

Revisiting the Architectures like Pointer Networks to Efficiently Improve the Next Word Distribution, Summarization Factuality, and Beyond

Haw-Shiuan Chang^{*†§} Zonghai Yao^{*†‡} Alolika Gon[‡] Hong Yu[‡] Andrew McCallum[‡]

[‡] CICS, University of Massachusetts, Amherst

[§] Amazon Alexa AI

chawshiu@amazon.com, zonghaiyao@cs.umass.edu, agonagon@umass.edu,

{hongyu,mccallum}@cs.umass.edu

Abstract

Is the output softmax layer, which is adopted by most language models (LMs), always the best way to compute the next word probability? Given so many attention layers in a modern transformer-based LM, are the pointer networks redundant nowadays? In this study, we discover that the answers to both questions are no. This is because the softmax bottleneck sometimes prevents the LMs from predicting the desired distribution and the pointer networks can be used to break the bottleneck efficiently. Based on the finding, we propose several softmax alternatives by simplifying the pointer networks and accelerating the word-by-word rerankers. In GPT-2, our proposals are significantly better and more efficient than mixture of softmax, a state-of-the-art softmax alternative. In summarization experiments, without significantly decreasing its training/testing speed, our best method based on T5-Small improves factCC score by 2 points in CNN/DM and XSUM dataset, and improves MAUVE scores by 30% in BookSum paragraph-level dataset.

1 Introduction

When recurrent neural networks such as LSTM (Hochreiter and Schmidhuber, 1997) are the mainstream language model (LM) architecture, pointer networks, or so-called copy mechanisms (Gu et al., 2016), have been shown to improve the state-of-the-art LMs for next word prediction (Merity et al., 2017) and summarizations (See et al., 2017) by a large margin. However, after transformer (Vaswani et al., 2017) becomes the dominating LM architectures, the pointer networks are rarely used in the state-of-the-art pretrained LMs. One major reason is that the attention mechanism in every transformer layer can learn to copy the words from the context, so it

^{*}indicates equal contribution

[†]The work is done while the author was at UMass

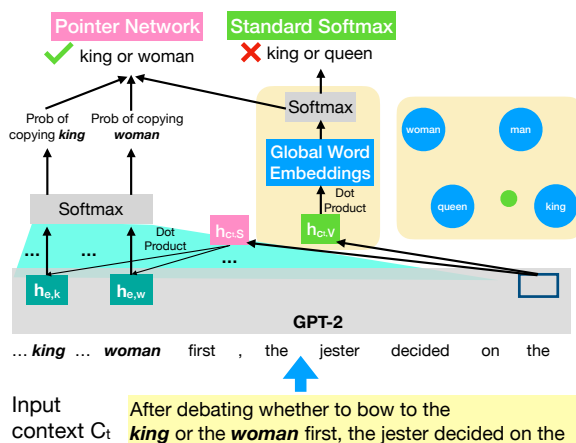


Figure 1: Illustration of the softmax bottleneck and pointer network using an example from Chang and McCallum (2022). GPT-2 cannot output both *king* or *woman* as the possible next word due to the parallel-gram structure in the output word embedding space, while the pointer network could solve this by directly copying words from the context. The standard softmax estimate the probabilities of outputting *king* and *woman* by the dot products between the hidden state $h_{c,S}$ and their global word embeddings. By contrast, The pointer networks compute the dot products between the projected current hidden state $h_{c,S}$ and projected hidden states $h_{e,S}$ for *king* and *woman* to estimate their probabilities.

seems to be redundant to add a copying mechanism on top of the transformer.

In this paper, we demonstrate that the architectures like pointer networks can still substantially improve the state-of-the-art transformer LM architectures such as GPT-2 (Radford et al., 2019) and T5 (Raffel et al., 2020) mainly due to breaking the bottleneck of their final softmax layer (Yang et al., 2018; Chang and McCallum, 2022).

In Figure 1, we illustrate a simple example from Chang and McCallum (2022) to explain the softmax bottleneck and why the pointer networks could alleviate the problem. When predicting the next

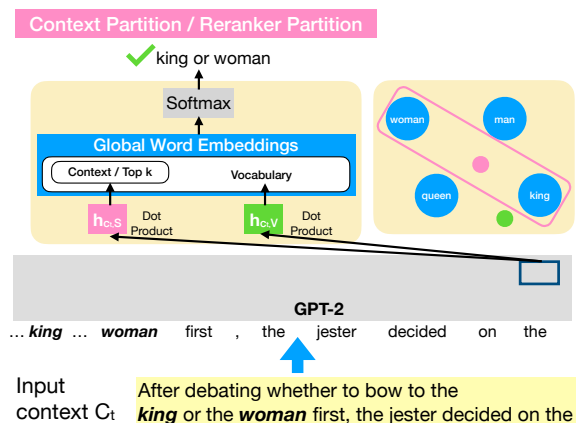


Figure 2: We simplify the pointer network / reranker by using another embedding $h_{ct,S}$ for the words in the context / the top-k likely words.

word, most LMs would try to output a hidden state $h_{ct,V}$ that is close to all the next word possibilities. For example, when the next word should be either *king* or *woman* with similar probabilities, the ideal hidden state is supposed to be the average of the global output word embeddings of *king* and *woman*. However, there might be other interfering words (*queen* and *man* in this case) between the ideal next word candidates, which force the LM to output the wrong distribution.

To solve this problem, we can let the LMs predict the probability of copying the words in the context separately by paying attention to the previous hidden states (Gu et al., 2016) and we call this kind of architecture pointer networks in this paper. That is, we can compute the dot products with the hidden states of *king* $h_{e,k}$ and the hidden states of *woman* $h_{e,w}$ rather than with their global output word embeddings in order to estimate the probabilities of copying these two words in the context. Our experiments show that the pointer networks consistently improve the performance of GPT-2 in next word prediction and the quality of summarization from T5 and BART.

Contrary to the mainstream explanation in previous pointer network literature, we discover that most of the improvements in our experiments do not come from the attention mechanism. To study these improvements, we propose a very simple pointer network variant that does not use any previous hidden states and we show that the proposed method can achieve similar improvements.

As shown in Figure 2, we simply project the last hidden state into two embeddings. One embedding

$h_{ct,S}$ is to compute the dot product with the context words, and $h_{ct,V}$ is for the dot product of the other words. Then, the GPT-2 can output the hidden state for context words $h_{ct,S}$ as the average embedding of the *king* and *woman* without interfered by the words of *man* and *queen* that are handled by $h_{ct,V}$. We call this method context partition. In addition to words in the context, we can also use another embedding for the top-k likely next words. This can be viewed as a very simple and efficient alternative to a reranker, so we call it reranker partition.

In our experiments, we show that the context partition performs similarly to pointer networks while combining a pointer network, context partition, and reranker partition would significantly outperform each individual method. Compared to the state-of-the-art solutions for alleviating the softmax bottleneck such as mixture of softmax (Yang et al., 2018; Chang and McCallum, 2022), our proposed method is more efficient while achieving lower perplexity on GPT-2. Furthermore, we find that adding a very expensive word-by-word reranker only improves our method slightly, which suggested the difficulty of further improving the final softmax layer over the proposed alternatives.

In the text completion task using GPT-2, we find that the proposed softmax alternatives reduce hallucination by copying more proper nouns from the context even though we did not provide any part-of-speech information during training. In summarization, our methods and pointer networks output a more specific summary, increase the factuality, and consistently improve 9 metrics, especially in the smaller language models. Finally, we show that the softmax bottleneck problem is not completely solved in GPT-3.5 in the limitation section.

1.1 Main Contributions

- We propose a series of efficient softmax alternatives that unify the ideas of pointer network, reranker, multiple embeddings, and vocabulary partitioning.¹
- We evaluate the proposed softmax alternatives in text completion tasks and summarization tasks using various metrics to identify where our methods improve the most.
- Our experiments indicate pointer networks and our proposed alternatives can still improve the modern transformer-based LMs. By breaking

¹Our codes are released at <https://github.com/iesl/Softmax-CPR>

the softmax bottleneck, our methods learn to sometimes copy the context words to reduce generation hallucination and sometimes exclude the context words to reduce the repetition. Besides, we find that the softmax bottleneck problem won't be completely solved by the huge size of GPT-3.5.

2 Background

Before introducing our method, we would first briefly review the problem we are solving and its state-of-the-art solutions.

2.1 Softmax Bottleneck Problem

Most LMs use a softmax layer to compute the final probability of predicting the word x :

$$P_M(x|c_t) = \frac{\exp(\text{Logit}(x, c_t))}{\sum_{x'} \exp(\text{Logit}(x', c_t))}, \quad (1)$$

where c_t is the context words. Typically, the logit $\text{Logit}(x, c_t) = (\mathbf{h}_{c_t}^M)^T \mathbf{w}_x$, $\mathbf{h}_{c_t}^M$ is the M th-layer hidden state given the input context c_t and \mathbf{w}_x is the output word embeddings for x .

One problem is that the output word embeddings \mathbf{w}_x are global and independent to the context. After pretraining, the similar words would have similar output word embeddings. However, the similarity structure in the word embedding space might prevent LMs from outputting the desired distribution. The parallelogram structure among the embeddings of *king*, *queen*, *woman*, and *man* is a simple example. Chang and McCallum (2022) generalize this observation and show that some words in a small subspace would create some multi-mode distributions that a LM cannot output using a single hidden state \mathbf{h}_{c_t} in the softmax layer.

2.2 Mixture of Softmax Method

To overcome the bottleneck, one natural solution is to have multiple hidden states and each hidden state corresponds to a group of possible words (Yang et al., 2018). For example, we can have one hidden state for *king* and another hidden state for *woman*.

