DeBERTaV3: Improving DeBERTa using ELECTRA-Style Pre-Training with Gradient-Disentangled Embedding Sharing

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Abstract

This paper presents a new pre-trained language model, DeBERTaV3, which improves the original DeBERTa model by replacing mask language modeling (MLM) with replaced token detection (RTD), a more sample-efficient pre-training task. Our analysis shows that vanilla embedding sharing in ELECTRA hurts training efficiency and model performance. This is because the training losses of the discriminator and the generator pull token embeddings in different directions, creating the "tug-of-war" dynamics. We thus propose a new gradient-disentangled embedding sharing method that avoids the tug-of-war dynamics, improving both training efficiency and the quality of the pre-trained model. We have pre-trained DeBERTaV3 using the same settings as DeBERTa to demonstrate its exceptional performance on a wide range of downstream natural language understanding (NLU) tasks. Taking the GLUE benchmark with eight tasks as an example, the DeBERTaV3 Large model achieves a 91.37% average score, which is 1.37% over DeBERTa and 1.91% over ELECTRA, setting a new state-of-the-art (SOTA) among the models with a similar structure. Furthermore, we have pre-trained a multi-lingual model mDeBERTa and observed a larger improvement over strong baselines compared to English models. For example, the mDeBERTa Base achieves a 79.8% zero-shot cross-lingual accuracy on XNLI and a 3.6% improvement over XLM-R Base, creating a new SOTA on this benchmark. We have made our pre-trained models and inference code publicly available at https://github.com/microsoft/DeBERTa 1.

1 Introduction

Recent advances in pre-trained language models (PLMs) have created new state-of-the-art results on many natural language processing (NLP) tasks. While scaling up PLMs with billions or trillions of parameters [1, 2, 3, 4, 5] is a well-proved way to improve the capacity of the PLMs, it is more important to explore more energy-efficient approaches to build PLMs with fewer parameters and less computation cost while retaining high model capacity.

Towards this direction, there are a few works that significantly improve the efficiency of PLMs. The first is RoBERTa [6] which improves the model capacity with a larger batch size and more training data. Based on RoBERTa, DeBERTa [4] further improves the pre-training efficiency by incorporating disentangled attention which is an improved relative-position encoding mechanism. By scaling up to 1.5B parameters, which is about an eighth of the parameters of xxlarge T5 [1], DeBERTa surpassed human performance on the SuperGLUE [7] leaderboard for the first time. The second

¹The models are also publicly available at https://huggingface.co/models?other=deberta-v3

new pre-training approach to improve efficiency is replaced token detection (RTD), proposed by ELECTRA [8]. Unlike BERT [9] which uses a transformer encoder to predict corrupted tokens with masked language modeling (MLM), RTD uses a generator to generate ambiguous corruptions and a discriminator to distinguish the ambiguous tokens from the original inputs, similar to Generative Adversarial Networks (GAN). The effectiveness of RTD is also verified by follow-up works, including CoCo-LM [10], XLM-E [11], and SmallBenchNLP [12].

In this paper, we explore two methods of improving the efficiency of pre-training DeBERTa. Following ELECTRA-style training, we replace MLM in DeBERTa with RTD where the model is trained as a discriminator to predict whether a token in the corrupted input is either original or replaced by a generator. We show that DeBERTa trained with RTD significantly outperforms the model trained using MLM.

The second is a new embedding sharing method. In ELECTRA, the discriminator and the generator share the same token embeddings. However, our analysis shows that embedding sharing hurts training efficiency and model performance, since the training losses of the discriminator and the generator pull token embeddings into different directions. This is because the training objectives between the generator and the discriminator are very different. The MLM used for training the generator tries to pull the tokens that are semantically similar close to each other while the RTD of the discriminator tries to discriminate semantically similar tokens and pull their embeddings as far as possible to optimize the binary classification accuracy. This creates the "tug-of-war" dynamics, as illustrated in [13]. On the other hand, we show that using separated embeddings for the generator and the discriminator results in significant performance degradation when we fine-tune the discriminator on downstream tasks, indicating the merit of embedding sharing, e.g., the embeddings of the generator are beneficial to produce a better discriminator, as argued in [8]. To seek a tradeoff, we propose a new gradient-disentangled embedding sharing (GDES) method where the generator shares its embeddings with the discriminator but stops the gradients in the discriminator from back propagating to the generator embeddings to avoid the tug-of-war dynamics. We empirically demonstrate that GDES improves both pre-training efficiency and the quality of the pre-trained models.

We pre-train three variants of DeBERTaV3 models, i.e., DeBERTaV3_{large}, DeBERTaV3_{base} and DeBERTaV3_{small}. We evaluate them on various representative natural language understanding (NLU) benchmarks and set new state-of-the-art numbers among models with a similar model structure. For example, DeBERTaV3_{large} surpasses previous SOTA models with a similar model structure on GLUE [14] benchmark with an average score over +1.37%, which is significant. DeBERTaV3_{base} achieves a 90.6% accuracy score on the MNLI-matched [15] evaluation set and an 88.4% F1 score on the SQuAD v2.0 [16] evaluation set. This improves DeBERTa_{base} by 1.8% and 2.2%, respectively. Without knowledge distillation, DeBERTaV3_{small} surpasses previous SOTA models with a similar model structure on both MNLI-matched and SQuAD v2.0 evaluation set by more than 1.2% in accuracy and 1.3% in F1, respectively. We also train DeBERTaV3_{base} on the CC100 [17] multilingual data using a similar setting as XLM-R [17] but with only a third of the training passes. We denote the model as mDeBERTa_{base}. Under the cross-lingual transfer setting, mDeBERTa_{base} achieves a 79.8% average accuracy score on the XNLI [18] task, which outperforms XLM-R_{base} and mT5_{base} [19] by 3.6% and 4.4%, respectively. This makes mDeBERTa the best model among multi-lingual models with a similar model structure. All these results strongly demonstrate the efficiency of DeBERTaV3 models and set a good base for future exploration towards more efficient PLMs.

