On Data Augmentation for Extreme Multi-label Classification

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Abstract

In this paper, we focus on data augmentation for the extreme multi-label classification (XMC) problem. One of the most challenging issues of XMC is the long tail label distribution where even strong models suffer from insufficient supervision. To mitigate such label bias, we propose a simple and effective augmentation framework and a new state-of-the-art classifier. Our augmentation framework takes advantage of the pre-trained GPT-2 model (Radford et al., 2019) to generate label-invariant perturbations of the input texts to augment the existing training data. As a result, it present substantial improvements over baseline models. Our contributions are two-factored: (1) we introduce a new state-of-the-art classifier that uses label attention with RoBERTa (Liu et al., 2019) and combine it with our augmentation framework for further improvement; (2) we present a broad study on how effective are different augmentation methods in the XMC task.

1 Introduction

The extreme multi-label classification (XMC) problem aims to assign a set of inter-dependent labels to an input text. Such labeling can come in handy for industrial applications including product searching (McAuley et al., 2015), document categorization (McAuley and Leskovec, 2013), and social media recommendation (Jain et al., 2016). The extremeness is two-factored. In the task definition, it lies in the size of output space which ranges from few hundreds (Katakis et al., 2008; Tsoumakas et al., 2008) to many thousands (Mencia and Fürnkranz, 2008; Zubiaga, 2012; Partalas et al., 2015). In practice, real-world data often has labels that are extremely unbalanced. For instance, the AmazonCat-13K dataset is dominated by examples with media-related labels cover ~ 60% of the data.

Recent works have shown impressive improvements in terms of accuracies with the emerging neural architectures (eg Devlin et al., 2019; Liu et al., 2019). However, they nonetheless are powered by large amount of training data and taking the unbalanced data as-is. As a result, even state-of-the-art models perform poorly on the tail labels (i.e. tail distribution) (Chang et al., 2019). This problem can be much more prominent when training data is limited, such as non-English corpus, or limited budget for data annotation.

One immediate approach to address the problem is data augmentation which can compensate the scarce data for tail labels. To this end, we study two general augmentation strategies: 1) off-the-shelf rule-based augmentation, and 2) language-model-based augmentation. Here we aim to compare how
they impact the downstream XMC task.

For rule-based system, we examine the EDA (Wei and Zou, 2019) system and a simplified WordNet-only system. For the language-model-based data augmentation, we propose a simple and effective approach called GDA (GPT-2 based data augmentation) to generate label-invariant examples using GPT-2 model. Specifically, given an unbalanced dataset, we first group examples pairs with the same label sets, then fine-tune the pre-trained GPT-2 to generate label-invariant perturbations. Such perturbed examples, such as shown in Fig 1, are then used to augment the existing training data, particularly for those with tail labels.

In our experiments, we focus on the AmazonCat13K dataset (McAuley and Leskovec, 2013) to validate the above augmentation approaches. We sample different percentages of the training data to see how augmentation affects downstream XMC models from low data scenario to large data scenario. We start with the vanilla RoBERTa (Liu et al., 2019) model and propose a new state-of-the-art model LA-RoBERTa by using label attention (You et al., 2019). We take both models as our base models and apply them on augmented datasets. As a result, our augmented models outperform baseline (even the new state-of-the-art baseline) in terms of both overall precision and tail label precision.

In summary, our contributions include:

- We propose GDA, a simple and effective augmentation approach for the XMC task by using GPT-2 model. Our augmented system achieves better performances on tail labels.
- We propose a new state-of-the-art classifier LA-RoBERTa, by combining RoBERTa and label attention it outperforms prior best model by 0.7% in top-5 precision.
- We conduct so far the broadest study on data augmentation methods for the XMC task, showing that GPT-2 augmentation performs better when training data is rich, while rule-based system is relatively better when data is limited.

2 Model

In this section, we will introduce the data augmentation framework for the XMC task. In Section 2.1, we will present three augmentation models, two for rule-based and one for language-model-based. In Section 2.2, we will present our state-of-the-art classifier. In Section 2.3, we will cover how to use the generated examples for augmentation.

2.1 Generation

Here, we study two types of augmentations: 1) rule-based; 2) language-model-based. As noted in Section 1, the training data of XMC is often very unbalanced. Here we focus on generating examples for tail labels.

