Neural Semi-supervised Learning for Text Classification Under Large-Scale Pretraining

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Abstract

The goal of semi-supervised learning is to utilize the unlabeled, in-domain dataset \( U \) to improve models trained on the labeled dataset \( D \). Under the context of large-scale language-model (LM) pretraining, how we can make the best use of \( U \) is poorly understood: Is semi-supervised learning still beneficial with the presence of large-scale pretraining? Should \( U \) be used for in-domain LM pretraining or pseudo-label generation? How should the pseudo-label based semi-supervised model be actually implemented? How different semi-supervised strategies (e.g., self-learning) affect performances regarding \( D \) of different sizes, \( U \) of different sizes, etc.

In this paper, we conduct comprehensive studies on semi-supervised learning in the task of text classification under the context of large-scale LM pretraining. Our studies shed important lights on the behavior of semi-supervised learning methods. We find that: (1) with the presence of in-domain LM pretraining on \( U \), open-domain LM pretraining (Devlin et al., 2018) is unnecessary, and we are able to achieve better performance with pretraining on the in-domain dataset \( U \); (2) both the in-domain pretraining strategy and the pseudo-label based strategy introduce significant performance boosts, with the former performing better with larger \( U \), the latter performing better with smaller \( U \), and the combination leading to the largest performance gain; (3) vanilla self-training (pretraining first on the pseudo-label dataset \( D' \) and then fine-tuning on \( D \)) yields better performances when \( D \) is small, while joint training on the combination of \( D' \) and \( D \) yields better performances when \( D \) is large.

Using semi-supervised learning strategies, we are able to achieve a performance of around 93.8% accuracy with only 50 training data points on the IMDB dataset, and a competitive performance of 96.6% with the full IMDB dataset. Our work marks an initial step toward understanding the behavior of semi-supervised learning models under the context of large-scale pretraining.

1 Introduction

Because of the fact that obtaining supervised training labels is costly and time-intensive, and that unlabeled data is relatively easy to obtain, semi-supervised learning (Chapelle et al., 2006; Zhu, 2005), which utilizes in-domain unlabeled data \( U \) to improve models trained on the labeled dataset \( D \), is of growing interest. Under the context of large-scale of language model pretraining (Devlin et al., 2018; Yang et al., 2019; Liu et al., 2019; Lewis et al., 2019; Bao et al., 2020; Joshi et al., 2020), where a language model is pretrained on an extremely large, open-domain dataset (denoted by \( \text{large} U \), with \( |\text{large} U| \gg |U| \)), how we can make the best use of the in-domain unlabeled dataset \( U \) is poorly understood. There are basically two ways to take advantages of the unlabeled, in-domain dataset \( U \): in-domain pretraining\(^2\), where a language model is pretrained on the in-domain dataset \( U \), and then fine-tuned on \( D \); pseudo-label based approach (Lee, 2013; Reed et al., 2015; Iscen et al., 2019; Shi et al., 2018; Arazo et al., 2020), where unlabeled data points are assigned with labels predicted by the model trained on \( D \) (referred to as the teacher model), forming a new dataset \( D' \). A new model (referred to as the student model) is trained for final predictions by considering \( D' \).

Many important questions regarding the behavior of

\(^1\)Code, models and datasets can be found at https://github.com/ShannonAI/Neural-Semi-Supervised-Learning-for-Text-Classification

\(^2\)To note, the pretraining on the in-domain dataset \( U \) is distinguished from the pretraining on the large-scale, open-domain dataset \( \text{large} U \). The model for in-domain pretraining can be randomly initialized or taking a pretrained model based on the open-domain dataset \( \text{large} U \) (Gururangan et al., 2020).
semi-supervised learning models under the context of large-scale LM pretraining remain unanswered: Is semi-supervised training still beneficial with the presence of large scale pretraining on large $U$? Should $U$ be used for in-domain LM pretraining or pseudo-label generation? How should pseudo-label based semi-supervised models be implemented? How different semi-supervised strategies (e.g., self learning) affect performances regarding $D$ of different sizes, and $U$ of different sizes, etc.

