A Simple but Tough-to-Beat Data Augmentation Approach for Natural Language Understanding and Generation

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Abstract

Adversarial training has been shown effective at endowing the learned representations with stronger generalization ability. However, it typically requires expensive computation to determine the direction of the injected perturbations. In this paper, we introduce a set of simple yet efficient data augmentation strategies dubbed cutoff, where part of the information within an input sentence is erased to yield its restricted views (during the fine-tuning stage). Notably, this process relies merely on stochastic sampling and thus adds little computational overhead. A Jensen-Shannon divergence consistency loss is further utilized to incorporate these augmented samples into the training objective in a principled manner. To verify the effectiveness of the proposed strategies, we apply cutoff to both natural language understanding and generation problems. On the GLUE benchmark, it is demonstrated that cutoff, in spite of its simplicity, performs on par or better than several competitive adversarial-based approaches. It has been observed that the representations from pre-trained models, after being fine-tuned on specific downstream tasks, tend to degrade and become less generalizable (Zhu et al., 2019; Jiang et al., 2019; Aghajanyan et al., 2020).

To alleviate this issue, adversarial training objectives have been proposed to regularize the learned representations during the fine-tuning stage (Zhu et al., 2019; Liu et al., 2020b; Jiang et al., 2019). Specifically, label-preserving perturbations are performed on the word embedding layer, and the model is encouraged to make consistent predictions regardless of these noises. Although the model’s robustness can be improved with these perturbed examples, adversarial-based methods typically require additional backward passes to decide the direction of the inject perturbations. As a result, these methods give rise to significantly more computational and memory overhead (relative to standard SGD training).

In this paper, we introduce a set of simple yet efficient data augmentation strategies. They are inspired by the consensus principle in multi-view learning (Blum and Mitchell, 1998; Xu et al., 2013; Clark et al., 2018), which states that maximizing the agreement/consensus between two different views of data can lead to lower error rate. Specifically, we propose to erase/remove part of the information within a training instance to produce multiple perturbed samples. To ensure that the model cannot utilize the information from the removed input at all, the erasing process happens at the input embeddings layer. In contrast to Dropout, which converts individual elements within the word em-
We extend cutoff with a BLEU score of 37 while being much more computationally efficient.

The proposed methods greatly outperform adversarial-based approaches, including adversarial examples (Goodfellow et al., 2014), PGD (Madry et al., 2017), etc, have been introduced. It has been demonstrated that these methods can improve the robustness and generalization ability of a model by augmenting the perturbed examples into the original training instances. Recently, adversarial-based approaches emerged as a popular research trend in NLP, which have been successfully applied to a wide variety of NLU tasks, including sentence classification, machine reading comprehension (MRC) and natural language inference (NLI) tasks, etc. Despite its success, computational overhead is typically required to calculate the perturbation directions. Several research efforts have been devoted to accelerate adversarial training (Shafahi et al., 2019; Zhang et al., 2019). However, additional forward-backward passes are still needed for adversarial training. Our proposed cutoff methods are much more computationally efficient from this perspective. Besides, the connection between adversarial training and data-augmentation-based approaches has not previously been well-established. Our work bridges this gap by unifying the two types of methods under the consistency training framework.

2 Related Work

Adversarial Training

Adversarial training was originally proposed to attack neural-network-based models by applying small perturbations to the input (Szegedy et al., 2013). Thereafter, several adversarial-based approaches, including adversarial examples (Goodfellow et al., 2014), PGD (Madry et al., 2017), etc, have been introduced. It has been demonstrated that these methods can improve the robustness and generalization ability of a model by augmenting the perturbed examples into the original training instances. Recently, adversarial-based approaches emerged as a popular research trend in NLP, which have been successfully applied to a wide variety of NLU tasks, including sentence classification, machine reading comprehension (MRC) and natural language inference (NLI) tasks, etc. Despite its success, computational overhead is typically required to calculate the perturbation directions. Several research efforts have been devoted to accelerate adversarial training (Shafahi et al., 2019; Zhang et al., 2019). However, additional forward-backward passes are still needed for adversarial training. Our proposed cutoff methods are much more computationally efficient from this perspective. Besides, the connection between adversarial training and data-augmentation-based approaches has not previously been well-established. Our work bridges this gap by unifying the two types of methods under the consistency training framework.