2.1.1 Augmenting with rule-based system

We will briefly present two rule-base augmentation systems: EDA (Wei and Zou, 2019) and a WordNet-based one. Both systems utilize external knowledge base WordNet (Fellbaum, 1998), and take input from the given training data $D$ and make further editions.

EDA EDA is a light-weight rule-based system that generates perturbations by random replacement, insertion, deletion, and swapping. The replacement operation uses WordNet (Fellbaum, 1998) while others modify in-place. Examples generated in such way are often no longer natural, and should hypothetically benefit downstream models in terms of robustness. Interestingly, prior works have shown that the generated examples can improve accuracy in multi-class classification task (Wei and Zou, 2019). In this paper, we aim to study its impact on the XMC task.

WordNet only To generate natural perturbations while keep the design simple, we simplify the EDA system by removing those random editing operations and only keep the synonym-swapping part. N non-stop words from the sentence are randomly chosen and are replaced with one of its synonyms chosen at random.

2.1.2 Augmenting with pre-trained language model

We use the GPT-2 model to demonstrate the use of language model for data augmentation. Fig 2 shows the overview of the language-model-based data augmentation framework. (Kumar et al., 2020) have shown successful application of label-to-text generation for multi-class classification task. However, such method does not directly apply to the XMC task due to the fact that labels in XMC are not order-dependent. (Yang et al., 2020) have used back-translation to augment existing training data which yields examples more like paraphrases.
However, as noted in Sec 1, XMC examples that have the same label set can be substantially different. Therefore, inspired by (Anaby-Tavor et al., 2020), we fine-tune a pre-trained GPT-2 model on paired XMC textual inputs.

Given a dataset $D = \{(x_i, y_i) : i = 1, 2, ..., N\}$ and $K$ labels, where $x_i$ is the input sequence and $y_i \in \mathbb{R}^K$ is the binary label vector of $x_i$, i.e. if $y^k_i = 1$, then label $k$ is one of the assigned labels of $x_i$. We group a set of example pairs $(x_i, x_j)$ that have the same assigned labels, i.e. $y_i = y_j$. We then fine-tune a pre-trained GPT-2 model to generate $x_j$ given $x_i$, where $(x_i, x_j)$ are subsamples from the training set of XMC (e.g. in Fig 3).

For training, we use the standard token-wise cross entropy loss with teacher forcing.

At inference time, we use the fine-tuned GPT-2 model to generate label-invariant perturbations for the rest training sets. Note that we omit the dominant label and only focus on generation for tail labels.

### 2.2 Classification

To validate the impact of our augmentation framework, we will start with two base models: vanilla RoBERTa as a strong baseline and a new state-of-the-art model based on RoBERTa with label attention (LA-RoBERTa). Let us first denote the augmented dataset $\tilde{D}$.

**RoBERTa**  Given an example $(x_i, y_i) \in \tilde{D}$ (in the absence of augmentation, $\tilde{D} = D$), we score association between the input sequence $x_i$ and a particular label $y^k_i$ by:

$$e_i = \text{cls}(\text{RoBERTa}(x_i))$$

$$s^k_i = f_k(e_i)$$

$$\hat{y}^k_i = \sigma(s^k_i)$$

where the $\text{cls}()$ function returns the encoding of the [CLS] token. $f_k$ is a label-wise linear layer without activation, $\hat{y}^k_i$ is the prediction probability for the $k$-th label.

**Label Attention RoBERTa (LA-RoBERTa)**  We adopted the multi-label attention design from AttentionXML (You et al., 2019) and built it upon the vanilla RoBERTa. Specifically:

$$\alpha^k_{ti} = \frac{\exp h^k_{iw_k}}{\sum_{t=1}^{T} \exp h^k_{iw_k}}$$

$$m^k_i = \sum_{t=1}^{T} \alpha^k_{ti} h^t_i$$

$$s^k_i = f_k(m^k_i)$$

$$\hat{y}^k_i = \sigma(s^k_i)$$

where $h^t_i$ is the encoding of the $t$-th token of input $x_i$, $\alpha^k_{ti}$ is the attention parameters for label $k$ on token $t$ for input $x_i$. Here we assume input $x_i$ consists of $T$ tokens including [CLS] and [SEP] tokens. By introducing label attention, each token embedding can have different impact on each label.

