training and question answering also includes [1]. Our proposed model differs from their approach that we do not employ marginalization on the top-k retrieved results. In contrast, our model counts on the attention mechanism to attend to all previously retrieved suffix embeddings such that the cross-entropy loss is minimized.

3. PROPOSED APPROACH

Our proposed approach extends causal language models with suffix retrieval. Denote a sentence \( W = w_1 w_2 \ldots w_N \). Then our model defines the negative log likelihood of \( W \) as follows:

\[
\mathcal{L}(W; \Theta) = -\log P(W; \Theta) = -\sum_{i=1}^{N} \log P(w_i | p_i, f(p_i); \Phi) \tag{1}
\]

where \( p_i \) denotes the word history (or prefix) of the word token \( w_i \). \( f(p_i; \Phi) \) denotes a retrieval function parameterized by \( \Phi \), to search for sentences that have similar prefixes in a data store. Then the suffixes of the retrieved sentences are augmented into the language model via suffix embedding. Although the true future context is unseen in causal language models, we hypothesize that such future context may be estimated by leveraging sentences that share similar prefixes. Thus, our model, SUfix REtrieval-Augmented LM (SUREALM), achieves a bi-directional modeling as in BERT and still be able to generate sentences in an autoregressive manner as in GPT. In summary, our proposed approach has three steps: (1) Data preprocessing and indexing; (2) SUREALM training; (3) SUREALM decoding. We describe the steps in Section 3.1–3.3.

3.1. Data pre-processing and indexing

Given a training corpus \( D = \{ W \} \) containing a set of unique sentences \( W \), each sentence \( W \) generates all possible partitions of \( W \) into 3 parts: prefix, current word, and suffix, denoted as \( (p_i, w_i, s_j) \) where \( p_i = w_1 w_2 \ldots w_{i-1}, s_j = w_{i+1} \ldots w_N \) with valid word position \( 0 < i < N \). Motivated from masked language modeling, we exclude the current word \( w_i \) so that each data entry for indexing into a data store is a prefix-suffix pair \( (p_i, s_j) \). This formulation enforces our model to use information from the prefix (left context) and the retrieved suffixes (“right context”) from other training sentences. Thanks to the recent development in sentence embedding retrieval, we employ pre-trained sentence transformer [2] to encode prefixes and suffixes such that retrieval is based on similarity of prefix embeddings. Then the data store returns the prefix and suffix embeddings. The rationale of encoding variable-length prefix and suffix into a fixed dimensional vector is to make the prefix and suffix representation smoother to mitigate word-level noises that are irrelevant to the current prefix under consideration. Intuitively, \((\text{emb}(p_i), \text{emb}(s_j)) \in \mathbb{R}^d\) can be viewed as a key-value pair where \( d \) is the embedding dimension. To preserve positional information in representation, we use absolute positions in the original sentence when computing the prefix and suffix embeddings. We employ FAISS [3] for embedding search.

The final number of prefix-suffix pairs to index is \( O(M \cdot N) \) where \( M \) is the number of unique training sentences and \( N \) is the maximum sequence length of a sentence. Essentially, our model requires to perform embedding retrieval at every word position. Therefore, we introduce a hyperparameter \( \delta \) to control the frequency of embedding retrieval. For example, if embedding retrieval occurs at time \( t \), then the next time to retrieve will be at time \( t + \delta \). This implies that during time interval \([t + 1, t + \delta - 1]\), all the previously retrieved suffix embeddings are reused to save computation. This allows us to explore the tradeoff between computation and accuracy.

Regarding the suffix representation, we apply suffix truncation assuming that word tokens in a suffix that are closer to prediction time \( t \) may be more helpful. We introduce a hyper-parameter \( m \) for suffix truncation so that a truncated suffix \( s'_i = w_{i+1} \ldots w_{i+m} \) with \( m < N \) is fed into a sentence transformer for encoding. When the number of tokens \( N \) is large, we conjecture that a right \( m \) may avoid an overly smoothed suffix embedding representation due to the pooling mechanism in a sentence transformer. Table 1 shows sample retrieval results using some prefixes as input queries.

| Input Query                  | Retrieved Word | Retrieved Suffix |
|------------------------------|----------------|-----------------|
| ‘I also want’               | ‘free’         | ‘wifi’          |
| ‘I’d like to’               | ‘book’         | ‘this hotel’    |
| ‘is the hotel equipped with’| ‘elevator’     | ‘for convenience’|
| ‘I have several’            | ‘options’      | ‘for you. would you like a particular area...’ |

3.2. SUREALM training

3.2.1. Offline retrieval

One complication in SUREALM is the embedding retrieval required for each prefix \( p_i \) at each word position \( i \). First, it would be computationally expensive to perform on-the-fly embedding retrieval during training. Since we freeze the sentence transformer for encoding, top-K similar prefix and suffix embeddings can be precomputed offline using FAISS to speed up training. \( K \) is a hyper-parameter to determine the number of retrieved suffix embeddings to be included for SUREALM training. To avoid cheating, we exclude all the embedding results belonging to the same training sentence ID. Empirically, we found this step to be crucial for SUREALM to learn from additional suffix information from other similar training sentences.