One major concern of this mixture of softmax (MoS) approach is the computational overhead. MoS needs to compute the final softmax multiple times and merge their resulting distributions. That is, we need to compute the dot products between every hidden state and all the words in the vocabulary, which is expensive especially when the vocabulary size is large.

	Abbr.	Partition (S)	Word Emb (e_x)
Context Partition	C	Decoder context	Global word emb
Encoder Partition	E	Encoder input	Global word emb
PS (LD) (Merity et al., 2017)	P	Decoder context	Decoder state
PG (LE) (See et al., 2017)	P	Encoder input	Encoder state
Reranker Partition	R	Top k	Global word emb

Table 1: Comparison of different softmax alternatives and their abbreviation (Abbr.) using Equation 3. PS: Pointer Sentinel. PG: Pointer Generator. LD: local decoder embedding. LE: local encoder embedding.

2.3 Multiple Input State Enhancement

In MoS, the multiple hidden states come from the linear projections of the last hidden state. Chang and McCallum (2022) point out that the total degree of freedom among the multiple hidden states is limited by the dimensionality of the hidden state.

To allow LMs to move multiple hidden states more freely, Chang and McCallum (2022) propose to concatenate the projection of a block of hidden state with the last hidden state $\mathbf{h}_{c_t}^M$ so as to increase its dimensionality:

$$\mathbf{q}_{c_t} = \mathbf{h}_{c_t}^M \oplus GELU \left(L^h \left(\oplus_{i,m} \mathbf{h}_{c_{t-i}}^{M-m} \right) \right), \quad (2)$$

where $GELU$ is the non-linear transformation used in GPT-2 and L^h is a linear transformation that allows us to consider more hidden states without significantly increasing the model size. $\oplus_{i,m} \mathbf{h}_{c_{t-i}}^{M-m}$ is the concatenation of a block of hidden states. We set the block size to be 3x3 in our GPT-2 experiments and 1x3 in our summarization experiments (i.e., considering the last 3 hidden states in the last layer as shown in Figure 3).

3 Methods

To break the softmax bottleneck more efficiently compared to MoS, our overall strategy is simple. If we can identify a small partition of words that are very likely to become the next word, we can just compute the dot products between a hidden state and the embeddings of these likely words instead of all the words as in MoS. For example, if we can identify *king* and *woman* are much more likely to appear than *queen* and *man*, we can only compute the dot product between a hidden state and the embeddings of *king* and *woman* without being interfered by other words.

Specifically, when we compute the next word probability in Equation 1, the logit of the word x given the context c_t

$$\text{Logit}(x, c_t) = \begin{cases} \mathbf{f}_{c_t, S}^T e_x & \text{if } x \in S \\ \mathbf{f}_{c_t, V}^T \mathbf{w}_x & \text{O/W} \end{cases}, \quad (3)$$

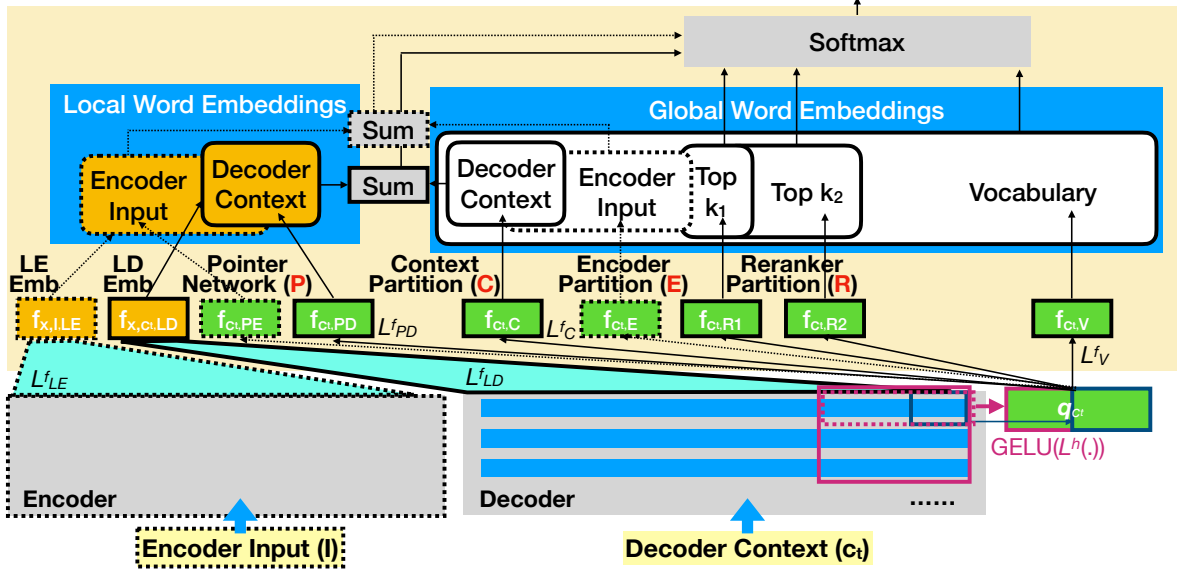


Figure 3: Architectures of our method for T5/BART that computes Logit_{CEPR} in Equation 6. In GPT-2, we use same architecture except that we take the 3x3 input hidden state block rather than the 1x3 block and there are no encoder-related components, which are marked by dotted lines.

where $f_{c_t,S} = L_S^f(q_{c_t})$ and $f_{c_t,V} = L_V^f(q_{c_t})$ are the linear projections of the hidden state concatenation q_{c_t} in Equation 2. As shown in Table 1, different softmax alternatives have different ways of constructing this set S and use different word embeddings e_x .

To simplify our explanation, we will focus on the decoder-only LM (i.e., GPT-2) first and extend our method to encoder-decoder LM (i.e., T5 and BART).

3.1 GPT-2

We will explain each softmax alternative individually and their connections to previous work such as pointer networks or rerankers.

3.1.1 Pointer Network (P) as Local Word Embedding

Similar to Pointer Sentinel (PS) (Merity et al., 2017), we treat the words in the context differently ($S = \{x|x \in c_t\}$) and let their word embeddings e_x come from the previous hidden states:

$$e_x = f_{x,c_t,LD} = \frac{\sum_{i=1}^t \mathbb{1}_{c_t^i=x} L_{LD}^f(q_{c_t^i})}{\sum_{i=1}^t \mathbb{1}_{c_t^i=x}}, \quad (4)$$

where c_t^i is the i th input words in the context c_t , L_{LD}^f is a linear layer, and $\mathbb{1}_{c_t^i=x} = 1$ if $c_t^i = x$.

As a result, we can use the GPT-2 model to not only predict the hidden state $f_{c_t,S} = f_{c_t,PD} =$

$L_{PD}^f(q_{c_t})$ and $f_{c_t,V}$ but also predict the word embedding of context words e_x . Unlike the global word embedding w_x , the local word embedding e_x is context-dependent, so the LM can break the softmax bottleneck by adjusting the similarity of words based on the context. For example, GPT-2 could increase the similarity between e_{king} and e_{woman} to output the high probability for both words easily.

We call this version of pointer network local decoder (LD) embedding, which has some minor differences compared to PS (Merity et al., 2017) and other variants. For example, we merge their logits while PS merges their probabilities. PS does not do normalization when computing e_x . In our experiments, we would show that these pointer network variants all have very similar improvements in modern LMs.

3.1.2 Context Partition (C)

To understand the source of the improvements from pointer networks, we simplify their architectures by setting the word embedding $e_x = w_x$ and the partition S is still the set of context words. Although much simpler, the LM with this context partition method can still break the softmax bottleneck by properly coordinating the hidden state specifically for the context words $f_{c_t,S} = f_{c_t,C} = L_C^f(q_{c_t})$ and the hidden state for other words $f_{c_t,V}$. Compared to the pointer network, one advantage of context partition is that the LM can still leverage the learned global word similarity when estimating

the probabilities of context words.

3.1.3 Reranker Partition (R)

In some cases, the possible next words might not be mentioned in the context. For example, in the context *My favorite actor is Ryan [MASK]*, the next word could be *Reynolds, Gosling*, or the last names of other *Ryan*. Hence, using only the context partition does not completely solve the multimodal distribution problem.

Inspired by the idea of the reranker, we set S to be the top k words with the highest logits $\mathbf{f}_{c_t, V}^T \mathbf{w}_x$. In practice, finding an ideal k could be difficult. When k is small, the reranker partition might not include the very likely next word. When k is large, the reranker partition might not be able to separate the output candidates and the interfering words. To alleviate the problem, we can have multiple reranker partitions and use different hidden state embeddings (e.g., $\mathbf{f}_{c_t, R1}$ and $\mathbf{f}_{c_t, R2}$) for different partitions.

3.1.4 Hybrid Approach (CPR)

Local embeddings in the pointer networks and global embeddings in the context partition are complementary. Using local embeddings is representational powerful while using global embedding can leverage the global similarity of words. Hence, we can combine the two methods by summing their dot products.

For the methods that use different S , we can simply determine an order of computing the dot products and let the later dot products overwrite the existing values. In our experiments, we always use the order illustrated in Figure 3. That is, we compute the logits ($\text{Logit}_{CPR}(x, c_t)$) by

$$\begin{cases} \mathbf{f}_{c_t, C}^T \mathbf{w}_x + \mathbf{f}_{c_t, PD}^T \mathbf{f}_{x, c_t, LD} & \text{if } x \in c_t \\ \mathbf{f}_{c_t, R1}^T \mathbf{w}_x & \text{if } x \in W(k_1) - c_t \\ \mathbf{f}_{c_t, R2}^T \mathbf{w}_x & \text{if } x \in W(k_2) - W(k_1) - c_t \\ \mathbf{f}_{c_t, V}^T \mathbf{w}_x & \text{O/W} \end{cases}, \quad (5)$$

where $W(k_2)$ is the top k_2 words with the highest $\mathbf{f}_{c_t, V}^T \mathbf{w}_x$ and $W(k_1)$ is the top k_1 words with the highest $\max(\mathbf{f}_{c_t, V}^T \mathbf{w}_x, \mathbf{f}_{c_t, R2}^T \mathbf{w}_x)$.

