F²-Softmax: Diversifying Neural Text Generation via Frequency Factorized Softmax

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Abstract

Despite recent advances in neural text generation, encoding the rich diversity in human language remains elusive. We argue that the sub-optimal text generation is mainly attributable to the imbalanced token distribution, which particularly misdirects the learning model when trained with the maximum-likelihood objective. As a simple yet effective remedy, we propose two novel methods, F²-Softmax and MefMax, for a balanced training even with the skewed frequency distribution. MefMax assigns tokens uniquely to frequency classes, trying to group tokens with similar frequencies and equalize frequency mass between the classes. F²-Softmax then decomposes a probability distribution of the target token into a product of two conditional probabilities of (i) frequency class, and (ii) token from the target frequency class. Models learn more uniform probability distributions because they are confined to subsets of vocabularies. Significant performance gains on seven relevant metrics suggest the supremacy of our approach in improving not only the diversity but also the quality of generated texts.

1 Introduction

Neural text generation is one of the extensively studied tasks of natural language processing (NLP), as it forms the basis for dialogue systems (Chen et al., 2017), machine translation (Chaudhary and Patel, 2018), and text summarization (Kryscinski et al., 2019). However, often monotonous or dull, texts generated from existing methods do not fully reflect the rich diversity and expression in human language (Welleck et al., 2020). In particular, models tend to overproduce words frequently appearing in the data, while hardly utilizing informative words (Dinan et al., 2020). Even pre-training techniques on large corpora fail to resolve the issue (Holtzman et al., 2019).

Possible causes for text degeneration have been illuminated, such as a defect specific to model architectures (Vig, 2018) or the discrepancy between training data and a true distribution (Holtzman et al., 2018; Jiang et al., 2019). Recently, the emphasis has been placed on investigating the flaws in the maximum likelihood objective (Holtzman et al., 2019). Concretely, the likelihood training pays little attention to the top ranks in terms of the target token probabilities (Welleck et al., 2020), or maximizing likelihood itself does not adequately reflect human language processing (Holtzman et al., 2019). Therefore, with the likelihood training, models learn to produce tokens frequently appearing in the data more often.

We argue, however, that the primary reason behind the sub-optimal performance of the likelihood objective is essentially the imbalanced token distribution inherent in natural language. Natural language is extremely skewed in distribution, where the top hundred most frequently-used (top-100) words occupy nearly half of the total corpus (Fagan and Gençay, 2011) following the Zipf’s law (Zipf, 1949). Training a classifier with the inherently imbalanced data on the maximum likelihood estimation (MLE) leads to biased classification boundaries in favor of majority classes (Khan et al., 2019).

In other words, models play a difficult role in learning with the imbalanced label (i.e., token) distribution (He et al., 2008b). We hypothesize that text generation can be enriched by balancing out the training data distribution. To this end, we introduce F²-Softmax (Fig. 1(B), Section 3.2), which factorizes the probability distribution of the target token into a product of two conditional probabilities of (i) frequency class, and (ii) token from the target frequency class. It ensures training over balanced data, since the frequency classes are designed to have the distribution close to uniformity, and token distributions...
within a class are confined to subsets of vocabularies grouped with similar frequencies. To this end, all unique tokens are assigned to a frequency class prior to the training, by our novel mean efficiency maximization (MefMax; Fig. 1(A), Section 3.3). MefMax evaluates and maximizes the class-labeling performance with the normalized entropy (i.e., efficiency), having the probability distributions to be learned as uniform as possible.

We conduct extensive performance evaluations on seven relevant metrics that quantify the diversity and quality of generated texts. In terms of the diversity of generated texts, our approach significantly outperforms not only the MLE baseline (Radford et al., 2019) but also other diversity-promoting alternatives (Welleck et al., 2020; Jiang et al., 2019). We also achieve state-of-the-art results on most of the quality performances.

2 Related Works

2.1 Diversity-promoting Text Generation

In the field of neural text generation, prior studies either take a training-based approach or a decoding-based approach to promote the diversity in the generated texts.

Training-based Approach. In dialogue generation, stimulating models to generate texts that share high mutual information with the contexts (Li et al., 2016) has shown to improve the diversity of output tokens by adding a maximum mutual information (MMI) constraint to the standard likelihood objective. Meanwhile, FACE (Jiang et al., 2019) dynamically weights the cross-entropy losses based on target token frequencies, to prevent excessive weight-updates of some frequently used words. In another line of works for language modeling, text diversity has been promoted by a learning-to-cooperate framework in which multiple discriminators cooperate to reach a common goal (Holtzman et al., 2018). Also, the unlikelihood training strategy penalizes repetition with auxiliary loss terms (Welleck et al., 2020). Such works are orthogonal to ours since F²-Softmax focuses on decomposing the softmax function without employing an auxiliary loss or re-scaling.

Decoding-based Approach. One of the widely used decoding tactics for promoting the diversity and richness of texts is stochastic decoding. Top-k sampling stochastically samples the next token from the top-k candidates in the predicted probability distribution (Fan et al., 2018). Another pillar of stochastic decoding is nucleus sampling, which selects the next token from the top-p portion of the probability mass (Holtzman et al., 2019). Other studies include beam blocking (Paulus et al., 2017) in which the probabilities of tokens are set to zero if they were to create repeating n-grams, diverse beam search (Vijayakumar et al., 2018) which integrates dissimilarity terms into beam scores. Iterative beam search (Kulikov et al., 2019) enhances diverse beam search with multiple iterations of beam search with different search spaces. These techniques are agnostic about model architecture or training methods. Our approach can be harmonically combined with the above techniques.
2.2 Softmax Decomposition

Decomposing the softmax function has long been studied in language modeling. Goodman (2001) decomposed the softmax function using a two-level hierarchy. This idea was generalized to deeper hierarchies in a later study (Mnih and Hinton, 2009). Approaches to construct softmax hierarchies have followed, such as utilizing word clusters obtained from k-means algorithms (Le et al., 2011) or implementing Huffman coding with word frequencies (Mikolov et al., 2013). Furthermore, dynamic programming has been applied to obtain an optimal set of word classes with minimal computational costs for calculating the softmax function (Zweig and Makarychev, 2013). The same process has also been streamlined to fit into modern GPU environments (Grave et al., 2017). These techniques bear a resemblance to ours for the use of softmax decomposition. However, our goal is fundamentally different: we aim to balance the data distribution in training, whereas previous approaches share the primary goal of reducing computational costs.

