Neural Machine Translation with Imbalanced Classes

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Abstract
We cast neural machine translation (NMT) as a classification task in an autoregressive setting and analyze the limitations of both classification and autoregression components. Classifiers are known to perform better with balanced class distributions during training. Since the Zipfian nature of languages causes imbalanced classes, we explore the effect of class imbalance on NMT. We analyze the effect of vocabulary sizes on NMT performance and reveal an explanation for why certain vocabulary sizes are better than others.

1 Introduction
NLP tasks such as sentiment analysis (Maas et al., 2011; Zhang et al., 2015), spam detection, etc., are modeled as classification tasks where instances are independently classified. Tasks such as part-of-speech tagging (Zeman et al., 2017), and named entity recognition (Tjong Kim Sang and De Meulder, 2003) are some examples for sequence tagging in which tokens are classified into tags within the context of sequences. Similarly, we can cast neural machine translation (NMT), an example of a natural language generation (NLG) task, as a form of classification task where tokens are classified within an autoregressor (see Section 2).

Since the parameters of ML classification models are estimated from training data, certain biases in the training data affect the final performance of model. Among those biases, class imbalance is a topic of our interest. Class imbalance is said to exist when one or more classes are not of approximately equal frequency in data. The effect of class imbalance has been extensively studied in several domains where classifiers are used (see Section 6.3). With neural networks, the imbalanced learning is mostly targeted to computer vision tasks; NLP tasks are underexplored (Johnson and Khoshgoftaar, 2019).

Word types in natural language models follow a Zipfian distribution, i.e. in any natural language corpus, we observe that a few types are extremely frequent and the vast number of others lie on the long tail of infrequency. The Zipfian distribution thus causes two problems to the classifier based NLG systems:

1. Open-ended Vocabulary: Treating each word type in the vocabulary as a class of ML classifier does not cover the entire vocabulary, because the vocabulary is open-ended and classifiers model a finite set of classes only.

2. Imbalanced Classes: There are a few extremely frequent types and many infrequent types, causing an extreme imbalance. Such an imbalance, in other domains where classifiers are used, has been known to cause undesired biases and severe degradation in the performance (Johnson and Khoshgoftaar, 2019).

Subwords obtained through e.g. byte pair encoding (BPE) (Sennrich et al., 2016) addresses the open-ended vocabulary problem by using only a finite set of subwords. Due to the benefit and simplicity of BPE, it is rightfully part of the majority of current NMT models. However, the choice of vocabulary size used for BPE is a hyperparameter whose effect is not well understood. In practice, BPE vocabulary choice is either arbitrary or chosen from several trial-and-errors.

Regarding the problem of imbalanced classes, Steedman (2008) states that “the machine learning techniques that we rely on are actually very bad at inducing systems for which the crucial information is in rare events”. However, to the best of our knowledge, this problem has not yet been directly addressed in the NLG setting.
In this work, we attempt to find answers to these questions: ‘What value of BPE vocabulary size is best for NMT?’ and more crucially an explanation for ‘Why that value?’. As we will see, the answers and explanations for those are an immediate consequence of a broader question, namely ‘What is the impact of Zipfian imbalance on classifier-based NLG?’

The contributions of this paper are as follows: We offer a simplified view of NMT architectures by re-envisioning them as two high-level components: a classifier and an autoregressor (Section 2). For the best performance of the classifier, we argue that the balanced class distribution is desired, and describe a method to measure class imbalance in a Zipfian distribution (Section 2.1). For the best performance of the autoregressor, we argue that it is desired to have shorter sequences (Section 2.2). In Section 2.3, we describe how BPE vocabulary relates with the desired settings for both classifier and autoregressor. Our experimental setup is described in Section 3, followed by the analysis of results in Section 4 that offers an explanation for why some vocabulary sizes are better than others. Section 5 uncovers the impact of class imbalance, particularly the discrimination on infrequent classes. Frequency-based bias leads to a poor recall of infrequent classes.

Machine translation is commonly defined as the task of transforming sequences from the form \( x = x_1 x_2 x_3 \ldots x_m \) to \( y = y_1 y_2 y_3 \ldots y_n \), where \( x \) is from source language \( X \) and \( y \) is from target language \( Y \) respectively. NMT accomplishes the translation objective using artificial neural networks.