Multi-view Learning

The main idea of multi-view learning is to produce distinct subsets (views) of features corresponding to the same data, and the predictions by the model according to different views are repelled to be consistent (Xu et al., 2013). Our approach is slightly different from such algorithms, e.g., co-training (Blum and Mitchell, 1998) and co-regularization (Sindhwani et al., 2005), in the sense that the multiple views from cutoff have certain overlaps, rather than being entirely independent.

The intuition of our method bears resemblance to cross-view training (CVT) (Clark et al., 2018), which also proposes to improve sentence representations by encouraging consistent predictions across different views of the input. However, there are several key differences that make our work unique (except that CVT focuses on a semi-supervised setting, rather than a supervised one as in our case): i) CVT generates partial views
on top of latent representations, while \textit{cutoff} operates at the input embedding layer. As a result, our method is more generic and model-agnostic; ii) CVT adds an auxiliary prediction module during the training stage, while span cutoff requires no changes to the original model at all; iii) we leverage Jensen-Shannon Divergence consistency loss to match the predictions with various views, which maximize their consensus in a more natural and stable manner (also more efficient than the multiple KL divergence terms used in CVT).

3 Proposed Approach

In this section, we first discuss the motivation behind the \textit{cutoff} data augmentation strategies, which leverage restricted views of a training instance. Then, we propose three simple but effective ways of obtaining partial views and highlight the advantages of each. A novel consistency loss is introduced to naturally integrate multiple cutoff samples into the training framework. Finally, we further extend the \textit{cutoff} approach to the text generation scenario.

3.1 Motivation

In the context of fine-tuning large pre-trained models, our hypothesis is that data augmentation could endow the original data with stronger ability to extract useful semantic information. Let \( f \) denote the transformation to convert an input sample \( x \) into its augmented examples. An ideal \( f \) should be label-preserving, \( i.e., \) the label of \( f(x) \) should be the same as \( x \). Besides, \( f(x) \) should also be diverse and different enough from \( x \), so that it could help to enrich the empirical observations and thus better cover the data space.

Different choices of \( f \) to introduce slight modifications on the original training instances have been proposed previously, such as adding Gaussian noise, adversarial training (Liu et al., 2020b; Zhu et al., 2019) and back-translation (Yu et al., 2018; Xie et al., 2019). Concretely, adversarial training performs perturbations on the word embedding layer to improve the model robustness. However, it takes additional backward passes to estimate the optimal perturbation direction and thus gives rise to additional computational and memory overhead. As to back translation, it first translates an existing example to another language, and then translate it back to obtain an augmented sample. Although effective, the quality of augmented data is usually sensitive to the mistakes made by the initial translation models (Chapelle et al., 2009; Wang et al., 2018). Motivated by these observations, we aim to propose data augmentation schemes that are computationally efficient, and yet do not rely on any additional models or external data sources (\textit{e.g.}, paired translation data).

Taking inspiration from multi-view learning, where the connection between the consensus of predictions on two views and their error rates has been established (Dasgupta et al., 2002). Suppose we have two views \( x_1 \) and \( x_2 \) obtained with the same example, and let \( p_1 \) and \( p_2 \) denote a model’s prediction on these views, respectively. The following holds true (Dasgupta et al., 2002):

\[
P(p_1 \neq p_2) \geq \max\{P_{err}(p_1), P_{err}(p_2)\}
\]

The inequality above states that the error rates of the two hypotheses are both upper bounded by the probability of a disagreement between them. In other words, the accuracy of each prediction can be improved by minimizing their disagreement. Thus, encouraging consistent predictions among different views of a sentence, which contains only part of its entire information, could improve the generalization ability of the resulting models and reduce their error rates accordingly. In the next section, we will discuss how these views may be produced in detail.