2.3 Imbalanced Classification

That we assign tokens to classes of balanced distribution shares a similar goal with overcoming imbalanced classification in computer vision domains. One of the widely adopted techniques for imbalanced classification is re-sampling, which includes removing examples from the majority classes (under-sampling) and adding samples for the minority classes (over-sampling) (Buda et al., 2018). Techniques for over-sampling include interpolating samples from neighboring samples (Chawla et al., 2002) and adaptively synthesizing samples (He et al., 2008a). Cost-sensitive learning dynamically re-weights costs based on sample difficulties (Dong et al., 2017) or effective number of samples (Cui et al., 2018). Other studies for the data imbalance problem consider metric learning (Huang et al., 2016), knowledge transfer (Wang et al., 2017), and Bayesian estimation (Khan et al., 2019).

3 Methods

3.1 Maximum Likelihood

The goal of language modeling is to learn a model \( \hat{p}(x) \) which best describes a joint probability distribution \( p(x) \), where \( x = [x_1, \ldots, x_T] \) is a sequence of tokens and \( x_t \in \mathcal{V} \) is a token from a vocabulary set. In an auto-regressive manner, \( p(x) \) can be factorized into a product of conditional probabilities of tokens: \( p(x) = \prod_t p(x_t | x_{<t}) \). A conventional approach for the training is to maximize log-likelihood of a sequence \( x \) as the following:

\[
L_{\text{MLE}}(\hat{p}, x) = \sum_{t=1}^{T} \log \hat{p}(x_t | x_{<t}).
\] (1)

3.2 F^2-Softmax

We propose to factorize the posterior \( \hat{p}(x_t | x_{<t}) \) into a product of two conditional probabilities:

\[
\hat{p}(x_t | x_{<t}) = \hat{p}_1(c_t | x_{<t}) \times \hat{p}_2(x_t | c_t, x_{<t}),
\] (2)

where \( c_t \in \mathcal{C} \) denotes a frequency class label assigned to the token \( x_t \) given the global frequency of the token in a corpus, belonging to a set of frequency classes \( \mathcal{C} \). Following Eq. (2), the updated objective \( L_{F^2}(\hat{p}) \) is then formulated as:

\[
L_{F^2}(\hat{p}, x) = \sum_{t=1}^{T} [\log \hat{p}_1(c_t | x_{<t}) + \log \hat{p}_2(x_t | c_t, x_{<t})].
\] (3)

The objective is thus learning how to classify the target frequency of the token and selecting the exact token given the target frequency class. The factorized probabilities \( \hat{p}_1(c_t | x_{<t}) \) and \( \hat{p}_2(x_t | c_t, x_{<t}) \) are defined empirically using softmax functions:

\[
\hat{p}_1(c_t | x_{<t}) = \frac{\exp(h_{t-1} \cdot u^c_t)}{\sum_{m \in \mathcal{C}} \exp(h_{t-1} \cdot u^m)}
\]

\[
\hat{p}_2(x_t | c_t, x_{<t}) = \frac{\exp(h_{t-1} \cdot o^{c_t})}{\sum_{n \in \mathcal{V}_{c_t}} \exp(h_{t-1} \cdot o^{n})},
\] (4)

where \( h_{t-1} \) is a hidden state of the context \( x_{<t} \); \( o^t \) and \( u^c \) can be viewed as output embedding vectors for \( i \in \mathcal{V}_{c_t} \) and \( j \in \mathcal{C} \), respectively, while \( \mathcal{V}_{c_t} \) is a subset of vocabularies assigned to the class \( c_t \). Note that \( \hat{p}_2(x_t | c_t, x_{<t}) \) is computed from the narrowed pool of tokens \( \mathcal{V}_{c_t} \) rather than the full vocabularies set \( \mathcal{V} \). Since classes are differentiated based on the token frequency, tokens with the same class have similar frequencies. It ensures within-class frequency distribution of tokens is closer to uniform than that of the full vocabulary set.

3.3 MefMax for Class Optimization

The more uniform a label distribution is, the less likely decision boundaries are biased in favor of frequent classes. Therefore, we aim to maximize
the degree of uniformity of frequency distributions for both (i) tokens within each class and (ii) classes themselves (i.e., the sum of token frequencies within each class), to avoid the class imbalance problem (Buda et al., 2018) over the course of training. It is formalized as follows:

\[ C' = \arg \max_C \{ U(C) + \frac{1}{|C|} \sum_{i \in C} U(V_i) \}, \quad (5) \]

where \( U \) is a function that measures the uniformity of the frequency distribution of a given set. While any tests of uniformity can be used as \( U \), we adopt Shannon’s entropy (Shannon, 1948). The entropy is a decent proxy for measuring the uniformity (Dudewicz and Van Der Meulen, 1981).

