Rare Words Degenerate All Words

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Abstract

Despite advances in neural network language model, the representation degeneration problem of embeddings is still challenging. Recent studies have found that the learned output embeddings are degenerated into a narrow-cone distribution which makes the similarity between each embeddings positive. They analyzed the cause of the degeneration problem has been demonstrated as common to most embeddings. However, we found that the degeneration problem is especially originated from the training of embeddings of rare words. In this study, we analyze the intrinsic mechanism of the degeneration of rare word embeddings with respect of their gradient about the negative log-likelihood loss function. Furthermore, we theoretically and empirically demonstrate that the degeneration of rare word embeddings causes the degeneration of non-rare word embeddings, and that the overall degeneration problem can be alleviated by preventing the degeneration of rare word embeddings. Based on our analyses, we propose a novel method, Adaptive Gradient Partial Scaling(AGPS), to address the degeneration problem. Experimental results demonstrate the effectiveness of the proposed method qualitatively and quantitatively.

1 Introduction

From RNN(Graves, 2013) to Transformer(Vaswani et al., 2017), various improved model architectures for neural language generation have been developed over the past several years(Sutskever et al., 2014; Bahdanau et al., 2015; Wu et al., 2016; Gehring et al., 2017; Vaswani et al., 2017). Despite the difference in the architecture mechanisms, these models usually share the same process for embeddings. They process word embeddings as inputs to encode contextualized hidden features, and subsequently decode the hidden features into a categorical distribution of target words at the output softmax layer(Merity et al., 2017; Yang et al., 2018; Vaswani et al., 2017; Press and Wolf, 2017). At present, it is common practice to share input embeddings with the role of inputs and output embeddings with the role of the weight of the output layer(Vaswani et al., 2017; Merity et al., 2017; Yang et al., 2018), which is known as weight sharing(Inan et al., 2017; Press and Wolf, 2017). For sequence-to-sequence model task such as machine translation(Sutskever et al., 2014), the model shares word embeddings in three parts: encoder input embedding, decoder input embedding and output embedding when they use source-target joint dictionary setting.

Although word embeddings are very important for the model performance, several problems remain with training word embeddings of high quality. In recent work, Gao et al. (2019) observed that learned word embeddings are degenerated into a narrow cone region in the embedding space, with a positive correlation exhibited between any of these. They demonstrated that this phenomenon limits the semantic expressiveness of word embeddings, and they referred to it as the representation degeneration problem. The authors analyzed the cause of the problem as common to most words in model vocabulary. They treated most words with equally low frequency according to Zipf’s law, which is the reason for the commonly applied analysis. Following the analysis, they introduced a method common to all word embeddings to alleviate the problem. Other methods proposed in later works(Wang et al., 2019; Wang et al., 2020) also followed the same perspective of the analysis of Gao et al. (2019).

In this study, we reanalyze the reason for the representation degeneration problem from a slightly different perspective. We theoretically and empirically analyze the representation degeneration problem with the training dynamics of word embeddings. According to the analysis, we argue that
only the embeddings of the rare words are responsible for the representation degeneration problem. Once the degeneration of the rare word embedding occurs, the degeneration of the non-rare word embedding is induced. Moreover, we demonstrate that the whole problem can be solved by just treating the rare words through empirical analysis.

Based on the analysis, we introduce a method to mitigate the representation degeneration problem, Adaptive Gradient Partial Scaling (AGPS). The core idea of AGPS is to negatively scale the gradient part of rare word embedding which causes degeneration problem during training process. The scale factor is adaptive to the relative frequency of rare words in training corpus. Our method are shown to improve translation quality in machine translation task. We observe the improved BLEU score and the improved word alignment between source and target language. In language modeling task, our method greatly improves the perplexity metric of rare tokens while maintaining the performance in non-rare tokens. We also find that our method is connected to the frequency bias problem of embedding learning researched by Gong et al. (2018).

2 Analysis of the Problem

In this section, we introduce the notations in this paper and propose our analysis of the problem empirically and theoretically based on training dynamics led by rare words.