There are many variations of NMT architectures with a varied range of differences (Section 6.1), however, all share the common objective of maximizing \( \prod_{t=1}^{m} P(y_t | y_{<t}, x_{1:m}) \) for pairs \((x_{1:m}, y_{1:n})\) sampled from a parallel dataset. NMT architectures are commonly viewed as a pair of encoder-decoder networks. We instead re-envision the NMT architecture as two higher level components: an autoregressor \( R \) and a token classifier \( C \), as shown in Figure 1.

Autoregressor \( R \), (\cite{Box2015}) being the main component of the NMT model,\(^2\) has many implementations based on various neural network architectures: RNNs such as LSTM and GRU, CNN, and Transformer (Section 6.1). For any given time step \( t \), \( R \) transforms the input context consisting of \( y_{<t}, x_{1:m} \) into a hidden state vector as \( h_t = R(y_{<t}, x_{1:m}) \).

Classifier \( C \) is the same across all architectures. It maps \( h_t \) to a probability distribution \( P(y_j|h_t) \forall y_j \in V_Y \), where \( V_Y \) is the vocabulary of \( Y \). Intuitively, \( C \) scores \( h_t \) against an embedding of every class type, then transforms those arbitrarily ranged scores into a probability distribution using the SOFTMAX normalizer. In machine learning, input to classifiers such as \( C \) is generally described as features that are either hand-engineered or automatically extracted using neural networks. In this high-level view of NMT architecture, \( R \) is a neural network that serves as an automatic feature extractor for \( C \).

2 Classifier based NLG

2.1 Balanced Classes for Token Classifier

Untreated, class imbalance leads to bias based on class frequencies. Specifically, classification learning algorithms focus on frequent classes while paying relatively less importance to infrequent classes. Frequency-based bias leads to a poor recall of infrequent classes.

When a model is used in a domain mismatch scenario, i.e. where a test set’s distribution does not match the training set’s distribution, model performance generally degrades. It is not surprising that

\footnote{\( ^1 \)type and class are used interchangeably.}

\footnote{\( ^2 \)the autoregressor is commonly associated with only the decoder of NMT. An ablation of Transformer NMT showed that the NMT functions even if the encoder is completely removed, which lead to this simplification.}
frequency-biased classifiers show particular degradation in domain mismatch scenarios, as types that were infrequent in the training distribution and were ignored by learning algorithm may appear with high frequency in the newer domain. Koehn and Knowles (2017) showed empirical evidence of poor generalization of NMT to out-of-domain datasets.

In other classification tasks, where each instance is classified independently, methods such as up-sampling the infrequent classes and down-sampling frequent classes are used. In NMT, since the classification is done within the context of sequences, it is possible to accomplish the objective of balancing by altering the lengths of sequences. This phenomenon of achieving balance by altering the sequence lengths is indirectly achieved by, e.g., BPE subword segmentation (Sennrich et al., 2016).

**Quantification of Zipfian Imbalance:** The class imbalance of an observed distribution of training classes is quantified as Divergence \((D)\) from a balanced (uniform) distribution. Divergence is measured using a simplified version of Earth Mover Distance, in which the total cost for moving a probability mass between any two bins (analogous to class types) is the sum of the total mass moved. Since any mass moved out of one bin is moved into another, we divide the total per-bin mass moves in half to avoid double counting. Therefore, the imbalance measure \(D\) on \(K\) class distributions where \(p_i\) is the observed probability of class \(i\) in the training data is computed as:

\[
D = \frac{1}{2} \sum_{i=1}^{K} |p_i - \frac{1}{K}|
\]

The range of \(D\) is \(0 \leq D \leq 1\), and we argue that a lower value of \(D\) a desired setting for \(C\).

**2.2 Shorter Sequences for Autoregressor**

Every autoregressive model is an approximation, some maybe better than others, but no model is a perfect one. Therefore, there is a non-zero probability of an error at each time step. The total error accumulated along the sequence grows in proportion to the length of the sequence. These accumulated errors alter the prediction of subsequent tokens in the sequence. Even though beam search attempts to mitigate this, it does not completely resolve it. These challenges with respect to long sentences and beam size are examined by Koehn and Knowles (2017). If sequence encoders such as BPE subwords can reduce the steps in the sequences, this indirectly reduces the errors in language generation by imperfectly approximated autoregressors.

