

# Improved Pretraining for Domain-specific Contextual Embedding Models

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## Abstract

We investigate methods to mitigate *catastrophic forgetting* during domain-specific pretraining of contextual embedding models such as BERT, DistilBERT, and RoBERTa. Recently proposed domain-specific models such as BioBERT, SciBERT and ClinicalBERT are constructed by continuing the pretraining phase on a domain-specific text corpus. Such pretraining is susceptible to catastrophic forgetting, where the model forgets some of the information learned in the general domain. We propose the use of two continual learning techniques (rehearsal and elastic weight consolidation) to improve domain-specific training. Our results show that models trained by our proposed approaches can better maintain their performance on the general domain tasks, and at the same time, outperform domain-specific baseline models on downstream domain tasks.

## 1 Introduction

Recently proposed pretrained contextual word embedding (CWE) models such as BERT (Devlin et al., 2018), ELMO (Peters et al., 2018), GPT (Radford et al., 2018), XLNet (Yang et al., 2019) RoBERTa (Liu et al., 2019), DistilBERT (Sanh et al., 2019) and ALBERT (Lan et al., 2019) are widely used in natural language processing tasks. CWE models use unsupervised pretraining to train RNN or Transformer based neural network models on large general corpora like Wikipedia and Gigaword. Simply replacing the hidden layers in an existing neural architecture by a pretrained CWE model leads to large performance improvements.

Due to their massive success in NLP applications combined with their ease of use and access, researchers have worked on adapting these embeddings for specific sub-domains. Here, adap-

tation works as a simple domain transfer technique (SDT) by using the pretrained CWE model weights as initialization and continuing the pretraining on a large domain-specific unlabeled text corpus. This domain-specific CWE model is then used as initialization for supervised finetuning on domain-specific downstream tasks. This process has been followed in the biomedical, clinical, and scientific domains to produce BioBERT (Lee et al., 2019), ClinicalBERT (Alsentzer et al., 2019) and SciBERT (Beltagy et al., 2019) models. For this paper, we call the pretraining on general domain as “GD-pretraining”, the continued pretraining on domain-specific corpora as “DS-pretraining”, and the final supervised training on the downstream domain-specific task as “finetuning”.

We refer to the aforementioned domain transfer technique as SDT (simple domain transfer) and treat it as a baseline. SDT is susceptible to *catastrophic forgetting* (Kirkpatrick et al., 2017; McCloskey and Cohen, 1989). It forces the model to forget some of the information learned during GD-pretraining. We observe this behavior in our experiments when we evaluate the performance of SDT models on general domain tasks. SDT models show improved performance on the domain-specific tasks at the cost of losing information learned from the general domain corpus.

In this work, we hypothesize that high capacity models such as BERT, when trained with methods that mitigate *catastrophic forgetting*, can produce CWE models that adapt well to domain-specific tasks while retaining general domain information. In addition, we also hypothesize that reducing *catastrophic forgetting* or retaining more general domain information can lead to *positive forward transfer* (Lopez-Paz and Ranzato, 2017), and therefore, can improve performance in domain-specific tasks while still preserving high performance in general domain.

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We evaluate our hypothesis by analyzing three commonly used CWE models: BERT, ROBERTa, and DistilBERT. We evaluate two different approaches to mitigate the effects of *catastrophic forgetting*: a simple multi-task Rehearsal scheme (Ratcliff, 1990) and Elastic Weight Consolidation (EWC) (Kirkpatrick et al., 2017). We use the bio-medical domain as an example of our target domain and use extractive question answering and natural language inference as our downstream tasks.

Our contributions are three-fold:

- We propose and evaluate improved domain-specific continual training procedures for CWE models. These methods often outperform standard DS-pretraining baselines, while retaining general domain performance.
- We release BERT, ROBERTa, and DistilBERT models trained using our proposed approaches for the bio-medical domain.
- We also release code to pre-process the bio-medical dataset and DS-pretrain any CWE model on PyTorch using EWC and Rehearsal.