Notation For a neural language model, there exists a vocabulary of words (indices) $V = \{1, \ldots, N\}$, and embedding vectors $\{\mathbf{w}_1, \ldots, \mathbf{w}_N\}$ where $\mathbf{w}_i$ corresponds to word index $i$. At each training step the model get a mini-batch target text corpus represented as a sequence of words $\mathbf{y} = (y_1, \ldots, y_M)$, where $y_i \in V$. We define the joint probability of sequence $\mathbf{y}$ as the following product of conditional probabilities

$$P(\mathbf{y}) = \prod_{i=1}^{M} P(y_i | \mathbf{h}_i),$$

where $\mathbf{h}_i$ is a fixed-size hidden state encoded by the model from input. The conditional probability is calculated through the softmax layer as follows.

$$P(y_i | \mathbf{h}_i) = \frac{\exp(\mathbf{w}^T \mathbf{y}_i \mathbf{h}_i)}{\sum_{l=1}^{N} \exp(\mathbf{w}^T \mathbf{l} \mathbf{h}_i)}.$$  

We approximate update process of embedding $\mathbf{w}$ to SGD update:

$$\mathbf{w}_{k+1} = \mathbf{w}_k - \alpha \frac{\partial L_{\text{NLL}}}{\partial \mathbf{w}_k},$$

where $\mathbf{w}_k$ is embedding vector for the $k$-th word at $t$-th training step, and $\alpha$ is the learning rate.

2.1 Word Embedding Training Dynamics led by Rare Words

To analyze the training procedure of word embeddings, We divide the whole vocabulary word into three groups: high-frequency, mid-frequency, low-frequency groups. Roughly speaking, we set a low-frequency groups as having relative frequency less than $10^{-6}$ in whole vocabulary, mid-frequency groups as having relative frequency between $10^{-5}$ and $10^{-6}$ in whole vocabulary, and high-frequency groups as remainders. We visualize the training dynamics of these three groups through projection
The definition means that if \( h \) term of Eq. (5): of the word embeddings into 2-dimensional using SVD projection. As we can see in figure 1, word embeddings in low-frequent groups degenerate first as they come out of the whole word embedding distribution. Then, other embeddings degenerate following degeneration of low-frequent group’s embeddings, making narrow cone distribution shape. We start our analysis from representation degeneration of words in low-frequent group.

The gradient of word embedding vector about negative log-likelihood function is written as follows.

\[
\frac{\partial L_{NLL}}{\partial w_k} = \sum_{h_i \in H^k_0} p(k | h_i) h_i \tag{a} - \sum_{h_i \in H^k_1} (1 - p(k | h_i)) h_i, \tag{b} \]

where \( H^k_0 \) and \( H^k_1 \) are set of hidden states \( h_i \). We define \( H^k_0 \) and \( H^k_1 \) as follows.

\[
h_i \in H^k_0 \Rightarrow y_i \neq k \]

\[
h_i \in H^k_1 \Rightarrow y_i = k \]

The definition means that if \( h_i \) is in \( H_0 \), \( w_k \) is not target word embedding about \( h_i \), and for \( h_i \) in \( H_1 \), \( w_k \) is target word embedding about \( h_i \). From the definition, we say the role of two terms of Eq. (5):

term (a) make \( w_k \) far from the hidden states whose target words are not \( k \)-th word, and term (b) make \( w_k \) close to the hidden states whose target words are \( k \)-th word.

We define rare word embedding group \( E_r \) as follows.

For \( w_r \in E_r, |H^k_r| \) is negligibly small.

From the definition of \( E_r \), we say (b) term of \( \frac{\partial L_{NLL}}{\partial w_r} \) can be negligible, which means that \( w_r \)’s update direction is opposite to that of most \( h_i \). In practice, we observe that \( w^T_r h_i < 0 \) for almost \( i \), and \( E[w^T_r h_i] < 0 \) soon after \( w_r \) participating in training stage. Finally, we argue that any two rare word embeddings \( w_{r_1} \) and \( w_{r_2} \) degenerate to become similar after some point of training stage.