### 2.3 Training with Augmented Data

We treat the original example and the generated ones differently, since in practice, there can be
We use two sets of metrics to measure performances over all labels and tail labels.¹

### Metrics for all labels
We follow (Bhatia et al., 2016) to use \( P@k \) (Precision at k) and \( N@k \) (nDCG@k: normalized Discounted Cumulative Gain at k) as our evaluation metrics. The two metrics are the most widely used evaluation metrics for XMC benchmarks. Specifically:

\[
P@k = \frac{1}{k} \sum_{i=1}^{k} \frac{y_{r(i)}}{\sum_{i=1}^{k} \log(1 + \frac{min(k,|y_{i}|)}{y_{i}})}
\]

\[
\text{DCG@}k = \sum_{i=1}^{k} \frac{y_{r(i)}}{\log(1 + i)}
\]

\[
i\text{DCG@}k = \sum_{i=1}^{k} \frac{1}{\log(1 + i)}
\]

\[
n\text{DCG@}k = \frac{\text{DCG@}k}{i\text{DCG@}k}
\]

where \( r(i) \) denotes the rank of the \( i \)-th label in the top-k labels. Note when \( k=1 \), we have \( P@1 = \text{DCG@1} = \text{nDCG@1} \).

### Metrics for tail labels
We follow (Jain et al., 2016) and use \( \text{PSP}@k \) to describe the propensity precision of the top-k labels, and \( \text{PnDCG}@k \) to describe the normalized cumulative gain at top-k. Specifically:

\[
\text{PSP}@k = \frac{1}{k} \sum_{i=1}^{k} \frac{y_{r(i)}}{P_{r(i)}}
\]

\[
\text{PDCG}@k = \sum_{i=1}^{k} \frac{y_{r(i)}}{P_{r(i)} \log(1 + i)}
\]

\[
\text{PSnDCG}@k = \frac{\text{PDCG}@k}{i\text{DCG}@k}
\]

\( P_{r(i)} \) is the propensity score for the rank of the \( i \)-th label, and the score is calculated from the training dataset.

Across our experiments in Sec 4, we will consider \( P@5 \) and \( \text{PSP}@5 \) the primary precision metrics, similarly, \( \text{nDCG}@5 \) and \( \text{PSnDCG}@5 \) the primary ranking metrics.

### 4 Experiments
In this section, we will explain how we subsample the AmazonCat-13K dataset in Sec 4.1. Then we will present details of our rule-based and neural-based generators in Sec 4.2, and RoBERTa baselines in Sec 4.3. Across our experiments, we aim to study the effectiveness of different augmentation methods with respect to the sizes of training data.

#### 4.1 Dataset
We follow the standard approach in (Chang et al., 2019; You et al., 2019) to split the train/development sets of the AmazonCat-13K dataset. We set aside 10% of the training instances as the validation set for hyper-parameter searching. This results in training data of 1,067,615 examples, validation set of 118,624, and testing set of 306,782. Furthermore, we subsample 1%, 5%, 50%, and 100% of the effective training data to study in low-training and high-training scenario. Finally, we use both of the product title and description as input text. For efficiency, we limit the maximal input length to 500 words.

#### 4.2 Generators
For rule-based augmentation, we use the textattack package (Morris et al., 2020) for the EDA and WordNet Data Augmentation experiments.

For neural-based augmentation, we use the small version of GPT-2 model released by (Wolf et al., 2019). Furthermore, we set a thread on the input text length that we only keep the texts with 5 to 200 words. We also filter out the input pairs with high similarity score ² (over 0.95) so that the model can focus on generating diversified examples instead of just paraphrasing. For training, we set the learning rate 0.0001 and beam search with width 10. For decoding, we set the temperature as 0 to smooth decoding probabilities and set the penalty to repeated prediction to 1. We grid-searched hyperparameters by measuring the BLEU scores (Papineni et al., 2002) of fine-tuned model. In practice, we found such setting generally produces good examples.

¹For reference, evaluation scripts can be found at https://github.com/kunaldahiya/pyxclib and http://manikvarma.org/downloads/XC/XMLRepository.html.

