Multi-Layer Random Perturbation Training for Improving Model Generalization

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Abstract

We propose a simple yet effective Multi-Layer Random Perturbation Training algorithm (RAPT) to enhance model robustness and generalization. The key idea is to apply randomly sampled noise to each input to generate label-preserving artificial input points. To encourage the model to generate more diverse examples, the noise is added to a combination of the model layers. Then, our model regularizes the posterior difference between clean and noisy inputs. We apply RAPT towards robust and efficient BERT training, and conduct comprehensive fine-tuning experiments on GLUE tasks. Our results show that RAPT outperforms the standard fine-tuning approach, and adversarial training method, yet with 22% less training time.

1 Introduction

Although deep learning models have been very successful in various kinds of NLP problems, they are known to be sensitive towards input data distribution change which are pervasive across language tasks. Motivated by this, a recent line of work investigates the adversarial training technique to enhance the model robustness. Adversarial training has proven effective in improving model generalization and robustness in computer vision (Madry et al., 2017; Goodfellow et al., 2014) and natural language processing (NLP) (Zhu et al., 2019; Jiang et al., 2019; Cheng et al., 2019; Liu et al., 2020a; Pereira et al., 2020, 2021; Cheng et al., 2020). This causes a significant overhead in training time. Moreover, such methods tend to add the adversarial perturbation only to the embedding layer, which might not be optimal.

By contrast, in this paper, we investigate a simpler direction by using only randomly sampled noise to generate label-preserving artificial input points. We thus propose a simple yet effective Random Perturbation Training algorithm (RAPT) for enhancing model robustness and generalization. For each instance, instead of using gradient steps to generate adversarial examples, RAPT adds randomly sampled noise to the hidden representations of a randomly chosen layer, among multiple intermediate transformer layers (i.e. BERT layers). We hypothesize this might encourage the model to generate more diverse examples, and improve model generalization capability. Our model then regularizes the model posterior difference between clean and noisy inputs.

On the overall GLUE benchmark, RAPT outperforms the standard fine-tuning approach, and
matches or improves the performance of strong adversarial training methods such as SMART (Jiang et al., 2019), yet with a significantly reduced training time. Figure 1 shows the accuracy gain and training time drop of RAPT compared to SMART on the MNLI (matched) development dataset.

2 RAPT

In this paper, we focus on fine-tuning BERT models (Devlin et al., 2019), as this approach has proven very effective for a wide range of NLP tasks.

The standard training algorithm seeks to learn a function \( f(x; \theta) : x \rightarrow C \) as parametrized by \( \theta \), where \( C \) is the class label set. Given a training dataset \( D \) of input-output pairs \((x, y)\) and the loss function \( l(\cdot) \) (e.g. cross entropy), the standard training objective would minimize the empirical risk:

\[
\min_\theta \mathbb{E}_{(x,y) \sim D} [l(f(x; \theta), y)].
\]

By contrast, in adversarial training, as pioneered in computer vision (Goodfellow et al., 2014; Hsieh et al., 2019; Madry et al., 2017; Jin et al., 2019), the input would be augmented with a small perturbation that maximize the adversarial loss:

\[
\min_\theta \mathbb{E}_{(x,y) \sim D} [\max_\delta l(f(x + \delta; \theta), y)],
\]

where the inner maximization can be solved by projected gradient descent (Madry et al., 2017).

Recently, adversarial training has been successfully applied to NLP as well (Zhu et al., 2019; Jiang et al., 2019; Pereira et al., 2020). In particular, SMART (Jiang et al., 2019) regularizes the standard training objective using virtual adversarial training (Miyato et al., 2018), by performing an inner loop to search for the most adversarial direction:

\[
\min_\theta \mathbb{E}_{(x,y) \sim D} [l(f(x; \theta), y) + \alpha \max_\delta l(f(x + \delta; \theta), f(x; \theta))].
\]

Effectively, the adversarial term encourages smoothness in the input neighborhood, and \( \alpha \) is a hyperparameter that controls the trade-off between standard errors and adversarial errors.