2 Background

2.1 Transformer

A Transformer-based language model is composed of stacked Transformer blocks [20]. Each block contains a multi-head self-attention layer followed by a fully connected positional feed-forward network. The standard self-attention mechanism lacks a natural way to encode word position information. Thus, existing approaches add a positional bias to each input word embedding so that each input word is represented by a vector whose value depends on both its content and position. The positional bias can be implemented using absolute position embedding [3, 9, 20] or relative position embedding [21, 22]. Studies have shown that relative position representations are more effective for natural language understanding and generation tasks [4, 23, 24].

2.2 DeBERTa

DeBERTa improves BERT with disentangled attention and an enhanced mask decoder. The disentangled attention mechanism differs from existing approaches in that it represents each input word using two separate vectors: one for the content and the other for the position. Meanwhile, its attention weights among words are computed via disentangled matrices on both their contents and relative positions. Like BERT, DeBERTa is pre-trained using masked language modeling. The disentangled attention mechanism already considers the contents and relative positions of the context words, but not the absolute positions of these words, which in many cases are crucial for the prediction. DeBERTa uses an enhanced mask decoder to improve MLM by adding absolute position information of the context words at the MLM decoding layer.

2.3 ELECTRA

2.3.1 Masked Language Model

Large-scale Transformer-based PLMs are typically pre-trained on large amounts of text to learn contextual word representations using a self-supervision objective, known as MLM [9]. Specifically, given a sequence $X = \{x_i\}$, we corrupt it into \tilde{X} by masking 15% of its tokens at random and then train a language model parameterized by θ to reconstruct \tilde{X} by predicting the masked tokens \tilde{x} conditioned on \tilde{X} :

$$\max_{\theta} \log p_{\theta}(\boldsymbol{X}|\tilde{\boldsymbol{X}}) = \max_{\theta} \sum_{i \in \mathcal{C}} \log p_{\theta}(\tilde{x}_i = x_i|\tilde{\boldsymbol{X}})$$
(1)

where \mathcal{C} is the index set of the masked tokens in the sequence. The authors of BERT propose to keep 10% of the masked tokens unchanged, another 10% replaced with randomly picked tokens and the rest replaced with the [MASK] token.

2.3.2 Replaced token detection

Unlike BERT, which uses only one transformer encoder and trained with MLM, ELECTRA was trained with two transformer encoders in GAN style. One is called generator trained with MLM; the other is called discriminator trained with a token-level binary classifier. The generator is used to generate ambiguous tokens to replace masked tokens in the input sequence. Then the modified input sequence is fed to the discriminator. The binary classifier in the discriminator needs to determine if a corresponding token is either an original token or a token replaced by the generator. We use θ_G and θ_D to represent the parameters of the generator and the discriminator, respectively. The training objective in the discriminator is called RTD (Replaced Token Detection). The loss function of the generator can be written as,

$$L_{MLM} = \mathbb{E}\left(-\sum_{i \in \mathcal{C}} \log p_{\theta_G} \left(\tilde{x}_{i,G} = x_i | \tilde{\boldsymbol{X}}_G\right)\right)$$
 (2)

, where \tilde{X}_G is the input to the generator by randomly masking 15% tokens in X.

The input sequence of the discriminator is constructed by replacing masked tokens with new tokens sampled according to the output probability from the generator:

$$\tilde{x}_{i,D} = \begin{cases} \tilde{x}_i \sim p_{\theta_G} \left(\tilde{x}_{i,G} = x_i | \tilde{\boldsymbol{X}}_G \right), & i \in \mathcal{C} \\ x_i, & i \notin \mathcal{C} \end{cases}$$
 (3)

The loss function of the discriminator is written as,

$$L_{RTD} = \mathbb{E}\left(-\sum_{i} \log p_{\theta_{D}}\left(\mathbb{1}\left(\tilde{x}_{i,D} = x_{i}\right) \middle| \tilde{\boldsymbol{X}}_{D}, i\right)\right)$$
(4)

, where $\mathbb{1}(\cdot)$ is the indicator function and \tilde{X}_D is the input to the discriminator constructed via Equation 3. In ELECTRA, L_{MLM} and L_{RTD} are optimized jointly, $L = L_{MLM} + \lambda L_{RTD}$, where λ is the weight of the discriminator loss L_{RTD} , which was set to 50 in ELECTRA.

3 DeBERTaV3

This section describes DeBERTaV3, which improves DeBERTa by using the RTD training loss of [8] and a new weight-sharing method.

3.1 DeBERTa with RTD

Since RTD in ELECTRA and the disentangled attention mechanism in DeBERTa have proved to be sample-efficient for pre-training, we propose a new version of DeBERTa, referred to as *DeBERTaV3*, by replacing the MLM objective used in DeBERTa with the RTD objective to combine the strengths of both methods.

In our implementation, the generator is the same width as the discriminator but is half the depth of the discriminator. Wikipedia and the bookcorpus [25] are used as training data, following the base model configuration of (author?) [9]. The batch size is set to 2048, and the model is trained for 125,000 steps with a learning rate of 5e-4 and warming up steps of 10,000. Following [8], we use $\lambda = 50$ with the same optimization hyperparameters. We validate the effectiveness of DeBERTaV3 on two representative NLU tasks, i.e., MNLI and SQuAD v2.0. The results, presented in ① of Table 2, show that DeBERTaV3 significantly outperforms DeBERTa, i.e., +2.5% on the MNLI-m accuracy and +3.8% on the SQuAD v2.0 F1.

In the next two subsections, we will show that the performance of DeBERTaV3 can be further improved by replacing token Embedding Sharing (ES) used for RTD, originally proposed in [8], by a new Gradient-Disentangled Embedding Sharing (GDES) method. We start with an analysis of ES in Section 3.2.

3.2 Token Embedding Sharing in ELECTRA

In pre-training, ELECTRA uses a generator and a discriminator, which share token embeddings, as illustrated in Figure 1 (a). In what follows, we refer to this sharing method as Embedding Sharing (ES). Let E and g_E denote the parameters and the gradients of the token embeddings, respectively. In each training pass of ELECTRA, g_E is computed by back-propagation using accumulated errors with respect to both the MLM loss of the generator and the RTD loss of the discriminator, respectively, as

$$g_{\mathbf{E}} = \frac{\partial L_{MLM}}{\partial \mathbf{E}} + \lambda \frac{\partial L_{RTD}}{\partial \mathbf{E}}.$$
 (5)

Equation 5 presents a multitask learning problem, where the gradient from each task (i.e., the MLM task of the generator, or the RTD of the discriminator) pulls the solution towards its optimum, leading to a tug-of-war procedure [13], resulting in an equilibrium between the gradients of the two tasks.

