Exploiting Redundancy in Pre-trained Language Models for Efficient Transfer Learning

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Abstract

Large pre-trained contextual word representations have transformed the field of natural language processing, obtaining impressive results on a wide range of tasks. However, as models increase in size, computational limitations make them impractical for researchers and practitioners alike. We hypothesize that contextual representations have both intrinsic and task-specific redundancies. We propose a novel feature selection method, which takes advantage of these redundancies to reduce the size of the pre-trained features. In a comprehensive evaluation on two pre-trained models, BERT and XLNet, using a diverse suite of sequence labeling and sequence classification tasks, our method reduces the feature set down to 1–7% of the original size, while maintaining more than 97% of the performance.

1 Introduction

Contextualized embeddings have constantly improved the state-of-the-art in a wide variety of downstream NLP tasks. There has been a large influx of pre-trained neural language models, where every model has been introduced with deeper and wider architectures causing a significant increase in the number of parameters. For example, BERT large (Devlin et al., 2019), NVIDIA’s Megatron model,\(^1\) and Google’s T5 model (Raffel et al., 2019) are trained using 340 million parameters, 8.3 billion and 11 billion respectively.

The pre-trained models are applied to downstream tasks using either a feature-based strategy or a fine-tuning strategy. The former takes contextualized embeddings from the pre-trained model and uses them as static features in a task-specific architecture. The latter extends the training of the pre-trained model itself by adding task-specific parameters. There has not been a clear winner in terms of performance between the two strategies, as shown by Peters et al. (2019).

In this work, we focus on the feature-based strategy as it: i) enables us to use task-specific architectures (which may be different from the pre-trained model architectures), ii) allows for increased efficiency, as the contextualized embeddings can be pre-computed once for a specific dataset, after which iterating on a task-specific architecture can be much faster, and iii) facilitates feature selection to further improve efficiency and performance.

The feature-based transfer learning pipeline uses contextualized embeddings learned from pre-trained models as static feature vectors in the downstream classification task. Training a classifier with contextualized embeddings is expensive for two reasons. First, it requires a full forward pass over the pre-trained model to extract the contextualized vectors, which is a costly affair given the large number of model parameters. For example, a forward pass in BERT large requires computing 340 million parameters. Second, classifiers with large contextualized vectors are a) cumbersome to train, b) inefficient during inference, and c) may be sub-optimal when supervised data is insufficient (Hameed, 2018).

We aim to speed up the overall feature-based transfer learning pipeline by targeting the above two computational bottlenecks. We base our study on the following hypotheses:

- The distributive nature of the pre-trained models causes information redundancy at both the layer level and the feature level.
- Since pre-trained models can be used as universal feature extractors, not all features are equally relevant for a downstream task.

We ask whether it is necessary to extract contextualized embeddings from all the layers of the network for every task. Previous work on analyzing

\(^1\)https://nv-adlr.github.io/MegatronLM
deep NLP networks has shown that certain kinds of linguistic information (for example, word morphology) are learned at the lower layers of the network, whereas higher-level phenomena are learned at middle and higher layers (Liu et al., 2019). If knowledge about a specific task is mostly acquired up to an $i^{th}$ layer, can we ignore the layers above and still achieve optimal classification performance? Using fewer layers for a task saves the cost of a full forward pass, resulting in fewer parameters and efficient extraction of contextualized embeddings. To achieve this, we propose an iterative algorithm, LayerSelector, which selects the number of layers required by a task, while maintaining task-specific accuracy within a specified threshold. The algorithm not only limits the forward pass to fewer layers, but also reduces the size of contextualized vectors (since these embeddings are now obtained from $i$ layers instead of all layers), which are then used as features to train a classifier.

We then put forward a similar question for the features: do we need all the features for a downstream NLP task? First, due to the distributed nature of deep neural networks, the information contained among features may be redundant. Moreover, not all the features might be relevant or equally important for a particular task. We aim to identify the redundant and less relevant features and remove them from the feature set, while maintaining close to optimal performance on the task. To this end, we introduce CCFS, a combination of correlation clustering and ElasticNet-based (Zou and Hastie, 2005) feature selection. CCFS efficiently finds a minimal subset of features by taking into account both redundancy and relevancy of each feature for a downstream task while ensuring minimal loss in performance.