## 2 Proposed Methods

Contextual Word Embedding models (CWE) such as BERT, DistilBERT and ROBERTa are GD-pretrained using various language modeling (LM) objectives (along with distillation loss in case of DistilBERT) on large general domain unsupervised text corpora. Since LM loss is a negative log likelihood objective, we abstract the details of the loss for each model and refer to it as the likelihood objective  $\log P(D|\theta)$ . Here  $\theta$  denotes the parameters of the neural network and  $D$  is the training dataset. In the context of our training, we define the general domain unlabeled dataset as  $D_g$ , and the domain specific unlabeled dataset as  $D_d$ . A CWE model GD-pretrained on the general domain dataset  $D_g$  is DS-pretrained on the domain-specific dataset  $D_d$  to obtain a domain-specific CWE model. The domain-specific CWE model can then be used in supervised finetuning for a downstream task.

SDT’s DS-pretraining phase uses the objective  $\log P(D_d|\theta)$ . Our proposed methods improve DS-pretraining by attempting to eliminate catastrophic forgetting during this phase. For this, we employ two approaches, which are described in the following sub-sections.

### 2.1 Rehearsal

Rehearsal is a simple DS-pretraining scheme that avoids catastrophic forgetting by using a multi-task objective to rehearse the previous task (Ratcliff, 1990). It includes a few examples from the previous task (or dataset)  $D_g$  during DS-pretraining on  $D_d$ . This trains the model to do well on both datasets. The included  $D_g$  data is usually a small percentage compared to the data for the new task. This can be interpreted as a multi-task learning model with a smaller weight associated with  $D_g$ .

For our task, we need to ensure the model learns good representations for words in the new domain while also preserving its performance in the general domain. So in each training batch, we add some examples of text from the general corpus that the language model was originally trained on. The rehearsal objective is thus given by  $\log P(\theta|D_d, D_g) = \log P(D_d|\theta) + \alpha \log P(D_g|\theta)$ , where  $\alpha$  is a scaling parameter.

### 2.2 Elastic Weight Consolidation (EWC)

In a Continual learning (Kirkpatrick et al., 2017) framework, the goal is to learn on a new task while avoiding *catastrophic forgetting* in previously learned tasks. The continual learning procedure differs from the multi-task loss defined in 2.1 in that it uses the posterior probability of  $\theta$  given previous tasks. In our framework it translates to  $\log P(\theta|D_d, D_g) \propto \log P(D_d|\theta) + \log P(\theta|D_g)$ .

The posterior distribution  $\log P(\theta|D_g)$  is intractable in deep neural network models such as BERT. The procedure for elastic weight consolidation (Kirkpatrick et al., 2017) approximates this term by using Laplace approximation (MacKay, 1992). Intuitively, the term  $\log P(\theta|D_g)$  denotes information about the weights  $\theta$  in the context of the previous dataset  $D_g$ . Kirkpatrick et al. (2017) remark that this information refers to which parameter values are important for the previous task. The objective with laplace approximation is

$$\log P(\theta|D_d, D_g) = \log P(D_d|\theta) - \sum_i \frac{\lambda}{2} F_i (\theta_i - \theta_{g,i}^*)^2,$$

where  $\lambda$  is the importance of the previous dataset  $D_g$ , and  $F_i$  is the  $i^{th}$  element in the diagonal of the Fisher information matrix. The parameters  $\theta_g^*$  are produced by GD-pretraining on  $D_g$ . The term  $\log P(\theta|D_g)$  is approximated by a Gaussian with

mean  $\theta_g^*$  and diagonal precision  $F$ . The EWC term stops parameters that are important for the previous task  $D_g$  from changing too much during EWC training. For more details refer to [Kirkpatrick et al. \(2017\)](#).

### 3 Experimental Setup

We choose three popular word embedding models for our experiments: BERT, RoBERTa, and DistilBERT. We collect general domain and domain-specific corpora based on related efforts in literature. We use bio-medical domain for our domain-specific experiments. Further experimental details are included in the Appendix.

**General-Domain Corpus:** We use the WikiText corpus, which is a large common part of the datasets used for GD-pretraining BERT, RoBERTa and DistilBERT, as our general domain dataset  $D_g$ .