We analyze update process of \( (w^T_{r_1}) (w^T_{r_2}) \), where \( w^T_{r_1} \), \( w^T_{r_2} \) as follows.

\[
(w^T_{r_1}) (w^T_{r_1} + 1) = (w^T_{r_1} - \alpha \frac{\partial L_{NLL}}{\partial w^T_{r_2}}) (w^T_{r_1} - \alpha \frac{\partial L_{NLL}}{\partial w^T_{r_2}}) \]

\[
= w^T_{r_1} (w^T_{r_1} + 1) + \alpha^2 (\frac{\partial L_{NLL}}{\partial w^T_{r_1}}) (\frac{\partial L_{NLL}}{\partial w^T_{r_2}}) \]

\[
= \alpha (\frac{\partial L_{NLL}}{\partial w^T_{r_1}}) w^T_{r_1} - \alpha w^T_{r_1} (\frac{\partial L_{NLL}}{\partial w^T_{r_2}}) \]  

Since gradient of \( w_r \in E_r \) is uniformly negative direction of almost \( h_i \), term (i) of Eq. (7) is positive. Term (ii) of Eq. (7) is written as follows.

\[
\alpha (\frac{\partial L_{NLL}}{\partial w^T_{r_1}}) w^T_{r_2} = \alpha \sum_{h_i \in H^k_0} p(r_1 | h_i) h_i^T w^T_{r_2} - \alpha \sum_{h_i \in H^k_1} (1 - p(r_1 | h_i)) h_i^T w^T_{r_2} \tag{8} \]

where we can approximate second term of inner product as \( H^k_1 \) is negligibly small. Therefore, term (ii) become negative at some point of training stage at which \( h_i^T w^T_{r_2} \) is negative for almost \( i \). Term (iii) become negative in same way. In conclusion, \( w^T_{r_1} w^T_{r_2} > w^T_{r_1} w^T_{r_2} \) for \( t \geq t_c \). As the change
### Methods

| Methods                  | BLEU | \( S(w) \) |
|--------------------------|------|------------|
| Baseline                 | 27.3 | 0.528      |
| Freezing Rare Words      | 28.0 | 0.023      |

Table 1: Experimental results on WMT14 En→De translation.

In norm of \( w_r \in E_r \) is relatively small, we conclude any two embeddings in \( E_r \) become similar during training process. This means they degenerate into local region of embedding space like narrow cone. Next, we empirically study how much the degeneration of embeddings not in \( E_r \), non-rare word embeddings, is influenced by the degeneration of embeddings in \( E_r \), rare word embeddings. Among three groups in vocabulary, we consider embeddings of the words in low-frequent group as \( E_r \). During training stage of neural language model we freeze these low-frequent group word embeddings until some training point, and we start training of these embeddings after that point. As we can see in figure 2, inner products between the words in high and mid-frequent group increase steeply after the embeddings of words in low-frequent group participate in training stage. From the observation, we conclude once the degeneration of embeddings in \( E_r \) occurs at any point of training stage, embeddings not in \( E_r \) degenerate following the degeneration of embeddings in \( E_r \). In other words, the main cause of the representation degeneration of the embeddings of non-rare word is the degeneration of rare word embeddings.

#### 2.2 Experiment: Freezing Rare Words

In this section, we hypothesize that preventing the degeneration of embeddings in \( E_r \) can tackle the whole representation degeneration problem. To empirically verify our hypothesis, we conduct an experiment on machine translation task. With standard WMT 2014 English → German dataset, we train the base version of Transformer (Vaswani et al., 2017) as baseline method. Model configuration and training settings are same as Vaswani et al. (2017) except that we freeze the embeddings of the words in low-frequent group to prevent them from the degeneration.

We calculate two metrics to verify the correctness of the our hypothesis. First is BLEU score (Papineni et al., 2002) which is standard metric for the machine translation task. Second is average of cosine similarity between any two word embedding vectors. Because the representation degeneration problem occurs for word embedding vectors to become similar each other, the similarity metric for embedding vectors can be used to determine the severity of the problem. We calculate the similarity metric, \( S(w) \), as follows.

\[
S(w) = \frac{1}{N^2} \sum_{i}^{N} \sum_{j \neq i}^{N} \frac{w_i^T w_j}{\|w_i\| \|w_j\|}
\]

As we can see in table 1, just freezing the rare word embeddings shows the improvement of translation and word embedding quality. When measured the performance of the model with BLEU score, our simple method improves performance with 0.7. Similarity metric about embedding vectors also greatly decreased, which means the alleviation of the representation degeneration problem. Visualization of word embeddings trained by freezing rare words in figure 3 shows that the word embeddings are mapped onto more global regions in embedding space than baseline method. From this empirical analysis, we argue that the whole representation degeneration problem can be tackled by manipulating only the rare word embeddings.