We evaluate our approach using feature sets of two pre-trained language models – BERT (Devlin et al., 2019) and XLNet (Yang et al., 2019). The experiments were conducted on four core sequence labeling tasks and seven sequence classification tasks from the GLUE language understanding benchmark (Wang et al., 2018). Our results show that:

- We need as few as 4 layers to achieve close to optimal performance in most sequence labeling tasks, thus reducing the number of parameters to 47% during a forward pass.
- On the other hand, sequence classification tasks require higher layers (7 layers on average for XLNet and 11 layers on average for BERT) of the network to maintain decent performance.
- However, the feature set can be further reduced to 4% of the network for the majority of sequence labeling tasks and less than 1% for most of the sequence classification tasks.

The main novel contributions of our work are:

- **LayerSelector** – an algorithm to select the minimum number of layers required with respect to a task.
- **CCFS** – an efficient multivariate feature selection method.

Our method allows the users to control the trade-off between accuracy and efficiency through a set of hyper-parameters. This enables the use of state-of-the-art contextualized embeddings in computationally-limited configurations such as hand-held devices. The overall setup is general and applicable to any architecture and task. We present results in this paper maintaining up to 97% of the optimal performance of the original full model.

## 2 Approach

Consider a pre-trained neural network model $M$ with $L$ layers: $\{l_1, l_2, \ldots, l_L\}$, where each layer $l_i$ is of size $H$. Given a dataset $D = \{w_1, w_2, \ldots, w_T\}$ consisting of $T$ words, the contextualized embedding of word $w_j$ at layer $l_i$ is $z_j^i = l_i(w_j)$. Let $z_j^{>i}$ represent the concatenation of embeddings from layer $l_1$ to $l_i$. Therefore, $z_j^{>L}$ denotes the full representation from all the layers, and is of size $H \times L$, where each element represents a feature of the word $w_j$ from some layer $l_i$.

The **LayerSelector** module identifies the optimal number of layers $i$ required for a downstream task, i.e., reducing the size of contextualized embeddings $z_j^{>L}$ from $H \times L$ to $z_j^{>i}$ of size $H \times i$. The feature selector CCFS then removes redundant and irrelevant features, filtering a subset of features from $z_j^{>i}$, further reducing the number of features used to train a classifier. Both **LayerSelector** and CCFS make use of hyperparameters $\delta_l$ and $\delta_n$ respectively, to control performance loss, when selecting relevant features for a downstream task. $\delta_l$ and $\delta_n$ both define the relative loss from the full model that is acceptable, and hence tuning their sum defines the total relative loss that the final selected feature set will result in. In the following sections, we describe each module in detail.
2.1 LayerSelector Module

LayerSelector takes contextualized embeddings of a pre-trained model and \( \delta_l \) as input. The output of the module is the optimal number of layers required by the classifier to achieve performance with a relative loss of at most \( \delta_l \) w.r.t. to the oracle, which is trained on features from all the layers, i.e. \( z^{>l} \). The module operates iteratively, adding one layer at a time in each iteration starting from the first layer of the pre-trained model \( z^{l=1} \). The addition of layers is performed in the order of the forward-pass in the pre-trained model. By iterating in this manner, we do not waste any computation, since computing the features of a layer \( l_i \) necessitates the computation of all layers below it. At each iteration, a classifier is then trained on the limited set of features \( z^{>l} \) in iteration 1, \( z^{>2} \) in iteration 2 and so on. The algorithm stops when the difference between the oracle and the classifier’s performance is lower than the desired threshold \( \delta_l \). Selecting the \( i^{th} \) layer entails that the algorithm runs the forward pass only until layer \( l_i \), causing a significant reduction in parameters used from the pre-trained model, especially for tasks where \( i \) is small.

2.2 CCFS Module

Neural network models are designed to be distributed in nature, to avoid over-fitting and to overcome statistical noise in the training data. Deeper networks, in combination with various architectural choices such as dropout, also encourage distributedness. This, however, results in redundancy across the network. The redundant features present a challenge during transfer learning, they: a) cause an increase in the training and inference time, b) are harder to optimize when labeled data is inadequate (Hameed, 2018) and c) cause sub-optimal classifier performance (Kuhn and Johnson, 2019). Moreover, not all features are relevant to a specific task. Hence, the feature set can be reduced by removing these redundant and irrelevant features. CCFS targets these two types of features in a two step process: it first removes the redundant features through correlation clustering and then selects the relevant features using an ElasticNet classifier.