3.2 T5 and BART

In the encoder-decoder architectures, our local decoder embedding, context partition, and reranker partitions are still applicable. Besides, we can leverage the words in the encoder input to further improve the performance.

3.2.1 Encoder Partition (E) and Local Encoder Embedding (P)

Similar to the context partition, the encoder partition handles the words in the encoder input I differently by setting $S = \{x | x \in I\}$ and using the global word embedding $e_x = \mathbf{w}_x$.

As in Equation 4, we can also let the hidden states in the last layer pass through another linear layer $L_{LE}^f(\cdot)$ to predict the embeddings of the words in the encoder input. The method is called local encoder (LE) embedding.

3.2.2 Hybrid Approach (CEPR)

Similar to GPT-2, we combine local encoder embedding and encoder partition for computing the probabilities of the words that are in the encoder context but not in the decoder context. As shown in Figure 3, we compute $\text{Logit}_{CEPR}(x, c_t)$ by

$$\begin{cases} \mathbf{f}_{c_t, C}^T \mathbf{w}_x + \mathbf{f}_{c_t, PD}^T \mathbf{f}_{x, c_t, LD} & \text{if } x \in c_t \\ \mathbf{f}_{c_t, E}^T \mathbf{w}_x + \mathbf{f}_{c_t, PE}^T \mathbf{f}_{x, I, LE} & \text{if } x \in I - c_t \\ \mathbf{f}_{c_t, R1}^T \mathbf{w}_x & \text{if } x \in W(k_1) - c_t - I \\ \mathbf{f}_{c_t, V}^T \mathbf{w}_x & \text{O/W} \end{cases}, \quad (6)$$

which is the same as Equation 5 except that we add the encoder partition and local encoder embedding, and we remove the second reranker partition.

4 Experiments

The pointer network was a popular technique in language modeling (Merity et al., 2017) and summarization (See et al., 2017). Thus, we also focus on these two fundamental applications.

4.1 GPT-2

We follow the setup in Chang and McCallum (2022) to continue training GPT-2 on Wikipedia 2021 and OpenWebText (Radford et al., 2019).

4.1.1 Perplexity Comparison

In Table 2, we first compare their predictions on the next word distribution using the testing data perplexity, which is a standard metric in the LM architecture studies. In the table, Mi refers to multiple input state enhancement, which is proposed to break the softmax bottleneck more effectively (please see details in Section 2.3 and Chang and McCallum (2022)).

As we can see, **Softmax + CPR:20,100 + Mi**, which combines all the efficient approaches (i.e., context partition, reranker partition, and local decoder embedding), results in better performance

Model Name	GPT-2 Small				GPT-2 Medium			
	Size	Time (ms)	OWT (\downarrow)	Wiki (\downarrow)	Size	Time (ms)	OWT (\downarrow)	Wiki (\downarrow)
Softmax (GPT-2)	125.0M	82.9	18.96	24.28	355.9M	207.8	15.81	20.12
Softmax + Mi	130.9M	85.6	18.74	24.08	366.4M	213.8	15.71	20.07
Mixture of Softmax (MoS) (Yang et al., 2018)	126.2M	130.2	18.97	24.10	358.0M	262.9	15.71	19.95
MoS + Mi (Chang and McCallum, 2022)	133.3M	133.2	18.68	23.82	370.6M	268.2	15.61	19.86
Pointer Generator (PG) (See et al., 2017)	126.2M	106.0	18.67	23.70	358.0M	237.8	15.72	19.95
Pointer Sentinel (PS) (Merity et al., 2017)	126.2M	94.1	18.70	23.79	358.0M	218.3	15.72	19.95
Softmax + R:20 + Mi	132.1M	90.4	18.67	24.03	368.5M	203.6	15.64	19.94
Softmax + R:20,100 + Mi	133.3M	101.1	18.69	23.93	370.6M	228.5	15.61	19.89
Softmax + C + Mi	132.1M	94.8	18.48	23.56	368.5M	222.7	15.60	19.83
Softmax + P + Mi	133.3M	99.1	18.58	23.66	370.6M	214.7	15.63	19.90
PG + Mi	133.3M	111.2	18.43	23.43	370.6M	242.5	15.60	19.89
PS + Mi	133.3M	98.0	18.48	23.53	370.6M	224.6	15.60	19.87
Softmax + CR:20,100 + Mi	134.5M	113.3	18.46	23.48	372.7M	234.5	15.54	19.75
Softmax + CPR:20,100 + Mi	136.8M	119.9	18.43	23.42	376.9M	249.9	15.53	19.71
MoS + CPR:20,100 + Mi	139.2M	165.1	18.39	23.29	381.1M	300.6	15.44	19.57

Table 2: Comparison of different methods on top of GPT-2. Wiki and OWT refer to the testing perplexity of Wikipedia 2021 and OpenWebText, respectively. Lower perplexity is better. Time is the inference time of a batch; Mi is the multiple input hidden state enhancement; C is the context partition; R:20,100 is the reranker partition with $k_1 = 20$ and $k_2 = 100$; P is the pointer network (i.e., local decoder embedding). Please see Equation 5 for the details of CPR. The best scores are highlighted.

and faster inference speed than the mixture of softmax (MoS) (Yang et al., 2018; Chang and McCallum, 2022). The inference speed is measured by our pure PyTorch implementation, which we believe could be further accelerated by implementing some new PyTorch operations using CUDA code.

If only using one method, the context partition (Softmax + C + Mi) is better than the reranker partitions (Softmax + R:20,100 + Mi) while performing similarly compared to local decoder word embedding (Softmax + P + Mi), Pointer Generator (PG + Mi) (See et al., 2017), and Pointer Sentinel (PS + Mi) (Merity et al., 2017).² Their similar performances indicate that the improvement of pointer networks come from breaking the softmax bottleneck. The significantly better performance of PS + Mi compared to PS further supports the finding.

To know how well our method breaks the softmax bottleneck, we implement a word-by-word reranker model on GPT-2, which appends the most likely 100 words to the context when predicting each next word (see Appendix C.3 for more details). In Table 3, we show that our efficient softmax alternative Softmax + CPR:20,100 + Mi achieves significantly lower perplexity. Furthermore, the word-by-word reranker is at least 10 times slower during training. Combining word-by-word reranker with our method only improves the perplexity very

²Notice that the pointer networks from the previous work were originally designed for RNN. To add them on top of the transformer based LMs and make it more comparable to our methods, we simplify their architectures a little. Please see Appendix C.2 for more details.

Softmax + Mi	29.33	Softmax + wbwR:100 + Mi	28.89
Softmax + CPR:20,100 + Mi	28.46	Softmax + CPR:20,100 + wbwR:100 + Mi	28.40

Table 3: Comparison between our method and word-by-word reranker for the most likely 100 words (wbwR:100). The numbers are the validation perplexities on Wikipedia 2021 after training for 0.15 epochs.

Model Name	All		Proper Noun	
	Ref	Context	Ref	Context
Softmax + Mi	22.90	24.04	7.49	14.84
MoS + Mi	22.88	23.98	7.70	15.49
PS + Mi	22.85	25.01	8.16	18.21
Softmax + CPR:20,100 + Mi	23.05	25.36	8.16	17.92

Table 4: ROUGE-1 F1 (%) of different methods on GPT-2. We compare the scores between the generated text and the reference (i.e., continuation), and between the generation and context. More methods and metrics are reported in Table 8.

slightly, which suggests the challenges of further improving LM by breaking softmax bottleneck.

4.1.2 Generated Text Comparison

Next, we would like to understand how the distribution improvement affects the text generation. We sample some contexts in the test set of Wikipedia 2021 and compare the generated text quality of the different models given the contexts. The quality is measured by the ROUGE-1 F1 scores between the generated text and the actual continuation. To know how much the different models copy from the context, we also report the ROUGE-1 scores between the generation and the contexts.

The results in Table 4 show that different meth-

ods have very similar overall ROUGE-1 scores. Nevertheless, compared to **Softmax + Mi**, **Softmax + CPR:20,100 + Mi** is 21% more likely to copy the proper nouns (i.e., entity names) from the context and 9% more likely to generate the proper nouns in the actual continuation. This suggests that our method could alleviate the common incoherence problem of entities in generated text (Shuster et al., 2022; Papalampidi et al., 2022; Zhang et al., 2022; Guan et al., 2022; Goyal et al., 2022b). In Table 8, we compare methods using more metrics to further support the conclusion.

4.1.3 Qualitative Analysis

In Table 5, we visualize some distributions to explain our improvements. The softmax layer of GPT-2 is unable to properly learn to copy or exclude the word from the input context. For example, **Softmax + Mi** and **MoS + Mi** might output “*There are plates, keys, scissors, toys, and balloons in front of me, and I pick up the phone*”, which causes a hallucination problem, while **Softmax + CPR:20,100 + Mi** and **Pointer Sentinel (PS) + Mi** can output the mentioned options with similar probability by copying the words in the context. In addition, **GPT-2**, **MoS**, and **PS + Mi** are very likely to output “*I like tennis, baseball, golf, basketball, and tennis*”. This repetition problem happens because the next word should be some words similar to the listed sports names except for the sports that have been mentioned and the softmax layer has difficulties in outputting a donut-shape next word distribution in embedding space. In contrast, **Softmax + CPR:20,100 + Mi** can learn to exclude the listed sports by putting very negative logits on the context words, which yield the desired donut-shape distribution.