**Normalized Entropy.** Since the number of samples affects the entropy, entropy cannot be directly used. To marginalize the effect of the sample size, we use efficiency, which is also known as the normalized entropy (Wijesekera and Dillon, 1997), defined as:

\[ U(k) = -\sum_{k_i \in k} \frac{p(k_i) \log(p(k_i))}{\log(|k|)}. \quad (6) \]

It is equivalent to the ratio of the entropy to the maximum entropy, if the data were perfectly uniform. By applying the efficiency to Eq. (5), our objective is to find a set of classes and their vocabularies such that their mean efficiency is maximized.

**Greedy Approach.** The remaining issue is the computational overhead since the cost for exploring all possible class boundaries grows exponentially with the vocabulary size, not to mention the challenge of finding the optimal number of classes. To improve computational efficiency, we employ a straightforward greedy mechanism. It is based on the assumption that the mean efficiency is maximized when each class has approximately the same size of total frequency. This assumption allows us to reduce our objective to optimizing the number of classes. Given a sorted vocabulary set \( V' \) and a candidate number of classes \( K \), we divide classes so that each class has the same \( 1/K \) of total frequency. The optimal number of classes is the one that maximizes the mean efficiency. Algorithm 1 shows the complete pseudo-code. Computation time is linear to the vocabulary size.

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**Algorithm 1** Pseudo-code for MefMax

**Inputs**: Array \( V' \) of length \( n \) sorted by the decreasing order of token frequency

**Outputs**: Number of classes, class boundary tokens

1: \( V' \leftarrow V' / \text{sum}(V') \)  \( \triangleright \) get relative frequencies
2: maxMeanEfficiency \( \leftarrow 0 \)
3: maxClassNum \( \leftarrow 1/V'[0] \)
4: for \( K \) in \([1, 2, ..., \text{maxClassNum}]\) do
5: \( B \leftarrow \) empty list  \( \triangleright \) lists for candidate boundaries
6: \( \text{tar} \leftarrow 1/K \)  \( \triangleright \) target frequency
7: \( \text{cum}, \text{idx} \leftarrow 0, 0 \)  \( \triangleright \) cumulative frequency & index
8: while \( \text{tar} \leq 1 \) do  \( \triangleright \) compute cumulative boundary
9: \( \text{cum} \leftarrow \text{cum} + V'[\text{idx}++] \)
10: if \( \text{cum} \geq \text{tar} \) then
11: \( \text{tar} \leftarrow \text{tar} + 1/K \)
12: \( B.append(\text{idx}) \)
13: \( \text{meanEfficiency} \leftarrow \text{mean efficiency based on} B \)
14: if maxMeanEfficiency < \( \text{meanEfficiency} \) then
15: maxMeanEfficiency \( \leftarrow \text{meanEfficiency} \)
16: \( O_u \leftarrow B \)
17: return len(Out), Out

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### 3.4 Decoupled Decoding

For the decoding stage, we decouple \( \hat{p}_1 \) from \( \hat{p} \) in Eq. (2) by first selecting a single frequency class from \( \hat{p}_1 \) and then generating the next token based on the selected class. For the target class \( c_t = i \) sampled from the distribution \( \hat{p}_1(c_t|x_{<t}) \), the probability for the next token is defined as:

\[ \hat{p}'(x_t|x_{<t}) = \begin{cases} \hat{p}_2(x_t|c_t = i, x_{<t}) & \text{if } x_t \in V_i \\ 0 & \text{otherwise.} \end{cases} \quad (7) \]

The target class can be sampled in both deterministic or stochastic manners, depending on decoding strategies. We found that the advantages of training balanced data distributions can be fully leveraged by sequentially performing tasks of frequency class prediction and token generation from the selected class.

### 4 Experiments

#### 4.1 Training and Evaluation Details

In this section, experimental details are illustrated. Exact hyperparameter settings and data statistics are described in Appendix.

##### 4.1.1 Datasets

Two datasets that differ in language and text types are selected for the implementations. The target class can be sampled in both deterministic or stochastic manners, depending on decoding strategies. We found that the advantages of training balanced data distributions can be fully leveraged by sequentially performing tasks of frequency class prediction and token generation from the selected class.

**Wikitext-103** \(^1\) is a collection of English articles extracted from Wikipedia. Containing more than

\(^1\) https://s3.amazonaws.com/research.metamind.io/wikitext/wikitext-103-v1.zip
100 million words, it is widely regarded as a benchmark dataset for language modeling. **Melo-Lyrics** is a Korean lyrics dataset we crawled from multiple music streaming websites, including Soribada\(^2\), Genius\(^3\), etc. Tokens in lyrics show a distribution largely different from general articles; for instance, repeated phrases are abundant in lyrics. Therefore it provides an additional unique angle for model evaluations and comparisons. It includes approximately 478 thousand songs with 51 million words in total.

### 4.1.2 Model Architecture
We use the Transformer (Vaswani et al., 2017), an architecture well-suited for neural text generation (Lewis et al., 2019; Welleck et al., 2020). Specifically, we apply the Transformer decoder used in the GPT-2 model (Radford et al., 2019). Input texts are tokenized with the byte pair encoding (Sennrich et al., 2016).

### 4.1.3 Baseline Models
For the baseline, we consider maximum likelihood estimation (MLE), a standard approach for text generation. Also compared are alternative models for promoting text diversities, including recently proposed FACE\(^4\) (Jiang et al., 2019) and unlikelihood training\(^5\) (UL) (Welleck et al., 2020). FACE improves text diversity by dynamically scaling losses, while the latter employs auxiliary losses.

### 4.1.4 Training
Training is carried out on a single GPU environment with 24GB of memory. We set all hyperparameters equal for all approaches by tuning them based on the validation losses of the MLE baseline for fair comparisons. We additionally optimize approach-specific hyperparameters of diversity-promoting baselines.