2.2.1 Correlation Clustering

Formally, every feature \( f \) in \( z^{>l} \) when calculated over the dataset \( \mathbb{D} \) can be represented as a vector of size \( T \), where each index represents the value of the feature for a token \( t \in \mathbb{D} \). We calculate the Pearson product-moment correlation of every feature with every other feature. This results in a \( T \times T \) matrix \( \text{corr} \) where \( \text{corr}(x, y) \) represents correlation between \( f_x \) and \( f_y \). The correlation values are in the range of \([-1, 1]\). We convert to represent distance by applying \( \text{dist}(x, y) = 1 - |\text{corr}(x, y)| \). In the case of highly correlated features, say \( f_x \) and \( f_y \), the value of \( \text{dist}(x, y) \) is close to zero. We cluster the distance matrix \( \text{dist} \) using agglomerative hierarchical clustering.\(^2\) The clusters are formed using average linkage, which minimizes the average distance, of all data points in pairs of clusters. It uses a hyper-parameter \( c_t \) to define the maximum distance between any two features to consider them as part of a cluster. Given a cluster of features, we randomly select one feature from each cluster and include it in our new reduced feature set.

2.2.2 Feature Selection

Clustering features helps remove redundant information. However, for a specific task, not all remaining features are relevant. We therefore perform feature selection to filter-out irrelevant features for the task at hand. To avoid searching through all possible subsets of features (an NP-complete problem), we utilize an ElasticNet logistic regression model that is trained on the non-redundant feature set. The ElasticNet model uses both Lasso and Ridge regularizers, the former encouraging sparsity (so irrelevant features are given very low weights), while the latter encourages feature grouping, allowing us to detect feature subsets that work together to perform a task. Once the ElasticNet model is trained, we follow the same procedure as Dalvi et al. (2019), who used such a network for neuron-level analysis in neural networks. In essence, we use the weights assigned to each input feature to determine its importance, rank features by their importance and select enough features to maintain accuracy within a relative performance loss of a hyper parameter \( \delta_n \).

3 Experiments

3.1 Models

We present results on two transformer based architectures – BERT (Devlin et al., 2019) and XLNet (Yang et al., 2019), based on autoencoding and auto-regressive language modeling respectively.

\(^2\)We experimented with other clustering algorithms such as k-means and DBSCAN, and did not see any noticeable difference in the resulting clusters.
We use base models for our experiments. These consist of 13 layers each (one embedding layer and 12 encoder layers) of size 768 with approximately 110M parameters. We use the transformers library (Wolf et al., 2019) to fine-tune the pre-trained models towards a sequence classification task, and to extract activations (features) from these models.

### 3.2 Datasets

For sequence labeling tasks, we used the Penn TreeBank (Marcus et al., 1993) for POS-tagging, CCGBank (Hockenmaier, 2006) for CCG, CoNLL 2003 shared task dataset (Tjong Kim Sang and De Meulder, 2003) for NER, Parallel Meaning Bank data (Abzianidze et al., 2017) for semantic tagging and CoNLL 2000 shared task dataset (Tjong Kim Sang and Buchholz, 2000) for syntactic chunking. We use training sets of 150K tokens, and standard development and test splits. For sequence classification tasks, we perform experiments on seven tasks from the GLUE (Wang et al., 2018) benchmark, namely sentiment analysis (SST-2) using the Stanford sentiment treebank (Socher et al., 2013), Semantic equivalence classification using the Microsoft Research paraphrase corpus (MRPC) (Dolan and Brockett, 2005), natural language inference using the MultiNLI corpus (MNLI) (Williams et al., 2018), Question NLI (QNLI) using the SQUAD dataset (Rajpurkar et al., 2016), Question pair similarity using the Quora Question Pairs dataset (QQP), textual entailment using recognizing textual entailment dataset (RTE) (Bentivogli et al., 2009), and semantic textual similarity using the STS-B dataset (Cer et al., 2017).

For the sequence classification tasks, we use the embedding of the CLS token, extracted from the pre-trained models after they are fine-tuned for a particular sentence classification task. The CLS token from a base unfine-tuned model is not adapted towards any particular task, and thus leads to suboptimal performance in classification.

