Data Augmentation using Pre-trained Transformer Models

Varun Kumar
Alexa AI
kuvrun@amazon.com

Ashutosh Choudhary
Alexa AI
ashutoch@amazon.com

Eunah Cho
Alexa AI
eunahch@amazon.com

Abstract

Language model based pre-trained models such as BERT have provided significant gains across different NLP tasks. In this paper, we study different types of pre-trained transformer based models such as auto-regressive models (GPT-2), auto-encoder models (BERT), and seq2seq models (BART) for conditional data augmentation. We show that prepending the class labels to text sequences provides a simple yet effective way to condition the pre-trained models for data augmentation. On three classification benchmarks, pre-trained Seq2Seq model outperforms other models. Further, we explore how different pre-trained model based data augmentation differs in-terms of data diversity, and how well such methods preserve the class-label information.

1 Introduction

Data augmentation (DA) is a widely used technique to increase the size of the training data. Increasing training data size is often essential to reduce overfitting and enhance robustness of machine learning models in low-data regime tasks.

In natural language processing (NLP), several word replacement based methods have been explored for text DA. In particular, Wei and Zou (2019) show that simple word replacement using knowledge bases like WordNet (Miller, 1998) improves classification performance. Further, Kobayashi (2018) utilized language models (LM) to augment training data. However, such methods struggle with preserving class labels. For example, non-conditional DA for an input sentence of sentiment classification task *"a small impact with a big movie"* leads to *"a small movie with a big impact"*. Using such augmented data for training, with the original input sentence's label (i.e. negative sentiment in this example) would negatively impact the performance of the resulting model.

To alleviate this issue, Wu et al. (2019) proposed conditional BERT (CBERT) model which extends BERT (Devlin et al., 2018) masked language modeling (MLM) task by considering class labels to predict the masked tokens. Since their method relies on modifying BERT model's segment embedding, it cannot be generalized to other pre-trained LMs which do not have segment embeddings.

Similarly, Anaby-Tavor et al. (2019) used GPT2 (Radford et al., 2019) for DA where examples are generated for a given class by providing class as input to a fine-tuned model. In their work, GPT2 is used to generate 10 times the number of examples required for augmentation and select the candidates based on the model confidence score. As data selection is applied only to GPT2 but not to the other models, the augmentation methods can not be fairly compared. Due to such discrepancies, it is not straightforward to comprehend how the generated data using different pre-trained models varies from each other and their impact on downstream model performance.

This paper proposes a unified approach to use pre-trained transformer (Vaswani et al., 2017) based models for data augmentation. In particular, we explore three different pre-trained model types for DA, including 1) an auto-regressive (AR) LM: GPT2, 2) an autoencoder (AE) LM: BERT, and 3) a pre-trained seq2seq model: BART (Lewis et al., 2019). We applied the data generation for three different NLP tasks: sentiment classification, intent classification (IC), and question classification. In order to understand the significance of DA, we simulated a low-resource data scenario, where we utilized only 1% of the existing labeled data.

We show that all three types of pre-trained models can be effectively used for DA, and using the generated data leads to improvement in classification performance. Among three types of methods,

pre-trained seq2seq model provides the best performance, due to its ability to generate diverse data while retaining the label information. Our code will be made public at[1].

Our contribution is three-fold: (1) implementation of a seq2seq pre-trained model based data augmentation, (2) experimental comparison of different conditional pre-trained model based data augmentation methods, (3) a unified data augmentation approach with practical guidelines for using different types of pre-trained models.

2 DA using Pre-trained Models

LM pre-training has been studied extensively (Radford et al., 2018; Devlin et al., 2018; Liu et al., 2019). During pre-training, such models are either trained in an AE setting or in an AR setting. In the AE setting, certain tokens are masked in the sentence and the model predicts those tokens. In an AR setting, the model predicts the next word given a context. Recently, pre-training for seq2seq model has been explored where a seq2seq model is trained for denoising AE tasks (Lewis et al., 2019; Raffel et al., 2019). Here, we explore how these models can be used for DA to potentially improve text classification accuracy.