²For reference, we used the SequenceMatcher from the difflib python package to calculate similarity score. https://docs.python.org/2/library/difflib.html.
| Model       | P@1  | P@3  | P@5  | nDCG@3 | nDCG@5 |
|-------------|------|------|------|--------|--------|
| XML-CNN     | 93.26| 77.06| 61.40| 86.20  | 83.43  |
| AttentionXML| 95.65| 81.93| 66.90| 90.71  | 89.01  |
| PfastreXML  | 91.75| 77.97| 63.68| 72.00  | 64.54  |
| RoBERTa     | 95.58| 83.06| 67.64| 91.85  | 90.00  |
| LA-RoBERTa  | 96.28| 83.06| 67.64| 91.85  | 90.00  |

Table 1: Model comparison on AmazonCat-13K using P@k and nDCG@k metrics.

| Model       | PSP@1 | PSP@3 | PSP@5 | PSnDCG@3 | PSnDCG@5 |
|-------------|-------|-------|-------|----------|----------|
| XML-CNN     | 52.42 | 62.83 | 67.10 | -        | -        |
| AttentionXML| 53.52 | 68.73 | 76.38 | -        | -        |
| PfastreXML  | 69.52 | 73.22 | 75.48 | 72.21    | 73.67    |
| RoBERTa     | 49.05 | 60.81 | 64.81 | 58.79    | 62.95    |
| LA-RoBERTa  | 51.01 | 66.52 | 74.86 | 63.28    | 69.91    |

Table 2: Model comparison on AmazonCat-13K using PSP@k and PSnDCG@k metrics. Fields marked with “-” are not provided in the original works.

As noted in Sec 2.1, we focus on generating examples for tail labels. To this end, since media-related labels cover ~60% of the data, we extract media-related labels in Table 3 and filter them out. Furthermore, we found examples with media labels pose challenge to augmentation models since such examples are extremely diverse and often not even semantically related.

| Label | Coverage |
|-------|----------|
| books | 24.88%   |
| music | 13.62%   |
| movies| 6.24%    |
| tv    | 8.99%    |
| games | 1.16%    |

Table 3: Media labels in the AmazonCat-13K dataset. We filtered out examples having these labels and focus on augmentation for tail labels.

4.3 Base Classifiers

Our baseline classifiers use the large version of pre-trained RoBERTa. We further fine-tune it on the AmazonCat-13K dataset and we manually tune the learning rate and the number of epochs. We train RoBERTa models using a learning rate of 1e-6, and 5e-6 for LA-RoBERTa models. For 100%, 50%, 5% and 1% of the data, we train the models for 10, 40, and 100 epochs respectively.

In Table 1, we present the performances of our baseline systems along with prior best models, i.e. XML-CNN (Liu et al., 2017), AttentionXML (You et al., 2019), and PfastreXML (Jain et al., 2016). We see that the vanilla RoBERTa model is positioned strongly with cleaner model architecture. With label attention, the LA-RoBERTa strongly outperforms the prior best model by 0.7 in P@5 and 1.0 in nDCG@5.

To our surprise, the AttentionXML achieves better PSP@5 than LA-RoBERTa while the later has much better P@5. Note that the only major difference between AttentionXML and our LA-RoBERTa is BiLSTM encoder v.s. transformer encoder. In our preliminary experiments, we indeed found that BiLSTM encoder tends to have better PSP@k performances than transformer encoder. But this comes at the cost of the P@k metric.

In Table 2, we show their precision scores for tail labels. The new state-of-the-art LA-RoBERTa has subpar performances on tail labels compared to the PfastreXML, since PfastreXML optimizes over the propensity scored losses to get optimal performance for tail labels.

4.4 Classifiers with Data Augmentation

In Table 4 and 5, we show the impact of different augmentation methods on the vanilla RoBERTa baseline. We see that our proposed GDA method is more effective than rule-based ones when training data is very large. For instance, with ~1M training examples, GDA outperforms the baseline by 1.0 in P@5 and 0.9 in nDCG@5. For tail labels, GDA also improve over baseline by 3.2 in PSP@5 and 1.5 in PSnDCG@5.

To our surprise, rule-based methods failed to improve over baseline with large training data. We hy-

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3 According to (You et al., 2019), this difference only applies to the AmazonCat-13K.
pothetize this is because rule-based augmentations could not bring much richer vocabulary diversity and, often, they yield grammatically incorrect texts. In contrast, our GDA framework can generate substantially diversified input while maintaining natural inputs in general.4

4Generation is an evolving field. At this point, even strong models sometimes still output artificial texts, e.g. repeated phrases and off-context phrases.