In this paper, we conduct comprehensive studies on the behavior of semi-supervised learning in NLP with the presence of large-scale language model pretraining. We use the task of text classification as an example, the method of which can be easily adapted to different NLP tasks. Our work sheds important lights on the behavior of semi-supervised learning models: we find that (1) with the presence of in-domain pretraining LM on $U$, open-domain LM pretraining (Devlin et al., 2018) is unnecessary, and we are able to achieve better performance with pretraining on the in-domain dataset $U$; (2) both the in-domain pretraining strategy and the pseudo-label based strategy lead to significant performance boosts, with the former performing better with larger $U$, the latter performing better with smaller $U$, and the combination of both performing the best; (3) for pseudo-label based strategies, self-training (pretraining first on the pseudo-label dataset $D'$ and then fine-tuning on $D$) yields better performances when $D$ is small, while joint training on the combination of $D'$ and $D$ yields better performances when $D$ is large.

Using semi-supervised learning models, we are able to achieve a performance of around 93 – 94% accuracy with only 50 training data points on the IMDB dataset, and a competitive performance of 96.6% with the full dataset. More importantly, our work marks an initial step toward understanding the behavior of semi-supervised learning models in the context of large-scale pretraining.

The rest of this paper is organized as follows: related work is detailed in Section 2. Different strategies for training semi-supervised models are shown in Section 3. Experimental results and findings are shown in Section 4, followed by a brief conclusion in Section 5.

2 Related Work

2.1 Semi-Supervised Learning

The goal of semi-supervised learning (Chapelle et al., 2006; Zhu, 2005) is to use massive amount of unlabeled data to improve the models trained on labeled data. One widely-used type of semi-supervised method is the pseudo-label based method (Lee, 2013; Reed et al., 2015; Iscen et al., 2019; Shi et al., 2018; Arazo et al., 2020), where unlabeled data points are assigned with labels predicted by a trained model, forming a large pseudo labeled dataset to train a model. Self-training (Scudder, 1965; Riloff and Wiebe, 2003) is a specific type of pseudo-label based method that is of growing interest. Self-training involves training two models: a “teacher” used to label unlabeled data, which is used as an augmented labeled dataset. Then a “student” is trained on the newly augmented dataset. This process can be iterated to further boost performances. Self-training has been successfully applied in different fields such as computer vision (Yalniz et al., 2019; Babakhin et al., 2019; Xie et al., 2020; Chen et al., 2020; Zoph et al., 2020), automatic speech recognition (ASR) (Parthasarathi and Strom, 2019). In Vision, Yalniz et al. (2019) adopted the self-training paradigm in image classification, and achieves the state-of-the-art top-1 result on ImageNet benchmark; Xie et al. (2020) proposed the strategy of Noisy Student Training, a variant of self-training built on top of EfficientNet (Tan and Le, 2020). In ASR, Parthasarathi and Strom (2019) trained an ASR model on one million hours of unlabeled speech data using a teacher-student self-training model. Park et al. (2020) proposed the concept of normalized filtering score that filters out low-confident utterance-transcript pairs generated by the teacher to mitigate the noise introduced by the teacher model.

In the context of natural language processing (NLP), the concept of semi-supervised learning has been adopted in different NLP tasks such as machine translation (Cheng et al., 2016; Tu et al., 2016; Ramachandran et al., 2016; Edunov et al., 2018; Clark et al., 2018), information extraction (Liao and Veeramachaneni, 2009; Peters et al., 2017), text classification (Nigam et al., 2006; Dai and Le, 2015; Miyato et al., 2016; Howard and Ruder, 2018; Karanamolakis et al., 2019; Li et al., 2019a), and text generation (Zang and Wan, 2019; Qader et al., 2019; Shang et al., 2019). Particularly, He et al. (2019)
studied the efficacy of self-training on sequence generation tasks and found that self-training can significantly boost performances, particularly when labeled data is scarce. Besides, they also pointed out that the core of self-training for sequence generation tasks is the noise injected into the neural model, which can be interpreted to smooth the latent sequence space.