### 4.1.5 Generation
We generate texts for the evaluation by completing sequences from prefixes. Specifically, we batchify a test set, select the first 50 tokens from each batch as prefixes, and guide models to generate a continuation of 100 tokens from the prefixes. The experiments include both deterministic and stochastic decoding. We apply greedy search for deterministic decoding, and use top-\(k\) sampling for stochastic decoding.

### 4.1.6 Evaluation Metrics
From seven total quantitative metrics we adopt to evaluate our model, Perplexity (Bengio et al., 2003), KL-Divergence (Kullback, 1997), and MS-Jaccard (Alihosseini et al., 2019) are closely related to the likelihood of generated texts. The other four metrics, namely Self-BLEU (Zhu et al., 2018), Distinct-n (Li et al., 2016), Repetition (Holtzman et al., 2019), and Uniq (Welleck et al., 2020) measure the text diversity.

- **Perplexity** quantifies the prediction difficulty over the next token. It is regarded as a general performance metric for text generation.
- **KL-Divergence** measures the difference between two probability distributions. We use unigram distributions of the generated texts and the test data.
- **MS-Jaccard** computes the similarity between the model’s output and the ground truths by matching \(n\)-grams.
- **Self-BLEU** evaluates the inter-text diversity by computing BLEU (Papineni et al., 2002) score for each generated text by regarding other outputs as reference.
- **Distinct-\(n\)** quantifies the intra-text diversity based on distinct \(n\)-grams in each text.
- **Repetition** examines whether texts are stuck in repetitive loops.
- **Uniq** quantifies the richness of models using the number of unique generated tokens.

### 4.2 Quantitative Comparisons
In Table 1, we report the scores computed from fully-trained models on the two benchmarks, Wikitext-103 and Melo-Lyrics, compared against baselines. This section focuses on the results of stochastic decoding. Results of deterministic decoding, which also support the supremacy of our approach, are reported in Appendix.

#### 4.2.1 Wikitext-103
The desired qualities we aim for a text generation model is to generate human-like texts with a wide spectrum of token choices. Coupled with top-\(k\) sampling, our F\(^2\)-Softmax achieves both goals by outperforming baselines with nearly all metrics compared, and closely approaching the human gold standard. As shown in Table 1(a), our model is particularly effective in capturing the token diversity in
the corpus. Notably, $F^2$-Softmax significantly improves both Self-BLEU and Distinct performances, having relative gaps to the human gold standard of 3.4% and 3%, respectively. The performance gaps of the second-best scores are 6.5% (FACE) and 8.1% (UL-token+seq), respectively. A surprising result is that $F^2$-Softmax improves Rep performance by 50% over MLE, without an explicit penalty on repeating tokens. Another seminal contribution is the 30% relative increase in unique tokens used for the generation, from the previously state-of-the-art level of 10.6k to 15.7k, as shown by the Uniq metric. This level closely reflects the human use of 15.2k tokens.

In PPL, which reflects the likelihood of the generated texts, the diversity-promoting baselines tend to perform worse than MLE, presumably due to the trade-offs between text diversity and the likelihood of texts. In contrast, $F^2$-Softmax maintains the smallest performance drop on PPL. $F^2$-Softmax also improves KLD and MS-Jaccard by 59% and 19% over MLE, respectively, which are large margins compared to the other comparatives.

### 4.2.2 Melo-Lyrics

Significant performance gains of $F^2$-Softmax are also observed in lyrics generation in Table 1(b). Meanwhile, the diversity-promoting baselines display severer degradation in PPL, KLD, and MS-Jaccard compared to the Wikitext-103 dataset. We attribute this observation to the distinctive characteristics of lyrics, in which the same phrases are rhythmically repeated throughout the songs in the form of chorus or hook. Thus, for lyrics dataset, forcing models to discourage reusing previously used tokens may adversely affect the likelihood of the generated texts. Since $F^2$-Softmax helps models to diversify the output without an explicit regularization, models learn to generate well-thought-out tokens from the diversified token pool of 25.2k (Uniq), with state-of-the-art performances in KLD, MS-Jaccard, Self-BLEU, Distinct, and Rep.

### 4.3 Learning Balanced Distribution

The characteristic markers of monotonous texts are an overproduction of frequently used tokens and under-representation of rare tokens. To compare how models differentially generate tokens from frequent and rare tokens, we count the number of generated tokens corresponding to four defined categories of frequent, medium, rare and very rare. Tokens in each category are predefined from the Wikitext-103 training set. Fig. 3 plots the distribu-
Figure 2: Bigram performance on the Melo-lyrics test set with different numbers of classes. Green and brown lines indicate models with tokens are distributed based on frequency mass and token size, respectively. Blue dotted lines and star marks represent the MLE baseline and the choice of MefMax, respectively.

Figure 3: Frequency distribution comparisons on the Wikitext-103 test set. Tokens in each group are defined based on the frequency mass of the training set. Tokens occupying the top 40% of the frequency mass are assigned to frequent, while those corresponding to the bottom 10% are classified to very rare.

4.4 Ablation Studies

In this section, we justify the pivotal roles of MefMax (Section 3.3) and the decoupled decoding strategy (Section 3.4). In order to assess contributions toward the final performances, we conduct a series of ablation tests.

4.4.1 Ablation on MefMax

MefMax finds a desirable number of classes, with an objective to balance the frequency distribution of tokens between classes. Does MefMax help achieve better generation results than possible variants of class assignment? We answer this question by comparing the final performances against two simpler variants of MefMax. We name the first variant as fixed-eq-token in which tokens are distributed in equal numbers to a fixed number of classes. The second variant, fixed-eq-freq, also assumes a fixed number of classes, but tokens are assigned to minimize the difference in the frequency distribution between classes.