4.2 T5 and BART in Summarization

We test our methods on two popular encoder-decoder LMs, T5 (Raffel et al., 2020) and BART (Lewis et al., 2020). We fine-tune the pre-trained LMs with different softmax alternatives on two news summarization datasets: CNN/DM (See et al., 2017) and XSUM (Narayan et al., 2018), one narrative summarization dataset: BookSum at paragraph level (Kryściński et al., 2021), and one dialogue summarization dataset: SAMSUM (Gliwa et al., 2019).

In the main paper, we evaluate the quality of summaries using four metrics. ROUGE-1 F1 (Lin, 2004) measures the unigram overlapping between the generated summary and the ground truth sum-

mary; CIDEr (Vedantam et al., 2015) adds a tf-idf weighting on the n-gram overlapping score to emphasize correct prediction of rare phrases; factCC (Kryscinski et al., 2020) evaluates the factuality of the summary; MAUVE (Pillutla et al., 2021) compares the word distribution of summary and ground truth in a quantized embedding space. To further support our conclusions, we also compare the quality measured by several other metrics and their model sizes in Table 9 and Table 10.

The results are reported in Table 6. Similar to the GPT-2 experiments, the results are generally better as we combine more partitions and local embedding approaches. This demonstrates that we can directly fine-tune the LMs with our softmax alternatives without expensive pretraining.

Unlike the GPT-2 experiments, multiple input hidden state enhancement (Mi) is not very effective, so we mainly compare the methods without Mi (i.e., $\mathbf{q}_{ct} = \mathbf{h}_{ct}^M$, unlike Equation 2). We hypothesize one possible reason is that we haven’t pretrained the T5 and BART with our softmax alternatives.

Our improvements are larger in smaller models. This is probably because in a smaller word embedding space, there are more likely to be interfering words between the desired next word possibilities. Compared to our methods, the pointer networks perform well in BART-base but usually perform worse in other LMs. We need further investigations in the future to explore the reasons.

Compared to ROUGE-1 score, the improvement percentage of CIDEr is overall higher. One major problem of the summarization LMs is that the generated summary contains too many commonly used phrases (King et al., 2022) and our considerably higher CIDEr scores indicate the alleviation of the problem. Our improvement on the factCC is also significant (Cao and Wang, 2021). Finally, our MAUVE improvement percentage on BookSum Paragraph dataset could reach around 30% in T5-Small. We hypothesize this is because we often mention the global entity names in the news (e.g., Obama) while the meaning of names in stories (e.g., John) is often defined by the context.

5 Related Work

Repetition and hallucination are two common problems in language generation tasks. One common solution for repetition is to avoid outputting the words in the context, which is often called unlikelihood training (Welleck et al., 2020; Jiang et al.,

word embeddings. Nevertheless, their side effect of breaking the similarity structure in the word embedding space might hurt the generation quality in some cases. Concurrently to our work, [Wan et al. \(2023\)](#) also use the softmax bottleneck theory ([Chang and McCallum, 2022](#)) to explain the improvement of a pointer network. Their empirical results also support our conclusion that softmax bottleneck is a major reason that causes the factuality problem of LMs.

Our work is motivated and inspired by [Chang and McCallum \(2022\)](#). In their work, they also propose to use different hidden states for different vocabulary partitions, but their partitioning is global and needs to be combined with the mixture of softmax (MoS) approach, which adds a significant overhead compared to the standard softmax layer. Our dynamic partitioning methods not only perform better but greatly reduce the overhead by removing the reliance on MoS.

6 Conclusion

Since the transformer becomes the mainstream encoder and decoder for LMs, the output softmax layer seems to be the only reasonable option for computing the word probability distribution. Although being simple and efficient, the softmax layer is inherently limited while the existing solutions are relatively slow ([Chang and McCallum, 2022](#)). This work proposes a series of softmax alternatives that can improve the text generation models without increasing the computational costs significantly. Our experiments suggest that the main improvement of the pointer network on top of a transformer comes from breaking the softmax bottleneck. Our results also indicate that the alternatives could alleviate some problems of hallucination, repetition, and too generic generation. Furthermore, all of the proposed alternatives can be applied to the LMs that have already been pretrained using softmax without requiring retraining from scratch. For the practitioner, we recommend using all the partitioning methods together to get the best performance, or using only the simple context partition to keep the architecture simple while getting the majority of the gain.

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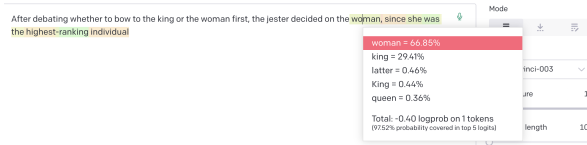
ence and the Center for Intelligent Information Retrieval, in part by the Chan Zuckerberg Initiative under the project Scientific Knowledge Base Construction, in part by the IBM Research AI through the AI Horizons Network, in part using high performance computing equipment obtained under a grant from the Collaborative R&D Fund managed by the Massachusetts Technology Collaborative, and in part by the National Science Foundation (NSF) grant numbers IIS-1922090 and IIS-1763618. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect those of the sponsor.

8 Limitations

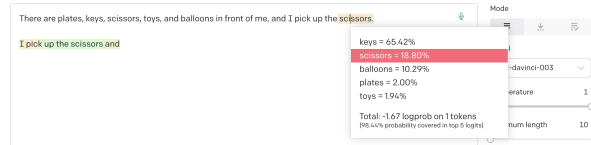
In our experiments, we find that the improvement of our methods tend to be larger in relatively smaller language models. Due to our limited access of computational resources, we are not able to try our methods on larger LMs. To know if a larger LM still suffers from the softmax bottleneck problem, we input the examples we used in [Table 5](#) to GPT-3.5 and report their results in [Figure 4](#).

We find that although GPT-3.5 greatly reduces the chance of hallucination compared to GPT-2, the next word distribution is still not ideal. For example, in [Figure 4a](#), although the incorrect answer *queen* receives only a small probability, GPT-3.5 puts around 67% probability on *woman*. Similarly, even though GPT-3.5 is unlikely to hallucinate the sentence: *There are plates, keys, scissors, toys, and balloons in front of me, and I pick up the phone* as GPT-2, [Figure 4b](#) and [Figure 4d](#) show that the output distribution is still heavily biased toward one of the options and the most likely next word could change if the order of the options in the context changes. These results suggest that increasing model size indeed alleviates the softmax bottleneck problem but the problem is not completely solved even if a huge hidden state size (12k) and model size (175B) are used ([Brown et al., 2020](#)). We expect that adding our methods to the large LMs could rectify the biased distributions as shown in our experiments on smaller LMs ([Table 5](#)). Therefore, although improving smaller LMs has already had wide applications in practice, trying our methods on a larger LM is a promising next step, which we haven't been able to do.

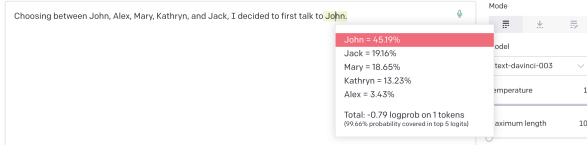
The current implementation of our methods also has some room for improvements. Our codes cur-



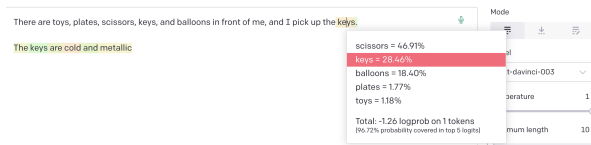
(a) The example where the next word should be either *woman* or *king* (or their synonym such as former and latter).



(b) The example where the next word *plates*, *keys*, *scissors*, *toys*, and *balloons* should receive similar probabilities.



(c) The example where the next word *John*, *Alex*, *Mary*, *Kathryn*, and *Jack* should receive similar probabilities.



(d) Same as above except that the order of the objects in the context is different.

Figure 4: The next word probabilities outputted by GPT-3.5 (text-davinci-003).

rently contain some unnecessary computation to circumvent the restrictions of PyTorch library, so we should be able to further accelerate it by writing CUDA code. Furthermore, our codes haven't supported the pretraining of BART or T5. We expect that completing the future work could make our method faster and better.

Since the focus of this paper is improving the architecture of general transformer decoder, our evaluation of each application is not as comprehensive as the studies for a particular application. For example, although we test our methods using many metrics and the metrics show a consistent trend, there are many other factuality metrics we haven't tried (Li et al., 2022). We also haven't conducted human evaluation to further verify our conclusion because conducting human evaluation properly is challenging (Karpinska et al., 2021) and time-consuming. In addition, if we include more words in a context partition, the performance might be better at the cost of extra computational overhead. We leave the analyses of the tradeoff as future work.

9 Ethics Statement

In our experiments, we find that our methods usually copy more words from the context or encoder input. The tendency might have some potential issues. For example, our improvements might be reduced on the languages with more morphology. Furthermore, in some summarization applications, increasing the factuality by increasing the extractiveness might not be ideal (Ladhak et al., 2022; Goyal et al., 2022a).

As described in Section 2.1, one major limitation of the popular softmax layer is its global word

embeddings. The problem would become more serious when there are more tokens whose meanings are locally defined (e.g., names in the BookSum dataset). Our methods would be more useful in those circumstances and might alleviate some biases described in Shwartz et al. (2020) and Ladhak et al. (2023). Moreover, the meaning of tokens are also locally defined in many other applications such as variables in code or math problems, the new terminologies in a scientific paper, or the products in a sequential recommendation problem. We believe that our methods could become an efficient alternative of reranker (Cobbe et al., 2021; Welleck et al., 2022) and create impacts in those areas.

Finally, our results show that when there are some uncertainties in the next word (e.g., could be *king* or *woman*), existing LMs could have some difficulties of copying the words from the context and our methods alleviate the problem. Thus, our methods should also be able to improve the lexically controllable language generation models that put the desired keywords into the context such as Goldfarb-Tarrant et al. (2019) and Lu et al. (2021).