Word vector models (Mikolov et al., 2013b,a; Pennington et al., 2014; Mikolov et al., 2013a; Levy and Goldberg, 2014) and language modeling pretraining (Devlin et al., 2018; Yang et al., 2019; Liu et al., 2019; Lewis et al., 2019; Bao et al., 2020; Joshi et al., 2020) can also be viewed as a specific type of semi-supervised learning model, by leveraging the information of data in the general domain. Other strategies for training semi-supervised models involve co-training (Qiao et al., 2018; Chen et al., 2019), low-density separation (Grandvalet and Bengio, 2005; Dai et al., 2017).

2.2 Data Augmentation

Data augmentation aims at increasing the amount of training data by adding slightly modified copies of existing data points or created new synthetic data based on existing data points (Krizhevsky et al., 2012; Paulin et al., 2014; Laine and Aila, 2016; Sajjadi et al., 2016; Cubuk et al., 2018; Inoue, 2018; Cubuk et al., 2020). The concept consistencies training (Rasmus et al., 2015; Sajjadi et al., 2016; Laine and Aila, 2017; Tarvainen and Valpola, 2018; Miyato et al., 2018; Luo et al., 2018; Athiwaratuk et al., 2019; Li et al., 2019b; Verma et al., 2019; Liu et al., 2020) is widely used as a regulation to force the label of modified copies to the same as the original label.

In NLP, modified copies of existing data points are generated usually by synonym replacement and text editing (Zhang et al., 2015; Kobayashi, 2018; Wei and Zou, 2019; Gao et al., 2019), back-translation (Sennrich et al., 2016; Edunov et al., 2018; Xie et al., 2019), noise injection (Wang and Yang, 2015; Xie et al., 2017, 2018), mixup (Guo et al., 2019), generation (Anaby-Tavor et al., 2019; Wu et al., 2019; Kumar et al., 2020). Data augmentation has introduced significant performance boost especially in low-resource scenarios (Fadaee et al., 2017; Bergmanis et al., 2017; Şahin and Steedman, 2018; Xia et al., 2019; Shleifer, 2019; Singh et al., 2019).

3 Models

3.1 Notations

We use the task of text classification for illustration purposes, in which the goal is to assign a label $y$ to a given input $x$. $x$ is a sequence of words. We have a given labeled set $D = \{x_i, y_i\}, i \in [1, N_D]$, where $N_D$ denotes the number of data points in $D$. In addition, we have an in-domain unlabeled dataset $U$ of size $N_U$, where $N_U \gg N_D$. The goal of semi-supervised learning is to explore how the unlabeled in-domain dataset $U$ can be leveraged at the training time. At test time, inference remains the same as the original setup.

3.2 In-domain LM Pretraining

A direct way to take advantage of $U$ is to pretrain a BERT (Devlin et al., 2018), RoBERTa (Liu et al., 2019) or GPT3 (Brown et al., 2020) style language model on $U$ by predicting a masked word given surrounding contexts or predicting a subsequent word given proceeding contexts. Pretraining on the in-domain data facilitates the learning of in-domain semantics and word compositions.

For training, the LM model can be trained from scratch with random initialization or initialized using an existing BERT or RoBERTa model trained on an open-domain dataset, the latter of which is similar to the idea in Gururangan et al. (2020), which continues LM pretraining in different domains and tasks. The LM model trained on $U$ is used as initialization to be further finetuned on $D$.

3.3 Pseudo-label Based Approach

Another way to take advantage of $U$ is to use the model trained on $D$ to assign pseudo labels to data points in $U$. Specifically, the model trained on $D$ is referred to as the teacher model. The teacher model is used to assign pseudo labels to $U$ or a specific portion of $U$, forming the augmented dataset $D'$. Let $N_{D'}$ denote the number of selected examples in $D'$. There are different options on how to generate $D'$, how $D$ and $D'$ are combined, and how the new model can be trained on the combination. The model trained on the combination is referred to as the student model.