### 3.3 Experimental Settings

#### Contextualized Embeddings

For the sequence labeling tasks, we use the contextualized embedding of a word as its features for classification. For sequence classification tasks, we use the embedding of the CLS token, extracted from the pre-trained models after they are fine-tuned for a particular sentence classification task. The CLS token from a base unfine-tuned model is not adapted towards any particular task, and thus leads to suboptimal performance in classification.

**LayerSelector Module** For all tasks, we find the optimal number of layers with a performance threshold $\delta_l = 2$ on the dev sets.

**CCFS Module** For correlation clustering, we tuned for several values and choose $c_l = 0.3$, meaning that we consider two points with a correlation distance of less than 0.3 to belong to the same cluster. Section 5.5 presents a detailed discussion of this choice. We observed minimal loss in the overall accuracy from the resulting clusters, while gaining a significant reduction in the overall number of features. For feature selection, we selected both $\lambda_1$ (Lasso) and $\lambda_2$ (Ridge) regression parameters to be $1e^{-5}$, as this set resulted in optimal classifier performances across tasks, but also provided us with an adequate ranking to eliminate irrelevant features.

To select the final set, we search over the ranked list of features with performance threshold $\delta_n$ set to 1, i.e., accepting a relative loss of 1% accuracy drop on the development set while selecting relevant features. Overall, our proposed method allows a maximum loss of $\delta_l + \delta_n$ (3%), thus maintaining 97% performance from the original baseline classifier. These parameters enable the user to control the trade-off between efficiency and accuracy.

### 4 Results

#### 4.1 Sequence Labeling Tasks

**LayerSelector Module** Table 1 presents the results of sequence labeling tasks. Top rows (Oracle) show the accuracy of the classifier when using the entire network (embedding and 12 layers – 9984 features). The next rows show the accuracy of LayerSelector module (LS). Our results show that features from the lower half of the network (0-6) layers are sufficient to maintain classification accuracy for the desired threshold $\delta_l = 2$. In most of the tasks, we actually required less than 4 layers (2 in the case of XLNet), resulting in a significant reduction in the feature set and faster computation of the forward-pass. We reduced the parameters for BERT by 65% for POS, SEM and NER tasks, 52% for Chunking and 39% for the CCG task. In XLNet,
Table 1: Results of sequence labeling tasks using \textit{LayerSelector} (LS) with performance threshold \( \delta_l = 2 \) and \textit{CCFS} with performance threshold \( \delta_n = 1 \). Oracle is using a concatenation of all layers (embedding + 12 layers) for classification. Layer# shows the number of layers selected. \% Reduct. shows the percentage reduction in features by \textit{CCFS} compared to Oracle. Features are the final number of features used for classification. All hyper parameters are tuned on the development sets, while results presented here are on the test sets.

|        | POS  | SEM  | CCG  | Chunking |
|--------|------|------|------|----------|
| Oracle | 95.2%| 92.0%| 90.0%| 94.6%    |
| LS     | 94.8%| 91.2%| 88.7%| 93.5%    |
| Layer# | 2    | 2    | 6    | 4        |
| BERT   |      |      |      |          |
| CCFS   | 94.0%| 90.1%| 89.8%| 92.3%    |
| Features | 300 | 400 | 400 | 600     |
| % Reduct. | 97%↓| 96%↓| 96%↓| 94%↓    |
| Oracle | 95.9%| 92.5%| 90.8%| 94.2%    |
| LS     | 96.2%| 92.9%| 90.3%| 93.5%    |
| Layer# | 1    | 1    | 2    | 2        |
| XLMNet|      |      |      |          |
| CCFS   | 95.5%| 91.9%| 90.2%| 92.3%    |
| Features | 300 | 400 | 400 | 700     |
| % Reduct. | 97%↓| 96%↓| 96%↓| 93%↓    |

The parameter reduction is even more significant, with 72% reduction for POS, SEM and NER tasks, and 65% reduction in CCG and Chunking tasks. In both BERT and XLNet, low-level linguistic properties like morphology (POS) and lexical semantics (SEM) need fewer layers than high-level linguistic properties such as syntactic structures (CCG and Chunking).