### 3 Method: Adaptive Gradient Partial Scaling

In this sections, we propose our method to tackle the representation degeneration problem based on analysis of section 2.2. We rewrite the gradient of word embedding vector about negative log-likelihood function in terms of the rare word em-
At the Eq. (12), first term means the sum of gradients from hidden states of rare words. We also consider too-rare words in rare word group. For these too-rare words, first term of the Eq. (12) need to be reduced slightly.

To implement our method, we use the situation of mini-batch training of the model. At each training step the model get mini-batch data to train including batch target corpus \( y = (y_1, ..., y_M) \), where \( y_i \in V \). We discriminate the each rare words whether they are in the \( y \) and train them to receive a full, unscaled gradient only if they are in the \( y \). For the rare words not in \( y \) we train them to receive gradient whose second term of Eq. (12) is scaled by their relative frequency in whole vocabulary, \( f_r^1 \). Since appearance frequency to \( y \) is as lower as rare in the whole vocabulary, each rare words receive adaptively scaled gradient term according to their rarity in train corpus in terms of accumulated gradient. We calculate relative frequency of rare word indexed as \( r \) in the whole vocabulary \( f_r^1 \) as follows.

\[
f_r^1 = \frac{c[r]}{\mu_1},
\]

where \( c[k] \) is the number of appearance of \( k \)-th word in whole train data corpus and \( \mu_1 \) is a hyperparameter which is bigger than \( c[r] \) for all rare words \( r \). Additionally, we scale the gradient term that roles to be far away from hidden states of other rare words for too-rare words. At first term of the Eq. (12), using relative frequency of rare word in the rare word group, \( f_r^2 \). We calculate \( f_r^2 \) as follows.

\[
f_r^2 = \min \left( \frac{c[r]}{\mu_2} \right),
\]

where \( \mu_2 \) is a positive hyperparameter that adjusts the degree to which rare word embeddings repel each other. Finally the formula of the partially scaled gradient adaptive for rare word embeddings \( w_r \) is written as follows.

\[
\frac{\partial L_{NLL}}{\partial w_r} = \mathbb{1}_y(r) \cdot \left[ \sum_{h_i \in H^*_r} p(r|h_i)h_i \right] - \sum_{h_i \in H^*_r} (1 - p(r|h_i))h_i + \left( 1 - \mathbb{1}_y(r) \right) \cdot \left[ \sum_{i=1}^{M} \mathbb{1}_{E_r}(w_{y_i})p(r|h_i)h_i \right] + f_r^1 \sum_{i=1}^{M} \mathbb{1}_{E_r}(w_{y_i})p(r|h_i)h_i + f_r^2 \sum_{i=1}^{M} \mathbb{1}_{E_r}(w_{y_i})p(r|h_i)h_i
\]

The pseudo code algorithm to calculate the loss function of AGPS can be founded in Appendix A.
Table 2: Comparison of different methods in terms of BLEU scores on the task of WMT14 En→De machine translation.

| Method                     | Transformer Base BLEU | Transformer Big BLEU |
|----------------------------|------------------------|-----------------------|
| Baseline (Vaswani et al., 2017) | 27.30                  | Baseline (Vaswani et al., 2017) | 28.40 |
| CosReg (Gao et al., 2019)   | 28.38                  | CosReg (Gao et al., 2019)   | 28.94 |
| Adv MLE (Wang et al., 2019) | 28.43                  | Adv MLE (Wang et al., 2019) | 29.52 |
| SC (Wang et al., 2020)      | 28.45                  | SC (Wang et al., 2020)      | 29.32 |
| AGPS (Ours)                 | 28.61                  | AGPS (Ours)              | 29.58 |

Table 3: Comparison of different methods in terms of alignment similarity of each word groups on the task of WMT14 En→De machine translation. ‡ denotes for our implementation.

| Method                     | High-freq | Mid-freq | Low-freq | Total |
|----------------------------|-----------|----------|----------|-------|
| Baseline (Vaswani et al., 2017)‡ | 0.0087    | 0.0056   | 0.0026   | 0.0054|
| CosReg (Gao et al., 2019)‡   | 0.0577    | 0.0585   | 0.0316   | 0.0495|
| AGPS (Ours)                 | 0.0996    | 0.1121   | 0.1163   | 0.1103|

4 Experiments

To demonstrate the effectiveness of our method, we conduct experiments on two tasks: neural machine translation and neural language modeling. Moreover, we observe that our method can mitigate the frequency bias problem of word embedding vectors through qualitative analysis.