The teacher and the student can share a similar model backbone. In the text classification task, various structures can be used as the backbone such as LSTMs (Hochreiter and Schmidhuber, 1997; Tang et al., 2016), CNNs (Kim, 2014), BERT (Devlin et al., 2018), and many others. The teacher model trains the student model on the augmented dataset $D'$, which is constructed by combining the teacher's predictions and the original data $D$. This process can be iterated, allowing the model to continuously improve its performance through self-training.
3.3.1 Different strategies to construct \( D' \)

Here we discuss different strategies to generate \( D' \).

**Naive Strategy** \( D' = U \): The teacher model is used to label all instances in \( U \) to form \( D' \). The shortcoming for this strategy is that incorrect and low-confident labels included in \( D' \) can be severely detrimental to the student model.

**Top-K Model Predictions:** To avoid the negative effect from the low-confident labels assigned by the teacher, we can only pick the confident ones. The teacher model is run on each example in \( U \) to obtain the probability of all classes. Then for each class \( l \), we rank all instances in \( U \) based on the corresponding probabilities. The top-\( K \) instances for each class are selected to form \( D' \).

3.3.2 Different Strategies for Student Training

Here we discuss how models can be trained given \( D' \) and \( D \).

**Training on \( D + D' \):** This strategy is denoted by \( T(D + D') \). The most straightforward strategy is to train the student model on the union of \( D \) and \( D' \). The potential risk with this naive strategy is that the influence from clean labels in \( D \) can be diluted if the size of \( D' \) is large and that incorrect labels in \( D' \) can exert negative effects on the student model.

**Pretraining on \( D' \) and Fine-tuning on \( D \):** This strategy is denoted by \( T(D')F(D) \). To make the model more immune to incorrectly labeled examples in \( D' \), and be able to take advantage of the large amount of data in \( D' \) at the same time, we can first train the student model on the newly collected dataset \( D' \) to predict the pseudo labels, and then fine-tune the model on the original labeled dataset \( D \). This strategy ensures that the final model is fine-tuned on the dataset with clean labels. This process actually mimics the idea of the self-training (Devlin et al., 2018; Xie et al., 2020; Chen et al., 2020; Grill et al., 2020) in semi-supervised learning literature.

**Pretraining on \( D + D' \) and Fine-tuning on \( D \):** This strategy is denoted by \( T(D + D')F(D) \). A minor change can be made to the strategy described above, where the model is pretrained on the concatenation of \( D \) and \( D' \), and then fine-tuned on \( D \). Practically, we find that \( T(D + D')F(D) \) consistently outperforms \( T(D')F(D) \), which is expected since adding examples with golden labels for pre-training does no harm the performance. We thus only report results for \( T(D + D')F(D) \), and omit \( T(D')F(D) \) for brevity.

**Iterative Training** The process of training the teacher and the student can be iterated: the student model trained in the previous iteration can be used as a new teacher model to relabel the unlabeled dataset \( U \), from which the top-\( K \) examples are regenerated to form the new \( D' \). Based on the new \( D' \), a new student model is trained. This process is repeated until the pre-defined value of iterations \( N \) is reached.

3.4 Combining In-domain LM Pretraining and Pseudo-label Based Approach

The in-domain LM pretraining and the pseudo-label based strategy can be combined: an LM model is first pretrained on the in-domain data \( U \). Next, the model is used to initialize the teacher, which will be trained on \( D \). The teacher model is then used to generate pseudo labels for \( U \), which are used to train the student. In this way, \( U \) is used twice, both in LM pretraining and pseudo-label generation for student training.