When training data is limited such as 1% of training data (~10k examples), both rule-based augmentation and our GDA yield outperform baseline in P@k and N@k metrics. And rule-based models yield more improvement than GDA. We should note that such small amount of data brings challenge to fine-tune GPT-2 model, especially considering the label space is 13k and the label distribution is extremely biased. As a result, rule-generated examples, while being unnatural often, outperform those generated by GPT-2 models.

For the much stronger baseline LA-RoBERTa, we present similar comparison in Table 6 and 7. In general, we see similar observations as above when comparing different augmentation methods with respect to training sizes. Note that, when using 100% of the training data, GDA only performs on par with the baseline when measuring the overall label precisions (i.e. P@k and nDCG@k) while performances on tail labels are still better (e.g. 0.2 improvement in PSP@5 and 0.1 in PSnDCG@5). Again, rule-based systems failed to improve precisions for both all and tail labels.

| DA | %Train | $N_{train}$ | weight | P@1 | P@3 | P@5 | nDCG@3 | nDCG@5 |
|----|--------|-------------|--------|-----|-----|-----|--------|--------|
| -  | 100%   | 1,067,615   | NA     | 95.58 | 80.76 | 63.70 | 89.88 | 86.49 |
| GDA | 100% | 1,284,855 | 0.5 | 95.71 | 81.39 | 64.70 | 90.38 | 87.35 |
| EDA | 100% | 1,284,855 | 0.5 | 95.45 | 80.42 | 63.14 | 89.55 | 85.95 |
| WordNet | 100% | 1,284,855 | 0.5 | 95.48 | 80.34 | 63.04 | 89.47 | 85.86 |

| DA | %Train | $N_{train}$ | weight | P@1 | P@3 | P@5 | nDCG@3 | nDCG@5 |
|----|--------|-------------|--------|-----|-----|-----|--------|--------|
| -  | 50%    | 533,807     | NA     | 95.26 | 80.08 | 62.87 | 89.28 | 85.69 |
| GDA | 50% | 642,400 | 0.5 | 95.26 | 80.46 | 63.65 | 89.56 | 86.34 |
| EDA | 50% | 642,400 | 0.5 | 95.21 | 80.00 | 62.79 | 89.16 | 85.55 |
| WordNet | 50% | 642,400 | 0.5 | 95.21 | 79.81 | 62.44 | 89.00 | 85.25 |

| DA | %Train | $N_{train}$ | weight | P@1 | P@3 | P@5 | nDCG@3 | nDCG@5 |
|----|--------|-------------|--------|-----|-----|-----|--------|--------|
| -  | 5%     | 53,380      | NA     | 91.61 | 74.65 | 38.01 | 84.02 | 80.23 |
| GDA | 5% | 64,297 | 0.5 | 92.91 | 76.24 | 59.27 | 85.59 | 81.73 |
| EDA | 5% | 64,297 | 0.5 | 92.85 | 76.56 | 59.47 | 85.84 | 81.94 |
| WordNet | 5% | 64,297 | 0.5 | 92.78 | 76.30 | 59.24 | 85.60 | 81.67 |

| DA | %Train | $N_{train}$ | weight | P@1 | P@3 | P@5 | nDCG@3 | nDCG@5 |
|----|--------|-------------|--------|-----|-----|-----|--------|--------|
| -  | 1%     | 10,676      | NA     | 89.68 | 71.09 | 54.04 | 80.79 | 76.23 |
| GDA | 1% | 12,832 | 0.5 | 89.76 | 71.50 | 54.46 | 81.08 | 76.61 |
| EDA | 1% | 12,832 | 0.5 | 89.99 | 71.92 | 54.80 | 81.49 | 77.00 |
| WordNet | 1% | 12,832 | 0.5 | 89.83 | 71.75 | 54.74 | 81.30 | 76.89 |

Table 4: Performances on AmazonCat-13k all labels of augmentation over RoBERTa baseline.