We summarize sequence lengths using **Mean Sequence Length**, \(\mu\), computed trivially as the arithmetic mean of the lengths of target language sequences after encoding them:

\[
\mu = \frac{1}{N} \sum_{i} |y^{(i)}|
\]

We argue that a smaller \(\mu\) is a desired setting for \(R\).

**2.3 Choosing the Vocabulary Size Systematically**

BPE vocabulary is learned using a greedy and iterative algorithm (Sennrich et al., 2016). The BPE learning algorithm starts with characters as its initial vocabulary. In each iteration, it greedily selects a pair of the most frequent types (either characters or subwords) that co-occur, and replaces them with a newly created compound type. During segmentation, BPE splitting is performed left-to-right with greedily selecting the longest matched code in the vocabulary. These operations have an effect on both \(D\) and \(\mu\).

**Effect of BPE on \(\mu\):** BPE segmentation in comparison to word segmentation, expands rare words into two or more subwords, thus increases the sequence length. In comparison to character segmentation, BPE groups frequent characters as subwords thus reduces the length. BPE vocabulary size is more general that the words and characters are special cases that are attained at the two extremes (Morishita et al., 2018). It can be used to create sequences that are long as character sequences (undesired for \(R\)), or short as word sequences (desired for \(R\)).

**Effect of BPE on \(D\):** Whether viewed as a merging of frequent subwords into a relatively less frequent compound, or splitting of rare words into relatively frequent subwords, it alters the class distribution by moving the probability mass of classes. Hence, by altering class distribution, it also alters \(D\).

Figure 2 shows the relation between the BPE vocabulary size on both \(D\) and \(\mu\). A smaller vocabulary of BPE, after merging a few extremely frequent pairs, has smallest \(D\) which is a desired setting for \(C\), but at the same point \(\mu\) is large and undesired for \(R\). When BPE vocabulary is set to a
Table 1: A comparison of sequence encoding schemes with respect to Vocabulary Size (V), Class Imbalance (D), and Mean Sequence Length (µ). The row titled Desired describes an ideal encoding scheme for C and R. BPE Subword scheme has Variable values indicating that it can be tuned towards Desired values.

| Scheme | V | D | µ |
|--------|---|---|---|
| Word   | Large | High | Low |
| Character | Small | High | High |
| BPE    | Variable | Variable | Variable |
| Desired | Small | Low | Low |

large one, the effect is reversed i.e. D is large and unfavorable to C while µ small and favorable to R. As seen with evidence in Section 4, there exists optimal vocabulary size of BPE that achieve the best setting for both C and R. Hence, BPE vocabulary size is not arbitrary since it can be tuned to reduce D while keeping µ short enough as well.

For a comparison, word and character segmentation have no influence on µ. However, the trim size of word and character vocabulary has an effect on class imbalance D and Out-of-Vocabulary (OOV) tokens and is presented in Figures 3 and 4, respectively. The summary of word, character, and BPE with respect to D and µ is presented in Table 1.

3 Experimental Setup

We perform NMT experiments using the base Transformer architecture ( Vaswani et al., 2017). A common practice, as seen in Vaswani et al. (2017)’s experimental setup, is to learn BPE vocabulary jointly for the source and target languages, which facilitates three-way weight sharing between the encoder’s input, the decoder’s input, and the decoder’s output embeddings (classifier’s class embeddings) ( Press and Wolf, 2017). To facilitate fine-grained analysis of source and target vocabulary sizes and their effect on class imbalance, our models separately learn source and target vocabularies; weight sharing between the encoder’s and decoder’s embeddings is thus not possible. For the target language, however, we share weights between the decoder’s input embeddings and the classifier’s class embeddings.

3.1 Dataset

We use the publicly available Europarl v9 parallel data set for training German (De) and English (En) languages. We use 1.8M sentences of this corpus and build models in English to German and

Figure 2: Effect of BPE vocabulary size on mean sequence length µ and class imbalance D.

Figure 3: Effect of word vocabulary size on OOV tokens and imbalance D. At any specified trim size on the horizontal axis, all the OOV words are mapped to UNK type.