Current adversarial methods for NLP are slower than standard training, due to the inner maximization. SMART, for instance, requires an additional \( K \) projected gradient steps to find the perturbation that maximizes the adversarial loss (violation of local smoothness) (Liu et al., 2020a). In practice, \( K = 1 \) suffices SMART, and it is roughly 2 times slower compared to standard training. By contrast, RAPT completely removes the adversarial steps that use gradient steps from SMART and instead optimizes for stabilizing the model local smoothness using only randomly sampled noise for regularization:

\[
\min_\theta \mathbb{E}_{(x,y) \sim D} [l(f(x; \theta), y) + \alpha l(f(x + \delta; \theta), f(x; \theta))]]
\]

RAPT does not require extra backward computations and empirically works as well as or better than SMART. We consider the posterior regularization using the KL-divergence. For all tasks in this work, an input text sequence is divided into subword units \( w_t \), \( t = 1, \ldots, T \). The tokenized input sequence is then transformed into embeddings, \( x_1, \ldots, x_T \in \mathbb{R}^n \), through a token encoder, which combines a token embedding, a (token) position embedding and a segment embedding (i.e. which text span the token belongs to) by element-wise summation. The embedding layer is used as

**Algorithm 1 RAPT**

**Input:** \( N \): the number of training epochs, \( D, \{(x_1, y_1), \ldots, (x_n, y_n)\} \): the dataset, \( \lambda \) : the minibatch of the dataset, \( f(x; \theta) \) : the machine learning model parametrized by \( \theta \), \( \sigma \) : the variance of the random noise \( \delta \), \( \eta \) : the number to control the size of the noise, \( L \) : the number of transformer based model’s layers, \( f^{layer} \), the function that computes the hidden representations of a given layer, \( h \) : the hidden representations of a layer of the model, \( \delta_r \) : the noise added to the hidden states of layer \( r \) , \( \tau \) : the global learning rate, \( \alpha \) : the hyperparameter for balancing the standard loss and the regularization term, \( max\_layer \) : the number of the maximum layer where the noise can be added during training.

1. \( \text{for epoch} = 1, 2, \ldots, N \) do
2. \( \text{for} \ \lambda \ \epsilon \ D \) do
3. \( \text{Generate a random integer} \ \lambda \ \epsilon \ {1, \ldots, \text{max}\_\lambdaer} \) do
4. \( \text{for} \ (x, y) \ \epsilon \ X \) do
5. \( \delta \sim N(0, \sigma^2 I) \)
6. \( \delta \leftarrow \eta \frac{\delta}{\|\delta\|} \)
7. \( \# x : \text{forward pass to the last layer of the model} \)
8. \( \text{for layer} = 1, 2, \ldots, L \) do
9. \( h \leftarrow f^{layer}(h) \)
10. if layer is \( r \) then
11. \( h \leftarrow h + \delta_r I \)
12. end if
13. end for
14. \( g_\theta \leftarrow \nabla_\theta l(f(x; \theta), y) + \alpha \nabla_\theta l(f(x + \delta_r; \theta), f(x; \theta)) \)
15. \( \theta \leftarrow \theta - \gamma g_\theta \)
16. end for
17. end for
18. end for
19. end for
20. Output: \( \theta \)
the input to multiple transformer layers (Vaswani et al., 2017) to generate the contextual representations, $h_1^{layer}, \ldots, h_T^{layer} \in \mathbb{R}^d$, which are the hidden states of an intermediate layer of the BERT model.

In RAPT, we sample noise vectors $\delta_1, \ldots, \delta_T$ from $\mathcal{N}(0, \sigma^2 I)$, where the noise vector can be added. In each epoch, for each mini-batch selected, the noise vector is added to its hidden states, i.e., $h_t^{layer} + \eta \delta_t$, with mean $0$ and variation of $\sigma^2$. Specifically, the model first performs a forward pass up to the chosen layer, then the noise vector is added to its hidden states. The algorithm of RAPT is shown in Algorithm 1.

The model is then updated according to the task-specific objective for the task. To preserve the semantics, we constrain the noise to be small, and assume the model’s prediction should not change after adding the perturbation. The algorithm of RAPT is shown in Algorithm 1.