Fig. 2 presents the results. Clearly, fixed-eq-freq outperforms fixed-eq-token. It indicates that a decomposition of the softmax function without consideration of the data distribution (i.e., frequency distribution) aggravates both the likelihood and token diversity performances, regardless of the number of classes. For fixed-eq-token, we find that models tend to overclassify the target class to the first class, which contains most of the total frequency, having most tokens generated from a fraction of the total vocabulary. This finding also justifies the hypothesis that balanced data distribution is an important factor in text generation.

Assigning classes based on the frequency (i.e., fixed-eq-freq) continues to improve MS-Jaccard and Self-BLEU until the number of classes reaches the class choice of MefMax. With a larger number of classes than the choice, performances either plateau or decrease, demonstrating that MefMax is capable of selecting the optimal class size. Inter-
Table 2 compares generated texts from the same prefix. While our F²-Softmax exhibits the highest usage of rare tokens, we observe two issues from the baselines. The first is that models tend to repeat the same rare token across all sentences after its first appearance (MLE). The other issue is that generated rare tokens are mostly pronouns (UL-token). Unlike the baselines, F²-Softmax utilizes the broadest range of rare tokens with significantly less, but more likely, repetitions. Further, F²-Softmax is shown to be adept at utilizing non-pronoun rare tokens, such as ‘eccentric’ or ‘vanished’.

5 Conclusion

In this paper, we proposed F²-Softmax, a simple but effective method for better learning the rich diversity in text. F²-Softmax encourages models to diversify text generation by readjusting class formation and motivating models to learn a more balanced token distribution. Quantitative and qualitative analyses validate the diversity-promoting performances of our approach. Since it can be easily adopted in replace to the traditional likelihood objective, we believe in broader applicability of F²-Softmax. Future work thus involves extending the method to other related tasks, such as machine translation and text summarization, and investigating the potential gains from transfer learning.

![Table 2: Generated texts on the Wikitext-103 test set. A prefix from the first batch was selected to avoid cherry-picking. VR denotes the ratio of very rare tokens (see Section 4.3 for the definition) against the text length. While all colored and bold-faced tokens indicate very rare tokens, green color denotes repeated tokens, and red color is reserved for non-pronoun words.](image)

| Model          | Decoupled Decoding | KLD (%) | MSJ (%) | SB (%) | Uniq |
|----------------|--------------------|---------|---------|--------|------|
| F²-Softmax     | ×                  | 0.34    | 47.3    | 83.1   | 22.4k |
| MLE            | ×                  | 0.31    | 47.4    | 81.9   | 22.6k |
| F²-Softmax     |                    | 0.13    | 52.4    | 76.1   | 25.2k |
| MLE            |                    | 0.13    | 52.4    | 76.1   | 25.2k |

Table 3: Ablation study on the decoupled decoding. MSJ and SB stand for MS-Jaccard and Self-BLEU, respectively. Scores are measured on bigram level.

![Table 3: Ablation study on the decoupled decoding. MSJ and SB stand for MS-Jaccard and Self-BLEU, respectively. Scores are measured on bigram level.](image)
Acknowledgments

This work was supported by Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No. 2020-0-01371, Development of brain-inspired AI with human-like intelligence).

References

Danial Alighosseini, Ehsan Montahaei, and Mahdieh Soleymani Baghsahi. 2019. Jointly measuring diversity and quality in text generation models. In Proc. of Workshop on Methods for Optimizing and Evaluating Neural Language Generation, pages 90–98.

Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. 2003. A neural probabilistic language model. Journal of machine learning research, 3(Feb):1137–1155.

Mateusz Buda, Atsuto Maki, and Maciej A Mazurowski. 2018. A systematic study of the class imbalance problem in convolutional neural networks. Neural Networks, 106:249–259.

Janhavi R Chaudhary and Ankit C Patel. 2018. Machine translation using deep learning: a survey. International Journal of Scientific Research in Science, Engineering and Technology, 4(2):145–150.

Nitesh V Chawla, Kevin W Bowyer, Lawrence O Hall, and W Philip Keegelmyer. 2002. Smote: synthetic minority over-sampling technique. Journal of artificial intelligence research, 16:321–357.

Hongshen Chen, Xiaorui Liu, Dawei Yin, and Jiliang Tang. 2017. A survey on dialogue systems: Recent advances and new frontiers. Acm Sigkdd Explorations Newsletter, 19(2):25–35.

Yin Cui, Yang Song, Chen Sun, Andrew Howard, and Serge Belongie. 2018. Large scale fine-grained categorization and domain-specific transfer learning. In Proc. of IEEE conference on computer vision and pattern recognition (CVPR), pages 4109–4118.

Emily Dinan, Varvara Logacheva, Valentin Malych, Alexander Miller, Kurt Shuster, Jack Urbanek, Douwe Kiela, Arthur Szlam, Iulian Serban, Ryan Lowe, et al. 2020. The second conversational intelligence challenge (convai2). In The NeurIPS’18 Competition, pages 187–208. Springer.

Qi Dong, Shaoogang Gong, and Xiatian Zhu. 2017. Class rectification hard mining for imbalanced deep learning. In Proc. of IEEE International Conference on Computer Vision (CVPR), pages 1851–1860.

Edward J Dudewicz and Edward C Van Der Meulen. 1981. Entropy-based tests of uniformity. Journal of the American Statistical Association, 76(376):967–974.

Stephen Fagan and Ramazan Gençay. 2011. An introduction to textual econometrics. Handbook of empirical economics and finance, pages 133–154.

Angela Fan, Mike Lewis, and Yann Dauphin. 2018. Hierarchical neural story generation. In Proc. of Annual Meeting of the Association for Computational Linguistics (ACL), pages 889–898.

Joshua Goodman. 2001. Classes for fast maximum entropy training. In Proc. of IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), volume 1, pages 561–564. IEEE.