3.2 Constructing Partial Views

To obtain partial views of a given sentence, (Clark et al., 2018) proposed to carefully select hidden representations at the top of a Bi-LSTM sentence encoder. However, this strategy is not generic enough since it relies on the unidirectional nature of LSTM. For transformer-based architectures that are widely adopted nowadays, each output hidden unit has access to the information of all the input tokens (given the property of self-attention networks). In this regard, we argue that collecting restricted views at the input embedding space could be a more model-agnostic solution.

Given a text sequence \( x = [x_1, \ldots, x_L] \), whose input embedding matrix is denoted by \( W \in \mathbb{R}^{L \times d} \). Note that \( w_{i,j} \) represents the \( j \)-th dimension of the embedding vector corresponding to the \( i \)-th token, and \( d \) is the dimension of the input embeddings. We suppose that partial views may be obtained by cutting vectors along either dimensions off, hence the proposed approach is dubbed \textit{Cutoff}. Cutoff removes the information from the input embedding matrix in a more structured manner, as opposed
to Dropout, which randomly sets elements within the matrix to 0. Specifically, either the entire embedding of an individual word or one embedding dimension of every word within the sequence are converted to a vector of zeros (see Figure 1).

In the context of pre-trained transformer models, such as BERT or RoBERTa, the input embedding matrix consists of tokens, segments and positional embeddings. To make sure that no information corresponding to the removed tokens is left, all three types of embeddings, in the case of token cutoff, are converted to 0. Moreover, all embedding types are considered while sampling the feature dimensions to be erased. Intuitively, with augmented data, the learned model is encouraged to be robust enough so that it can produce consistent predictions with a few words removed from the sentence. For feature cutoff, since each input embedding dimension contains certain semantic information, the model is impelled to encapsulate rich and meaningful features w.r.t. each word given that it needs to make the correct predictions with a certain number of features erased entirely.

Span Cutoff Moreover, (Joshi et al., 2019) advocated that predicting spans, relative to predicting individual tokens, provides a more challenging objective for self supervision tasks. Thus, we conjecture that easing a contiguous span of text may also lead to harder augmented examples, which can benefit the model during the fine-tuning stage to a larger extent. Therefore, we propose an additional strategy to obtain partial views of the input. First, a preset coefficient $\alpha$ is defined, which indicates the ratio between the length of removed span to that of the original sequence. Then, to obtain a span with the length of $l = \lfloor \alpha \times L \rfloor$ ($\lfloor \cdot \rfloor$ denotes the floor function), the starting index $s$ for the span is first randomly sampled as: $s \in \{0, 1, ..., L - l\}$. Afterwards, the embeddings w.r.t. the tokens between the $s$-th and $(s + l - 1)$-th positions are all converted to vectors of zeros.

As illustrated in Figure 2, span cutoff removes a continuous chunk of texts away, and the remaining sentences preserve the same label (e.g. sentiment) as the original example. Since certain semantic information within a sentence has been removed, these augmented samples could better encourage the model to fully leverage different features that may be helpful for predicting the sentiment of the original input (rather than merely relying on a small set of salient ones).

### 3.3 Incorporating Augmented Samples

Suppose there are $N$ cutoff samples constructed from the same original input $x$ (with a label of $y$), which are denoted by $x_1^{\text{cutoff}}, x_2^{\text{cutoff}}, ..., x_N^{\text{cutoff}}$, respectively. Since their semantic meanings are approximately preserved with the cutoff operation, we may incorporate them into the training objective by encouraging the model to make similar predictions across different samples. The training objective can be written as:

$$
\mathcal{L} = \mathcal{L}_{ce}(x, y) + \alpha \sum_{i=1}^{N} \mathcal{L}_{ce}(x_i^{\text{cutoff}}, y) + \beta \mathcal{L}_{\text{divergence}}(x, x_1^{\text{cutoff}}, x_2^{\text{cutoff}}, ..., x_N^{\text{cutoff}}, y),
$$

where $\mathcal{L}_{ce}$ denotes the cross-entropy loss, which
Figure 2: Illustration of the proposed span cutoff method with one specific example (from the SST-2 dataset). In this case, the model is supposed to produce consistent predictions (i.e., sentiments) for all three augmented samples (with various spans of tokens removed).