3 Experiments

3.1 Datasets

We evaluate our model on the GLUE\(^1\) benchmark, a collection of nine natural language understanding (NLU) tasks. It includes question answering (Rajpurkar et al., 2016), linguistic acceptability (Warstadt et al., 2018), sentiment analysis (Socher et al., 2013), text similarity (Cer et al., 2017), paraphrase detection (Dolan and Brockett, 2005), and natural language inference (NLI) (Dagan et al., 2006; Bar-Haim et al., 2006; Giampicolo et al., 2007; Bentivogli et al., 2009; Levesque et al., 2012; Williams et al., 2018). The diversity of the tasks makes GLUE very suitable for evaluating the generalization and robustness of NLU models. The GLUE tasks used in our experiments are summarized in Table 1.

3.2 Implementation Details

Our model implementation is based on the MT-DNN\(^2\) framework (Liu et al., 2019, 2020b). We use BERT\(_{\text{BASE}}\) (Devlin et al., 2019) as the text encoder. We used ADAM (Kingma and Ba, 2015) as our optimizer with a learning rate in the range $\in \{1 \times 10^{-5}, 2 \times 10^{-5}, 8 \times 10^{-6}\}$ and a batch size $\in \{16, 32\}$. The maximum number of epochs was set to 6. A linear learning rate decay schedule with warm-up over 0.1 was used, unless stated otherwise. To avoid gradient exploding, we clipped the gradient norm within 1. All the texts were tokenized using wordpieces and were chopped to spans no longer than 512 tokens. For SMART, we follow (Jiang et al., 2019) and set the perturbation size to $1 \times 10^{-5}$. We choose the step size from $\{1 \times 10^{-3}, 1 \times 10^{-2}, 1 \times 10^{-1}, 1, 1.5, 2, 2.5, 3\}$. We set the variance for initializing the perturbation to $1 \times 10^{-5}$. The $\alpha$ parameter (Equation 1 and Equation 2) were both set to 1. During RAPT, we select $\eta$ from $\{0.01, 1.5, 2, 2.3, 2.5\}$. We found that adding the noise to the layers 1 to 3 worked best in our experiments, therefore, the $\max\_layer$ parameter in Algorithm 1 was set to 3. For more details, please refer to Section 4.

3.3 Main Results

We apply RAPT to BERT\(_{\text{BASE}}\) and evaluate its performance on GLUE. Our results are shown in Table 2. We compare RAPT with the standard fine-tuning approach (Standard) and with the adversarial training method SMART. For our model RAPT, we compare a model that adds the noise to the embedding layer only, RAPT (Embedding), with the model that adds the noise to the other layers. We report the model that uses $\eta = 2$, RAPT ($\eta = 2$), and the model that selects the best $\eta$ value, RAPT (BEST $\eta$).

Overall, we observed that SMART and RAPT were able to outperform standard fine-tuning, without using any additional knowledge source, and without using any additional dataset other than the target task datasets. These results suggest that adding noisy input points during training lead to a more robust model and help generalize better on unseen data. RAPT consistently outperforms standard training (with an average score of 81.9% vs. 81.1% on the test set).

Remarkably, RAPT outperforms SMART on most GLUE tasks, and obtains the highest average score among all tasks on both dev and test sets (85.1% and 81.9%, respectively), yet with a smaller training time (86.7 minutes on average, as shown in Table 3). This indicates that using only randomly sampled noise leads to better results. We also observe pronounced gains of RAPT on the smaller datasets such as RTE (with a test set accuracy of
### Table 1: Summary information of the GLUE benchmark.

| Corpus   | Task             | #Train | #Dev | #Test | #Label | Metrics          |
|----------|------------------|--------|------|-------|--------|------------------|
| CoLA     | Acceptability    | 8.5k   | 1k   | 1k    | 2      | Matthews corr    |
| SST      | Sentiment        | 67k    | 872  | 1.8k  | 2      | Accuracy         |

| Single-Sentence Classification                                   |               |
|-----------------------------------------------------------------|---------------|
| **Corpus**                                                      | **Task**      | **#Train** | **#Dev** | **#Test** | **#Label** | **Metrics**          |
| CoLA                                                            | Acceptability | 8.5k       | 1k       | 1k       | 2         | Matthews corr       |
| SST                                                             | Sentiment     | 67k        | 872      | 1.8k     | 2         | Accuracy           |