4.1 Neural Machine Translation

Setting We use dataset from standard WMT 2014 containing 4.5M English-German sentence pairs. Source and target sentences are encoded by 37K shared sub-word tokens based on byte-pair encoding (Sennrich et al., 2016). Concatenation of newstest2012 and newstest2013 is used as the validation set and newstest2014 become test set. We adopt the two version of Transformer (Vaswani et al., 2017) as the baseline model for applying our method: base and big. The model configuration is the same as that in Vaswani et al. (2017). Our implementation is based on the open-sourced code provided by Ott et al. (2018b). More details about hyperparameter setting can be founded in Appendix B.

4.1.1 BLEU Score

To quantitatively evaluate our method in neural machine translation task, we first measure BLEU score. Table 2 presents comparison of our method and other methods in terms of the BLEU score. Our method achieves 1.31 and 1.18 BLEU score improvements on this task for base and big baseline models. Also our method is better than all other previous works about representation degeneration problem that reported BLEU score in same tasks.

4.1.2 Word Alignment Similarity between Source and Target Language

In addition to the analyzes in section 2, we observe additional issues about representation degeneration in neural machine translation task. In source-target joint dictionary setting, common to NMT system in practice, there exist the words which are frequent in source language corpus, but rare in target language corpus. Because the decoder processes the frequency of words based on the target language corpus, these words are considered rare when trained in the decoder’s output layer although they appear frequently as input for the whole language model. Therefore they degenerate to become similar each other during training even if they are not related semantically. That means the model cannot learn correct word alignment between source and target language which is very important for the performance of the translation task. For example, the English word ‘happiness’ corresponds to the German word ‘Glück’. So we expect the translation model to learn that the word embedding vectors of these two words are similar. However, in practice, the word ‘happiness’ is rare at German language corpus, so the model learns the embedding vector of ‘happiness’ similarly to other semantically
Table 4: Perplexity of each word groups on the task of WikiText-103 language modeling task. ‡ denotes for our implementation. The lower is the better.

| Method                    | High-freq | Mid-freq | Low-freq | Total   |
|---------------------------|-----------|----------|----------|---------|
| Transformer Baseline‡     | 17.95     | 314.68   | 2953.56  | 30.04   |
| CosReg (Gao et al., 2019)‡| 17.44     | 321.12   | 3648.26  | 29.66   |
| AGPS (Ours)               | 18.44     | 379.21   | 1751.66  | 30.50   |

Figure 4: Visualization of word embeddings from WMT14 En→De translation task using PCA. Red points represent low-frequent group words, green points represent mid-frequent group words, and blue points represent high-frequent group words. (a), (b), (c) show visualization of each methods applied to train Transformer model.

4.2 Language Modeling

Setting We use WikiText-103 dataset which was introduced by Merity et al. (2018). WikiText-103 is a significantly large dataset for language modeling task with around 103M words and 260K vocabulary size. We adopt the 6-layer Transformer (Vaswani et al., 2017) decoder model for baseline model. Model configuration and hyperparameter details can be founded in Appendix B. Our implementation is based on the open-sourced code³ provided by Ott et al. (2018b).

4.2.1 Perplexity for Each Frequency Group

To quantitatively evaluate our method in language modeling task, we measure perplexity (ppl) score for each word group: low, mid, and high-frequent group, and total words in vocabulary. Table 4 shows the test perplexity of baseline, previous

alignment vector. We measure mean of alignment similarity of the words in each word group: low-frequent, mid-frequent, high-frequent group and total vocabulary. As shown in table 3, our method significantly outperforms baseline and previous work. The baseline model to measure alignment similarity is Transformer base model. Other qualitative analysis about word alignment problem can be founded in Appendix C.
method (Gao et al., 2019) and our method on WikiText-103 dataset. The results demonstrate that our method significantly improves for the low-frequent words while maintaining performance in other word groups.