Edouard Grave, Armand Joulin, Moustapha Cissé, Hervé Jégou, et al. 2017. Efficient softmax approximation for gpus. In Proc. of International Conference on Machine Learning (ICML), pages 1302–1310. JMLR.

Haibo He, Yang Bai, Edwaro A Garcia, and Shutao Li. 2008a. Adasyn: Adaptive synthetic sampling approach for imbalanced learning. In Proc. of IEEE international joint conference on neural networks (IJCNN), pages 1322–1328. IEEE.

Zhongjun He, Qin Liu, and Shouxun Lin. 2008b. Improving statistical machine translation using lexicalized rule selection. In Proc. of International Conference on Computational Linguistics (COLING), pages 321–328.

Ari Holtzman, Jan Buys, Maxwell Forbes, Antoine Bosselut, David Golub, and Yejin Choi. 2018. Learning to write with cooperative discriminators. In Proc. of Annual Meeting of the Association for Computational Linguistics (ACL), pages 1638–1649.

Ari Holtzman, Jan Buys, Maxwell Forbes, and Yejin Choi. 2019. The curious case of neural text degeneration. In International Conference on Learning Representations (ICLR).

Chen Huang, Yining Li, Chen Change Loy, and Xiaou Tang. 2016. Learning deep representation for imbalanced classification. In Proc. of IEEE conference on computer vision and pattern recognition (CVPR), pages 5375–5384.

Shaojie Jiang, Pengjie Ren, Christof Monz, and Maarten de Rijke. 2019. Improving neural response diversity with frequency-aware cross-entropy loss. In Proc. of World Wide Web Conference (WWW), pages 2879–2885.

Salman Khan, Munawar Hayat, Syed Waqas Zamir, Jianbing Shen, and Ling Shao. 2019. Striking the right balance with uncertainty. In Proc. of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 103–112.

Wojciech Kryscinski, Nitish Shirish Keskar, Bryan McCann, Caiming Xiong, and Richard Socher. 2019. Neural text summarization: A critical evaluation. In Proc. of Empirical Methods in Natural Language Processing (EMNLP), pages 540–551.
Ilia Kulikov, Alexander Miller, Kyunghyun Cho, and Jason Weston. 2019. Importance of search and evaluation strategies in neural dialogue modeling. In Proc. of International Conference on Natural Language Generation (INLG), pages 76–87.

Solomon Kullback. 1997. Information theory and statistics. Courier Corporation.

Hai-Son Le, Ilya Oparin, Alexandre Allauzen, Jean-Luc Gauvain, and François Yvon. 2011. Structured output layer neural network language model. In Proc. of International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 5524–5527. IEEE.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016. A diversity-promoting objective function for neural conversation models. In Proc. of North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL), pages 110–119.

Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.

Andriy Mnih and Geoffrey E Hinton. 2009. A scalable hierarchical distributed language model. In Proc. of Advances in neural information processing systems (NIPS), pages 1081–1088.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proc. of Annual Meeting on Association for Computational Linguistics (ACL), pages 311–318. Association for Computational Linguistics.

Romain Paulus, Caiming Xiong, and Richard Socher. 2017. A deep reinforced model for abstractive summarization. In International Conference on Learning Representations (ICLR).

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. OpenAI Blog, 1(8):9.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proc. of Annual Meeting of the Association for Computational Linguistics (ACL), pages 1715–1725.

Claude E Shannon. 1948. A mathematical theory of communication. Bell system technical journal, 27(3):379–423.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Proc. of Advances in neural information processing systems (NIPS), pages 5998–6008.

Jesse Vig. 2018. Deconstructing bert: Distilling 6 patterns from 100 million parameters. Medium.

Ashwin K Vijayakumar, Michael Cogswell, Ram-prasaath R Selvaraju, Qing Sun, Stefan Lee, David Crandall, and Dhruv Batra. 2018. Diverse beam search for improved description of complex scenes. In Proc. of AAAI Conference on Artificial Intelligence (AAAI).

Yu-Xiong Wang, Deva Ramanan, and Martial Hebert. 2017. Learning to model the tail. In Proc. of Advances in Neural Information Processing Systems (NIPS), pages 7029–7039.

Sean Welleck, Ilia Kulikov, Stephen Roller, Emily Dinan, Kyunghyun Cho, and Jason Weston. 2020. Neural text generation with unlikelihood training. In International Conference on Learning Representations (ICLR).

Hemantha W Wijesekera and Thomas M Dillon. 1997. Shannon entropy as an indicator of age for turbulent overturns in the oceanic thermocline. Journal of Geophysical Research: Oceans, 102(C2):3279–3291.

Yaoming Zhu, Sidi Lu, Lei Zheng, Jiaxian Guo, Weinan Zhang, Jun Wang, and Yong Yu. 2018. Texygen: A benchmarking platform for text generation models. In Proc. of ACM SIGIR Conference on Research & Development in Information Retrieval (SIGIR), pages 1097–1100.

George Kingsley Zipf. 1949. Human behavior and the principle of least effort.

Geoffrey Zweig and Konstantin Makarychev. 2013. Speed regularization and optimality in word classing. In Proc. of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 8237–8241. IEEE.
A Datasets

A.1 Melo-Lyrics Data Collection

Few datasets have been publicly available for Korean text generation, and none of them has gained public consensus as a benchmark dataset, partly due to their small sample sizes. We collect lyrics data for three rationales. First, we test our model on a language other than English. Second, a large number of songs and lyrics are available. Lastly, lyrics show distributional characteristics at odds with Wikipedia. The crawling session was held between 5th July 2019 to 29th July 2019. After crawling enough data, we discarded those containing more than ten foreign language words, except for English. English was an exception since using English in Korean lyrics is natural and common. We also manually refined the lyrics by deleting noises, including advertisements and unnecessary meta-information about the lyrics writer transcriber. The remaining data consist of roughly 478 thousand lyrics with 51 million words. Indexed data can be downloaded from the url below. We plan to release the raw data for research purposes only.