| Pairwise Text Classification                                    |               |
|-----------------------------------------------------------------|---------------|
| MNLI                                                            | NLI           | 393k       | 20k      | 20k      | 3         | Accuracy         |
| RTE                                                             | NLI           | 2.5k       | 276      | 3k       | 2         | Accuracy         |
| QQP                                                             | Paraphrase    | 364k       | 40k      | 391k     | 2         | Accuracy/F1     |
| MRPC                                                            | Paraphrase    | 3.7k       | 408      | 1.7k     | 2         | Accuracy/F1     |
| QNLI                                                            | QA/NLI        | 108k       | 40k      | 391k     | 2         | Accuracy         |

| Text Similarity                                                 |               |
|-----------------------------------------------------------------|---------------|
| STS-B                                                           | Similarity    | 7k         | 1.5k     | 1.4k     | 1         | Pearson/Spearman corr |

Table 2: Comparison of standard fine-tuning (Standard), adversarial training (SMART) and our methods (RAPT) on GLUE. We use the BERT\_BASE model as the text encoder for all models. For a fair comparison, all these results are produced by ourselves. These scores are the average of each model across 5 random seeds. The GLUE test results are scored using the GLUE evaluation server.

| Methods            | MNLI-m/mm Acc | QQP Acc/F1 | RTE Acc | QNLI Acc | MRPC Acc/F1 | CoLA Mcc | SST Acc | STS-B P/S Corr | Average Score |
|--------------------|---------------|------------|---------|----------|-------------|----------|---------|----------------|---------------|
| Standard\_dev       | 84.1/84.3     | 90.5/87.3  | 69.3    | 90.9     | 86.9/90.7   | 58.3     | 92.4    | 89.9/89.4      | 84.5          |
| SMART\_dev          | 84.7/85.2     | 90.9/87.9  | 70.8    | 91.4     | 86.4/90.5   | 58.6     | 92.8    | 90.2/89.7      | 84.9          |
| RAPT\_dev (Embedding)| 85.2/85.5     | 91.2/88.3  | 69.5    | 91.7     | 86.1/90.1   | 58.3     | 92.9    | 90.1/89.8      | 84.9          |
| RAPT\_dev (η = 2)   | 85.2/85.5     | 91.2/88.2  | 70.6    | 91.8     | 86.9/90.8   | 58.7     | 92.8    | 89.9/89.6      | **85.1**      |
| RAPT\_dev (BEST η)  | 85.3/85.6     | 91.2/88.2  | 70.6    | 91.8     | 86.9/90.8   | 58.7     | 92.8    | 90.1/89.7      | **85.1**      |
| Standard\_test      | 84.2/83.2     | 88.6/70.6  | 67.9    | 90.2     | 84.0/88.3   | 52.1     | 93.1    | 86.3/85.0      | 81.1          |
| SMART\_test         | 85.0/84.2     | 89.1/71.8  | 68.4    | 90.7     | 83.6/88.1   | 52.8     | 93.5    | 85.6/85.6      | 81.6          |
| RAPT\_test (Embedding)| 85.3/84.4     | 89.1/71.8  | 68.4    | 91.1     | 84.1/88.2   | **53.0** | 93.7    | **87.5/86.4**  | **81.9**      |
| RAPT\_test (η = 2)  | 85.4/84.7     | 89.1/71.9  | 67.4    | 91.1     | 84.0/88.3   | 51.1     | **93.8** | 87.2/86.1      | 81.7          |
| RAPT\_test (BEST η) | 85.5/84.7     | 89.1/71.9  | 68.0    | 91.1     | 84.0/88.3   | 52.3     | **93.8** | 86.8/85.5      | 81.8          |

Table 2: Comparison of standard fine-tuning (Standard), adversarial training (SMART) and our methods (RAPT) on GLUE. We use the BERT\_BASE model as the text encoder for all models. For a fair comparison, all these results are produced by ourselves. These scores are the average of each model across 5 random seeds. The GLUE test results are scored using the GLUE evaluation server.