4 Experiments

In this section, we conduct extensive experiments to better understand the behavior of semi-supervised learning. We give insights gathered from extensive experimental studies and also discuss several considerations towards obtaining a successful model. We use the following two datasets for detailed explorations:

1. The labeled dataset \( D \) is the IMDB dataset collected by Maas et al. (2011). This dataset contains an even number of positive and negative movie reviews. The training and test sets respectively contain 25k and 25k examples. The task is formalized as a binary classification task to decide the polarity of sentiment for a review. To explore models’ behavior on training datasets of different sizes, we use 10, 20, 50, 100, 1k, 5k and 25k for training.

For the unlabeled dataset \( U \), we crawled the IMDB
and collected about 3.4M movie reviews. We release this large-scale IMDB movie review dataset to public.

(2) The labeled dataset $D$ is the deceptive opinion spam dataset (Ott et al., 2011; Li et al., 2014) to separate fake hotel reviews generated by Turkers and hotel employees from genuine reviews from real customers. The task is formulated as a three-class classification task, and $D$ contains 800/280/800 reviews, which respectively denote fake reviews from Turkers, fake reviews from hotel employees and genuine reviews from real customers. For the unlabeled dataset $U$, we crawled TripAdvisor, an online travel website and collected about 1M reviews from roughly 5k hotels.

The sentiment analysis task on movie reviews is a significantly easier task than the deceptive review detection task, since the latter requires to model to identify subtle changes in language usage for spam generation, while the former focuses more on identifying sentiment-indicative tokens.

**Training Details** For in-domain LM pretraining, we use the RoBERTa structure (Liu et al., 2019) as the backbone. We use both the small model, a 12-layer transformer with the hidden size of each layer being 768, and a large model, a 24-layer transformer with the hidden size of each layer being 1,024. Models are trained using using Adam (Kingma and Ba, 2014) with $\beta = (0.9, 0.98)$, $\epsilon = 10^{-6}$, a polynomial learning rate schedule, warmup for 4K steps and weight decay with $10^{-3}$. Dropout rate is set to 0.2. The pretrained LM model on the in-domain $U$ is then finetuned on $D$. For training the teacher and the student, we use Adam for optimization. Learning rate, batch-size and dropout rate are treated hyperparameters tuned on the dev set.

For reference purposes, we also implement the BiLSTM model, where the representation at the last time step from the left-to-right direction is concatenated with the the representation at the first time step from the right-to-left direction, which is next fed to the softmax function for golden label prediction. Word vectors are initialized using GloVe (Pennington et al., 2014).

**4.1 Teacher Performances**

We first examine teacher performances for BiLSTMs, *In-domain pretraining*, *Open-domain pretraining* and *Open-domain+In-domain pretraining* on the IMDB and the deceptive spam datasets regarding different values of $|D|$, as shown in Figure 1. For *In-domain pretraining*, a randomly initialized LM model is first pretrained on the in-domain dataset $U$, and then fine-tuned on $D$. For *Open-domain pretraining*, we directly take the pretrained RoBERTa model, which is pretrained on the open-domain dataset $largeU$. For *open-domain+In-domain pretraining*, the LM model is first pretrained on $largeU$, then on the in-domain dataset $U$, and last fine-tuned on $D$. The pseudo-label based semi-supervised strategy is applied in none of these setups. The accuracy progressively increases as we increase the size of the labeled dataset $D$, which is in line with our expectation.

**Is open-domain pretraining still necessary?**

Take the IMDB dataset as an example. As can be seen from Figure 1, the performance of *In-domain pretraining* (95.87 when $|D| = 25k$) on the 3.4M unlabeled reviews performs nearly the same as *open-domain+In-domain pretraining* (95.82), both
of which significantly outperform open-domain pretraining (95.20). Similar phenomena are observed for the deceptive spam dataset, where In-domain pretraining, open-domain+In-domain pretraining and open-domain pretraining respectively obtains 82.5, 82.0 and 78.2 accuracy. This demonstrates that with the presence of relatively large in-domain data, the extremely time-intensive training of LM on a huge amount of open-domain data is unnecessary.