**Domain-Specific Corpus:** The bio-medical text corpus is created by crawling through a snapshot of all the abstracts of papers made available by PubMed Central <sup>1</sup>. PubMed Central is a free full-text archive of biomedical and life sciences journal literature at the U.S. National Institutes of Health’s National Library of Medicine (NIH/NLM). We also extract all the clinical notes from the MIMIC-III corpus ([Johnson et al., 2016](#)), which consists of electronic health records of patients who stayed within the intensive care units at Beth Israel Deaconess Medical Center. This corpus is identical to the one used by [Alsentzer et al. \(2019\)](#) and a superset of [Lee et al. \(2019\)](#).

**Tasks:** We evaluate the performance of our embedding models on two tasks, Question-Answering (QA) and Natural Language Inference (NLI). For the general domain, we pick SQuAD 2.0 ([Rajpurkar et al., 2018](#)) for QA and SNLI ([Bowman et al., 2015](#)) for NLI. For the bio-medical domain, we evaluate on emrQA ([Pamprai et al., 2018](#)) <sup>2</sup> and MedNLI ([Romanov and Shivade, 2018](#)).

**Resources:** Our experiments are based on Huggingface’s PyTorch library ([Wolf et al., 2019](#)). We use the publicly released model weights as

our GD-pretrained models<sup>3</sup>. We performed DS-pretraining on eight 1080ti and 2080ti GPUs each, with an overall batch size in the range 8-32 for five days due to computational constraints. The supervised finetuning experiments for downstream evaluation tasks were run on two titanx GPUs.

### 4 Results and Discussion

Table 1 documents all our experimental results. On general tasks, we observe prominent drops in performance for the baseline Simple Domain Transfer (SDT) models that are built by simply continuing pretraining on the bio-medical corpus.

**BERT:** These drops are most noticeable in models with the BERT configuration, where SDT reduces the base model’s performance on SQuAD by 6.4 accuracy points and on SNLI by 1.7 accuracy points. Rehearsal mitigates this slightly by reducing the drop by 1 point. BERT models trained with EWC, on the other hand, perform almost as well as the BERT-base model; they are within 0.5 accuracy points of the base models’ performance. Furthermore, we observe *positive forward transfer* for BERT models with EWC on bio-medical tasks. BERT models trained with EWC outperform BERT-base and BERT-SDT on emrQA and MedNLI tasks. We attribute these improvements to improved regularization and continual learning that is induced by the EWC penalty for high capacity models such as BERT, as originally hypothesized.

**RoBERTa:** We see similar trends for RoBERTa models. The performance numbers across all tasks are higher for the RoBERTa variants than BERT, which is in line with results described in [Liu et al. \(2019\)](#). We observe that RoBERTa models trained with Rehearsal and EWC are closer to the base RoBERTa models on general tasks compared to SDT models. At the same time, they also outperform RoBERTa-SDT baseline on the MedNLI task. For emrQA however, the results were too close to each other to draw any conclusions.

**DistilBERT:** For this setting, we see the same trend for NLI tasks. EWC outperforms all other approaches on MedNLI, while also staying closest to the base model on SNLI. However, on emrQA, the SDT model achieves the higher performance, beating both Rehearsal and EWC. We be-

<sup>1</sup><https://www.ncbi.nlm.nih.gov/pmc/>

<sup>2</sup>The emrQA dataset was transformed into SQuAD-style and examples which could not be transformed were removed.

<sup>3</sup> bert-base-uncased, roberta-base, and distilbert-base-uncased from <https://github.com/huggingface/transformers>