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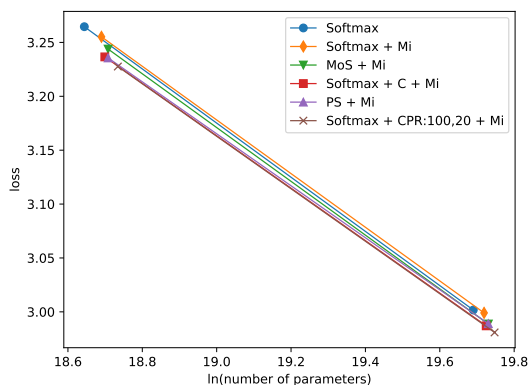


Figure 5: The model size versus the model loss in Wikipedia test data after training for 0.4 epochs. The left side points are the results from GPT-2 Small and the right side points come from GPT-2 Medium. The lower curves are better.

A Appendix Overview

In the appendix, we first analyze our methods using more metrics in Appendix B and describe what we learn from the results. Next, we provide some details of our methods and baselines in Appendix C. Finally, we specify some experiment setups and hyperparameters in Appendix D.

B More Results and Analysis

In this section, we will report more results and provide more detailed analyses accordingly to investigate the advantages of different methods.

B.1 GPT-2 Experiments

Kaplan et al. (2020); Henighan et al. (2020) demonstrate that the loss decreases linearly as the log of the model size increases. Therefore, a new architecture needs to perform better than the old architecture with a similar model size to verify that the improvement does not come from memorizing more information through the extra parameters. From the loss versus log(model size) curve in Figure 5, we can see that our proposed methods are significantly better than MoS and slightly better than a pointer network baseline as the model becomes larger.

We use the following metrics to measure the text generated by GPT-2.

- **ROUGE-1 (R1)**: The prediction F1 for unigram in the actual continuation.
- **ROUGE-1 Context (R1C)**: The prediction F1 for unigram in the context.

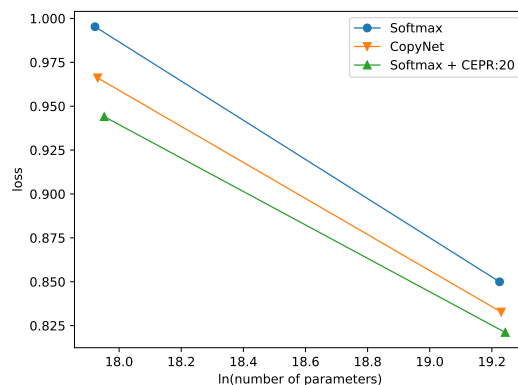


Figure 6: The model size versus the model loss in CNN/DM test set. The left side points are the results from T5-Small and the right side points come from T5-Base. The lower curves are better.

- **ROUGE-1 Proper (R1P)**: The same as ROUGE-1 except that only the proper nouns are considered. We measure this metric because the correctness of the entity name prediction is critical to the factuality of the generation.
- **ROUGE-1 Proper Context (R1PC)**: The same as ROUGE-1 Context (R1C) except that only the proper nouns are considered.
- **ROUGE-2 (R2)**: The prediction F1 for bigram in the actual continuation.
- **Proper Noun Ratio (P Ratio)**: The average number of proper nouns in the generation divided by the average number of proper nouns in the actual continuation. The LMs usually generate fewer proper nouns compared to the actual continuation (See et al., 2019), so the values are usually lower than 1. The P Ratio closer to 1 is better.
- **CIDEr (Vedantam et al., 2015)**: A metric for measuring the quality and specificity of the generation.
- **NIST (Doddington, 2002)**: Similar to CIDEr. CIDEr uses tf-idf to weigh the n-gram while NIST measures the information gain.

The results are reported in Table 8. In terms of R1, R2, CIDEr, and NIST, our proposed methods such as **Softmax + C + Mi** and **Softmax + CPR:20,100 + Mi** are significantly better than the pointer network baselines **PS + Mi** and **PG + Mi**. Comparing with **Softmax + CPR:20,100 + Mi**, **PS + Mi** has a significantly higher P Ratio and R1PC but similar R1P. This indicates that **PS + Mi** copies

Analogy Relation Types → Models ↓	Diagonal (e.g., <i>king</i> or <i>woman</i>)					Edge (e.g., <i>king</i> or <i>queen</i>)				
	valid	capital- common	capital- world	city-in- state	family	valid	capital- common	capital- world	city-in- state	family
Softmax + Mi	2.27	3.36	1.94	2.32	3.09	2.13	2.61	1.90	2.21	2.49
MoS + Mi (Chang and McCallum, 2022)	1.86	2.62	1.66	1.86	3.59	1.87	2.24	1.66	1.90	3.10
Softmax + C + Mi	1.78	2.19	1.62	1.87	2.17	1.79	2.13	1.63	1.88	2.07
Softmax + CPR:20,100 + Mi	1.69	2.03	1.54	1.81	2.09	1.69	2.01	1.55	1.81	1.97

Table 7: Comparing the perplexity of different *GPT-2 Small* models using the synthetic dataset from Chang and McCallum (2022).

Model Name	R1	R1C	R1P	R1PC	R2	P Ratio	CIDEr	NIST
Softmax (GPT-2)	22.668	23.548	7.323	14.340	3.219	0.885	0.182	1.792
Softmax + Mi	22.903	24.036	7.493	14.840	3.289	0.877	0.190	1.829
Mixture of Softmax (MoS) (Yang et al., 2018)	22.965	24.233	7.760	15.762	3.260	0.885	0.188	1.846
MoS + Mi (Chang and McCallum, 2022)	22.876	23.979	7.703	15.493	3.270	0.889	0.188	1.829
Pointer Generator (PG) (See et al., 2017)	23.055	24.872	8.052	17.830	3.311	0.889	0.193	1.856
Pointer Sentinel (PS) (Merity et al., 2017)	23.007	24.444	7.677	16.146	3.302	0.873	0.189	1.840
Softmax + R:20 + Mi	22.941	23.970	7.467	14.733	3.303	0.896	0.188	1.833
Softmax + R:20,100 + Mi	22.909	23.938	7.537	15.066	3.280	0.870	0.190	1.829
Softmax + C + Mi	23.116	25.027	7.894	17.048	3.372	0.917	0.197	1.873
Softmax + P + Mi	23.015	25.080	7.895	17.184	3.346	0.877	0.196	1.847
PG + Mi	22.827	24.759	8.049	17.874	3.289	0.914	0.191	1.819
PS + Mi	22.846	25.008	8.159	18.208	3.307	0.921	0.194	1.823
Softmax + CR:20,100 + Mi	23.017	25.056	8.089	17.798	3.328	0.894	0.198	1.858
Softmax + CPR:20,100 + Mi	23.053	25.361	8.160	17.921	3.363	0.882	0.197	1.863
MoS + CPR:20,100 + Mi	23.047	25.173	8.187	18.198	3.314	0.902	0.198	1.868

Table 8: Comparison of the continuation generated by *GPT-2 Small* in Wikipedia test data. Table 4 is a short summary of this table. The meaning of the metrics is described in Appendix B.1. Higher R1C and R1PC mean copying more words from the context. A higher P Ratio means generating more proper nouns. All ROUGE scores are percentages.

more proper nouns from the context while there is a similar number of proper nouns that are in actual continuation, so **Softmax + CPR:20,100 + Mi** actually has a higher accuracy on the proper noun prediction.

In text corpus such as Wikipedia, we do not know the ground truth next word distribution and which context leads to multiple probable next words, so we cannot quantitatively analyze the improvement on the ambiguous contexts. To alleviate the concern, we test our methods on the synthetic dataset constructed by Chang and McCallum (2022). The dataset is built using templates and Google analogy dataset (Mikolov et al., 2013), so we know the ground truth next word distribution. The dataset consists of the ambiguous contexts such as *I went to Paris and Germany before, and I love one of the places more, which is,* where the next word is either the diagonal words of the parallelogram such as *Paris* and *Germany* or the edge words such as *Paris* and *France*. For the details of the experimental setup, please refer to Chang and McCallum (2022).

In Table 7, we can see that **Softmax +**

CPR:20,100 + Mi achieves the lowest perplexity in all subsets and outperforms the **Softmax + Mi** baseline by a large margin, especially in the diagonal subset where the ground truth word embedding distribution has multiple modes. Notice that the performance of **MoS + Mi** is worse than what reported in Chang and McCallum (2022) probably because we shared the input and output word embeddings.

B.2 Summarization

Compared to Figure 5, Figure 6 shows that our methods improve the loss of T5 in CNN/DM more than *GPT-2* in Wikipedia.