are applied to both original and augmented samples. Furthermore, to explicitly minimize the gap between the predictions w.r.t all the sentences, \( \mathcal{L}_{\text{divergence}} \) is utilized to measure the consensus between all the predictions. KL-divergence has been widely adopted as the divergence metric in previous works (Miyato et al., 2017, 2018; Clark et al., 2018; Xie et al., 2019). However, since there are multiple cutoff samples’ predictions, calculating KL divergence in a pair-wise manner will lead to \( 2^{N+1} \) terms, and thus can be quite computationally intensive. To this end, we propose to leverage the Jensen-Shannon (JS) divergence consistency loss as \( \mathcal{L}_{\text{divergence}} \). Concretely, the \( \mathcal{L}_{\text{divergence}} \) term can be obtained as follows:

\[
p_{\text{avg}} = \frac{1}{N+1} \sum_{i=0}^{N} p(y|x_{\text{cutoff}}^i)
\]

\[
\mathcal{L}_{\text{divergence}} = \frac{1}{N+1} \sum_{i=0}^{N} \text{KL}(p(y|x_{\text{cutoff}}^i)||p_{\text{avg}})
\]

(3)

To be more specific, the average over all the predictions are first calculated, which is then employed to match with each individual prediction. With such a scheme, the consensus between multiple augmented data along with the original sample is measured in an efficient way. Moreover, it has been shown that the JS divergence loss can endow the model with more stability and consistency across a diverse set of inputs (Bachman et al., 2014; Zheng et al., 2016; Kannan et al., 2018; Hendrycks et al., 2020).

3.4 Extension to Language Generation

The various types of cutoff strategies proposed above can be naturally extended to conditional text generation scenario as well. Given a sentence pair \((x_{\text{input}}, x_{\text{output}})\), the cutoff operation can be performed on both sentences to synthesize an augmented training pair. Intuitively, the model has access to a restricted view of the input, while being asked to predict part of the output sequence. It has been shown that neural text generation systems are highly sensitive to input noise (Lee et al., 2018), and we suppose that adding such augmented examples could improve the model’s generalization ability. We evaluate this hypothesis on the machine translation task empirically (see Sec 5.2).

3.5 Computational Complexity

We now compare the asymptotic complexity of cutoff to adversarial-based approaches. FreeLB (Zhu et al., 2019) and SMART (Jiang et al., 2019) are two representative adversarial training methods applied to NLP domain. Both require additional ascent steps to determine the perturbation directions. Let \( T \) denote the number of ascent steps needed for adversarial training, where we have \( T \geq 1 \). The numbers of forward and backward passes for FreeLB and SMART are both \( 1 + T \). On the other hand, cutoff requires no extra backward passes (and thus has a backward pass number of 1). As to the forward pass, given that the size of augmented samples is the same as that of original training instances, the number of forward passes is doubled to 2, which is smaller relative to adversarial training. Overall, the cutoff approach takes less computational overhead compared to standard SGD-based training.

4 Experimental Setup

4.1 Datasets

We evaluate the effectiveness of the proposed Cut-off approach on both natural language understanding and generation tasks. To facilitate comparisons with other baseline methods, we employ the GLUE benchmark, which consists of a wide vari-
4.2 Training Details

We finetune the pre-trained models using Adam (Kingma and Ba, 2014), with the learning rate selected from \{5e-6, 6e-6, 1e-5, 2e-5\} for all parameters. The same learning rate decay scheme as (Liu et al., 2019) is employed, with a warmup ratio of 0.06 and a linear decay schedule. We also apply a weight decay of 0.1 during training. The max number of epochs is set as either 5 or 10. The batch size is chosen as 16 for all model variants. The coefficients \(\alpha\) (corresponding to the cross-entropy loss on the cutoff samples) and \(\beta\) (associated with the \(\mathcal{L}_{\text{divergence}}\) term) are both selected from \{0.1, 0.3, 1, 3\} on the validation set.