		General domain			Bio-medical domain		
		SQuAD		SNLI	EMRQA		MedNLI
		EM	F-score	Accuracy	EM	F-score	Accuracy
BERT	Base	72.4	75.7	90.4	74.7	80.3	78.5
	SDT	66.0 (-6.4)	69.7 (-6.0)	88.7 (-1.7)	75.2 (+0.5)	80.8 (+0.5)	78.8 (+0.3)
	Rehearsal	67.1 (-5.3)	70.8 (-4.9)	89.4 (-1.0)	75.7 (+1.0)	81.0 (+0.7)	78.2 (-0.3)
	EWC	<b>71.9 (-0.5)</b>	<b>75.2 (-0.5)</b>	<b>89.9 (-0.5)</b>	<b>76.1 (+1.4)</b>	<b>81.7 (+1.4)</b>	<b>79.7 (+1.2)</b>
ROBERTa	Base	77.2	80.7	91.5	74.5	80.4	79.9
	SDT	73.6 (-3.6)	77.3 (-3.4)	90.7 (-0.8)	<b>74.7 (+0.2)</b>	80.3 (-0.1)	82.2 (+2.3)
	Rehearsal	76.2 (-1.0)	79.7 (-1.0)	91.0 (-0.5)	74.6 (+0.1)	<b>80.6 (+0.2)</b>	82.5 (+2.6)
	EWC	<b>76.8 (-0.4)</b>	<b>80.4 (-0.3)</b>	<b>91.2 (-0.3)</b>	74.2 (-0.3)	80.4 (+0.0)	<b>82.6 (+2.7)</b>
DistilBERT	Base	66.9	69.6	89.9	73.4	79.2	75.9
	SDT	66.7 (-0.2)	69.7 (+0.1)	88.5 (-1.4)	<b>75.0 (+1.6)</b>	<b>80.5 (+1.3)</b>	77.6 (+1.7)
	Rehearsal	<b>67.7 (+0.8)</b>	<b>70.3 (+0.7)</b>	88.6 (-1.3)	74.4 (+1.0)	80.1 (+0.9)	77.2 (+1.3)
	EWC	67.3 (+0.4)	69.7 (+0.1)	<b>89.1 (-0.8)</b>	74.4 (+1.0)	80.3 (+1.1)	<b>78.3 (+2.4)</b>

Table 1: Results from our experiments across all models and techniques. We see that EWC models are consistently closest to the base models on general tasks and outperform SDT and Rehearsal models on bio-medical tasks.

lieve the small parameter size of DistilBERT can explain this. The high capacity of BERT and ROBERTa results in a large free-parameter size to meet the constraints of both domain-specific and general domain datasets. The smaller size of DistilBERT does not have enough capacity to perform “well” on complex question answering tasks for both domains. For effective continual learning in such models, we may have to employ methods that also continually increase model capacity (Schwarz et al., 2018). Also surprisingly, in the SQuAD task, we observe *positive backward transfer* for Rehearsal and EWC models, i.e. they beat DistilBERT-base’s performance on this task. Since we are unable to replicate this for BERT and ROBERTa models, we believe this behaviour could be an artifact of the distillation based training process of DistilBERT and our datasets. Details are provided in the Appendix.

Finally, we note that our models are pretrained on the domain-specific corpus for a shorter period of time than other models in literature such as ClinicalBERT or BioBERT due to computational constraints. However, we believe our results are still supportive of our hypotheses since continuing the pretraining on the biomedical corpus will only lead to more catastrophic forgetting in SDT models.

## 5 Related Work

**Domain-Specific Pretraining:** The task of adapting pretrained language models for

a specific domain is popular in literature. BioBERT (Lee et al., 2019) and ClinicalBERT (Alsentzer et al., 2019) were built for the bio-medical domain from a baseline BERT model by finetuning on a biomedical corpus consisting of PubMed articles and the MIMIC-III dataset, just like ours. However, these models are finetuned by simply training further on new text. SciBERT (Beltagy et al., 2019) is also trained in this fashion but also has its own domain-specific vocabulary. We train simple domain transfer models on our data as one of our baselines.

**Continual Learning:** Several existing works in continual learning focus on overcoming *catastrophic forgetting* when learning on new tasks. Methods like EWC (Kirkpatrick et al., 2017), Variational Continual Learning (Nguyen et al., 2017), and Synaptic Intelligence (Zenke et al., 2017) use different regularization approaches to constrain the training on new tasks. Methods like Progress and Compress (Schwarz et al., 2018) use modifications to the neural network architecture to increase the capacity of the neural network for a new task. For our purposes, we focus only on a regularization based continual learning scheme like EWC. The high capacity of contextual word embedding models like BERT precludes the use of capacity increasing methods used in Progress and Compress.