| DA | %Train | $N_{train}$ | weight | PSP@1 | PSP@3 | PSP@5 | PSnDCG@3 | PSnDCG@5 |
|----|--------|-------------|--------|------|------|------|----------|----------|
| -  | 100%   | 49.05       | 60.81  | 64.81 | 58.79 | 62.95 |
| GDA | 100% | 49.41 | 61.91 | 67.00 | 59.63 | 64.42 |
| EDA | 100% | 49.22 | 60.43 | 63.75 | 58.57 | 62.31 |
| WordNet | 100% | 49.18 | 60.43 | 63.63 | 58.54 | 62.24 |

| DA | %Train | $N_{train}$ | weight | PSP@1 | PSP@3 | PSP@5 | PSnDCG@3 | PSnDCG@5 |
|----|--------|-------------|--------|------|------|------|----------|----------|
| -  | 50%    | 48.52       | 59.90  | 63.32 | 58.03 | 61.86 |
| GDA | 50% | 48.77 | 60.69 | 65.24 | 58.62 | 63.10 |
| EDA | 50% | 49.02 | 59.80 | 62.72 | 58.07 | 61.59 |
| WordNet | 50% | 49.26 | 60.23 | 63.48 | 58.44 | 62.14 |

| DA | %Train | $N_{train}$ | weight | PSP@1 | PSP@3 | PSP@5 | PSnDCG@3 | PSnDCG@5 |
|----|--------|-------------|--------|------|------|------|----------|----------|
| -  | 5%     | 46.67       | 55.39  | 57.94 | 54.28 | 57.53 |
| GDA | 5% | 47.67 | 56.82 | 59.14 | 55.56 | 58.71 |
| EDA | 5% | 47.95 | 57.11 | 59.45 | 55.77 | 58.94 |
| WordNet | 5% | 47.59 | 56.85 | 59.13 | 55.56 | 58.67 |

| DA | %Train | $N_{train}$ | weight | PSP@1 | PSP@3 | PSP@5 | PSnDCG@3 | PSnDCG@5 |
|----|--------|-------------|--------|------|------|------|----------|----------|
| -  | 1%     | 45.58       | 52.00  | 52.36 | 51.64 | 53.57 |
| GDA | 1% | 45.80 | 52.32 | 52.95 | 51.90 | 53.99 |
| EDA | 1% | 45.86 | 52.77 | 53.42 | 52.23 | 54.36 |
| WordNet | 1% | 45.81 | 52.71 | 53.44 | 52.16 | 54.33 |

Table 5: Performances on AmazonCat-13k tail labels of augmentation over RoBERTa baseline.
| DA   | %Train | N_train | weight | P@1   | P@3 | P@5   | nDCG@3 | nDCG@5 |
|------|--------|---------|--------|-------|-----|-------|--------|--------|
| -    | 100%   | 1,067,615 | NA     | 96.28 | _   | 96.29 | 83.06  | 91.85  | 90.00  |
| GDA  | 100%   | 1,284,855 | 0.5    | 96.19 | 82.85 | 67.41 | 91.64  | 89.74  |
| EDA  | 100%   | 1,284,855 | 0.5    | 95.95 | 82.58 | 67.11 | 91.32  | 89.39  |
| WordNet | 100% | 1,284,855 | 0.5    | 95.73 | 82.22 | 67.07 | 91.03  | 89.05  |
| -    | 50%    | 533,807  | NA     | 96.19 | 82.25 | 67.64 | 91.84  | 89.06  |
| GDA  | 50%    | 642,400  | 0.5    | 96.29 | 82.56 | 67.79 | 91.84  | 89.07  |
| EDA  | 50%    | 642,400  | 0.5    | 95.95 | 82.25 | 67.69 | 91.07  | 89.06  |
| WordNet | 50% | 642,400   | 0.5    | 95.76 | 82.22 | 67.63 | 91.03  | 89.05  |
| -    | 10%    | 10,676   | NA     | 95.73 | 82.12 | 66.66 | 90.94  | 88.95  |
| GDA  | 10%    | 12,832   | 0.5    | 95.76 | 82.12 | 66.66 | 90.94  | 88.95  |
| EDA  | 10%    | 12,832   | 0.5    | 95.76 | 82.12 | 66.66 | 90.94  | 88.95  |
| WordNet | 10% | 12,832    | 0.5    | 95.76 | 82.12 | 66.66 | 90.94  | 88.95  |

Table 6: Performances on AmazonCat-13k all labels of augmentation over LA-RoBERTa baseline.