In Table 9 and Table 10, we compare the different summarization models by their model size, evaluation losses, inference time, and other metrics which we use in subsection B.1. The pointer network baselines and our methods significantly improve most metrics over the softmax baseline, which is used ubiquitously in nearly all LMs. Although our method generally improves less on the T5-Base model, the percentages of additional parameters and inference time overhead are much

Models	Size	CNN/DM					XSUM				
		Loss (\downarrow)	R2	R1P	P Ratio	NIST	Loss (\downarrow)	R2	R1P	P Ratio	NIST
T5-Small											
Softmax (S)	60.8M	0.995	15.147	0.462	0.915	4.650	0.538	7.098	0.292	0.853	2.738
CopyNet (Gu et al., 2016)	61.3M	0.966	14.942	0.458	0.985	4.607	0.533	7.055	0.286	0.865	2.742
PG (See et al., 2017)	61.3M	0.978	14.789	0.453	0.943	4.589	0.535	7.211	0.288	0.849	2.744
PS (Merity et al., 2017)	61.3M	0.970	14.866	0.455	0.946	4.629	0.535	7.000	0.283	0.853	2.718
S + R:20	61.0M	0.985	14.831	0.456	0.928	4.603	0.534	7.085	0.287	0.858	2.730
S + E	61.0M	0.956	14.935	0.457	0.950	4.629	0.530	7.152	0.292	0.864	2.759
S + CE	61.3M	0.954	15.124	0.462	0.956	4.691	0.528	7.304	0.297	0.873	2.815
S + CER:20	61.5M	0.953	14.996	0.463	0.953	4.667	0.527	7.194	0.296	0.871	2.800
S + CEPR:20	62.6M	0.944	15.194	0.476	0.971	4.739	0.525	7.363	0.305	0.878	2.844
S + CEPR:20 + Mi	65.5M	0.943	15.094	0.471	0.976	4.720	0.523	7.340	0.305	0.874	2.840
T5-Base											
Softmax (S)	223.5M	0.850	16.410	0.491	0.959	4.948	0.417	10.773	0.386	0.910	3.454
CopyNet (Gu et al., 2016)	224.7M	0.833	16.253	0.486	0.979	4.915	0.416	10.804	0.387	0.915	3.467
PG (See et al., 2017)	224.7M	0.840	16.134	0.485	0.955	4.923	0.417	10.815	0.389	0.915	3.466
PS (Merity et al., 2017)	224.7M	0.836	16.275	0.490	0.978	4.908	0.417	10.838	0.386	0.915	3.473
S + CEPR:20	227.6M	0.821	16.292	0.497	0.990	4.966	0.412	10.778	0.389	0.930	3.477
S + CEPR:20 + Mi	234.1M	0.821	16.457	0.499	0.987	4.997	0.412	10.921	0.391	0.929	3.511
BART Base											
Softmax (S)	140.0M	0.874	15.613	0.471	1.028	4.641	0.391	12.944	0.428	0.928	3.833
CopyNet (Gu et al., 2016)	141.2M	0.837	15.675	0.470	1.013	4.685	0.387	12.740	0.424	0.934	3.818
PG (See et al., 2017)	141.2M	0.845	15.485	0.465	1.018	4.669	0.389	12.849	0.425	0.928	3.827
PS (Merity et al., 2017)	141.2M	0.838	15.689	0.468	0.996	4.750	0.387	12.690	0.423	0.926	3.796
S + R:20	140.6M	0.863	15.486	0.468	1.028	4.655	0.389	12.804	0.426	0.941	3.824
S + E	140.6M	0.852	15.412	0.466	1.018	4.652	0.389	12.893	0.428	0.933	3.844
S + CE	141.2M	0.851	15.555	0.471	1.013	4.692	0.388	12.830	0.426	0.934	3.827
S + CER:20	141.8M	0.850	15.550	0.469	1.022	4.672	0.387	12.787	0.423	0.940	3.821
S + CEPR:20	144.1M	0.841	15.778	0.471	1.025	4.724	0.387	12.824	0.423	0.942	3.829
S + CEPR:20 + Mi	150.6M	0.843	15.632	0.472	1.027	4.700	0.387	12.969	0.426	0.939	3.847
BART Large											
Softmax (S)	407.3M	0.794	16.386	0.488	1.091	4.654	0.359	15.386	0.476	1.006	4.136
CopyNet (Gu et al., 2016)	409.4M	0.774	16.268	0.485	1.113	4.619	0.358	15.293	0.473	0.995	4.144
PG (See et al., 2017)	409.4M	0.780	16.344	0.486	1.097	4.656	0.358	15.544	0.475	0.995	4.186
PS (Merity et al., 2017)	409.4M	0.774	16.142	0.484	1.099	4.654	0.358	15.547	0.475	1.000	4.227
S + CEPR:20	414.7M	0.780	16.394	0.488	1.073	4.767	0.359	15.466	0.476	0.982	4.240
S + CEPR:20 + Mi	426.2M	0.769	16.085	0.483	1.032	4.811	0.347	15.371	0.475	0.957	4.292

Table 9: Comparison of the summaries generated by different models in the test sets of CNN/DM and XSUM datasets. We also report the number of parameters of each model. From top to bottom, the four sections are the results of T5-Small, T5-Base, BART Base, and BART Large. The meaning of the metrics are described in Appendix B.1. R2 (ROUGE 2-F1) scores are percentages. Within each section, we highlight the smallest loss, the P Ratio that is closest to 1, and highest numbers in the other metrics.

smaller. Although our methods tend to improve less in larger language model, we still improve BART Large very significantly in NIST, CIDEr, and MAUVE, and Mi seems to become more effective in BART Large.

The testing set of SAMSUM dataset only has 819 samples, so some metrics such as R1 and R2 are not as stable as other three datasets. PG (See et al., 2017) for T5-Small and T5-Base perform much worse in SAMSUM dataset. We hypothesize that it is because the dialog input in SAMSUM dataset is very different from the pretraining data of T5, which makes training PG unstable.

In most datasets and models, the R Ratio from our method is significantly closer to 1 than the softmax baseline, which means the average number of

proper nouns in our summaries is much closer to the average number of proper nouns in the human-written summary. For example, in BookSum Paragraph, we improve its R Ratio by 26%, which partially explains our large MAUVE improvement in Table 6. Notice that our methods do not always output more proper nouns. For example, for BART Base in CNN/DM dataset, our methods reduce the R Ratio of the softmax baseline, which is larger than 1. This shows that our methods could learn when we should copy the proper nouns according to the training data.

C Method Details

We describe some details of our methods and baselines in this section.

Models	Time (ms)	BookSum Paragraph					SAMSUM				
		Loss (\downarrow)	R2	R1P	P Ratio	NIST	Loss (\downarrow)	R2	R1P	P Ratio	NIST
T5-Small											
Softmax (S)	30.1	0.654	1.673	0.149	0.589	1.383	0.383	13.806	0.605	0.873	3.945
CopyNet (Gu et al., 2016)	37.0	0.646	1.722	0.183	0.747	1.440	0.381	14.210	0.594	0.809	3.965
PG (See et al., 2017)	43.4	0.648	1.669	0.160	0.631	1.413	0.392	10.673	0.542	0.711	1.665
PS (Merity et al., 2017)	37.6	0.646	1.627	0.177	0.700	1.417	0.383	13.817	0.583	0.794	3.960
S + R:20	32.9	0.652	1.663	0.159	0.677	1.403	0.380	13.728	0.598	0.870	3.995
S + E	33.8	0.645	1.710	0.171	0.673	1.421	0.370	13.557	0.602	0.892	3.906
S + CE	34.0	0.644	1.734	0.173	0.680	1.436	0.368	14.136	0.619	0.892	3.971
S + CER:20	35.8	0.642	1.710	0.174	0.693	1.434	0.367	14.281	0.627	0.911	3.968
S + CEPR:20	38.4	0.641	1.768	0.184	0.725	1.461	0.365	14.451	0.639	0.909	4.034
S + CEPR:20 + Mi	41.7	0.641	1.733	0.185	0.721	1.458	0.365	14.193	0.630	0.922	4.011
T5-Base											
Softmax (S)	102.4	0.587	1.876	0.160	0.650	1.443	0.308	17.662	0.672	0.915	4.559
CopyNet (Gu et al., 2016)	110.3	0.582	1.867	0.187	0.744	1.481	0.307	17.556	0.678	0.901	4.544
PG (See et al., 2017)	117.7	0.585	1.832	0.159	0.647	1.434	0.317	14.649	0.611	0.740	1.870
PS (Merity et al., 2017)	112.0	0.582	1.899	0.176	0.718	1.465	0.308	17.502	0.660	0.897	4.453
S + CEPR:20	115.3	0.580	1.842	0.191	0.771	1.482	0.300	18.082	0.677	0.950	4.553
S + CEPR:20 + Mi	116.3	0.584	1.860	0.187	0.770	1.477	0.301	17.617	0.677	0.938	4.521
BART Base											
Softmax (S)	46.6	0.624	1.807	0.141	0.656	1.425	0.327	19.379	0.672	0.995	4.546
CopyNet (Gu et al., 2016)	57.8	0.613	1.866	0.166	0.728	1.454	0.326	18.227	0.662	0.944	4.535
PG (See et al., 2017)	64.8	0.624	1.864	0.140	0.668	1.428	0.328	18.791	0.673	0.963	4.537
PS (Merity et al., 2017)	57.9	0.613	1.867	0.163	0.723	1.461	0.324	18.367	0.674	0.951	4.573
S + R:20	50.5	0.627	1.807	0.154	0.720	1.430	0.326	19.022	0.671	0.971	4.608
S + E	54.2	0.620	1.825	0.150	0.688	1.429	0.324	18.902	0.680	0.970	4.501
S + CE	56.5	0.619	1.847	0.153	0.685	1.441	0.323	18.739	0.672	0.949	4.537
S + CER:20	57.2	0.618	1.834	0.156	0.727	1.444	0.321	19.267	0.678	0.981	4.561
S + CEPR:20	58.8	0.618	1.865	0.157	0.742	1.457	0.321	18.631	0.670	0.992	4.516
S + CEPR:20 + Mi	63.2	0.620	1.827	0.158	0.733	1.442	0.322	18.681	0.670	0.987	4.439
BART Large											
Softmax (S)	143.5	0.554	2.094	0.171	0.722	1.472	0.303	20.848	0.711	1.006	4.621
CopyNet (Gu et al., 2016)	168.9	0.548	2.087	0.184	0.762	1.490	0.298	21.703	0.708	1.026	4.727
PG (See et al., 2017)	178.3	0.731	2.090	0.174	0.725	1.479	0.301	21.428	0.706	1.051	4.604
PS (Merity et al., 2017)	168.5	0.726	2.083	0.184	0.760	1.493	0.300	22.144	0.710	1.036	4.779
S + CEPR:20	169.9	0.552	2.069	0.178	0.763	1.505	0.302	21.326	0.691	1.017	4.595
S + CEPR:20 + Mi	177.4	0.544	2.024	0.175	0.737	1.500	0.294	21.244	0.713	0.959	4.746

Table 10: Comparison of the summaries generated by different models in the test sets of BookSum and SAMSUM datasets. We also report the inference time of one samples. The meaning of the metrics are described in Appendix B.1. R2 (ROUGE 2-F1) scores are percentages. Within each section, we highlight the smallest loss, the P Ratio that is closest to 1, and highest numbers in the other metrics.