Adding the perturbation to multiple intermediate layers leads to better results on the dev set than adding the random perturbation to the embedding layer only (average score of 85.1% vs. 84.9%, respectively). However, on the test set, adding the random perturbation to the embedding layer only leads to slightly better results than adding the random perturbation to multiple intermediate layers (81.9% vs. 81.8%, respectively). Still, both settings outperform SMART and standard fine-tuning.

Regarding the training time, on the overall GLUE benchmark, RAPT takes on average 22% less time to train compared to SMART (86.7 vs 110.9 minutes, respectively), as shown in Table 3. 68.4) and STS-B (with a test set Pearson/Spearman correlation scores of 87.5/86.4), which illustrates the benefits of RAPT on improving model generalizability.

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4 Analysis

Here, we take a closer look at the embeddings and hidden representations of the intermediate layers of BERT using standard fine-tuning (Standard), SMART, and RAPT. After training, we extract the embeddings (for Standard and SMART) and the intermediate layer representations (where noise has been added) of the second intermediate layer (for RAPT) of a sentence. Then, we compute the top most similar words for each word in the sentence. We use the cosine similarity for computing the similarity between the vectors. As shown in Table 4, adding the noise to the intermediate layers using RAPT introduces more diversity. For instance, among the top-10 closest words to the word country, SMART shares eight words with the Standard fine-tuning methods, while RAPT shares only five.
Table 3: Training time comparison between standard fine-tuning (Standard), SMART, and RAPT. RAPT/SMART denotes the ratio between the training time of RAPT and SMART. We used a A100-PCIE-40GB GPU to measure the training time.

| Time (min) | MNLI | QQP | RTE | QNLI | MRPC | CoLA | SST | STS-B | Average |
|-----------|------|-----|-----|------|------|------|-----|-------|---------|
| Standard  | 220  | 175 | 2.5 | 40   | 2.5  | 4.8  | 17.5| 3.8   | 69.6    |
| SMART     | 370  | 270 | 4   | 102  | 4.1  | 8    | 31.5| 6     | 110.9   |
| RAPT      | 280  | 220 | 3   | 80   | 3.4  | 6.5  | 24.5| 4.9   | 86.7    |
| RAPT/SMART| 0.76 | 0.81| 0.75| 0.78 | 0.81 | 0.79 | 0.77| 0.8   | 0.78    |

Table 4: Top-10 closest words to the vector of the word country using standard fine-tuning (Standard), SMART, and RAPT on the RTE development dataset. The words in red are the words not shared with the Standard fine-tuning method. RAPT has five different words, while SMART has only two.

Table 5 and Table 6 compare the embeddings produced by SMART before and after adding the perturbation and the hidden representations produced by RAPT before and after adding the noise. For SMART, we can observe that the top-10 similar words to the word country do not change after adding the perturbation, and the cosine similarity scores are kept around the same. In our experiments, increasing the perturbation size leads to a drop in accuracy. For RAPT, we extract the hidden representations from the second layer of BERT. As we can see, the cosine similarity scores change and more diversity is introduced. In our development experiments, the accuracy instead increases, indicating that the hidden representations from the intermediate layers might be less sensitive to noise compared to the embedding layer.

Figure 2: Performance on the MNLI development set as we change the layer combination to add the noise. On the x-axis, \textit{max\_layer} = embed denotes that the noise is added to the embedding layer only. All the other values denote that, for each mini-batch, a layer among the layer 1 up to this layer value is randomly chosen. The model is then updated according to the task-specific objective for the task.

Figure 3: Performance on the MRPC development set as we change the layer combination to add the noise. On the x-axis, \textit{max\_layer} = embed denotes that the noise is added to the embedding layer only. All the other values denote that, for each mini-batch, a layer among the layer 1 up to this layer value is randomly chosen. The model is then updated according to the task-specific objective for the task.
Input: [CLS] by law, Mexico can only export half the oil it produces to the United States. [SEP]