It is well known that by carefully controlling the speed of parameter update (e.g., by using a small learning rate or gradient clipping) such a tug-of-war procedure does converge. However, the training can be highly inefficient if the two tasks are dramatically different so that they require parameters to be updated in very different directions.

Unfortunately, the tasks of MLM and RTD pull token embeddings into very different directions. MLM tries to map the tokens that are semantically similar to the embedding vectors that are close to each other. RTD, on the other hand, tries to *discriminate* semantically similar tokens, pulling their embeddings as far as possible to optimize the classification accuracy.

To verify our hypothesis, we implement a variant of ELECTRA without token embedding sharing, referred to as the No Embedding Sharing (NES) method, as illustrated in Figure 1 (b). In each training pass of NES, the generator and discriminator are updated alternatively. Specifically, we first run a forward pass with the generator to generate inputs for the discriminator, and then run a backward pass with respect to L_{MLM} to update the parameters of the generator, including its token embeddings E_G . After that, we run a forward pass for the discriminator using the inputs produced by the generator and run a backward pass with respect to L_{RTD} to update the discriminator, including its token embeddings E_D .

Now, we compare ES and NES in terms of training speed, quality of the resulting word embeddings, and performance on downstream NLU tasks.

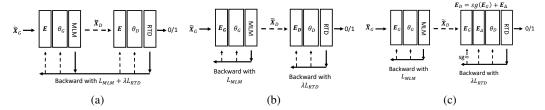


Figure 1: Illustration of different embedding sharing methods. (a) ES: ${\pmb E}, \theta_G$ and θ_D will be jointly updated in a single backward pass with regards to $L_{MLM}+\lambda L_{RTD}$. (b) NES: ${\pmb E}_G$ and θ_G will first be updated via the backward pass with regards to L_{MLM} , then ${\pmb E}_D$ and θ_D will be updated via the backward pass with regards to λL_{RTD} . (c) GDES: ${\pmb E}_G$ and θ_G will first be updated in the backward pass with regards to L_{MLM} , then ${\pmb E}_\Delta$ and θ_D will be updated via the backward pass with regards to λL_{RTD} and ${\pmb E}_G$. sg is the stop gradient operator that prevents the discriminator from updating ${\pmb E}_G$

As shown in Figure 2, NES does converge faster than ES. This is expected because NES does not suffer from training inefficiency due to the tug-of-war dynamics as in ES.

We then compute the average cosine similarity scores of token embeddings 2 . As shown in Table 1, NES produces two different embedding models. The average token similarity score computed using E_G is much higher than that of E_D . This is consistent with our hypothesis. However, the embeddings learned using NES does not lead to any visible performance gain on the two representative downstream NLU tasks (i.e., MNLI and SQuAD v2.0), as shown in Table 2. The result confirms the merit of the ES method as argued in [8]. In addition to parameter-efficiency, the embeddings of the generator are beneficial to produce a better discriminator. In the next subsection, we propose a new weight sharing method which not only retains the strength of ES, but also makes the model training as efficient as NES.

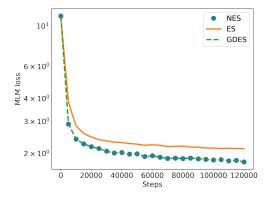


Figure 2: MLM training loss of the generator with different word embedding sharing methods.

| Word Embedding Sharing | $\mid E_G \mid$ | $oldsymbol{E}_D$ | $\overline{\mid m{E}_{\Delta} \mid}$ |
|------------------------|-----------------|------------------|--------------------------------------|
| ① ES | 0.02 | 0.02 | - |
| ② NES | 0.45 | 0.02 | _ |
| 3 GDES | 0.45 | 0.29 | 0.02 |

Table 1: Average cosine similarity of word embeddings of the generator and the discriminator with different embedding sharing methods.

²We sample 10% of the word pieces from the vocabulary and calculate the average cosine similarity of every pair of two word pieces.

| Model | MNLI-m/mm Acc | SQuAD v2.0 F1/EM |
|-----------------------------|------------------|---------------------|
| BERT _{base} [9] | 84.3/84.7 | 76.3/73.7 |
| ELECTRA _{base} [8] | 85.8/- | -/- |
| DeBERTa _{base} [4] | 86.3/86.2 | 82.5/79.3 |
| DeBERTa+RTD _{base} | | |
| ① ES | 88.8/88.4 | 86.3/83.5 |
| ② NES | 88.3/87.9 | 85.3/82.7 |
| ③ GDES | 89.3/89.0 | 87.2/84.5 |

Table 2: Fine-tuning results on MNLI and SQuAD v2.0 tasks of base models trained with different embedding sharing methods.

3.3 Gradient-Disentangled Embedding Sharing

The Gradient-Disentangled Embedding Sharing method is illustrated in Figure 1 (c). Like ES in Figure 1 (a), we share the token embeddings between the generator and the discriminator so as to retain the merit of ES mentioned above. But the sharing is restricted throughout the model training. In each training iteration, the gradients of the generator are computed only based on the MLM loss, but not on the RTD loss, thus avoiding the tug-of-war procedure and allowing the model to be trained as efficiently as NES. Unlike ES, the sharing in GDES is one-directional in that the gradients computed w.r.t. MLM are used for updating both E_G and E_D whereas the gradients computed w.r.t. RTD are used for updating E_D only.

GDES is implemented by re-parameterizing the token embeddings of the discriminator as

$$\boldsymbol{E}_D = sg(\boldsymbol{E}_G) + \boldsymbol{E}_{\Delta},\tag{6}$$

where sg is the stop gradient operator which only allows gradients propagation through E_{Δ} .

The training of GDES follows that of NES. E_{Δ} is initialized as a zero matrix. In each training pass, we first run a forward pass with the generator to generate the inputs for the discriminator, and then run a backward pass with respect to the MLM loss to update E_G , which is shared by both the generator and the discriminator. After that, we run a forward pass for the discriminator using the inputs produced by the generator and run a backward pass with respect to the RTD loss to update E_D by propagating gradients only through E_{Δ} . After model training, E_{Δ} is added to E_G and the sum is saved as E_D in the discriminator, as Equation 6.