4.3 Baselines

We consider several strong baselines to compare with the proposed methods, which can be approximately divided into two categories: \(i\) approaches based on adversarial training, including PGD (Madry et al., 2018), FreeAT (Shafahi et al., 2019), FreeLB (Zhu et al., 2019), ALUM (Liu et al., 2020b). Notably, these methods are more computationally intensive than \textit{Cutoff}; \(ii\) other data augmentation strategies for natural language. Back translation is evaluated and compared with our methods given its wide adoption. Consistency training objective is utilized for back translation in our implementation to ensure fair comparison. Although back translation, similar to \textit{Cutoff}, serves as a label-preserving transformation on original training instances, it requires additional data (i.e., language pairs) and translation model pre-training. From this perspective, the \textit{Cutoff} approach is easier to use as a drop-in replacement to standard training.

5 Experimental Results

We experimented three different \textit{Cutoff} variants in terms of the strategy to construct partial views, \textit{i.e.}, token cutoff, feature cutoff and span cutoff. They are evaluated and compared on the GLUE benchmark. Detailed analysis and ablation studies regarding the cutoff approach are further conducted, where the advantage of utilizing the JS divergence
framework is demonstrated. Besides, we also investigate the effectiveness of the Cutoff approach on German-to-English and English-to-German machine translation tasks.

5.1 GLUE Benchmark Evaluation

The empirical results of proposed Cutoff strategies (relative to other strong baselines) are presented in Table 1. It can be observed that the different Cutoff methods consistently outperform ALUM on top of the RoBERTa-base model, while being much more computationally efficient (see Section 3.5). Moreover, span cutoff delivers the strongest numbers on most datasets, which aligns with our assumption that easing a span from the input sequence could lead to more challenging and thus more useful augmented samples.

As to the case where RoBERTa-large is employed as the baseline, the cutoff data augmentation strategies again consistently exhibit competitive or better performance compared with several adversarial-based approaches. It is worth noting that the Cutoff approaches are related to adversarial-based training in the sense that they both try to produce additional samples with certain perturbations around the original input. However, adversarial-based methods require additional computations to determine the perturbation directions, whereas Cutoff simply remove one slice of information from the input embedding matrix (which could be at the token, feature or span level). This leverages the prior knowledge that the information is organized in a structured manner within the input embeddings, and thus a model with strong generalization ability should be able to make consistent predictions while only partial views are available.

Moreover, compared with back translation, the Cutoff approaches also demonstrate the same or stronger results on 6 out of 8 NLU tasks considered here. This further verifies the effectiveness of Cutoff as a data augmentation strategy despite its simplicity.

5.2 Application to Machine Translation

To investigate the effectiveness of cutoff on text generation problems, we further apply it to the neural machine translation tasks. Specifically, we leverage the 6-layer Transformer Base architecture (Vaswani et al., 2017) as the baseline. Cutoff is applied to both the input and output sequences to produce their partial views, which are used as augmented translation pairs for training purpose. To ensure fair comparison, the same beam decoding configuration with (Vaswani et al., 2017) is utilized.

| Model | BLEU score |
|-------|------------|
| Transformer Base (Vaswani et al., 2017) | 27.3 |
| Admin (Liu et al., 2020a) | 27.9 |
| Transformer Base' (So et al., 2019) | 28.2 |
| Evolved Transformer (So et al., 2019) | 28.4 |
| Weighted Transformer (Ahmed et al., 2017) | 28.4 |
| Adversarial Training (Wang et al., 2019) | 28.4 |
| Transformer Base & Cutoff (w/o JS loss) | 28.9 |
| Transformer Base & Cutoff (w/ JS loss) | **29.1** |

Table 2: BLEU scores of the proposed cutoff method on the WMT2014 English-to-German machine translation task, compared with adversarial-based baselines. All methods are built on top of 6-layer Transformer Base model (Vaswani et al., 2017).