Mexico produces more oil than any other country. [SEP]

| SMART | SMART (+noise) | RAPT | RAPT (+noise) |
|-------|---------------|------|--------------|
| word  | similarity    | word | similarity   | word | similarity |
| nation| 0.2991        | nation| 0.2992 | countries | 0.3976 | countries | 0.3141 |
| county| 0.2942        | county| 0.2945 | nation | 0.3328 | nation | 0.2714 |
| region| 0.2939        | region| 0.2941 | region | 0.3182 | region | 0.2546 |
| countries| 0.2736 | countries| 0.2738 | nations | 0.2934 | nations | 0.2430 |
| province| 0.2517 | province| 0.2515 | kingdom | 0.2929 | cities | 0.2337 |
| island| 0.2475        | island| 0.2473 | province | 0.2880 | kingdom | 0.2336 |
| state| 0.2449        | state| 0.2445 | island | 0.2810 | global | 0.2324 |
| territory| 0.2227 | territory| 0.2227 | city | 0.2702 | city | 0.2295 |
| homeland| 0.2106 | homeland| 0.2103 | countryside | 0.2682 | territory | 0.2293 |
| trade| 0.2090        | trade| 0.2087 | realms | 0.2670 | countryside | 0.2274 |

Table 5: Top-10 closest words to the vector of the word country using SMART and RAPT on the RTE development dataset. SMART (the leftmost column) denotes the embedding of the target vector (country) before adding the perturbation using SMART. SMART (+noise) denotes the embedding of the target vector (country) after adding the perturbation using SMART. In both cases, we compute the similarity between the embedding of the target word and the embeddings of the other words in the training set. RAPT (the second column from the right) denotes the hidden state vector of the second layer of BERT of the target vector (country) before adding the noise using RAPT. RAPT (+noise) denotes the hidden state vector of the second layer of BERT of the target vector (country) after adding the noise using RAPT. In both cases, we compute the similarity between the hidden state of the target word and the hidden states of the other words in the training set.

Input: [CLS] by law, Mexico can only export half the oil it produces to the United States. [SEP]

Mexico produces more oil than any other country. [SEP]

| SMART | SMART (+noise) | RAPT | RAPT (+noise) |
|-------|---------------|------|--------------|
| word  | similarity    | word | similarity   | word | similarity |
| could| 0.5857        | could| 0.5855 | could | 0.5656 | could | 0.4580 |
| may| 0.3869        | may| 0.3873 | cannot | 0.5162 | cannot | 0.4269 |
| cannot| 0.3774 | cannot| 0.3776 | couldn’t | 0.5098 | couldn’t | 0.4213 |
| might| 0.3736        | might| 0.3736 | allows | 0.3445 | allows | 0.2859 |
| couldn’t| 0.3651 | couldn’t| 0.3650 | helps | 0.3408 | must | 0.2759 |
| must| 0.3388        | must| 0.3388 | shall | 0.3218 | may | 0.2659 |
| will| 0.3312        | will| 0.3314 | should | 0.3183 | doesn’t | 0.2639 |
| should| 0.3119 | should| 0.3121 | must | 0.3130 | sees | 0.2531 |
| would| 0.2914        | would| 0.2915 | doesn’t | 0.3106 | helps | 0.2388 |
| shall| 0.2624        | shall| 0.2626 | may | 0.3083 | allow | 0.2318 |

Table 6: Top-10 closest words to the vector of the word can using SMART and RAPT on the RTE development dataset. SMART (the leftmost column) denotes the embedding of the target vector (can) before adding the perturbation using SMART. SMART (+noise) denotes the embedding of the target vector (can) after adding the perturbation using SMART. In both cases, we compute the similarity between the embedding of the target word and the embeddings of the other words in the training set. RAPT (the second column from the right) denotes the hidden state vector of the second layer of BERT of the target vector (can) before adding the noise using RAPT. RAPT (+noise) denotes the hidden state vector of the second layer of BERT of the target vector (can) after adding the noise using RAPT. In both cases, we compute the similarity between the hidden state of the target word and the hidden states of the other words in the training set.

5 Conclusion

We proposed RAPT, a simple and efficient random perturbation training algorithm for fine-tuning large scale pre-trained language models. Our experiments demonstrated that it achieves competitive results on GLUE tasks, without relying on
any additional resource other than the target task dataset. Moreover, our model can significantly reduce the training time compared to adversarial training. RAPT is model-agnostic, and can also be generalized to solve other downstream tasks as well, and we will explore these directions as future work.

Acknowledgments

We thank the reviewers for their helpful feedback. This work has been supported by the project KAKENHI ID: 21K17802.

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