Algorithm 1: Data Augmentation approach

Input : Training Dataset D_{train}
Pretrained model $G \in \{AE, AR, Seq2Seq\}$

Fine-tune G using D_{train} to obtain G_{tuned}
$D_{synthetic} \leftarrow \{\}$
foreach $\{x_i, y_i\} \in D_{train}$ **do**
  Synthesize s examples $\{\hat{x_i}, \hat{y_i}\}_p^1$ using G_{tuned}
  $D_{synthetic} \leftarrow D_{synthetic} \cup \{\hat{x_i}, \hat{y_i}\}_p^1$
end

DA Problem formulation: Given a training dataset $D_{train} = \{x_i, y_i\}_n^1$ where $x_i = \{w_j\}_m^1$ is a sequence of m words, and y_i is the associated label, and a pre-trained model G, we want to generate a dataset of $D_{synthetic}$. Algorithm 1 describes the data generation process. For all augmentation methods, we generate $s = 1$ synthetic example for every example in D_{train}. Thus, the augmented data is same size as the size of the original data.

2.1 Conditional DA using Pre-trained LM

For conditional DA, a model G incorporates label information during fine-tuning for data generation. Wu et al. (2019) proposed CBERT model where they utilized BERT's segment embeddings to condition model on the labels. Similarly, models can be conditioned on labels by prepending labels y_i to x_i (Keskar et al., 2019; Johnson et al., 2017).

Due to segment embedding reuse, CBERT conditioning is very specific to BERT architecture thus cannot be applied directly to other pre-trained LMs. Thus, we compare two generic ways to condition a pre-trained model on class label:

- `prepend` : prepending label y_i to each sequence x_i in the training data without adding y_i to model vocabulary
- `expand` : prepending label y_i to each sequence x_i in the training data and adding y_i to model vocabulary.

Note that in `prepend`, the model may split y_i into multiple subword units (Sennrich et al., 2015; Kudo and Richardson, 2018), `expand` treats a label as a single token.

Here, we discuss the fine-tuning and data generation process for both AE and AR LMs[2]. For all pre-trained models, during fine-tuning, we further train the learnable parameters of G using its default task and loss function.

2.1.1 Fine-tuning and generation using AE LMs

We choose BERT as a representative of AE models. For fine-tuning, we use the default masking parameters and MLM objective which randomly masks some of the tokens from the raw sequence, and the objective is to predict the original token of the masked words using the context. Both $\text{BERT}_{\text{prepend}}$ and $\text{BERT}_{\text{expand}}$ models are fine-tuned using the same objective.

2.1.2 Fine-tuning and generation using AR LMs

For AR LM experiments, we choose GPT2 as a generator model and follow the method proposed by Anaby-Tavor et al. (2019) to fine-tune and generate data. For fine-tuning GPT2, we create a training dataset by concatenating all sequences in D_{train} as follows:

[1] https://github.com/varinf/TransformersDataAugmentation

[2] For transformer based LM implementation, we use PyTorch based transformer package (Wolf et al., 2019)

$y_1 SEP x_1 EOS y_2 ... y_n SEP x_n EOS$. SEP denotes a separation token between label and sentence, and EOS denotes the end of a sentence.

For generating data, we provide $y_i SEP$ as a prompt to G, and we keep generating until the model produces EOS token. We use GPT2 to refer to this model.

We found that such generation struggles in preserving the label information, and a simple way to improve the generated data label quality is to provide an additional context to G. Formally, we provide $y_i SEP w_1..w_k$ as prompt where $w_1..w_k$ are the first k words of a sequence x_i. In this work, we use $k = 3$. We call this method $\text{GPT2}_{\text{context}}$.

2.2 Conditional DA using Pre-trained Seq2Seq model

Like pre-trained LM models, pre-training seq2seq models such as T5 (Raffel et al., 2019) and BART (Lewis et al., 2019) have shown to improve performance across NLP tasks. For DA experiments, we choose BART as a pre-trained seq2seq model representative for its relatively lower computational cost.

2.2.1 Fine-tuning and generation using Seq2Seq BART

Similar to pre-trained LMs, we condition BART by prepending class labels to all examples of a given class. While BART can be trained with different denoising tasks including insertion, deletion, and masking, preliminary experiments showed that masking performs better than others. Note that masking can be applied at either word or subword level. We explored both ways of masking and found subword masking to be consistently inferior to word level masking. Finally, we applied word level masking in two ways:

- $\text{BART}_{\text{word}}$: Replace a word w_i with a mask token $< mask >$
- $\text{BART}_{\text{span}}$: Replace a continuous chunk of k words $w_i, w_{i+1}..w_{i+k}$ with a single mask token $< mask >$.

Masking was applied to 20% of the words. We fine-tune BART with a denoising objective where the goal is to decode the original sequence given a masked sequence.

Hyperparameter setting and other preprocessing details for all models can be found in Section 2.3. For all models, validation set performance was used to select the best model.