C.1 Proposed Methods

To allow us to start from existing LMs that are pretrained using softmax, we keep the modified softmax layer initially working almost the same as the original softmax layer. We initialize the linear transformation weights of $L_{PD}^f()$, $L_{LD}^f()$, $L_{PE}^f()$, and $L_{LE}^f()$ as $10^{-10} \cdot \mathbb{I}$. The other linear weights $L^f()$ are initialized as the identity matrix \mathbb{I} .

In the local decoder embedding method **Softmax + P + Mi**, the initialization would give the 0 logit to all context words. To solve the issue, we revise Equation 3 a little and compute $\text{Logit}_P(x, c_t)$ by

$$\begin{cases} \mathbf{f}_{c_t, V}^T \mathbf{w}_x + \mathbf{f}_{c_t, PD}^T \mathbf{f}_{x, c_t, LD} & \text{if } x \in c_t \\ \mathbf{f}_{c_t, V}^T \mathbf{w}_x & \text{O/W} \end{cases} \quad (7)$$

That is, we initially rely on the original softmax layer to compute all the logits and let the term

$\mathbf{f}_{c_t, PD}^T \mathbf{f}_{x, c_t, LD}$ gradually influences the logits of the context words.

In **MoS + CPR:20,100 + Mi**, our proposed method only revises the logit in one of the softmax.

C.2 Pointer Network Baselines

The pointer networks are originally designed for RNN, so we are unable to use exactly the same formula proposed in the papers. Nevertheless, we try our best to adapt the pointer networks for the transformer encoder while keeping the gist of the formulas. In all methods, to let the results more comparable to our methods, we use $\mathbf{f}_{c_t, PE}$ and L_{LE}^f to determine the probability of copying the words from the context, and use $\mathbf{f}_{c_t, V}^T \mathbf{w}_x$ to determine the probability of generating all the words in

the vocabulary.

In CopyNet (Gu et al., 2016), we compute the probability of outputting the word x as

$$\begin{aligned} \text{Prob}(x|I, c_t) &\propto \exp(\mathbf{f}_{c_t, V}^T \mathbf{w}_x) \\ &+ \sum_{j=1}^{|I|} \mathbb{1}_{I^j=x} \exp\left(\mathbf{f}_{c_t, PE}^T L_{LE}^f(\mathbf{h}_{I^j}^M) + b\right). \end{aligned} \quad (8)$$

Notice that CopyNet needs to sum up the exponential of dot products, which often causes overflow problems in GPT-2. We can set b to be a large negative value initially to solve the problem, but its perplexity is much worse than the other two pointer network variants. Thus, we choose to skip the CopyNet in the GPT-2 experiments.

In Pointer Generator (See et al., 2017), we compute the probability of x using

$$\begin{aligned} \text{Prob}(x|I, c_t) &= p_{gen} \frac{\exp(\mathbf{f}_{c_t, V}^T \mathbf{w}_x)}{Z_V} \\ &+ (1 - p_{gen}) \sum_{j=1}^{|I|} \mathbb{1}_{I^j=x} P_E(j|I, c_t), \end{aligned} \quad (9)$$

where $P_E(j|I, c_t) = \frac{\exp(\mathbf{v}^T \tanh(\mathbf{f}_{c_t, PE} + L_{LE}^f(\mathbf{h}_{I^j}^M) + b))}{Z_E}$, $p_{gen} = \sigma(\mathbf{q}^T \mathbf{h}_{c_t}^M + b_{ptr})$, the normalization term $Z_V = \sum_{x \in V} \exp(\mathbf{f}_{c_t, V}^T \mathbf{w}_x)$, and $Z_E = \sum_{j=1}^{|I|} \exp(\mathbf{v}^T \tanh(\mathbf{f}_{c_t, PE} + L_{LE}^f(\mathbf{h}_{I^j}^M) + b))$.

We skip the coverage mechanism in the pointer generator paper to make it more comparable to other methods. In T5 experiments, its training loss is sometimes very large, so we set b_{ptr} as 3 initially to keep the p_{gen} close to 1 (i.e., turn pointer part off initially). In other experiments, we set $b_{ptr} = 0$.

In Pointer Sentinel (Merity et al., 2017), the probability of x is computed by

$$\begin{aligned} \text{Prob}(x|I, c_t) &= g \frac{\exp(\mathbf{f}_{c_t, V}^T \mathbf{w}_x)}{Z_V} \\ &+ \sum_{j=1}^{|I|} \mathbb{1}_{I^j=x} \frac{\exp(\mathbf{f}_{c_t, PE}^T \tanh(L_{LE}^f(\mathbf{h}_{I^j}^M) + b))}{Z_p}, \end{aligned} \quad (10)$$

$$g = \frac{\exp(\mathbf{q}^T \mathbf{h}_{c_t}^M)}{Z_p}, \text{ and } Z_p = \exp(\mathbf{q}^T \mathbf{h}_{c_t}^M) + \sum_{j=1}^{|I|} \exp(\mathbf{f}_{c_t, PE}^T \tanh(L_{LE}^f(\mathbf{h}_{I^j}^M) + b)).$$

In our experiments, we find that the pointer network variants usually have similar performance (except that PG sometimes performs much worse

in summarization due to some training stability issues). This suggests that the differences in the pointer network variants often do not influence the performance significantly, which justifies our simplification of the formulas in the original paper and supports our conclusion that the improvement comes from breaking the softmax bottleneck.

Notice that in the above pointer network variants, the pointer part can only increase the probability of the context words from the generator part. As a result, it cannot alleviate the repetition problem in the last example of Table 5.

C.3 Word-by-word Reranker Baseline

We illustrate our word-by-word reranker (wbwR) in Figure 7. The method has two stages. In the first stage, we compute the logits using the projected hidden state $\mathbf{f}_{c_t, V}$ and retrieve the top k words. At the second stage, we append the top k words to the input context along with the hidden state $\mathbf{f}_{c_t, R}$ for reranking the context words.³ We use the same positional embeddings for all candidates to encourage the model to change the ranking of the words. Next, we use the hidden states corresponding to the candidates to compute their local word embeddings as $\mathbf{f}_{x, c_t, LD}$. Finally, we re-estimate the probabilities of top k words by

$$\begin{cases} \mathbf{f}_{c_t, V}^T \mathbf{w}_x + \mathbf{f}_{c_t, R}^T \mathbf{f}_{x, c_t, LD} & \text{if } x \in W(k) \\ \mathbf{f}_{c_t, V}^T \mathbf{w}_x & \text{O/W} \end{cases}. \quad (11)$$

To improve the quality of our top k candidates, the final loss is the addition of the wbwR loss at the second stage and the loss of the original softmax layer that only uses the logits from $\mathbf{f}_{c_t, V}^T \mathbf{w}_x$ at the first stage. When we combine the wbwR with **Softmax + CPR:20,100 + Mi**, we simply use **Softmax + CPR:20,100 + Mi** at the first stage and use the wbwR to overwrite the logits of **Softmax + CPR:20,100 + Mi** at the second stage.

Using this method, we can update the embeddings of the words that are not in the context and allow the candidates to interact with the input context to determine their probabilities as the classic two-stage reranker while keeping the model size roughly unchanged. Nevertheless, the method can only change the probability of the top k words and its computational overhead and memory requirement prevents us from using a very large k .

³The motivation is helping GPT-2 to output the local word embedding of a candidate closer to the $\mathbf{f}_{c_t, R}$ if GPT-2 wants to increase the probability of the candidate.

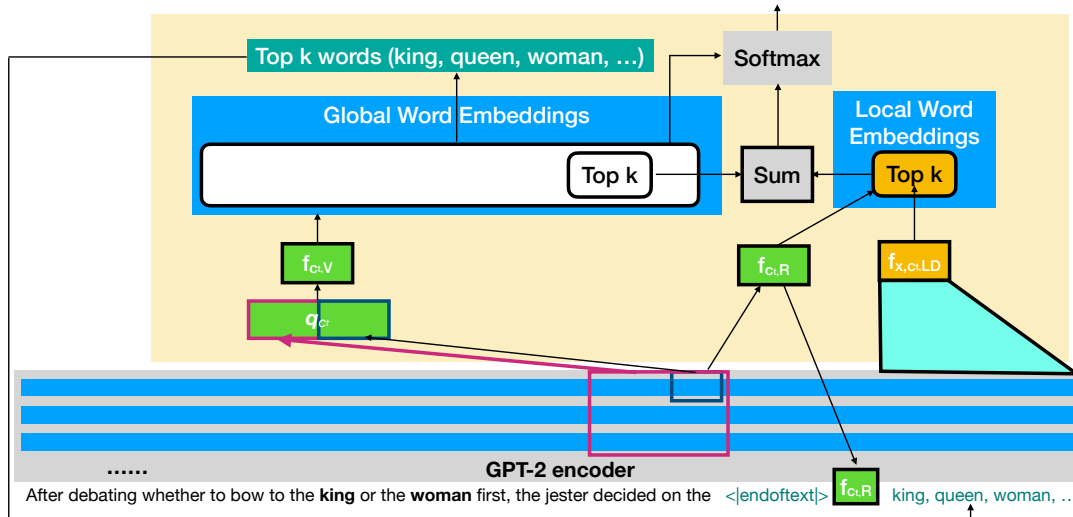


Figure 7: Word-by-word reranker architecture.