### 4.3 Frequency Agnostic Word Embeddings

To qualitatively study the effect of our method on word embeddings, we visualize word embeddings trained on WMT14 En→De dataset into 2-dimensional space using PCA. As shown in Figure 4(a), (b), the word embeddings trained with baseline and previous method are clustered by their frequencies rather than semantics. This frequency bias problem of word embeddings was introduced before by Gong et al. (2018). From our analysis, the cause of this problem is connected to representation degeneration problem: rare word embeddings become similar each other while becoming unrelated to non-rare word embeddings. Therefore, manipulating the training of the word embeddings for rare words can alleviate the frequency bias problem, and Figure 4(c) shows that the word embeddings trained with our method are distributed independent of frequency.

### 5 Related Work

Neural machine translation (NMT) aims to translate an input source sentence to the target one. NMT models usually use sequence-to-sequence architecture (Sutskever et al., 2014) which consists of an encoder, a decoder, and an attention module. The attention module can better align source and target words, and it was first introduced by Bahdanau et al. (2015). Various architectures have been adopted as the encoder and the decoder: LSTM (Hochreiter and Schmidhuber, 1997; Sutskever et al., 2014; Wu et al., 2016), CNN (Gehring et al., 2017), and Transformer (Vaswani et al., 2017). Nowadays, architectures based on Transformer achieve the state-of-the-art results for NMT (Barrault et al., 2020).

Representation degeneration problem is first pointed out by Gao et al. (2019). They analyze the mechanism of the problems and propose regularization method about cosine similarity between any two word embeddings. Several solutions to the problem are proposed after Gao et al. (2019). Instead of introducing regularization term to minimize similarity between each two word embeddings, Wang et al. (2020) explicitly manipulate the singular value distribution of embedding matrix through spectrum control. Wang et al. (2019) propose the idea to introduce adversarial noise to the output embedding layer while training the models. Recently, Zhang et al. (2020) analyze the limitation of cosine similarity regularization method and propose an alternative Laplacian regularization method.

For similar problems in word embedding learning, Mu et al. (2018) explores the anisotropic geometry of static word embeddings. They propose post-processing technique which eliminate the common mean vector and a few top dominating directions from the embedding vectors. There are a series of works that follow this line of research to fix the anisotropic geometry of word embeddings (Liu et al., 2019; Hasan and Curry, 2017; Zhou et al., 2019; Ethayarajh, 2019; Biš et al., 2021). Word embedding bias about frequency is another problem. Ott et al. (2018a) conduct a comprehensive study about under-estimation of rare (sub)words in neural machine translation. Gong et al. (2018) observe that word embeddings in language model are biased towards word frequency and propose an adversarial training scheme for the problem.

### 6 Conclusion and Future Work

In this paper, we theoretically and empirically analyzed the representation degeneration problem of the learned embeddings through training dynamics led by rare words. Based on the analysis, we propose a adaptive gradient partial scaling for the word embeddings of rare words to tackle the problem. Experiments and qualitative study about our method in neural machine translation and neural language modeling tasks demonstrate the effectiveness of our method.

In the future, we will apply our method to general language downstream tasks that are trained by softmax layer. While we now search rare word groups and hyperparameters of our method manually, this can be automated or adaptive on-line search in future study.

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A Pseudo code to calculate loss for AGPS

Algorithm 1 Pseudo-code for AGPS

Inputs:
- Output feature from model $H \in \mathbb{R}^{M \times d}$
- Word embedding matrix $W \in \mathbb{R}^{N \times d}$
- Target for current sample $y \in \mathbb{R}^M$
- Number of appearance of each word in training corpus $C \in \mathbb{R}^N$
- Hyperparameter $\mu_1, \mu_2$
- Minimum index of the word in rare group $i_r$