To verify the effectiveness of GDES, we compare it against ES and NES in terms of training speed, quality of the resulting token embeddings, and performance on downstream tasks. Several conclusions can be drawn from the experimental results in Figure 2, Tables 1 and 2. First, Figure 2 shows that the model with GDES converges faster than the model with ES, and the training with GDES is as efficient as the model with NES. Second, Table 1 shows that like NES, GDES also produces two different token embedding matrices, and the average token similarity score computed using E_G is higher than that of E_D . However, the gap is smaller than that in NES due to the restricted weight sharing in GDES. Third, Table 2 shows that the model pre-trained with GDES produces the best results, after fine-tuning, on two downstream tasks, MNLI and SQuAD v2.0. These results verify that GDES is an effective weight-sharing method for language model pre-trained with MLM and RTD.

4 Experiment

4.1 Main Results on NLU tasks

To further verify the effectiveness of those technologies, we combine RTD, DES and DA to train models of different sizes(i.e. large, base and small) using standard pre-training settings. Since all of our experiments are modified based on DeBERTa code base and follow most of the settings of DeBERTa, we denote the new models as DeBERTaV3_{large}, DeBERTaV3_{base} and DeBERTaV3_{small}. The discriminator part of DeBERTaV3_{large} and DeBERTaV3_{base} are the same as DeBERTalarge</sub> and

DeBERTa_{base}, respectively. The discriminator of DeBERTaV3_{small} has the same width and attention heads as DeBERTa_{base} and half the depth of DeBERTa_{base}, i.e. 6 layers with 768 hidden size and 12 attention heads. The generator of DeBERTaV3 has the same width as the discriminator and half the depth of the discriminator. We train those models with 160GB data which is the same as DeBERTaV2 and RoBERTa, and use the same SentencePiece [26, 27] vocabulary as DeBERTaV2 [4] which contains 128,000 tokens. All the models are trained for 500,000 steps with a batch size of 8192 and warming up steps of 10,000. The learning rate for base and small model is 5e-4, while the learning rate for large model is 3e-4. Following the DeBERTa setting, we use the AdamW [28] optimizer which is a fixed version of Adam [29] with weight decay, and set $\beta_1 = 0.9$, $\beta_2 = 0.98$ for the optimizer. After pre-training, the discriminators of those models are used for downstream task fine-tuning following the same paradigm as Transformer PLMs, such as BERT, RoBERTa, ELECTRA, and DeBERTa. We provide more details on the hyper parameters of pre-training and fine-tuning in the Appendix.

4.1.1 Performance on Large Models

Following previous studies on PLMs, we first evaluate our model on the eight NLU tasks in GLUE [14], which are the most representative sentence classification tasks. We fine tune the pre-trained models on those tasks by plugging a classification head on top of the hidden states of the [CLS] token at the last layer. We summarize the results in Table 3, where DeBERTaV3 is compared with previous Transform-based PLMs of similar structures (i.e. 24 layers with hidden size of 1024), including BERT, RoBERTa, XLNet [22], ALBERT [30], ELECTRA and DeBERTa. Compared to previous SOTA models, DeBERTaV3 performs consistently comparable or mostly better across all the tasks. Meanwhile, DeBERTaV3 outperforms XLNet in seven out of eight tasks. In terms of average GLUE score, DeBERTaV3 outperforms other SOTA PLMs with a large margin (> 1.3%). Particularly, compared with previous best numbers, there are big jumps on the performance of low resource tasks (i.e., RTE (+4.4%), CoLA (+4.8%)). This indicates DeBERTaV3 is more data efficient and has a better generalization performance. We also note that the improvements on SST-2, STS-B, and MRPC are relatively small (< 0.3%). We conjecture this is due to the performance on those tasks is close to be saturated, and thus even small but consistent improvements on them are valuable.

| Model | CoLA | QQP | MNLI-m/mm | SST-2 | STS-B | QNLI | RTE | MRPC | Avg. |
|----------------------------|------|------|-----------|-------|-------|------|------|------|-------|
| Model | Mcc | Acc | Acc | Acc | Corr | Acc | Acc | Acc | |
| #Train | 8.5k | 364k | 393k | 67k | 7k | 108k | 2.5k | 3.7k | |
| BERT _{large} | 60.6 | 91.3 | 86.6/- | 93.2 | 90.0 | 92.3 | 70.4 | 88.0 | 84.05 |
| RoBERTa _{large} | 68.0 | 92.2 | 90.2/90.2 | 96.4 | 92.4 | 93.9 | 86.6 | 90.9 | 88.82 |
| XLNet _{large} | 69.0 | 92.3 | 90.8/90.8 | 97.0 | 92.5 | 94.9 | 85.9 | 90.8 | 89.15 |
| ELECTRA _{large} | 69.1 | 92.4 | 90.9/- | 96.9 | 92.6 | 95.0 | 88.0 | 90.8 | 89.46 |
| DeBERTa _{large} | 70.5 | 92.3 | 91.1/91.1 | 96.8 | 92.8 | 95.3 | 88.3 | 91.9 | 90.00 |
| DeBERTaV3 _{large} | 75.3 | 93.0 | 91.8/91.9 | 96.9 | 93.0 | 96.0 | 92.7 | 92.2 | 91.37 |

Table 3: Comparison results on the GLUE development set.

To further evaluate the model performance, in addition to GLUE, DeBERTaV3_{large} is evaluated on three categories of representative NLU benchmarks: (1) Question Answering: SQuAD v2.0, RACE [31], ReCoRD [32] and SWAG [33]; (2) Natural Language Inference: MNLI; and (3) NER: CoNLL-2003 [34]. Among those tasks, RACE, SWAG, and MNLI are fine-tuned using the same way as sentence classification tasks. SQuAD v2.0, ReCoRD and NER are fine-tuned as sequence tagging tasks, where a token classification head is plugged on top of the hidden states of each token at the last layer. For comparison, we include ALBERT_{xxlarge} ³, DeBERTa_{large}, DeBERTa_{1.5B}, and Megatron [35] with three different model sizes, denoted as Megatron_{336M}, Megatron_{1.3B} and Megatron_{3.9B}, which are trained using the same dataset as RoBERTa. Note that Megatron_{336M} has a similar model size as other models mentioned above⁴.