### 4.2 In-domain Pretraining

As shown in Figures 1 and 4, the in-domain pretraining strategy has significantly better few-shot learning abilities and requires much smaller amount of data for training: the performance from in-domain pretraining drastically improves as $|D|$ increases from 10 to 50, achieving a performance of 93.8 accuracy on the IMDB dataset with only 50 training examples. This performance is higher than BiLSTMs with 25K training examples, and similar to the performance of vanilla RoBERTa with 5K training examples. This shows that LM pretraining on the in-domain dataset $U$ provides the model with the generality to rapidly figure out the necessary task-specific information for predictions.

Comparing with existing pretraining models that have few-shot learning ability such as GP3, the advantages of the semi-supervised in-domain pretraining are obvious: the model is easier to train, has significantly fewer parameters and does not have to rely on a vast amount of training data.

#### 4.2.1 Influence from the size of $|U|$.

It is widely accepted that LM pretraining requires a massive amount of training data. Results for $U$ of different sizes for LM pretraining are shown in Figure 2. The model is randomly initialized and then trained on the in-domain $U$ until convergence. The pretrained LM model is next fine-tuned on $D = 25k$.

As can be seen, the performance of in-domain pretraining highly relies on the size of the in-domain dataset $U$. With smaller sizes of $U$, in-domain pretraining underperforms open-domain pretraining, which is in line with our expectation since small $U$ cannot provide enough evidence for learning in-domain word semantics and compositions. Specifically, the performance of $|U| = 10k$ is only slightly better than the no-pretraining setup; the performance for in-domain pretraining outperforms open-domain pretraining only when the size of $U$ exceeds 1M.

### 4.3 Pseudo-label Based Approaches

Detailed results for pseudo-label based approaches based on open-domain pretraining are shown in Table 1. The trends can be summarized as follows:

(1) Generally, both $T(D + D')F(D)$ and $T(D + D')$ perform better than the vanilla setup $T(D)$. $T(D')$
underperforms the vanilla setup $T(D)$ when $D$ is small and $D$ is large, but outperforms $T(D)$ when $D$ is of medium size.

(2) The performance boost introduced by pseudo-label based methods gradually increases as the size of $D$ increases, and then shrinks. The explanation is as follows: with a small $D$, the accuracy of the teacher model is low. Most predicted labels on $D'$ are thus unreliable. Therefore, the advantage from the model trained on the noisy $D'$ is relatively small; with a large $D$, the teacher model is already good enough, reaching an accuracy higher than 0.9. Though almost all predicted labels on $D'$ are correct, their improvement upon an already pretty good teacher model is small. There is a sweet spot for the size of $D$, where pseudo-label based methods introduce the largest boost: with a medium-sized $D$, where the teacher model reaches an acceptable accuracy when the correctly labeled examples in $D'$ outweigh incorrectly labeled ones, the student model can take the most advantage of $D'$, leading to significant performance boosts of +5%. Similar trends are observed for $T(D')$, where $T(D')$ underperforms the vanilla setup $T(D)$ both when $D$ is small and $D$ is large, but outperforms $T(D)$ when $D$ is of medium size.

(3) For the three pseudo-label based strategies, $T(D')$, $T(D + D')F(D)$ and $T(D + D')$, $T(D')$ performs the worst for all $|D|$. This is in line with our expectation because for $T(D')$, only $D'$ is used for final predictions, and thus the influence of the golden-labeled dataset $D$ is diluted; $T(D + D')F(D)$ works best when $|D|$ is small, while $T(D + D')$ works best when $|D|$ is large. Our explanations are as follows: when $|D|$ is small, the student trained on $D + D'$ is inferior due to the massive amount of incorrect labels in $D'$. The model thus needs to be further fine-tuned on $D$, making $T(D + D')F(D)$ perform better than $T(D + D')$; When $|D|$ is large, most labels in $D'$ are correct and the student is more immune to the small proportion of incorrect labels in $D'$. Directly training on the larger $D + D'$ dataset provides the model with more generalization ability, while fine-tuning only on $D$ dilutes the influence from massive amount of correct labels in $D'$, making the performance of $T(D + D')F(D)$ worse than $T(D + D')$ when $|D|$ is large.