Figure 4: The relation between character vocabulary size with OOV tokens and imbalance D. At any specified trim size on the horizontal axis, all the OOV characters are mapped to UNK type.
vice versa. To segment initial words (i.e. before any subword processing) we use the Moses word tokenizer and detokenizer.\(^3\) We evaluate with the NewsTest2013 and NewsTest2014 datasets from the WMT 2014 news translation track.\(^4\)

### 3.2 Hyperparameters

Our Transformer NMT model has 6 layers in each of the encoder and decoder, 8 attention heads, 512 hidden vector units, and feed forward intermediate size of 2048. We use label smoothing at 0.1. We use the Adam optimizer (Kingma and Ba, 2015) with a controlled learning rate that warms up for 8,000 steps followed by the decay rate recommended for training Transformer models. All models are trained for 100,000 optimizer steps. Mini-batch size per step is no more than 4,200 tokens. We group mini-batches into sentences of similar lengths to reduce padding tokens per batch (Vaswani et al., 2017). We trim sequences longer than 512 time steps. The average training time per experiment is 10Hrs on Nvidia 1080Ti GPUs. For inference (i.e decoding the test sets), we use checkpoint averaging of the last 5 states each, saved at 1000 optimizer steps apart, and a beam size of 4.

### 4 Analysis

We use character, word, and BPE subword encoding with various vocabulary sizes to analyze the effect of \(D\) and \(\mu\). Each experiment is run twice and we report the mean of BLEU scores in Table 2. The BLEU scores were computed using SacreBLEU (Post, 2018)\(^5\). All results are in Table 2. We observe the following:

1. Experiments #1 and #2 use a word vocabulary, while #3 and #4 use a BPE vocabulary. The results show that with BPE, increasing the vocabulary size at this range reduces BLEU. Experiment #3 with a vocabulary as large as 64k BPE types even fails to reach the comparable Word model’s (#1) BLEU score\(^6\), which raises the need for a systematic understanding of ‘Why BPE model reduced BLEU when vocabulary increased from 32k to 64k?’ With increase in BPE vocabulary, \(\mu\) is reduced which is favorable to \(R\). An explanation is that the \(D\) increased which is unfavorable to \(C\). For Word models, there is an effect of OOVs along with \(D\), and it is beyond the scope of this work.

2. Experiments #3, #4, #5, #6 show that with BPE, decreasing the vocabulary indeed improves BLEU. Hence the larger BPE vocabulary such as 32k and 64k are not the best choice.

3. Experiments #7, #8, #9 and #10 with comparison to #6 showed that reducing vocabulary too much also negatively affects BLEU. Though Experiment #9 with 1k target vocabulary has the lowest \(D\) favoring the \(C\), in comparison to others, the BLEU is still lower than the others. An explanation for this reduction is that \(\mu\) is higher and unfavorable to \(R\). Hence a strictly smaller vocabulary is not the best choice either.

4. By comparing #6 with #11, we see that, both have the same target vocabulary of 8k, hence the same \(D\) and \(\mu\), however, the source vocabulary differs from 8k to 32k. Even though #11 had more imbalanced source types than #6, it has no adverse effect on BLEU. Therefore, imbalance on source vocabulary is not meaningful since source types are not the classes of \(C\). Increasing the source vocabulary and hence rows in embeddings matrix is a simple way of increasing parameters of NMT model without hurting the BLEU.\(^7\)

5. Experiments #6 and #12 have differences in BLEU that is more significant than the previous pair (#6, #11). Here, both have the same 8k as source vocabulary, but the target differs from 8k to 32k which lead to noticeable differences in \(D\) and \(\mu\). Even though #11 had more parameters in the target embeddings matrix, and smaller \(\mu\) than #6, the BLEU is noticeably lower. An explanation we offer is that the 32k target types became classes and raised the class imbalance \(D\), leading to a reduction in the performance of \(C\). This argument holds provided, there is enough gradient updates on the source embeddings.

\(^3\)https://github.com/moses-smt/mosesdecoder/tree/master/scripts/tokenizer

\(^4\)http://www.statmt.org/wmt14/translation-task.html

\(^5\)bleu+case.mixed+numrefs.1+smooth.exp+tok.13a+version.1.3.2

\(^6\)The OOV words were mapped to UNK during training and removed from the generated output before computing BLEU.
on both the directions of De-En and En-De. Thus, the class imbalance problem exists in NMT.