Interestingly, significantly fewer layers are required from XLNet compared to BERT to achieve the same level of overall performance. This perhaps explains XLNet’s superior results on several benchmarks, as learning the word-level features earlier in the network allows the remaining network to use the knowledge in more diverse ways, thus boosting overall performance. The auto-regressive nature of XLNet and the fact that it maximizes the expected log likelihood of a sequence w.r.t. all possible permutations of the factorization order, potentially allows it to learn contextual information more explicitly than BERT, helping it learn stronger word level features earlier in the network.

\textbf{CCFS Module} Next we eliminate redundant and unnecessary features from the selected layers. The last block of rows in Table 1 shows that \textit{CCFS} further reduces the number of features required for classification on top of \textit{LayerSelector}. The final number of features used for classification ranges between 300–700 (3% to 7% of the original feature set), down from a total of 9984 features.

To summarize, taking the POS task as an example: the pre-trained oracle BERT model has 9984 features and 110M parameters. The \textit{LayerSelector} reduced the feature set to 2304 (embedding + 2 layers) and the number of parameters used in the forward pass to 37M. \textit{CCFS} further reduced the feature set to 300, maintaining a performance close to oracle BERT’s performance on this task (95.2% vs. 94.0%).

4.2 Sequence Classifications Tasks

\textbf{LayerSelector Module} Table 2 summarizes the results on the sequence classification tasks. We found that sequence classification tasks require higher layers in the network to maintain classification performance, as opposed to the sequence labeling tasks that are essentially word-level tasks. The maximum reduction in the number of layers is for the task of SST-2, requiring up to 4 layers from XLNet and 6 layers from BERT. Averaging across all tasks, \textit{LayerSelector} leads to selection of 10.4 layers in BERT, while only 6.9 layers in XLNet. This again leads to the hypothesis that the superior performance of XLNet is because these sequence-level features are learned at much lower layers compared to BERT, allowing the remaining network to work with diverse combinations of these features to produce even richer features in the final layers of the network.

The greater reduction in the number of required layers in SST-2 (as compared to other tasks) in both BERT and XLNet can be attributed to the fact that SST-2 is a single sentence task, while all remaining tasks take sentence-pairs as inputs, thus requiring more of the network to produce relevant features. In terms of parameters, we see an average reduction of 10% for BERT and 33% for XLNet, which is still substantial considering that these underlying networks are very large with computationally-heavy forward passes.

\textbf{CCFS Module} Feature selection proved to be even effective on the sequence classification tasks compared to the labeling tasks as shown in Table 2. For example, it drastically reduced the number of features to as few as 10 features for the QNLI task.
|       | SST-2 | MRPC | MNLI | QNLI | QQP | RTE | STS-B |
|-------|-------|------|------|------|-----|-----|-------|
| Oracle Features | 90.6% | 86.0% | 81.7% | 90.2% | 91.2% | 69.3% | 89.7% |
| BERT Layer# | 6 | 11 | 11 | 11 | 11 | 12 | 11 |
| LS Layer# | 85.6% | 86.0% | 81.6% | 89.9% | 90.9% | 69.3% | 89.1% |
| CCFS Features % Reduction | 86.1% | 85.5% | 81.0% | 89.2% | 90.2% | 69.0% | 88.5% |
| Oracle Features | 92.4% | 86.5% | 78.9% | 88.7% | 87.2% | 71.1% | 88.9% |
| LS Layer# | 87.3% | 86.0% | 79.9% | 88.8% | 89.3% | 71.1% | 87.5% |
| CCFS Features % Reduction | 86.7% | 88.2% | 78.7% | 88.4% | 88.7% | 70.4% | 86.5% |
| Oracle Features | 92.4% | 86.5% | 78.9% | 88.7% | 87.2% | 71.1% | 88.9% |

Table 2: Results of sequence classification tasks using \textit{LayerSelector} (LS) with performance threshold \(\delta_l = 2\) and \textit{CCFS} with performance threshold \(\delta_n = 1\). Oracle is using a concatenation of all layers (embedding + 12 layers) for classification. \textit{Layer#} shows the number of layers selected. \textit{Features} are the final number of features used for classification. \% \textit{Reduction} shows the percentage reduction in features by \textit{CCFS} compared to Oracle. All hyperparameters are tuned on the development sets, while results presented here are on the test sets.

For several others, the set was reduced to around 100 features. This is more than 99% reduction in the number of features, while maintaining at least 97% of the oracles’ performance.