### 4.3.1 Influence from the size of $D'$

With a fixed in-domain dataset $U$, we select top-K examples for each label $l$. Different values of $K$ lead to different sizes of $D'$. There is apparently a tradeoff between the size of $D'$ and the confidence for examples included in $D'$: larger size of $D'$ means that more less-confident examples are selected.

Trends regarding different values of $|D'|$ are shown in Figure 5. We only run setups with $|D'|$ larger than $|D|$. As can be seen, for smaller $D$ ($|D| = 50, 100$), the final performance first increases as $|D'|$ gets larger, which means the model is taking advantage of evidence provided by the pseudo labels. Then, the performance decreases as $|D'|$ continues to increase, which means the model starts suffering from the incorrectness of the less-confident examples. For larger values of $D$ ($|D|$ larger than 1k), performances keep increasing as $|D'|$ gets larger. This is because the teacher model trained on $D$ is good enough to generate confident examples.
4.3.2 Influence from the size of $U$

The influence of the size of $U$ is already manifested in the size of $D'$, since the size of $U$ should be larger than the size of $D'$ ($D'$ is selected from $U$). Performances for different sizes of $U$ are shown in Figure 3, where we randomly sample examples from the 3.4 million IMDB reviews to form $U$ of different sizes. For a given $U$, we plot the performance achieved with the best $|D'|$. Larger $U$ should lead to better performances since more confident examples can be selected.

As shown in Figure 3, for $D$ of different sizes, the performance first increases as $|U|$ grows, but then immediately plateaus. Explanations are as follows: for larger $|D|$, the model is already good enough to provide confidently correct labels for points in $D'$, and the improvement from extra confident examples is marginal.

4.3.3 Iterative Training

We can iterate the teacher-student pattern for pseudo-label based approaches, where the teacher for the current iteration is initialized with the student in the previous iteration. Results are shown in Figure 6. As can be seen, additional performance boosts are observed for different $|D|$ as the iterative process goes on. For larger $|D|$, the performance becomes stagnant across the iterative process, while for smaller $|D|$, the curve keeps rising until convergence.

4.4 Combing In-domain Pretraining and Pseudo-label Based Approaches

In-domain pretraining and pseudo-label based approaches can be combined, where the teacher model is initialized with the pretrained model on the in-domain dataset $U$. Results for the combined strategy are shown in Table 2. As can be seen, both strategies lead to progressive performance boosts over Open-domain Pretraining, with a combined boost of +1.1 for the small model, and +1.0 for the large model.

5 Conclusion

In this paper, we conduct comprehensive analysis on semi-supervised learning in NLP under the con-
We find that even with the presence of large-scale LM pretraining, both the in-domain pretraining strategy and the pseudo-label based strategy introduce additional significant performance boost, with the former performing better with larger $U$, the latter performing better with smaller $U$, and the combination leading to the best performance. Using semi-supervised learning models, we are able to achieve a performance of around 93 – 94% accuracy with only 50 training data points on the IMDB dataset, and a competitive performance of 96.6% with the full dataset. Our work sheds light on the behavior of semi-supervised learning models in the context of large-scale pretraining.

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| Small $|D|\approx 25k$ | Open-domain Pretraining | 95.2 | Open-domain+In-domain Pretraining | 95.8 |
| | In-domain Pretraining | 95.8 | In-domain Pretraining + Pseudo-label | 96.3 |
| Large $|D|\approx 25k$ | Open-domain Pretraining | 95.6 | In-domain Pretraining | 96.2 |
| | In-domain Pretraining + Pseudo-label | 96.6 |

*Table 2: Results for Combining In-domain Pretraining and Pseudo-label based Approaches*
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