## 6 Conclusion

We proposed new approaches to mitigate the effect of *catastrophic forgetting* while adapting con-

textual word embedding models such as BERT to a specific domain. Our best continual learning model based on Elastic Weight Consolidation outperforms existing approaches on domain-specific downstream tasks while also maintaining higher performance on general domain tasks.

We would also like to explore the power of continual learning approaches on directly finetuning for downstream tasks. We leave this to future work.

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## A Implementation Details

To train models using Masked LM (MLM) objective, we create instances containing contiguous spans for text from the text corpus and mask a small random percentage of words in them. Following BERT’s implementation detail, we also mask 15% of the words. The model is then trained to predict these masked out words using all the visible words. For BERT we also used a next sentence prediction (NSP) objective which enables the model to learn language inference features by tasking the model to differentiate between two continuous spans of text and two randomly chosen spans of text. RoBERTa has shown that the NSP objective can be removed without affecting the performance of the overall model and hence doesn’t use NSP prediction objective for training.

For all SNLI and MedNLI downstream tasks, we used the default hyper-parameters provided by <https://github.com/huggingface/transformers> for NLI tasks. For SQuAD and emrQA, all the default parameters are kept same except the maximum number of training epochs. For emrQA, all models are run for 5 epochs. For SQuAD, BERT and RoBERTa are run for 2 epochs whereas DistilBERT is only run for 1 epoch. During experiments we observed that DistilBERT’s performance decreases significantly if trained for more than 1 epoch.

**Rehearsal Pretraining** For rehearsal DS-pretraining scheme we used 1 example from the original dataset ( $D_g$ ) for every 3 examples of domain specific dataset ( $D_d$ ) during finetuning. In the rehearsal objective, we weighted the loss of  $D_g$  samples by 0.1 ( $\alpha = 0.1$ ).

**Elastic Weight Consolidation (EWC) Pretraining** For EWC pretraining, we randomly choose 20% of the WikiText corpus to calculate the diagonal precision matrix. We use the default value of 1000 for the importance ( $\lambda$ ) of the EWC loss.

## B Dataset Details

For the question answering datasets, SQuAD and emrQA, we used a doc stride of 128 and a window size of 384 across all the datapoints for each model<sup>4</sup>. This results in upsampling of certain question answer pairs with different context passage windows. We also reject question answer pairs where the answer is not within the context size. For SNLI, the datapoints with ‘-’ as their gold label were ignored resulting in slightly fewer datapoints after processing. These processing steps results in different pre and post processed dataset size. These statistics are presented in Table 2.

	Pre-processed		Post-processed	
Dataset	# Train	# Test	# Train	# Test
SQuAD	130,319	11,873	135,228	12,661
emrQA	262,998	61,398	280,888	66,457
SNLI	560,151	9,999	559,208	9,823
MedNLI	12,626	1,421	12,626	1,421

Table 2: Number of original and post-processed datapoints for each dataset.

## C Explanation of DistilBERT’s behavior on QA

We have two surprising observations from the DistilBERT models on the QA tasks. We observe *positive backward transfer* for our Rehearsal and EWC models on the SQuAD dataset, with DistilBERT-Rehearsal achieving the highest overall performance among the DistilBERT models. A possible reason for this could be the additional WikiText data we use to DS-pretrain the Rehearsal model.

We also observe that the SDT model achieves the best performance on emrQA, beating EWC. Our hypothesis about *positive forward transfer* due to continual learning does not seem to hold here. We believe this is because of the capacity

<sup>4</sup>These are default values from <https://github.com/huggingface/transformers> implementation

of DistilBERT. DistilBERT contains way fewer parameters than BERT or RoBERTa. For language modeling on the general domain, we expect a lot of these parameters to be important i.e. the diagonal precision values in the Fisher information matrix are expected to be high for a large number of parameters. This hinders the domain-specific pre-training, which in turn affects our performance on emrQA. As suggested in the main paper, for effective continual learning in these models, we may have to employ methods that also continually increase model capacity.