2.3 Pre-trained Model Implementation

2.3.1 BERT based models

For AutoEncoder (AE) experiments, we use "bert-base-uncased" model with the default parameters provided in huggingface's transformer package [3]. In `prepend` setting we train model for 10 epochs and select the best performing model on dev data partition keeping initial learning rate at $4e-5$. For `expand` setting, training requires 150 epochs to converge. Moreover, a higher learning rate of $1.5e-4$ was used for SST and TREC datasets,and $1e-4$ for SNIPS dataset. The initial learning rate was adjusted for faster convergence. This is needed for `expand` setting as embeddings for labels are randomly initialized.

2.3.2 GPT2 model implementation

For GPT2 experiments, we use GPT2-Small model provides in huggingface's transformer package. We use default training parameters to fine-tune the GPT2 model. For all experiments, we use SEP as a separate token and $<|endoftext|>$ as EOS token. For text generation, we use the default nucleus sampling (Holtzman et al., 2019) parameters including $top\_k = 0$, and $top\_p = 0.9$.

2.3.3 BART model implementation

For BART model implementation, we use fairseq toolkit (Ott et al., 2019) implementation of BART. Additionally, we used bart_large model weights[4].

Since BART model already contains $< mask >$ token, we use it to replace mask words. For BART model fine-tuning, we use denoising reconstruction task where 20% words are masked and the goal of the decoder is to reconstruct the original sequence. Note that label y_i is prepended to each sequence x_i, and decoder also produces the y_i like any other token in x_i. We use fairseq's *label_smoothed_cross_entropy* criterion with a *label-smoothing* of 0.1. For generation, beam search with a beam size of 5 is used.

All experiments were conducted using a single GPU instance of Nvidia Tesla v100 type. For BART model, we use f16 precision.

Data	Label Names
SST-2	Positive, Negative
TREC	Description, Entity, Abbreviation, Human, Location, Numeric
SNIPS	PlayMusic, GetWeather, RateBook, SearchScreeningEvent, SearchCreativeWork, AddToPlaylist, BookRestaurant

Table 1: Label Names used for classification

	SST-2		SNIPS		TREC	
	All	1%	All	1%	All	1%
Train	6,229	61	13,084	127	5,406	51
Dev	693	10	700	35	546	30
Test	1,821		700		500	

Table 2: Data statistics for three corpora. Column "All" shows the data statistics without any sub-sampling. This setup is used to train a classifier for intrinsic evaluation, as described in Section 3.3. In order to simulate low-data regime, we sampled 1% of the data. For testing, we take the whole portion without sub-sampling.

3 Experimental Setup

3.1 Baseline Approaches for DA

In this work, we consider two models as our baseline. (1) **EDA** (Wei and Zou, 2019) is a simple effective word-replacement based augmentation method, which has shown to improve text classification performance in the low-data regime. (2) **CBERT** (Wu et al., 2019) language model which, to the best of our knowledge, is the latest model-based augmentation that outperforms other word-replacement based methods.

3.2 Data Sets

We use three text classification data sets. **SST-2** (Socher et al., 2013) (Stanford Sentiment Treebank) is a dataset for sentiment classification on movie reviews, which are annotated with two labels (Positive and Negative). **SNIPS** (Coucke et al., 2018) dataset contains 7 intents which are collected from the Snips personal voice assistant. **TREC** (Li and Roth, 2002) is a fine grained question classification dataset sourced from TREC. It contains six question types. All pre-trained methods relies on different byte pair encodings which might split labels into multiple tokens. For our experiments, we used the labels provided in Table 1.

3.2.1 Low-resourced data scenario

Following previous works to simulate low-data regime setting (Hu et al., 2019), for all three datasets, we randomly select 1% of the training and validation dataset.

In our preliminary experiments, we evaluated classification performance with various degrees of low-data regime settings, including 1% , 5% and 10% sampling of the existing datasets. We observed that state-of-the-art classifiers, such as the pre-trained BERT classifier, perform relatively very well for above test sets with a moderate low-data regime. For example, using 10% of training data from SNIPS, BERT classifier achieves 95.20 accuracy, without data augmentation. In order to simulate a realistic low-resourced data setting where we often face a very low performance, we focus on experiments with 1% data condition. As selecting only 1% data leads to a very small validation set, this may lead the model to achieve 100% accuracy in the first epoch. To avoid this and have a reliable development set, we select five validation examples per class. Table 2 shows the detailed statistics for the corpora.