Outputs: loss for AGPS

1. $C_{\text{clip}} \leftarrow C.\text{clip}(\text{max}=\mu_1)$
2. $f_1^r \leftarrow C_{\text{clip}}$
3. $f_2^r \leftarrow (C_{\text{clip}}).\text{clip}(\text{max}=1)$
   - get hyperparameter $f_1^r$ and $f_2^r$
4. $M_{\text{word}} \leftarrow N\text{-dim zero tensor}$
5. $M_{\text{word}}[y] \leftarrow 1$
6. $M_{\text{word}}[i_r] \leftarrow 1$
7. $M_{\text{wordrev}} \leftarrow (1 - M_{\text{word}}) \odot f_2^r$
8. $M_{\text{word}} \leftarrow (M_{\text{word}} + f_1^r).\text{clip}(\text{max}=1)$
   - get mask to partially scale the gradient for $W$
9. $W_{\text{mask}} \leftarrow M_{\text{word}} \odot W$
   - $+(1 - M_{\text{word}}) \odot W.\text{detach}()$
   - partially mask $W$ to get scaled gradient from non-rare features
10. $W_{\text{maskrev}} \leftarrow M_{\text{wordrev}} \odot W$
    - $+(1 - M_{\text{wordrev}}) \odot W.\text{detach}()$
    - partially mask $W$ to get scaled gradient from rare features
11. $Z \leftarrow -\text{LogSoftmax}(H W_{\text{mask}}^T)$
12. $M_{\text{tgt}} \leftarrow (y >= i_r).\text{float}()$
13. $i_{\text{raretgt}} \leftarrow M_{\text{tgt}}.\text{nonzero}()$
   - get index of rare words in current target
14. $H_{\text{rare}} \leftarrow (H.\text{detach})[i_{\text{raretgt}}]$
   - detach rare part of feature matrix to give them same gradient as original MLE training
15. $Z_{\text{rare}} \leftarrow -\text{LogSoftmax}(H_{\text{rare}} W_{\text{maskrev}}^T)$
16. $L_1 \leftarrow Z.\text{gather}(\text{dim}=-1, \text{index}=y)$
17. $L_2 \leftarrow Z_{\text{rare}}.\text{gather}(\text{dim}=-1, \text{index}=y[i_{\text{raretgt}}])$

18. $L \leftarrow L_1 + L_2$
19. return $L$

Algorithm 1 provides pseudo code to calculate loss function for AGPS. Pseudo code is written based on Pytorch. Notations in algorithm are same as main page. The words in vocabulary of the model are indexed decreasing order of frequency.

B Experimental details

B.1 Neural machine translation

| Hyperparameter | Transformer base | Transformer big |
|----------------|------------------|----------------|
| $i_r$          | 27000            |                |
| $\mu_1$        | $1.5 \cdot 10^3$ |                |
| $\mu_2$        | $4 \cdot 10^2$   |                |

Table 5: Hyperparameter settings for AGPS in WMT14 En→De dataset

Table 5 shows the detailed list of hyperparameters of AGPS in WMT14 En→De machine translation task. Hyperparameters are chosen from observing the training dynamics of word embedding vectors of baseline model.

| Hyperparameter | Transformer base | Transformer big |
|----------------|------------------|----------------|
| # of layers    | 6 - 6            | 6 - 6          |
| Hidden dimension | 512              | 1024           |
| Embedding dimension | 512          | 1024           |
| Projection dimension | 2048     | 4096           |
| # of heads     | 8                | 16             |
| Dropout        | 0.1              | 0.3            |
| Max tokens per batch | 8192       | 8192           |
| Learning rate  | $1 \cdot 10^{-3}$ | $1 \cdot 10^{-3}$ |
| Optimizer      | Adam             | Adam           |
| Weight decay   | 0.01             | 0.01           |

Table 6: Transformer base model training hyperparameter settings

Table 6, 7 shows the training configurations of base and big model in WMT14 En→De machine translation task. We use default Adam configurations in Pytorch. We trained the models until convergence.

| Hyperparameter | Transformer base | Transformer big |
|----------------|------------------|----------------|
| # of layers    | 6 - 6            | 6 - 6          |
| Hidden dimension | 1024             | 1024           |
| Embedding dimension | 1024          | 1024           |
| Projection dimension | 4096     | 4096           |
| # of heads     | 16               | 16             |
| Dropout        | 0.3              | 0.3            |
| Max tokens per batch | 8192       | 8192           |
| Learning rate  | $1 \cdot 10^{-3}$ | $1 \cdot 10^{-3}$ |
| Optimizer      | Adam             | Adam           |
| Weight decay   | 0.01             | 0.01           |