| DA   | %Train | weight | PSP@1 | PSP@3 | PSP@5 | PShnDCG@3 | PShnDCG@5 |
|------|--------|--------|-------|-------|-------|-----------|-----------|
| -    | 100%   |       | 51.01 | 66.52 | 74.86 | 63.28     | 69.91     |
| GDA  | 100%   | 0.5   | 51.29 | 66.73 | 75.08 | 63.49     | 70.12     |
| EDA  | 100%   | 0.5   | 51.24 | 66.34 | 74.31 | 63.20     | 69.61     |
| WordNet | 100% | 0.5     | 51.70 | 66.42 | 73.90 | 63.37     | 69.48     |
| -    | 50%    | 0.5   | 50.98 | 65.59 | 73.13 | 62.60     | 68.76     |
| GDA  | 50%    | 0.5   | 50.93 | 65.74 | 73.55 | 62.70     | 69.01     |
| EDA  | 50%    | 0.5   | 51.36 | 66.03 | 73.38 | 63.03     | 69.07     |
| WordNet | 50% | 0.5     | 50.92 | 65.70 | 73.30 | 62.67     | 68.88     |
| -    | 1%     |       | 47.46 | 56.49 | 59.16 | 55.28     | 58.60     |
| GDA  | 1%     | 0.5   | 48.67 | 59.04 | 62.89 | 57.34     | 61.33     |
| EDA  | 1%     | 0.5   | 48.49 | 58.84 | 62.51 | 57.16     | 61.06     |
| WordNet | 1%   | 0.5     | 48.62 | 58.88 | 62.49 | 57.22     | 61.09     |
| -    | 0.1%   |       | 45.79 | 52.46 | 53.01 | 51.99     | 54.05     |
| GDA  | 0.1%   | 0.5   | 46.28 | 52.73 | 53.71 | 52.32     | 54.64     |
| EDA  | 0.1%   | 0.5   | 46.25 | 52.56 | 53.41 | 52.17     | 54.41     |
| WordNet | 0.1% | 0.5     | 46.16 | 52.39 | 53.25 | 52.01     | 54.24     |

Table 7: Performances on AmazonCat-13k tail labels of augmentation over LA-RoBERTa baseline.

**When and which data augmentation is effective in the XMC task?** Given the above observations, we conclude that, when training data is very limited, both rule-based augmentation and GDA work better than base models. When training data is rich, DGA still improves over baseline while rule-based systems start to hurt precisions. Therefore, we recommend GDA since it improves more consistently against different training sizes.

## 5 Related Works

### 5.1 Extreme Multi-label Classification

Many prior XMC algorithms are based on sparse linear models that use TF-IDF features and label partitioning methods to reduce label space complexity. Recent works have focused on applying neural models to encode textual semantics (either query or document). This resulted in substantially better performances than using discretized features. XML-CNN (Liu et al., 2017), first deep learning paper in this area, used CNN and dynamic pooling to learn textual representation. AttentionXML (You et al., 2019) used BiLSTM and multi-label attention to capture better interaction between input tokens and individual output labels. X-BERT (Chang et al., 2019) fine-tuned pre-trained transformer models for the XMC task.

Prior works also focused on making more accurate tail label prediction. PfasteXML (Jain et al., 2016) optimizes over propensity scored objective function. Adversarial XMC (Babbar and Schölkopf, 2018) proposes to use regularized opti-
mization objective.

5.2 Data Augmentation in NLP

Data augmentation has shown successful application in the computer vision field, and have been a rising field in natural language processing. Common data augmentation techniques include rule-based data augmentation (e.g. EDA (Wei and Zou, 2019)) and seq2seq model (e.g. back translation (Wei and Zou, 2019; Xie et al., 2019; Xia et al., 2019), RNN-based variational autoencoder(Bowman et al., 2016), and models based on conditional language model (Kumar et al., 2020; Anaby-Tavor et al., 2020; Yang et al., 2020)).

Recent works have successfully applied data augmentation to NLP tasks like relation extraction (Panpanikolaou and Pierleoni, 2020), spoken language understanding (Peng et al., 2020) and text classification (Wei and Zou, 2019; Anaby-Tavor et al., 2020). But to the best of our knowledge, the impact of data augmentation has not been studied for the XMC task.

6 Conclusion & Future Work

In this paper, we conduct so far the broadest study on data augmentation methods for the XMC task. The results are promising and demonstrate that both the strong baseline vanilla RoBERTa and state-of-the-art LA-RoBERTa can benefit from various data augmentation methods. Our proposed GDA improves both the precision and ranking metrics, and have even larger improvement for tail labels. We also observe rule-based synonym replacement data augmentation method demonstrates good performances when training data is scarce. One potential next step is to further differentiate erroneous generations from good ones. Another possibility is to dynamically assign the loss weight $\lambda$ at instance level for the generated data.