A.2 Data Statistics

The number of articles (songs), and containing words for training, test and validation phases are reported in Table 4.

|             | train | test  | valid |
|-------------|-------|-------|-------|
| # of articles | 28,475 | 60    | 60    |
| # of words   | 113,655,420 | 269,551 | 236,966 |

(a) Wikitext-103 dataset

|             | train | test  | valid |
|-------------|-------|-------|-------|
| # of songs  | 430,837 | 23,935 | 23,935 |
| # of words  | 46,343,239 | 2,566,598 | 2,501,304 |

(b) Melo-Lyrics dataset

Table 4: Statistics on the datasets

B Hyperparameter Configurations

The detailed hyperparameters used are illustrated.

B.1 Model Hyperparameters

Table 5 reports the detailed list of model hyperparameters. The dropout and drop attention ratios are chosen from a set \{0, 0.1\} based on validation losses. Sequence length is selected from a set \{512, 1024\}. We assigned 10,000 more vocabularies to training models on the Melo-Lyrics dataset, illuminating the characteristics of Korean language where words with varying forms may have similar meanings.

| Hyperparameter | Wicktext-103 | Melo-Lyrics |
|----------------|---------------|-------------|
| # of layers    | 12            | 12          |
| Hidden dimension | 512          | 512         |
| Projection dimension | 2048      | 2048        |
| # of heads     | 8             | 8           |
| Head dimension | 64            | 64          |
| Dropout        | 0.1           | 0.1         |
| Drop attention | 0             | 0           |
| Sequence length | 1024          | 312         |
| Vocabulary size | 30,000       | 40,000      |
| Total # of parameters | 69.0M        | 76.5M       |

Table 5: Model hyperparameter settings

Table 6 shows the training configurations. The learning rate, gradient clipping norm, weight decay are selected from a set \{0.00005, 0.0001, 0.00015, 0.0002, 0.00025\}, \{0.25, 5.0\}, \{0, 0.001, 0.0001\}, respectively. Batch sizes are chosen to accommodate the GPU memory constraint. We use default Adam configurations in PyTorch. Finetuning learning rate, selected from a set \{0.00001, 0.00002\}, is used to finetune UL-token-seq and FACE. Of the four variants of FACE, we use FACE-OPR, which reportedly performs best.

| Hyperparameter | Wicktext-103 | Melo-Lyrics |
|----------------|---------------|-------------|
| Batch size     | 8             | 16          |
| Learning rate  | 0.0001        | 0.0002      |
| Finetuning LR  | 0.00001       | 0.00002     |
| Finetuning step | 1500         | 1500        |
| Gradient clipping | 0.25       | 0.25        |
| Weight decay   | 0.001         | 0           |
| Optimizer      | Adam          | Adam        |
| - \beta_1      | 0.9           | 0.9         |
| - \beta_2      | 0.999         | 0.999       |
| - \epsilon     | 1e-8          | 1e-8        |

Table 6: Training hyperparameter settings

C Additional Evaluation Results

C.1 Deterministic Decoding

We put our focus on stochastic decoding, namely the top-k method in the main manuscript, results of the greedy sampling are reported in Table 7. In deterministic decoding, there is no clear method...
that outperforms the others in all of the metrics. For example, UL-token+seq exhibits the best performance in Distinct and Rep, while presenting the worst score in MS-Jaccard. Similarly, FACE improves Self-BLEU in exchange for performance loss on PPL and MS-Jaccard. Since we have seven metrics to compare, we conduct pair-wise evaluations between the compared methods, in which a method outperforms the other when a majority of metrics record higher (Table 8). Our approach beats compared methods seven out of eight times.

C.2 Stochastic Decoding

Table 9 presents more results for $k$ choices over top-$k$ sampling method. Regardless of the sampling configurations, $F^2$-Softmax exhibits lower KL-Divergence and Self-BLEU scores and higher Uniq than the other baselines. Also, our $F^2$-Softmax performs better than the other baselines at any choice of the $k$ size.
| Models  | Metrics | PPL  | KLD  | MS-Jaccard | Self-BLEU | Distinct | Rep | Uniq |
|---------|---------|------|------|------------|-----------|----------|-----|------|
|         |         | n=1 | n=2 | n=3       | n=1      | n=2      | n=3 |      |
| MLE     | 24.7    | 2.17 | 45.6 | 29.9       | 20.5     | 92.8     | 83.6 | 73.2 |
| FACE    | 29.7    | 1.67 | 47.9 | 29.9       | 19.8     | 89.6     | 73.6 | 57.3 |
| UL-token| 25.8    | 1.88 | 47.2 | 30.7       | 20.9     | 92.9     | 83.7 | 73.3 |
| UL-token+seq | 27.5 | 2.06 | 41.5 | 26.9  | 18.4 | 95.6 | 86.6 | 74.2 |
| F^2-Softmax | 25.6 | 1.63 | 49.0 | 31.2 | 21.0 | 90.2 | 78.7 | 66.3 |
| Human   | -       | -    | -    | -          | -        | -        | 95.2 | 74.1 |

(a) Wikitext-103

| Models  | Metrics | PPL  | KLD  | MS-Jaccard | Self-BLEU | Distinct | Rep | Uniq |
|---------|---------|------|------|------------|-----------|----------|-----|------|
|         |         | n=1 | n=2 | n=3       | n=1      | n=2      | n=3 |      |
| MLE     | 13.1    | 0.46 | 64.5 | 44.2       | 31.6     | 91.4     | 71.8 | 51.5 |
| FACE    | 13.9    | 0.51 | 57.7 | 39.6       | 22.8     | 92.3     | 72.5 | 55.6 |
| UL-token| 13.8    | 0.51 | 62.8 | 42.7       | 30.7     | 92.3     | 73.0 | 53.5 |
| UL-token+seq | 16.6 | 0.74 | 50.6 | 34.1 | 23.9 | 95.7 | 78.7 | 56.3 |
| F^2-Softmax | 13.2 | 0.38 | 67.4 | 45.1 | 31.7 | 90.4 | 66.6 | 43.1 |
| Human   | -       | -    | -    | -          | -        | -        | 97.5 | 76.6 |