 $^{^{3}}$ The hidden dimension of ALBERT_{xxlarge} is 4 times of DeBERTa and the computation cost is about 4 times of DeBERTa.

⁴T5 [1] has more parameters (11B). [1] only report the test results of T5 which are not comparable with models mentioned above.

We summarize the results in Table 4. Compared to the previous SOTA PLMs with a similar model size (i.e., BERT, RoBERTa, XLNet, ALBERT_{large}, Megatron_{336M} and DeBERTa_{large}), DeBERTaV3_{large} shows superior performance on all six tasks. We see a big performance jump on RACE(+2.4%) and SWAG(+2.6%), which require the models to have non-trivial reasoning capability [31] and common-sense knowledge [33]. We conjecture those improvements indicate DeBERTaV3_{large} has a better capability of reasoning and common sense knowledge. Although it is well proved to improve the model capacity by increasing the number of parameters [1, 5], compared with larger models, DeBERTaV3_{large} outperforms ALBERT_{xxlarge} and Megatron_{1.3B} by a large margin on all three tasks, as well as outperforming Megatron_{3.3B} on both MNLI and SQuAD v2.0. Compared with DeBERTa_{1.5B}, which used to be the SOTA NLU models on GLUE and SuperGLUE leaderboards, DeBERTaV3_{large} is still on par with it on MNLI but outperforms it on SWAG.

| Model | MNLI-m/mm Acc | SQuAD v2.0 F1/EM | RACE Acc | ReCoRD F1/EM | SWAG Acc | NER F1 |
|----------------------------|------------------|---------------------|-------------|-----------------|-------------|-----------|
| BERT _{large} | 86.6/- | 81.8/79.0 | 72.0 | - | 86.6 | 92.8 |
| ALBERT _{large} | 86.5/- | 84.9/81.8 | 75.2 | - | - | - |
| RoBERTa _{large} | 90.2/90.2 | 89.4/86.5 | 83.2 | 90.6/90.0 | 89.9 | 93.4 |
| XLNet _{large} | 90.8/90.8 | 90.6/87.9 | 85.4 | - | - | - |
| ELECTRA _{large} | 90.9/- | -/88.1 | - | - | - | - |
| Megatron _{336M} | 89.7/90.0 | 88.1/84.8 | 83.0 | - | - | - |
| DeBERTa _{large} | 91.1/91.1 | 90.7/88.0 | 86.8 | 91.4/91.0 | 90.8 | 93.8 |
| DeBERTaV3 _{large} | 91.8/91.9 | 91.5/89.0 | 89.2 | 92.3/91.8 | 93.4 | 93.9 |
| ALBERT _{xxlarge} | 90.8/- | 90.2/87.4 | 86.5 | - | - | - |
| Megatron _{1.3B} | 90.9/91.0 | 90.2/87.1 | 87.3 | - | - | - |
| Megatron _{3.9B} | 91.4/91.4 | 91.2/88.5 | 89.5 | - | - | - |
| DeBERTa _{1.5B} | 91.7/91.9 | 92.2/89.7 | 90.8 | 94.5/94.0 | 92.3 | - |

Table 4: Results on MNLI in/out-domain, SQuAD v2.0, RACE, ReCoRD, SWAG, CoNLL 2003 NER development set. Note that missing results in literature are signified by "-".

4.1.2 Performance on Base and Small Models

We evaluate DeBERTaV3_{base} and DeBERTaV3_{small} on two representative tasks, i.e., MNLI and SQuAD v2.0, and summarize the results in Table 5. DeBERTaV3_{base} consistently outperforms DeBERTa_{base} and ELECTRA_{base} by a larger margin than that in the Large models. For example, on MNLI-m, DeBERTaV3_{base} obtains an improvement of +1.8 (90.6% vs. 88.8%) over both DeBERTa_{base} and ELECTRA_{base}. On SQuAD v2.0 in terms of the EM score, DeBERTaV3_{base} achieves an improvement of +4.9% (85.4% vs. 80.5%) over ELECTRA_{base} and +2.3% (85.4% vs. 83.1%) over DeBERTa_{base}.

Compared with small-size models with a similar model structure, DeBERTaV3 $_{small}$ outperforms BERT $_{small}$ [37] by a large margin on those two tasks (i.e., a 6.4% improvement on MNLI-m and a 9.7% F1 score improvement on SQuAD v2.0). Surprisingly, even though DeBERTaV3 $_{small}$ has only half the parameters of DeBERTaV3 $_{small}$, it performs on par or even better than DeBERTaV3 $_{small}$ on these two tasks. We conjecture that this is due to DeBERTaV3 $_{small}$ has deeper layers which allows to extract better semantic features. Without knowledge distillation, DeBERTaV3 $_{small}$ outperforms MiniLMv2 $_{small}$ [38] by 1.2% and 1.3% on MNLI-m and SQuAD v2.0, respectively. DeBERTaV3 $_{small}$ outperforms MiniLMv2 $_{small}$ [38] by 1.2% and 2.5% on MNLI-m and SQuAD v2.0, respectively. It's worth noting that, even though DeBERTaV3 $_{small}$ has only 1/4 backbone parameters of RoBERTabase and XLNetbase, the former significantly outperforms both models on these two representative tasks (i.e. 0.5% improvement on MNLI-m and 1.5% EM score improvement on SQuAD v2.0). This further demonstrates the efficiency of the DeBERTaV3 models.