Input for stage1:

T1 T2 T3 T4 T5 T6 T7 T8 T9

Input1 for stage2 with past-key-value in position1:

T1 k1.1 k1.2 k1.3

T1 T2 k2.1 k2.2 k2.3

T1 T2 T3 k3.1 k3.2 k3.3

Input2 for stage2 with past-key-value in position4:

T4 k4.1 k4.2 k4.3

T4 T5 k5.1 k5.2 k5.3

T4 T5 T6 k6.1 k6.2 k6.3

Input3 for stage2 with past-key-value in position7:

T7 k7.1 k7.2 k7.3

T7 T8 k8.1 k8.2 k8.3

T7 T8 T9 k9.1 k9.2 k9.3

Figure 8: Our efficient implementation of word-by-word reranker. T_i is tokens and $k_{i,j}$ is top- k tokens for T_i .

Unlike the standard GPT-2, we cannot get the probability of all positions in one forward pass because the input contexts are different when computing the probability at each position and the input of the second stage reranker depends on the results of the previous forward pass at the first stage. To speed up, we reuse the computed hidden states and batchify the forward passes.

In our implementation, we first get the top k candidates corresponding to all tokens in the stage1 (just original GPT2) as the input of stage2 reranker. To avoid recalculating the hidden states of the context at stage2, we store the hidden states using the past-key-value in Hugging Face and only compute the hidden states corresponding to the top k candi-

date tokens at stage2.

We divide the computation of the whole input sequence into several blocks as shown in Figure 8. In each block, we input a batch containing the last few tokens and top k candidates into the GPT-2 while reusing the hidden states of their common contexts from stage1. In this way, we can increase parallelism by increasing the block size if the GPU memory allows it.

Even though we spent substantial effort on optimizing the wbwR, the method is still too slow to be practically useful. Even if we use four RTX 8000 (a faster GPU with a larger memory), our wbwR implementation is still around 10 times slower than our proposed **Softmax + CPR:20,100 + Mi** that uses only one RTX 2080.

D Experiment Details

For the reproducibility, we provide some experimental configuration in this section. Please see our codes (<https://github.com/iesl/Softmax-CPR>) for more details.

D.1 GPT-2 Experimental Details

We mostly follow the experimental setup Chang and McCallum (2022) except that we share the input and output word embeddings as in the standard GPT-2 models. As in Chang and McCallum (2022), we use the last 2% of the corpus as the test set and the 2% before that as the validation set.⁴ In

⁴We do not shuffle the corpus before splitting the datasets. We found that our improvement could be even larger if we shuffle the corpus to let the training data distribution closer to

	Train	Val	Test
CNN/DM	287113	13368	11490
XSUM	204045	11332	11334
BookSum Paragraph	210931	27222	26025
SAMSUM	14732	818	819

Table 11: Dataset size of our four summarization tasks.

the word-by-word reranking experiment, we only use first 100k tokens in validation set to speed up the evaluation. To show that our model could be added to existing pretrained models, we continue training the pretrained GPT-2. For GPT-2 Small, we train for 1 epoch, and for GPT-2 Medium, we train for 0.4 epoch. We find that the performance improvements usually do not change significantly after training for 0.1 epoch.

As in [Chang and McCallum \(2022\)](#), we set the sequence length as 200, batch size as 4, and learning rate for AdamW as $1e - 5$. Our methods only have two hyperparameters, k_1 and k_2 , and we try values 20, 100, 200, 500 and select 20 and 100 using the validation data.

In the text completion experiment, we generate 360k continuations with a length of 50 given the prompts in Wikipedia. We first sample 40k sequences in the test data of Wikipedia 2021. Next, we use the first 20, 70, and 120 words in the sequence as our context and let the different models generate the next 50 words as continuations. The references are the actual next 50 words. All the methods use Top-K sampling and $K=5$.

D.2 Summarization Experimental Details

BookSum dataset ([Kryściński et al., 2021](#)) includes three summarization tasks: Summarizing a book, a chapter, and a paragraph. We test our methods using the paragraph summarization task due to the input length restriction of BART and T5. The dataset is constructed by automatically aligning the paragraphs in a chapter with the sentences in a chapter summary, which introduces noise to the dataset. Similarly, XSUM uses the first sentence in news instead of manually-written summary as the ground truth reference. The relatively noisier datasets such as XSUM and BookSum Paragraph, and smaller dataset like SAMSUM could test the stability of the methods. The sizes of the summarization datasets could be found in [Table 11](#).

We conduct the summarization experiments the testing data distribution.

based on a summarization example code from Hugging Face⁵. Most of our hyperparameters use the default value in the code. In our preliminary study, our improvement is not sensitive to the hyperparameter choice (e.g., the improvement gap is similar across different numbers of epochs). Thus, we do not tune the hyperparameters for each method or for each dataset unless we cannot reach a low training loss at the end.

In CNN/DM, XSUM, and SAMSUM datasets, We train models for 3 epochs. In BookSum datasets, We trained models for 5 epochs.⁶ The learning rate is set to be $5e - 05$ except for BART Large model in BookSum, where we use $1e - 05$ to stabilize the training of all methods.

All the experiments use batch size 8 and AdamW with betas=(0.9,0.999), epsilon= $1e - 06$, weight-decay= $1.2e - 6$. During the generation, we used Top-K sampling ($K=10$) as our decoding method. The maximum summary length is set as 128 and maximum input length is 1024. We use warmup for the first 1000 steps in all the experiments, which allows us to change the architecture of T5 and BART more significantly (e.g., using Mi) without having a training stability issue.

The k in the reranker partition and the block size of multiple input hidden states (Mi) is coarsely tuned based on validation performance of CNN/DM. Unlike considering the top 100 words in the open-end text completion using GPT-2, we find that reranking the top 20 words is sufficient for our summarization models, probably because next words are easier to predict in the summarization task.

For our evaluation metrics, we use the default setting for ROUGE⁷ and set use_stemmer=True. When reporting the ROUGE scores, we follow the conventions to show their percentages. We use the default setting for MAUVE⁸, CIDER⁹, NIST¹⁰. For MAUVE, we insert a new line symbol after every sentence as in the original Hugging Face

⁵https://github.com/huggingface/transformers/blob/main/examples/pytorch/summarization/run_summarization.py

⁶The BookSum Paragraph is noisier, so we train longer to be safe. And we find that different numbers of epochs do not change the trend of the results.

⁷<https://huggingface.co/spaces/evaluate-metric/rouge>

⁸<https://huggingface.co/spaces/evaluate-metric/mauve>

⁹<https://github.com/vrama91/cider>

¹⁰<https://www.nltk.org/api/nltk>

summarization example code. For factCC metric¹¹, we use the author-provided checkpoint to evaluate CNN/DM results since factCC is originally trained in CNN/DM. For the other three summarization datasets, we follow the author’s codes to constructed positive and negative data and continued training the CNN/DM factCC model on each dataset with one epoch respectively. Then we evaluate different summarization tasks with the corresponding factCC checkpoint.

D.3 Computational Environment and Software

We implement our methods by revising the Hugging Face library (Wolf et al., 2020). From Hugging Face, we load the pretrained LMs including GPT-2 Small¹², GPT-2 Medium¹³, T5-Small¹⁴, T5-Base¹⁵, BART Base¹⁶, and BART Large¹⁷. We use SpaCy (Honnibal et al., 2020) to detect the proper nouns.

For GPT-2 Medium, T5-Base, and BART Large, we use NVIDIA GeForce RTX 8000 to train the model and for other smaller models, we use NVIDIA GeForce RTX 2080. Most of experiments could be done within one week. In all the inference time experiments, we use NVIDIA GeForce GTX TITAN X, batch size 4 for GPT-2, and batch size 8 for BART and T5.

¹¹<https://github.com/salesforce/factCC>

¹²<https://huggingface.co/gpt2>

¹³<https://huggingface.co/gpt2-medium>

¹⁴<https://huggingface.co/t5-small>

¹⁵<https://huggingface.co/t5-base>

¹⁶<https://huggingface.co/facebook/bart-base>

¹⁷<https://huggingface.co/facebook/bart-large>

ACL 2023 Responsible NLP Checklist

A For every submission:

- A1. Did you describe the limitations of your work?
section 8
- A2. Did you discuss any potential risks of your work?
section 9
- A3. Do the abstract and introduction summarize the paper’s main claims?
section 1
- A4. Have you used AI writing assistants when working on this paper?
Grammarly

B Did you use or create scientific artifacts?

section 4

- B1. Did you cite the creators of artifacts you used?
section 4
- B2. Did you discuss the license or terms for use and / or distribution of any artifacts?
All the datasets and language models in the papers could be used for research purpose
- B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?
Not applicable. Left blank.
- B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?
Discussion of the privacy issues and offensive content in the language models is out of the scope of this paper
- B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?
People can check those information in the paper that releases the datasets
- B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.
section D

C Did you run computational experiments?

section 4 and section B

- C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?
Table 2, 8, and 9; section D.3

The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.

- C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?

section D

- C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?

For GPT-2 experiments, the perplexity on a large test set is known to have a very small variance. For summarization experiments, we provide the results of lots of different metrics and most of the metrics show the consistent trend. Due to sufficiently large test set, the papers in two domains (self-supervised language modeling and summarization) often do not report their error bars.

- C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?

section D

D Did you use human annotators (e.g., crowdworkers) or research with human participants?

Left blank.

- D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?

No response.

- D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants' demographic (e.g., country of residence)?

No response.

- D3. Did you discuss whether and how consent was obtained from people whose data you're using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?

No response.

- D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?

No response.

- D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?

No response.