(b) Melo-Lyrics

Table 7: Evaluation results on the greedy sampling. The abbreviations are the same as Table 1.

| Winner                   | Loser          | W-L | Dataset   |
|--------------------------|----------------|-----|-----------|
| F^2-Softmax              | MLE            | 6-1 | Wikitext-103 |
| F^2-Softmax              | FACE           | 6-1 |
| F^2-Softmax              | UL-token       | 6-1 |
| F^2-Softmax              | UL-token-seq   | 5-2 |
| FACE                     | MLE            | 4-3 |
| UL-token                 | FACE           | 4-3 |
| UL-token-seq             | FACE           | 4-3 |
| UL-token                 | MLE            | 4-3 |
| UL-token-seq             | MLE            | 4-3 |
| UL-token                 | UL-token-seq   | 4-3 |
| F^2-Softmax              | UL-token+seq   | 4-3 |
| F^2-Softmax              | UL-token       | 4-3 |
| F^2-Softmax              | MLE            | 4-3 |
| FACE                     | F^2-Softmax    | 4-3 |
| FACE                     | MLE            | 4-3 |
| UL-token                 | FACE           | 4-3 |
| UL-token                 | UL-token+seq   | 4-3 |
| MLE                      | UL-token       | 4-3 |
| MLE                      | UL-token+seq   | 4-3 |
| UL-token                 | UL-token+seq   | 4-3 |

(a) Results on pair-wise evaluations between models.

| Rank | Model          | Wins | Losses |
|------|----------------|------|--------|
| 1    | F^2-Softmax    | 7    | 1      |
| 2    | UL-token       | 5    | 3      |
| 3    | FACE           | 4    | 4      |
| 4    | MLE            | 2    | 6      |
| 5    | UL-token-seq   | 2    | 6      |

(b) Model ranking based on the number of wins in pair-wise evaluations.

Table 8: Analysis on the greedy sampling results.
| Models       | PPL | KLD  | MS-Jaccard  | Self-BLEU | Distinct | Rep | Uniq |
|--------------|-----|------|-------------|-----------|----------|-----|------|
|              | n=1 | n=2  | n=3         | n=1       | n=2      | n=3 |      |
| MLE          | 24.7| 1.51 | 52.1        | 35.6      | 24.3     | 93.4| 83.2 |
|              |     |      | 69.7        |           |          |     |      |
|              |     |      |             |           | 45.1     | 71.9| 83.0 |
|              |     |      |             |           | 0.67     |     | 8.48k|
| F^2-Softmax  | 25.6| 0.62 | 67.4        | 42.4      | 26.4     | 93.3| 71.9 |
|              |     |      | 48.1        |           | 65.7     | 89.7| 94.4 |
|              |     |      |             |           | 0.33     |     | 15.7k|
| F^2-Softmax  | 25.6| 0.59 | 67.3        | 41.9      | 25.9     | 93.4| 70.6 |
|              |     |      | 45.9        |           | 67.8     | 90.9| 95.0 |
|              |     |      |             |           | 0.22     |     | 16.2k|
| F^2-Softmax  | 25.6| 0.57 | 67.4        | 41.8      | 25.6     | 93.5| 69.5 |
|              |     |      | 44.2        |           | 69.1     | 91.5| 95.2 |
|              |     |      |             |           | 0.22     |     | 16.7k|
| F^2-Softmax  | 25.6| 0.54 | 67.2        | 41.2      | 25.2     | 93.4| 68.2 |
|              |     |      | 42.3        |           | 69.8     | 91.9| 95.3 |
|              |     |      |             |           | 0.16     |     | 17.1k|
| Human        | -   | -    | -           | -         | -        | 95.2| 74.1 |
|              |     |      |             |           | 69.1     | 92.1| 95.8 |
|              |     |      |             |           | 0.11     |     | 15.2k|

(a) Wikitext-103

| Models       | PPL | KLD  | MS-Jaccard  | Self-BLEU | Distinct | Rep | Uniq |
|--------------|-----|------|-------------|-----------|----------|-----|------|
|              | n=1 | n=2  | n=3         | n=1       | n=2      | n=3 |      |
| MLE          | 13.1| 0.39 | 64.6        | 44.9      | 31.8     | 94.7| 77.7 |
|              |     |      | 59.5        |           |          |     |      |
|              |     |      |             |           | 31.8     | 43.3| 51.3 |
|              |     |      |             |           | 11.7     |     | 22.0k|
| F^2-Softmax  | 13.2| 0.20 | 75.1        | 51.1      | 35.0     | 95.7| 75.4 |
|              |     |      | 52.5        |           | 44.5     | 57.2| 63.8 |
|              |     |      |             |           | 11.3     |     | 24.0k|
| F^2-Softmax  | 13.2| 0.19 | 76.1        | 51.7      | 35.1     | 96.3| 76.2 |
|              |     |      | 52.7        |           | 50.1     | 63.9| 70.4 |
|              |     |      |             |           | 7.5      |     | 24.3k|
|              |     |      |             |           |          |     |      |
| Human        | -   | -    | -           | -         | -        |     |      |
|              |     |      |             |           |          |     |      |

(b) Melo-Lyrics

Table 9: Evaluation results on different top-k.