In the initial experiments, we found that token cutoff performs the best on machine translation tasks. This may be attributed to the fact that removing spans from both the source and target sentences would result in large information mismatch between the input and output, and thus the resulting pairs may be too challenging. The results on the WMT2014 English-to-German dataset are presented in Table 2. Relative to several competitive baseline methods that are based upon 6-layer Transformer Base model, our token cutoff approach exhibits the best BLEU score. More importantly, cutoff outperforms the adversarial training approach introduced by (Wang et al., 2019). Concretely, they proposed to inject adversarial perturbations on the output word embeddings (in the softmax layer). Notably, their adversarial training strategy requires updating the model parameters and adversarial perturbation alternately. Thus it is more complicated and computationally expensive than our approach. Besides, it is observed that the JS divergence objective leads to further gains, demonstrating its complementary nature with the standard cross-entropy objective. In addition, on the IWSLT2014 German-to-English dataset, Cutoff again consistently exhibits significant gains over the Transformer Base model. Along with the JS loss term introduced, our model achieves a BLEU score of 37.6, greatly outperforming the adversarial-based method. As shown in Table 3, by simply employing Cutoff on top of a 6-layer Transformer model, our approach

\footnote{This number is reported in (So et al., 2019) for the Transformer Base model. The same evaluation settings are used for our cutoff method, i.e., case-sensitive tokenization and the compound splitting are both used.}
### 5.3 Ablation Study

#### 5.3.1 The effect of JS divergence loss

To investigate the importance of incorporating the Jensen-Shannon (JS) divergence consistency loss, we select different values of $\beta$ (ranging from 0.0 to 3.0) and explore how the dev set results (on the MNLI dataset) would change accordingly. The coefficient w.r.t. the cross-entropy (CE) loss term is set as 1 for all the ablation settings, and $\beta$ controls the relative weight of the (JS) divergence consistency loss term. As shown in Table 4, leveraging the JS loss term consistently improves the empirical performance (relative to only using the CE loss term), and a $\beta$ value of 1 gives rise to the best empirical result on the MNLI dataset.

| $\beta$ | 0.0  | 0.1  | 0.3  | 1.0  | 3.0  |
|---------|------|------|------|------|------|
| Accuracy | 88.21| 88.27| 88.32| **88.36**| 88.12|

Table 4: Ablation study for the span cutoff augmentation strategy with different choices of $\beta$, the coefficient w.r.t. the JS divergence loss term (the cross-entropy coefficient $\alpha$ is set as 1). The performance is measured with accuracy on the dev set of the MNLI dataset.

#### 5.3.2 The effect of Cutoff ratios

One important hyperparameter with the Cutoff approach is the ratio of elements to be removed, where the elements can be tokens, features or a span (depending on the specific Cutoff variant). The ratio can be regarded as the magnitude of perturbations applied to the input sentence.

As shown in Figure 3, we applied various cutoff ratios to the different Cutoff variants, including 0.05, 0.1, 0.15, 0.2, 0.3 and 0.4. It can be observed that determining a sweet point of the ratio is critical to the generalization ability of the resulting model. Specifically, token cutoff shows the best performance with a ratio of 0.15, whereas feature cutoff gives rise to the strongest number at a ratio of 0.2. Span cutoff, on the other hand, performs the best with a ratio of 0.1 (the length of the removed span w.r.t. the entire sentence). Using a ratio that is too large tends to result in smaller improvements. This may be attributed to the fact that the assumption that the label of the original data is preserved does not hold true (with larger perturbations).

### 6 Conclusion

In this paper, we introduced cutoff, a set of data augmentation strategies that can serve as a drop-in replacement to enrich original training data. The augmented samples are produced stochastically by obtaining partial views of an input sentence. Notably, this process requires no additional computational overhead, and is thus more efficient than adversarial-training-based approaches (which involves additional backward operation to determine the perturbation directions). With extensive experiments on natural language understanding and machine translation tasks, cutoff gave rise to significant gains, and performed on par or stronger than several competitive baselines based upon adversarial training (while taking a fraction of training time). It is worth noting that cutoff, combined with the proposed JS divergence loss, achieved state-of-the-art result on the IWSLT2014 German-English dataset, with a test BLEU score of 37.6.
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