4.2 Multilingual Model

As an important extension, we extend DeBERTaV3 to multi-lingual. We train the multi-lingual model with the 2.5T CC100 multi-lingual dataset which is the same as XLM-R. We denote the model as mDeBERTa_{base}. We use the same SentencePiece vocabulary as mT5 which has 250k tokens. The model structure is the same as our base model, i.e., 768 hidden size, 12 layers, and 12 attention heads.

| Model | Vocabulary Size(K) | Backbone #Params(M) | MNLI-m/mm ACC | SQuAD v2.0 F1/EM | | | | | | |
|-----------------------------|---|------------------------|------------------|---------------------|--|--|--|--|--|--|
| Base models:12 la | ` ′ | ` ′ | 7100 | 1 1/21/1 | | | | | | |
| BERT _{base} | 30 | 86 | 84.3/84.7 | 76.3/73.7 | | | | | | |
| RoBERTa _{base} | 50 | 86 | 87.6/- | 83.7/80.5 | | | | | | |
| XLNetbase | 32 | 92 | 86.8/- | -/80.2 | | | | | | |
| ELECTRAbase | 30 | 86 | 88.8/- | -/80.5 | | | | | | |
| DeBERTa _{base} | 50 | 100 | 88.8/88.5 | 86.2/83.1 | | | | | | |
| DeBERTaV3 _{base} | 128 | 86 | 90.6/90.7 | 88.4/85.4 | | | | | | |
| Small models:6 lay | yers,768 hidde | n size,12 heads | | | | | | | | |
| TinyBERT _{small} | 30 | 44 | 84.5/- | 77.7/- | | | | | | |
| MiniLMv2 _{small} | 30 | 44 | 87.0/- | 81.6/ | | | | | | |
| BERT _{small} | 30 | 44 | 81.8/- | 73.2/- | | | | | | |
| DeBERTaV3 _{small} | 128 | 44 | 88.2/87.9 | 82.9/80.4 | | | | | | |
| XSmall models:12 | XSmall models:12 layers,384 hidden size,6 heads | | | | | | | | | |
| MiniLMv2 _{xsmall} | 30 | 22 | 86.9/- | 82.3/ | | | | | | |
| DeBERTaV3 _{xsmall} | 128 | 22 | 88.1/88.3 | 84.8/82.0 | | | | | | |

Table 5: Results on MNLI in/out-domain (m/mm) and SQuAD v2.0 development set. TinyBERT $_{small}$ [36], MiniLMv2 $_{small}$ and MiniLMv2 $_{small}$ models are pre-trained with knowledge distillation while BERT $_{small}$, DeBERTaV3 $_{small}$ and DeBERTaV3 $_{small}$ are trained from scratch with MLM and RTD objective, respectively.

It is worth noting that, unlike XLM or XLM-E, we have not trained our model with any parallel data ⁵. The pre-training settings are similar to XLM-R, except that we only train the model with 500k steps instead of 1.5M steps. As XNLI is one of the major benchmarks to measure multi-lingual model generalization performance, we evaluate the performance of mDeBERTa on XNLI across 15 languages. Following previous multi-lingual PLMs, we report both the zero-shot cross-lingual transfer performance and the translate train all performance. Zero-shot cross-lingual transfer is to fine-tune the model with English data only and evaluate it on multi-lingual test sets. Translate train all is to fine-tune the model with English data and multi-lingual data translated from English data which is provided together with the XNLI dataset[18], and then evaluate the model on multi-lingual test sets. As shown in Table 6, mDeBERTa_{base} significantly outperforms previous SOTA model XLM-R_{base} on all languages under both settings. With regards to the average score, mDeBERTa_{base} obtains an improvement of +3.6% (79.8% v.s. 76.2%) compared with XLM-R_{base} in the cross-lingual transfer setting, as well as achieving an improvement of +3.1% (82.2% v.s. 79.1%) compared with XLM-R_{base} under the translate train all setting. These results clearly show the effectiveness of DeBERTaV3 and the disentanglement is simultaneously valuable to multi-lingual pre-training.

All these clearly demonstrate the efficiency of the DeBERTaV3 models. The consistent improvements over a large range of the downstream tasks also show the huge value of improving pre-trained language models. We make all the DeBERTaV3 models publicly available on https://huggingface.co/models?other=deberta-v3 with instructions to reproduce the performance of the tasks mentioned above, as well as leveraging DeBERTaV3 for other tasks.

5 Conclusions

In this paper we explored methods to further improve the pre-training efficiency of PLMs. We start with combining DeBERTa with ELECTRA which shows a significant performance jump. Next, we perform extensive analysis and experiments to understand the interference issues between the generator and the discriminator which is well known as the "tug-of-war" dynamics. Further we proposed *gradient-disentangled embedding sharing* as a new building block of DeBERTaV3 to avoid the "tug-of-war" issue and achieve a better pre-training efficiency.

⁵we expect to have a better model by continually pre-training on parallel data and will release a new model when available

| Model | en | fr | es | de | el | bg | ru | tr | ar | vi | th | zh | hi | sw | ur | Avg |
|--------------------------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| Cross-lingual transfer | | | | | | | | | | | | | | | | |
| XLM | 83.2 | 76.7 | 77.7 | 74.0 | 72.7 | 74.1 | 72.7 | 68.7 | 68.6 | 72.9 | 68.9 | 72.5 | 65.6 | 58.2 | 62.4 | 70.7 |
| mT5 _{base} | 84.7 | 79.1 | 80.3 | 77.4 | 77.1 | 78.6 | 77.1 | 72.8 | 73.3 | 74.2 | 73.2 | 74.1 | 70.8 | 69.4 | 68.3 | 75.4 |
| XLM-R _{base} | 85.8 | 79.7 | 80.7 | 78.7 | 77.5 | 79.6 | 78.1 | 74.2 | 73.8 | 76.5 | 74.6 | 76.7 | 72.4 | 66.5 | 68.3 | 76.2 |
| mDeBERTa _{base} | 88.2 | 82.6 | 84.4 | 82.7 | 82.3 | 82.4 | 80.8 | 79.5 | 78.5 | 78.1 | 76.4 | 79.5 | 75.9 | 73.9 | 72.4 | 79.8 |
| Trasnlate train all | | | | | | | | | | | | | | | • | |
| XLM | 84.5 | 80.1 | 81.3 | 79.3 | 78.6 | 79.4 | 77.5 | 75.2 | 75.6 | 78.3 | 75.7 | 78.3 | 72.1 | 69.2 | 67.7 | 76.9 |
| mT5 _{base} | 82.0 | 77.9 | 79.1 | 77.7 | 78.1 | 78.5 | 76.5 | 74.8 | 74.4 | 74.5 | 75.0 | 76.0 | 72.2 | 71.5 | 70.4 | 75.9 |
| XLM-R _{base} | 85.4 | 81.4 | 82.2 | 80.3 | 80.4 | 81.3 | 79.7 | 78.6 | 77.3 | 79.7 | 77.9 | 80.2 | 76.1 | 73.1 | 73.0 | 79.1 |
| mDeBERTa _{base} | 88.9 | 84.4 | 85.3 | 84.8 | 84.0 | 84.5 | 83.2 | 82.0 | 81.6 | 82.0 | 79.8 | 82.6 | 79.3 | 77.3 | 73.6 | 82.2 |

Table 6: Results on XNLI test set under cross-lingual transfer and translate train all settings.