3.2.2. Mini-batch training

Another challenge is to make SUREALM fit to mini-batch training where a batch of padded word sequences are fed into the model and different suffix embeddings should be applied at different time \( i \). To enable mini-batch training, we first concatenate all offline-retrieved suffix embeddings. Then we construct a suitable attention mask so that each word position \( i \) should only attend to the
allowed suffix embeddings in masked cross attention, and the previous word positions as in causal LM in masked self attention. Denote \( C_k^{\text{tr}}(W_{\leq i}) = \bigoplus_{j=1}^{i} \bigoplus_{p=1}^{k} \{(p_i^j, s_i^j)\} \) as a concatenation of all previously retrieved top-k prefix-suffix embedding pairs. Probability of generating a word sequence \( W \) becomes:

\[
P(W) = \prod_{i=1}^{N} P(w_i|W_{\leq i-1}, C_k^{\text{tr}}(W_{\leq i-1})).
\]

where \( W_{\leq i-1} = w_1w_2\ldots w_{i-1} \). SUREALM employs a transformer architecture which follows the Query-Key-Value inputs defined as follows (\( i = 1, 2, 3, \ldots |Q|, j = 1, 2, 3, \ldots |J| \)):

\[
Q = \text{Embedding}(W)
\]

\[
K = \text{Concat}(p_1, p_2, \ldots, p_J)
\]

\[
V = \text{Concat}(s_1, s_2, \ldots, s_J)
\]

\[
M_{i,j} = \begin{cases} 
0, & j \leq k([i/\delta] - 1) \\
-\infty, & \text{Otherwise.}
\end{cases}
\]

Here \( M \in \mathbb{R}^{Q \times J} \) is an attention mask which masks future positions in keys and values regarding the retrieved suffix embeddings. Finally, we obtain the output attention weights in the masked attention block as follows:

\[
\text{Attention}(Q, K, V, M) = \text{Softmax}\left( \frac{QK^T + M}{\sqrt{d_k}} \right)V
\]

where \( d_k \) denotes the embedding dimension of the keys and values. Figure 3.3 illustrates SUREALM architecture. Notice that SUREALM can be initialized with weights from any pre-trained transformer of the BERT or GPT model families. We fine-tune the model using the training text to minimize the cross-entropy loss.

3.3. SUREALM Decoding

SUREALM decoding is similar to any decoding algorithm in sequence generation except that suffix embedding retrieval is performed when the prefix is updated during generation. We start from the start symbol as the initial prefix. Then suffix embedding retrieval takes place using the current prefix as a query. The top-k suffix embeddings are added into the set \( C_k^{\text{tr}}(W_{\leq i}) \) as extra inputs to the transformer in a progressive manner. The next word is generated from the output word distribution and then appended to the prefix. The generation process is repeated until the end-of-sentence symbol is encountered. We follow the decoding algorithm implementation in the Huggingface transformers library [14] and augment an embedding retriever in our implementation.

4. EXPERIMENTS

In this section, we compare SUREALM of different configurations with baseline LMs for sequence generation. We report word perplexity for all experiments as well as the choice of hyper-parameters.

4.1. Setup

We used the dataset from the Dialogue System Technology Challenge 9 (DSTC9) [15]. The original dataset was designed for evaluating spoken dialogues that involves accessing an external knowledge base containing a list of question-answer pairs about each named entity, such as “Can I bring my pet to A and B Guest House?” and “No, pets are not allowed at this property.”. For language modeling purpose, we treated each dialogue turn as independent sentence and we only kept unique sentences in our training, validation and test sets. Then each sentence was assigned with an unique sentence ID so that they can be uniquely identified in embedding retriever. Our resulting training dataset contained 126,877 unique dialogue turns mentioning 145 named entities covering four domains: hotel, restaurant, taxi and train. Our validation dataset contained 18,037 unique dialogue turns. The test dataset had 18,021 unique dialogue turns covering 532 unseen named entities including a new domain on attraction. Due to the introduction of a new domain, we further split the test dataset into in-domain and out-of-domain portions and only evaluated on the in-domain portion. Since the test turns did not have the manual domain label, we applied named entity recognition on all dialogue turns and used the detected named entity and applied its corresponding domain label to dialogue turns. The question-answering knowledge base was not added into our data store. The data store only contained the prefix-suffix embeddings from the training sentences.