3.3 Evaluation

To evaluate DA, we performed both intrinsic and extrinsic evaluation. For **extrinsic evaluation**, we added the generated examples into low-data regime training data for each task and evaluated the performance on the test set discussed in Section 3.2. All experiments are repeated 15 times to account for stochasticity.

For **intrinsic evaluation**, we consider two aspects of the generated text. The first one is semantic fidelity, where we measure how well the generated text retains the meaning and class of the input

[3] https://github.com/huggingface/transformers

[4] https://dl.fbaipublicfiles.com/fairseq/models/bart.large.tar.gz

sentence. In order to measure this, we trained a classifier on each task by fine-tuning a pre-trained English BERT-base uncased model. To boost performance, we combined 100% of training and test partition of existing labeled data and used that for training. We chose the model based on the performance on the dev partition. Section 3.3.1 describes corpus and classifier performance details.

Another aspect we consider is text diversity. To compare different models' ability to generate diverse output, we measured type token ratio (Roemmele et al., 2017). Type token ratio is calculated by dividing the number of unique n-grams by the number of all n-grams in the generated text.

3.3.1 Classifiers for intrinsic evaluation

In this work, we measure semantic fidelity by evaluating how well the generated text retains the meaning and class of the input sentence. To measure this, we fine-tune a pre-trained English "bert-base-uncased" model.

In order to take full advantage of the labeled data and to make our classifier more accurate, we combined 100% of training and test partitions of the corresponding dataset, and used the combined data for training. The best classifier is selected based on the performance on the dev partition. Classification accuracy of the best classifier on dev partition for each corpus is provided in Table 3.

	SST-2	SNIPS	TREC
Dev	91.91	98.86	94.69

Table 3: Classifier performance on dev set for each corpus. Classifiers are used for intrinsic evaluation.

For this classifier, we use "bert-base-uncased" model provided Py-torch based transformer package (Wolf et al., 2019). The BERT model has 12 layers, 768 hidden states, and 12 heads. We use the pooled representation of the hidden state of the first special token ([CLS]) as the sentence representation. A dropout probability of 0.1 is applied to the sentence representation before passing it to the Softmax layer. Adam (Kingma and Ba, 2014) is used for optimization with an initial learning rate of $4e-5$. We train the model for 10 epochs and select the best performing model on dev data.

4 Results and Discussion

4.1 Generation by Conditioning on Labels

As described in Section 2.1, we choose BERT as a pre-trained model and explored different ways of conditioning BERT on labels: $\text{BERT}_{\text{prepend}}$ and $\text{BERT}_{\text{expand}}$.

Model	SST2 (1%)	SNIPS (1%)	TREC (1%)
No Aug	59.08 (5.59)	57.95 (10.74)	30.65 (8.29)
EDA	59.09 (5.69)	77.46 (7.60)	29.57 (10.55)
CBERT	59.85 (5.72)	80.55 (5.70)	29.96 (9.42)
$\text{BERT}_{\text{expand}}$	61.24 (4.42)	79.75 (5.74)	31.88 (10.03)
$\text{BERT}_{\text{prepend}}$	61.90 (6.78)	81.31 (5.25)	30.28 (8.50)
GPT2	58.62 (5.48)	68.25 (10.67)	26.24 (9.00)
$\text{GPT2}_{\text{context}}$	59.39 (6.61)	77.73 (7.56)	31.54 (10.21)
$\text{BART}_{\text{word}}$	62.35 (6.45)	79.98 (5.64)	**37.48** (10.82)
$\text{BART}_{\text{span}}$	**63.00** (6.64)	**81.68** (4.09)	37.25 (10.90)

Table 4: DA extrinsic evaluation in low-data regime. Results are reported as Mean (STD) accuracy on full test set. Experiments are repeated 15 times.

Table 4 shows $\text{BERT}_{\text{prepend}}$ outperforms $\text{BERT}_{\text{expand}}$ on two out of three datasets. Since the labels in the corpora are well-associated with the meaning of the class (e.g. *SearchCreativeWork*), prepending tokens allows the model to leverage label information for conditional word replacement. Note that BERT is pre-trained on a very huge corpus, but fine-tuning is applied on limited data. We hypothesize this makes it difficult for the model to learn new, meaningful label representations from scratch in case of $\text{BERT}_{\text{expand}}$.

This is supported by an intrinsic evaluation which shows that the generated text from `expand` models are less likely to retain the class label, reaching a lower accuracy compared to `prepand` (See Section 4.2). Given this insight, we use `prepend` technique for other pre-trained models.