5 Measuring Classifier Bias due to Imbalance

In a typical classification setting with imbalanced classes, the classifier learns an undesired bias based on frequencies. Specifically, a biased classifier overclassifies frequent classes, leading to overrecall but poor precision of frequent words, and underclassifies rare classes, leading to poor recall of rare words. An improvement in balancing the class distribution, therefore, debiases in this regard, leading to improvement in the precision of frequent classes as well as recall of infrequent classes. BLEU focuses only on the precision of classes; except for adding a global brevity penalty, it is ignorant to the poor recall of infrequent classes. Therefore, the numbers reported in Table 2 capture only a part of the improvement from balanced classes. In this section we perform a detailed analysis of the impact of class balancing by considering both precision and recall of classes.

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8The original reason BLEU was defined as a precision-only measure is to use multiple references. This is exceed-
We accomplish this in two stages: First, we define a method to measure the bias of the model for classes based on their frequencies. Second, we track the bias in relation to vocabulary size and class imbalance on all our experiments.

5.1 Class Frequency Bias Measurement

We measure frequency bias using the Pearson correlation coefficient, $\rho$, between class rank and class performance, where for performance measures we use precision and recall. We rank classes based on descending order of frequencies in the training data encoded with the same encoding schemes used for reported NMT experiments. With this setup, the class with rank 1, say $F_1$, is the one with the highest frequency, rank 2 is the next highest, and so on. More generally, $F_k$ is an index in the class rank list which has an inverse relation to class frequencies.

We define precision $P$ for a class similar to the unigram precision in BLEU and extend its definition to the unigram recall $R$. For the sake of clarity, consider a test dataset $T$ of $N$ pairs of parallel sentences, $(x^{(i)}, y^{(i)})$ where $x$ and $y$ are source and reference sequences respectively. We use single reference $y^{(i)}$ translations for this analysis. For each $x^{(i)}$, let $h^{(i)}$ be the translation hypothesis from an MT model.

Let the indicator $1_{f_k}^{(i)}$ have value 1 iff type $c_k$ exists in sequence $a$, where $a$ can be either hypothesis $h^{(i)}$ or reference $y^{(i)}$. The function $\text{count}(c_k,a)$ counts the times token $c_k$ exists in sequence $a$; $\text{match}(c_k,y^{(i)},h^{(i)})$ returns the times $c_k$ is matched between hypothesis and reference, given by $\min\{\text{count}(c_k,y^{(i)}),\text{count}(c_k,h^{(i)})\}$.

Let $P_k^{(i)}$ and $R_k^{(i)}$ be precision and recall of $c_k$ on a specific record $i \in T$, given by:

$$P_k^{(i)} = \frac{\text{match}(c_k,y^{(i)},h^{(i)})}{\text{count}(c_k,h^{(i)})}, \text{ defined iff } 1_{h_k}^{(i)}$$

$$R_k^{(i)} = \frac{\text{match}(c_k,y^{(i)},h^{(i)})}{\text{count}(c_k,y^{(i)})}, \text{ defined iff } 1_{y_k}^{(i)}$$

Let $P_k$, $R_k$ be the expected precision and recall for $c_k$ over the whole $T$, given by:

$$P_k = \mathbb{E}_{i \in T}[P_k^{(i)}] = \frac{\sum_{i=1}^{N} 1_{h_k}^{(i)} P_k^{(i)}}{\sum_{i=1}^{N} 1_{h_k}^{(i)}}$$

$$R_k = \mathbb{E}_{i \in T}[R_k^{(i)}] = \frac{\sum_{i=1}^{N} 1_{y_k}^{(i)} R_k^{(i)}}{\sum_{i=1}^{N} 1_{y_k}^{(i)}}$$

More generally, $F_k$ is matched between hypothesis and reference, $P_k$ and $R_k$ are reported NMT experiments. With this setup, the class with rank 1, say $F_1$, is the one with the highest frequency, rank 2 is the next highest, and so on. More generally, $F_k$ is an index in the class rank list which has an inverse relation to class frequencies.

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The Pearson correlation coefficients between $F_k$ vs. $P_k$, and $F_k$ vs. $R_k$ are reported in Table 3 as $\rho_{F,P}$ and $\rho_{F,R}$ respectively.

5.2 Analysis of Class Frequency Bias

A classifier that does not discriminate classes based on their frequencies is the one that exhibits no correlation between class rank vs precision and class rank vs recall. However, in the top rows of Table 3 where larger vocabularies such as 64k are used, we make two observations:

1. $\rho_{F,P}$ is strong and positive. This is an indication that frequent classes have relatively less precision than infrequent classes. If the rank increases (i.e frequency is decreases), precision increases in relation to it, leading to $\rho_{F,P} > 0$.