Table 7: Transformer big model training hyperparameter settings
B.2 Language modeling

| Hyperparameter | WikiText-103 |
|----------------|--------------|
| \( i_r \)      | 25000        |
| \( \mu_1 \)    | \( 5 \cdot 10^2 \) |
| \( \mu_2 \)    | \( 2 \cdot 10^1 \) |

Table 8: Hyperparameter settings for AGPS in WikiText-103 dataset

Table 8 shows the detailed list of hyperparameters of AGPS in WikiText-103 language modeling task. Hyperparameters are chosen from observing the training dynamics of word embedding vectors of baseline model.

Table 9: Transformer language model training hyperparameter settings

| Hyperparameter          | Transformer ln |
|-------------------------|----------------|
| # of layers             | 6              |
| Hidden dimension        | 512            |
| Embedding dimension     | 512            |
| Projection dimension    | 2048           |
| # of heads              | 8              |
| Dropout                 | 0.1            |
| Max tokens per batch    | 4096           |
| Learning rate           | \( 5 \cdot 10^{-4} \) |
| Optimizer               | Adam           |
| Weight decay            | 0.01           |

Table 9 shows the training configurations of Transformer decoder language model in WikiText-103 language modeling task. We use default Adam configurations in Pytorch. We trained the models until convergence.

C Qualitative analysis about word alignment

| optimum      | criminal      | happiness    |
|--------------|---------------|--------------|
| optimize     | Criminal       | happy        |
| appropriate  | criminals      | happ@@        |
| optimal      | crime          | satisfaction  |
| optimized    | crimin@@       | wellbeing     |
| maximum      | terrorist      | joy          |

Table 11: Top-5 nearest neighbors of the words. Word embedding is trained by Transformer model with CosReg method (Gao et al., 2019)

| optimum      | criminal      | happiness    |
|--------------|---------------|--------------|
| optimal      | criminals      | happy        |
| optimale*    | Criminal       | joy          |
| optimalen*   | krimi@@*       | happ@@       |
| maximum      | kriminellen*   | Glück*       |
| Optim@ @     | crime          | pleasure     |

Table 12: Top-5 nearest neighbors of the words. Word embedding is trained by Transformer model with AGPS method. Symbol * denotes the same meaning word of target language.

As we discussed in section 4.1.2, the words who is popular in source language but rare in target language can be degenerated severely, occurring word alignment problem. For qualitative analysis of this problem, we choose 3 words from the vocabulary: 'optimum', 'criminal', and 'happiness' in WMT14 En→De translation task. These words are frequent in source language corpus(En), but rare in target language corpus(De). We investigate top-5 neighbor words of them predicted by baseline model(Vaswani et al., 2017), CosReg method(Gao et al., 2019), and our AGPS method. Table 10, 11, 12 shows the results of the analysis. For baseline model, predicted neighbors are usually semantically unrelated. For CosReg method, all top-5 predicted neighbors are semantically related. Specially for our method, there are target language words which corresponds to the each chosen word among top-5 neighbors. This indicates that word alignment learning between source and target language is improved in our method.

Moreover, we plot the similarities of above 3 words between all other words in the vocabulary. Figure 5, 6, 7 shows the results of analysis. While the similarity between the other words increases as the other words become more rare for the target corpus in the baseline model and the CosReg method, there is no similarity bias regarding the frequency in the word embeddings trained by our method.

As we discussed in section 4.1.2, the words who is popular in source language but rare in target language can be degenerated severely, occurring...
Figure 5: Cosine similarity between the word "optimum" and whole vocabulary words. As the word index increases, the frequency of word decreases. (a), (b), (c) show similarity plot of each methods applied to train Transformer model.

Figure 6: Cosine similarity between the word "criminal" and whole vocabulary words. As the word index increases, the frequency of word decreases. (a), (b), (c) show similarity plot of each methods applied to train Transformer model.

Figure 7: Cosine similarity between the word "happiness" and whole vocabulary words. As the word index increases, the frequency of word decreases. (a), (b), (c) show similarity plot of each methods applied to train Transformer model.