References

Ateret Anaby-Tavor, Boaz Carmeli, Esther Goldbraich, Amir Kantor, George Kour, Segev Shlomov, Naama Tepper, and Naama Zwerdling. 2020. Do not have enough data? deep learning to the rescue! In AAAI, pages 7383–7390.

Rohit Babbar and Bernhard Schölkopf. 2018. Adversarial extreme multi-label classification. arXiv preprint arXiv:1803.01570.

K. Bhatia, K. Daihya, H. Jain, A. Mittal, Y. Prabhu, and M. Varma. 2016. The extreme classification repository: Multi-label datasets and code.

Samuel Bowman, Luke Vilnis, Oriol Vinyals, Andrew Dai, Rafal Jozefowicz, and Samy Bengio. 2016. Generating sentences from a continuous space. In Proceedings of The 20thSIGNLL Conference on Computational Natural Language Learning, pages 10–21.

Wei-Cheng Chang, Hsiang-Fu Yu, Kai Zhong, Yiming Yang, and Inderjit Dhillon. 2019. X-bert: extreme multi-label text classification with using bidirectional encoder representations from transformers. arXiv preprint arXiv:1905.02331.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In NAACL.

Christiane Fellbaum. 1998. WordNet: An Electronic Lexical Database. Bradford Books.

Himanshu Jain, Yashoteja Prabhu, and Manik Varma. 2016. Extreme multi-label loss functions for recommendation, tagging, ranking & other missing label applications. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pages 935–944.

Ioannis Katakis, Grigorios Tsoumakas, and Ioannis Vlahavas. 2008. Multilabel text classification for automated tag suggestion. In Proceedings of the ECML/PKDD, volume 18, page 5.

Varun Kumar, Ashutosh Choudhary, and Eunah Cho. 2020. Data augmentation using pre-trained transformer models. arXiv preprint arXiv:2003.02245.

Jingzhou Liu, Wei-Cheng Chang, Yuexin Wu, and Yiming Yang. 2017. Deep learning for extreme multi-label text classification. In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 115–124.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Julian McAuley and Jure Leskovec. 2013. Hidden factors and hidden topics: understanding rating dimensions with review text. In Proceedings of the 7th ACM conference on Recommender systems, pages 165–172.

Julian McAuley, Rahul Pandey, and Jure Leskovec. 2015. Inferring networks of substitutable and complementary products. In Proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining, pages 785–794.
Eneldo Loza Mencia and Johannes Fürnkranz. 2008. Efficient pairwise multilabel classification for large-scale problems in the legal domain. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases, pages 50–65. Springer.

John X. Morris, Eli Lifland, Jin Yong Yoo, and Yanjun Qi. 2020. Textattack: A framework for adversarial attacks in natural language processing.

Yannis Papamarkos and Andrea Pierleoni. 2020. Dare: Data augmented relation extraction with gpt-2. arXiv preprint arXiv:2004.13845.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th annual meeting of the Association for Computational Linguistics, pages 311–318.

Ioannis Partalas, Aris Kosmopoulos, Nicolas Baskiotis, Thierry Artieres, George Palioras, Eric Gaussier, Ion Androuotosopoulos, Massih-Reza Amini, and Patrick Galinari. 2015. Lshtc: A benchmark for large-scale text classification. arXiv preprint arXiv:1503.08581.

Baolin Peng, Chenguang Zhu, Michael Zeng, and Jianfeng Gao. 2020. Data augmentation for spoken language understanding via pretrained models. arXiv preprint arXiv:2004.13952.

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.

Grigorios Tsoumakas, Ioannis Katakis, and Ioannis Vlahavas. 2008. Effective and efficient multilabel classification in domains with large number of labels. In Proc. ECML/PKDD 2008 Workshop on Mining Multidimensional Data (MMD08), volume 21, pages 53–59.

Jason Wei and Kai Zou. 2019. Eda: Easy data augmentation techniques for boosting performance on text classification tasks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 6383–6389.

Thomas Wolf, L Debut, V Sanh, J Chaumond, C Delangue, A Moi, P Cistac, T Rault, R Louf, M Funtowicz, et al. 2019. Huggingfaces transformers: State-of-the-art natural language processing. ArXiv, abs/1910.03771.

Mengzhou Xia, Xiang Kong, Antonios Anastasopoulos, and Graham Neubig. 2019. Generalized data augmentation for low-resource translation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5786–5796.