2. $\rho_{F,R}$ is strong and negative. This is an indication that frequent classes have relatively higher recall than infrequent classes. If the rank increases, recall decreases in relation to it, leading to $\rho_{F,R} < 0$.

Figure 5, as a visualization of Table 3, shows a trend that the correlation (i.e. frequency bias) is lower with smaller vocabulary sizes. However, there still exists some correlation in $\rho_{F,R}$ since the class imbalance, $D > 0$. 
6 Related Work

We categorize the related work into the subsections as following:

6.1 NMT architectures

Several variations of NMT models have been proposed and refined: Sutskever et al. (2014); Cho et al. (2014b) introduced recurrent neural network (RNN) based encoder-decoder models for sequence-to-sequence translation learning. Bahdanau et al. (2014) introduced the attention mechanism and Luong et al. (2015) proposed several variations that became essential components of many future models. RNN modules, either LSTM (Hochreiter and Schmidhuber, 1997) or GRU (Cho et al., 2014a), were the popular choice for composing encoder and decoder of NMT. The encoder used bidirectional information, but the decoder was unidirectional, typically left-to-right, to facilitate autoregressive generation. Gehring et al. (2017) showed used convolutional neural network (CNN) architecture that outperformed RNN models. Vaswani et al. (2017) proposed another alternative called Transformer whose main components are feed-forward and attention networks. There are only a few models that perform non-autoregressive NMT (Libovický and Helcl, 2018; Gu et al., 2017). These are focused on improving the speed of inference and the generation quality is currently sub-par compared to autoregressive models. These non-autoregressive models can also be viewed as a token classifier with a different kind of feature extractor whose strengths and limitations are yet to be theoretically understood. Analyzing the non-autoregressive component, especially its performance with longer sequences, is beyond the scope of this work (however, an interesting direction).

6.2 Bye Pair Encoding subwords

Sennrich et al. (2016) introduced byte pair encoding (BPE) as a simplified way for solving OOV words without using back-off models. They noted that BPE improved the translation of not only the OOV words, but also some of rare in-vocabulary words. In their work, the vocabulary size was arbitrary, and large as $60k$ and $100k$.

Morishita et al. (2018) viewed BPE more generally in the sense that both character and word vocabularies as two special cases of BPE vocabulary. Their analysis was different than ours in a way that they viewed BPE with varied vocabulary sizes as hierarchical features which were used in addition to a fixed BPE vocabulary size of $16k$ on the target language. Salesky et al. (2018) offer an efficient way to search BPE vocabulary size for NMT. Kudo (2018) used BPE segmentation as a regularization by introducing sampling based randomness to the BPE segmentation. For the best of our knowledge, no previous work exists that analyzed BPE’s effect on class imbalance or answered ‘why certain BPE vocabularies are better than others?’.

6.3 Class Imbalance

The class imbalance problem has been extensively studied in classical ML (Japkowicz and Stephen, 2002). In the medical domain Mazurowski et al. (2008) found that classifier performance deteriorates with even modest imbalance in the training data. Untreated class imbalance has been known to deteriorate the performance of image segmentation, and Sudre et al. (2017) have investigated the sensitivity of various loss functions. Johnson and Khoshgoftaar (2019) surveyed imbalance learning with neural networks and reported that the effort is mostly targeted to computer vision tasks. Buda et al. (2018) provided a definition and quantification method for two types of class imbalance: step imbalance and linear imbalance. Since natural languages are Zipfian, where the class imbalance is neither single stepped nor linear, we defined a divergence measure in Section 2.1 to quantify it.

7 Conclusion

Envisioning NMT models as a token classifier with an autoregressor helped in analysing the weaknesses of each component independently. The class imbalance was found to cause bias in the token classifier. We showed that BPE vocabulary size is not arbitrary, and it can be tuned to address the class imbalance and sequence lengths appropriately. Our analysis provided an explanation why BPE encoding is more effective compared to word and character models for sequence generation.

Even though BPE encoding indirectly reduces the class imbalance compared to words and characters, it does not completely eliminate it. The class distributions after applying BPE contain sufficient imbalance for biasing the classes, and affecting the recall of rare classes. Hence more work is needed in directly addressing the Zipfian imbalance.
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