We evaluate the DeBERTaV3 on a broad range of representative NLU tasks and show the significant performance improvements over previous SOTA models, e.g., DeBERTaV3_{large} outperforms other models with a similar model structure by more than 1.37% with regards to GLUE average score and mDeBERTa_{base} outperforms XLM-R_{base} by 3.6% in terms of the cross lingual transfer accuracy on the XLNI task. Our results demonstrate the efficiency of all the DeBERTaV3 models and make DeBERTaV3 the new state-of-the-art PLMs for natural language understanding at multiple different model sizes, i.e., Large, Base, and Small. Meanwhile, this work clearly shows a huge potential to further improve model's parameter efficiency and provide some direction for future studies of far more parameter-efficient pre-trained language models.

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A Appendix

A.1 Dataset

| Corpus | Task | #Train | #Dev | #Test | #Label | Metrics | | | | |
|--|-----------------|---------|--------|-------|--------|-----------------------|--|--|--|--|
| General Language Understanding Evaluation (GLUE) | | | | | | | | | | |
| CoLA | Acceptability | 8.5k | 1k | 1k | 2 | Matthews corr | | | | |
| SST | Sentiment | 67k | 872 | 1.8k | 2 | Accuracy | | | | |
| MNLI | NLI | 393k | 20k | 20k | 3 | Accuracy | | | | |
| RTE | NLI | 2.5k | 276 | 3k | 2 | Accuracy | | | | |
| WNLI | NLI | 634 | 71 | 146 | 2 | Accuracy | | | | |
| QQP | Paraphrase | 364k | 40k | 391k | 2 | Accuracy/F1 | | | | |
| MRPC | Paraphrase | 3.7k | 408 | 1.7k | 2 | Accuracy/F1 | | | | |
| QNLI | QA/NLI | 108k | 5.7k | 5.7k | 2 | Accuracy | | | | |
| STS-B | Similarity | 7k | 1.5k | 1.4k | 1 | Pearson/Spearman corr | | | | |
| SuperGLUE | | | | | | | | | | |
| WSC | Coreference | 554k | 104 | 146 | 2 | Accuracy | | | | |
| BoolQ | QA | 9,427 | 3,270 | 3,245 | 2 | Accuracy | | | | |
| COPA | QA | 400k | 100 | 500 | 2 | Accuracy | | | | |
| СВ | NLI | 250 | 57 | 250 | 3 | Accuracy/F1 | | | | |
| RTE | NLI | 2.5k | 276 | 3k | 2 | Accuracy | | | | |
| WiC | WSD | 2.5k | 276 | 3k | 2 | Accuracy | | | | |
| ReCoRD | MRC | 101k | 10k | 10k | - | Exact Match (EM)/F1 | | | | |
| MultiRC | Multiple choice | 5,100 | 953 | 1,800 | - | Exact Match (EM)/F1 | | | | |
| | | Questio | n Answ | ering | | | | | | |
| SQuAD v1.1 | MRC | 87.6k | 10.5k | 9.5k | - | Exact Match (EM)/F1 | | | | |
| SQuAD v2.0 | MRC | 130.3k | 11.9k | 8.9k | - | Exact Match (EM)/F1 | | | | |
| RACE | MRC | 87,866 | 4,887 | 4,934 | 4 | Accuracy | | | | |
| SWAG | Multiple choice | 73.5k | 20k | 20k | 4 | Accuracy | | | | |
| Token Classification | | | | | | | | | | |
| CoNLL 2003 | NER | 14,987 | 3,466 | 3,684 | 8 | F1 | | | | |
| Multi-lingual Natural Language Inference(XNLI) | | | | | | | | | | |
| XNLI _{cross-lingual} | NLI | 393k | 37k | 75k | 3 | Accuracy | | | | |
| XNLI _{translate train} | NLI | 5.9M | 37k | 75k | 3 | Accuracy | | | | |

Table 7: Summary information of the NLP application benchmarks.

- **GLUE**. The General Language Understanding Evaluation (GLUE) benchmark is a collection of nine natural language understanding (NLU) tasks. As shown in Table 7, it includes question answering [39], linguistic acceptability [40], sentiment analysis [41], text similarity [42], paraphrase detection [43], and natural language inference (NLI) [15, 44, 45, 46, 47, 48]. The diversity of the tasks makes GLUE very suitable for evaluating the generalization and robustness of NLU models.
- **SuperGLUE**. SuperGLUE is an extension of the GLUE benchmark, but more difficult, which is a collection of eight NLU tasks. It covers a variety of tasks including question answering [32, 49, 50], natural language inference [44, 45, 46, 47, 51], coreference resolution [48] and word sense disambiguation [52].
- RACE is a large-scale machine reading comprehension dataset collected from English examinations in China designed for middle school and high school students [31].
- **SQuAD v1.1/v2.0** is the Stanford Question Answering Dataset (SQuAD) v1.1 and v2.0 [16, 39], two popular machine reading comprehension benchmarks from approximately 500 Wikipedia articles with questions and answers obtained by crowdsourcing. The SQuAD v2.0 dataset includes unanswerable questions about the same paragraphs.

- SWAG is a large-scale adversarial dataset for the task of grounded commonsense inference, which unifies natural language inference and physically grounded reasoning [33]. SWAG consists of 113k multiple choice questions about grounded situations.
- **CoNLL 2003** [34] is an English dataset consisting of text from a wide variety of sources. It has 4 types of named entities.
- XNLI [18] comes with ground truth dev and test sets in 15 languages, and a ground-truth English training set which is same as MNLI training set. The training set has been machine-translated to the remaining 14 languages, providing synthetic training data for these languages as well.