4.2 Pre-trained Model Comparison

Table 4 shows that seq2seq pre-training based BART outperforms other DA approaches on all data sets. Moreover, adding context as in $\text{GPT2}_{\text{context}}$ greatly boosts GPT2 performance.

Generated Data Fidelity As described in Section 3.3.1, we train a classifier for each test set and use the trained classifier to predict the label of the generated text.

Table 5 shows that prepending class labels to input example $\text{BERT}_{\text{prepend}}$ performs the best in terms of semantic fidelity of generated data. AR

Model	SST2	SNIPS	TREC
CBERT	96.94	**97.32**	95.29
$\text{BERT}_{\text{expand}}$	96.17	96.80	92.68
$\text{BERT}_{\text{prepend}}$	**97.38**	**97.32**	**96.08**
GPT2	58.80	42.89	24.44
$\text{GPT2}_{\text{context}}$	69.84	85.04	73.33
$\text{BART}_{\text{word}}$	88.99	94.86	87.06
$\text{BART}_{\text{span}}$	89.39	94.87	86.80

Table 5: Semantic fidelity of generated output. We trained a classifier using all labelled data in order to perform accuracy test on generated text. The higher accuracy score, the more we retain the class label of the input sentence.

models like GPT2 struggle to retain class label information in the generated text.

We learned that while BERT-based models' fidelity is higher than the GPT2-based model, the highest semantic fidelity was obtained by $\text{BERT}_{\text{prepend}}$ and CBERT model. We believe that the generated output from such models adds less diversity to the training data, which leads to a good performance in the intrinsic evaluation, but not necessarily in the extrinsic evaluation.

Generated Data Diversity To further analyze the results, we explored type token ratio for generated output, as described in Section 3.3. We learned that BART-based methods yield the highest type token ratio, especially for bi- and tri-grams.

Table 6 shows that Seq2Seq model BART generates the most diverse data.

4.3 Guidelines For Using Different Types Of Pre-trained Models For DA

AE models : We found that simply prepending the label to raw sequences provides competitive performance than modifying the model architecture. As expected, more complex AE models such as $\text{RoBERTa}_{\text{prepend}}$ (Liu et al., 2019) outperforms $\text{BERT}_{\text{prepend}}$ (33.6 vs 30.28 mean acc on TREC).

AR models : While AR based model such as GPT2 produces very coherent text, it does not preserve the label well. In our experiments, we found that providing a few starting words along with the label as in $\text{GPT2}_{\text{context}}$, is crucial to generate meaningful labeled data.

Seq2Seq models : Seq2Seq models provide an opportunity to experiment with various kinds of denoising autoencoder tasks including subword/word/span masking, random word insertion/deletion, text rotation. We observe that word/span masking performs better than other denoising objectives, and should be preferred for DA.

Overall, we found that while AE models are constrained to produce similar length sequences and are good at preserving labels, AR models excel at unconstrained generation but might not retain label information. Seq2Seq models lie between AE and AR by providing a good balance between diversity and semantic fidelity. Further, in Seq2Seq models, diversity of the generated data can be controlled by varying the length of span masking.

5 Conclusion And Future Work

We show that AE, AR, and Seq2Seq pre-trained models can be conditioned on labels by prepending label information and provide an effective way to augment training data. These DA methods can be easily combined with other advances in text content manipulation such as co-training the data generator and classifier (Hu et al., 2019). We hope that unifying different DA methods would inspire new approaches for universal NLP data augmentation.

Seq2Seq BART 강!

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Model	SST2			SNIPS			TREC		
n-gram	1	2	3	1	2	3	1	2	3
CBERT	0.466	0.906	0.980	0.411	0.794	0.923	0.488	0.870	0.961
$\text{BERT}_{\text{expand}}$	0.490	0.914	0.983	**0.432**	0.809	0.934	0.511	0.881	0.965
$\text{BERT}_{\text{prepend}}$	0.465	0.907	0.981	0.415	0.798	0.932	0.487	0.873	0.956
GPT2	0.519	0.929	0.985	0.383	0.803	0.914	0.514	0.802	0.896
$\text{GPT2}_{\text{context}}$	0.524	0.933	0.994	0.354	0.781	0.938	**0.571**	0.872	0.954
$\text{BART}_{\text{word}}$	**0.537**	**0.941**	**0.995**	0.415	**0.813**	**0.948**	0.529	0.849	**0.971**
$\text{BART}_{\text{span}}$	0.527	0.936	**0.995**	0.408	0.798	0.934	0.502	**0.882**	0.965

Table 6: Type token ratio for generated text using each model.

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