For data preprocessing, we followed Section 3.1 to generate prefix-suffix pairs of the training dataset, pre-compute the embedding pairs with pre-trained sentence transformers [2], and index and store them using FAISS [3]. We also pre-computed the prefix embeddings for validation/test sets to accelerate the retrieval process. To avoid cheating, such embeddings were not indexed in FAISS.

4.2. Training details

In SUREALM, there are two modeling components to consider: (1) encoding model; (2) language model. For the encoding model, we used pre-trained sentence transformers [2] to encode prefixes and suffixes. We tried small-scale models \(^2\) and standard-scale models \(^3\) respectively in our experiments. For the language model, we employed transformer-based language models with various weight

\(^2\)384-dimension with 6 to 12 layers

\(^3\)768-dimension with 12 layers
initialization strategies. Inspired by [16], we explored different sentence transformer checkpoints to initialize the language model weights. On small-scale model training, we used a batch size of 128, AdamW optimizer with learning rate of $2 \times 10^{-5}$, and linear learning rate scheduler with 500 warmup steps. On standard-scale model training, we used a batch size of 64 and learning rate of $1 \times 10^{-5}$ and kept the same settings as in the small-scale model training. Since our dataset was relatively small, we trained SUREALM for 200 epochs and chose the model with the minimum validation perplexity.

In our preliminary experiments, we chose the best hyperparameters based on the validation perplexity. Results showed that it was crucial to retrieve at each prediction time step $\delta = 1$. We chose $m = 10$ for suffix truncation and $K = 8$ for retrieving the top-k prefix-suffix embeddings, yielding the best perplexity results. We fixed these hyper-parameters for further experiments below.

### 4.3. Results

#### 4.3.1. Small-scale models

For baselines, we fine-tuned transformer-based masked LMs (MiniLM [17]) of 6 and 12 layers initialized with pre-trained weights. For encoding, we used pre-trained sentence transformers (multi-qa-MiniLM and all-MiniLM)\(^4\). Our LMs were initialized with the weights of the pre-trained sentence transformers or the masked LMs. Results in Table 2 show that:

1. SUREALM achieved lower perplexity compared to baselines in all experiments. Our best small model achieved relative test perplexity reduction of 19% compared to the baseline.

2. Note that we compared MiniLM based SUREALM with that initialized with Bert as they shared the same vocabulary. While SUREALM initialized with BERT achieved the best performance (21%), our small-scale models still achieved similar performance gain with 63% less parameters.

3. LM weights can be initialized differently from the pretrained ST used for encoding without any performance degradation. This implies flexibility for different weight combinations.

#### 4.3.2. Standard-scale models

We then compared standard-scale SUREALM with popular state-of-the-art LM baselines (BERT, RoBERTa and GPT2) of which the weights were used for initialization. However, since they used different tokenizers resulting in different output vocabulary sizes, we could only compare models with with similar vocabulary sizes. Bert initialized SUREALM in Table 2 achieved best relative test perplexity reduction by 21% across all experiments. Table 3 shows perplexity results with increased vocabulary size of 50k. SUREALM achieved relative test perplexity reduction by 13% and 19% compared to GPT2 and RoBERTa baseline respectively. We also experimented with the distilled version of the two architectures yielding consistent results. Note that some experiments with GPT2, while not implemented with the distilled version of the two architectures yielding the best perplexity results. We fixed these hyper-parameters for further experiments below.

### 5. DISCUSSIONS

During embedding retrieval, we investigated the inclusion of the current word into the suffix in a training sentence, meaning that we only split a training sentence into prefix and suffix instead of prefix, current word and suffix mentioned in Section 3.1. Then we followed the same procedure to encode the prefixes and suffixes and reran SUREALM training and evaluation. However, we observed no test perplexity reduction compared to the baseline. Excluding the current word from suffix may be analogous to applying a mask token in the mask LM. After excluding the current word, SUREALM focuses on information from the word history and the retrieved suffix context for word prediction. It is possible that the embedding retrieval results may contain sentences that share similar prefixes but having an identical suffix as in the current input sentence. From this perspective, excluding the current word from suffix is reasonable to avoid SUREALM from overly relying on the suffix embeddings and forgetting the word history in word prediction.

### 6. CONCLUSIONS

We have proposed a suffix retrieval-augmented language model to simulate bi-directional contextual effect while remains autoregressive so that our model can be used for sequence generation. Our proposed model shows promising perplexity performance compared to state-of-the-art LM baselines. In the future, we plan to evaluate our model on large corpora. In addition, we plan to extend our model on conditional generation such as dialogue response generation. Lastly, we will investigate domain LM adaptation using our proposed model.

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\(^4\)In Table 2, Multi stands for the former, and All stands for the latter.
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