A.2 Pre-training Dataset

For DeBERTa pre-training, we use Wikipedia (English Wikipedia dump⁷; 12GB), BookCorpus [25] ⁸ (6GB), OPENWEBTEXT (public Reddit content [53]; 38GB) and STORIES⁹ (a subset of CommonCrawl [54]; 31GB). The total data size after data deduplication [35] is about 78GB. In addition, CC-News [55] data is also added to the training data of DeBERTa_{1.5B} and DeBERTaV3. The multi-lingual version of DeBERTaV3 is trained with 2.5TB CC100 data which is the same as XLM-R. For pre-training, we also sample 5% of the training data as the validation set to monitor the training process. Table 8 compares datasets used in different pre-trained models.

| Model | Wiki+Book | OpenWebText | Stories | CC-News | Giga5 | ClueWeb | Common Crawl | CC100 |
|--------------------------|-----------|-------------|----------|----------|----------|----------|--------------|----------|
| | 16GB | 38GB | 31GB | 76GB | 16GB | 19GB | 110GB | 2.5TB |
| BERT | √ | | | | | | | |
| XLNet | √ | | | | √ | √ | ✓ | |
| RoBERTa | √ | √ | √ | √ | | | | |
| DeBERTa | √ | ✓ | √ | | | | | |
| DeBERTa _{1.5B} | ✓ | ✓ | ✓ | ✓ | | | | |
| DeBERTaV3 | ✓ | ✓ | ✓ | ✓ | | | | |
| mDeBERTa _{base} | | | | | | | | √ |

Table 8: Comparison of the pre-training data.

A.3 Implementation Details

Our pre-training almost follows the same setting as DeBERTa [4]. The generators are trained with MLM where we randomly replace 15% input tokens with <code>[MASK]</code> tokens. The discriminator is trained with RTD which is the same as <code>ELECTRA</code>. The experiments in Section 3 are trained using Wikipedia English data and Bookcorpus data with a batch size of 2k for 125k steps. The experiments in Section 4 are trained using data listed in Table 8 with a batch size of 8k for 500k steps. We list the detailed hyper parameters of pre-training in Table 9. For pre-training, we use Adam [29] as the optimizer with weight decay [28]. For fine-tuning, we use Adam [29] as the optimizer for a fair comparison. For fine-tuning, we train each task with a hyper-parameter search procedure, each run taking about 1-2 hours on a DGX-2 node. All the hyper-parameters are presented in Table 10. The model selection is based on the performance on the task-specific development sets. Our fine-tuning script and hyper parameters are also available at https://github.com/microsoft/DeBERTa/tree/master/experiments/

Our code is implemented based on DeBERTa [4]¹⁰ and ELECTRA [8]¹¹.

⁷https://dumps.wikimedia.org/enwiki/

⁸https://github.com/butsugiri/homemade_bookcorpus

⁹https://github.com/tensorflow/models/tree/master/research/lm_commonsense

¹⁰https://github.com/microsoft/DeBERTa

¹¹ https://github.com/google-research/electra

| Hyper-parameter | $ DeBERTaV3_{large} $ | DeBERTaV3 _{base} | $\big DeBERTaV3_{small}$ | $mDeBERTa_{base}$ | DeBERTaV3 _{base-analysis} |
|-----------------------|-----------------------|---------------------------|---------------------------|-------------------|------------------------------------|
| Number of Layers | 24 | 12 | 6 | 12 | 12 |
| Hidden size | 1024 | 768 | 768 | 768 | 768 |
| FNN inner hidden size | 4096 | 3072 | 3072 | 3072 | 3072 |
| Attention Heads | 12 | 12 | 12 | 12 | 12 |
| Attention Head size | 64 | 64 | | 6464 | 64 |
| Dropout | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| Warmup Steps | 10k | 10k | 10k | 10k | 10k |
| Learning Rates | 3e-4 | 6e-4 | 6e-4 | 6e-4 | 5e-4 |
| Batch Size | 8k | 8k | 8k | 8k | 2k |
| Weight Decay | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| Max Steps | 500k | 500k | 500k | 500k | 125k |
| Learning Rate Decay | Linear | Linear | Linear | Linear | Linear |
| Adam ϵ | 1e-6 | 1e-6 | 1e-6 | 1e-6 | 1e-6 |
| Adam β_1 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 |
| Adam β_2 | 0.98 | 0.98 | 0.98 | 0.98 | 0.999 |
| Gradient Clipping | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |

Table 9: Hyper-parameters for pre-training DeBERTaV3.

| Hyper-parameter | DeBERTaV3 _{large} | DeBERTaV3 _{base} | DeBERTaV3 _{small} | mDeBERTaV3 _{base} |
|-------------------------|----------------------------|-----------------------------|----------------------------|-----------------------------|
| Dropout of task layer | {0,0.15,0.3} | {0,0.1,0.15} | {0,0.1,0.15} | {0,0.1,0.15} |
| Warmup Steps | {50,100,500,1000} | {50,100,500,1000} | {50,100,500,1000} | {50,100,500,1000} |
| Learning Rates | {5e-6, 8e-6, 9e-6, 1e-5} | {1.5e-5,2e-5, 2.5e-5, 3e-5} | {1.5e-5,2e-5, 3e-5, 4e-5} | {1.5e-5,2e-5, 2.5e-5, 3e-5} |
| Batch Size | {16,32,64} | {16,32,48,64} | {16,32,48,64} | {16,32,48,64} |
| Weight Decay | 0.01 | 0.01 | 0.01 | 0.01 |
| Maximun Training Epochs | 10 | 10 | 10 | 10 |
| Learning Rate Decay | Linear | Linear | Linear | Linear |
| Adam ϵ | 1e-6 | 1e-6 | 1e-6 | 1e-6 |
| Adam β_1 | 0.9 | 0.9 | 0.9 | 0.9 |
| Adam β_2 | 0.999 | 0.999 | 0.999 | 0.999 |
| Gradient Clipping | 1.0 | 1.0 | 1.0 | 1.0 |
| | | | | |

Table 10: Hyper-parameters for fine-tuning DeBERTa on down-streaming tasks.