The drop in performance using our method varies across different tasks. For SST-2 with 99% reduction in feature set, we see a larger drop, while for QQP with a 99.7% reduction, we did not observe any. Note that we sometimes lose more than the desired 3% loss in accuracy, due to the fact that the parameters of the algorithm were tuned on the development set, while Table 2 reports performance on the test. For example, we saw a drop of 5% on SST-2. This discrepancy can be removed by careful finetuning of the performance deltas, and regularizing the classifier being used. But we did not choose to do so in this work. It is worth mentioning here that the trade-off between loss in accuracy and efficiency can be controlled through a parameter which can be adjusted to serve faster turn-around or better performance.

5 Analysis and Discussion

Here we investigate the usefulness of our setup in analyzing and comparing deep neural network models, and also provide additional discussion on the motivation behind the exact thresholds and parameters we chose for our experiments.

5.1 Efficiency Analysis

We discussed the general efficiency of the selection algorithm in terms of the number of parameters reduced and the final number of features. Let us now discuss what these savings translate into in real world performance. For the classifier, we simulate a test scenario with 100,000 tokens and compute the total runtime for 10 iterations of training. The numbers were computed on a 6-core 2.8 GHz AMD Opteron Processor 4184, and were averaged across 3 runs. Figure 1 shows the runtime of each run (in
Figure 2: Distribution of selected neurons (by running LayerSelector and CCFS) from embedding, lower-, middle- and top-layers for sequence classification tasks.

seconds) against the number of features selected. We can see that for the tasks in BERT, the classifier finished running in less than 10 seconds compared to the original runtime of around 50 seconds. The 5x speedup can be very useful in a heavy-use scenarios where the classifier is queried a large number times in a short duration.

5.2 Feature Reduction

While sequence labeling tasks require fewer layers compared to sequence classification tasks, the latter can do with significantly smaller sets of features (compare last row in tables 1 and 2). We hypothesize that this is due to the CLS token, which is used as a sequence representation. The model aggregates the entire sequence information in the CLS token representation which is then optimized for a specific task such as QQP and MNLI. The representation units (features) that are important for the task get boosted during fine-tuning and eventually become responsible for classification.

Additionally, although we needed higher layers for the sequence classification tasks, it would be interesting to see if the selected features also strictly belong to the higher layers. Figure 2 shows the distribution of selected features across layers. We see that the final feature set has a good mix of features from lower layers as well. This shows that the sentence-level tasks do not just depend on high-level features learned by the top most layers, but also on lower-level features that are learned much earlier in the network.

5.3 BERT vs. XLNet

In terms of overall performance, we achieved better results with XLNet – a lower drop in performance with a higher reduction in parameters used in the forward pass during feature extraction. However, the actual set of relevant features required by XLNet to learn a downstream classification task is bigger than BERT in most of the cases (compare Features row in Tables 1 and 2). We conjecture that this phenomenon occurs because LayerSelector chose lower layers for XLNet compared to BERT, and information is more dispersed in lower layers than higher in the network for the same task. To test this, we perform an experiment where we run CCFS with and without LayerSelector. Figure 3 shows that in four out of seven tasks, the number of selected features reduces when we use all layers from the original model, instead of limited number of layers selected by LayerSelector.

5.4 Alternative Feature Selection Methods

The CCFS module uses a feature selection strategy based on an Elastic Net classifier as proposed by Dalvi et al. (2019). We also carried experiments using a standard technique called Recursive Feature Elimination (RFE) (Guyon et al., 2002), as a feature selection method. We conducted comparative experiments for BERT as a case study on a subset of the tasks. Using the implementation provided in the scikit-learn package
### Table 3: Results of Recursive Feature Elimination as a feature selection method on three sequence labeling tasks.

|                | POS   | SEM   | Chunking |
|----------------|-------|-------|----------|
| **ElasticNet** |       |       |          |
| CCFS Features  | 94.0% | 90.1% | 92.3%    |
| % Reduct.      | 97%↓  | 96%↓  | 94%↓     |
| **RFE**        |       |       |          |
| CCFS Features  | 93.9% | 91.1% | 91.8%    |
| % Reduct.      | 97%↓  | 96%↓  | 94%↓     |

Dalvi et al. (2019) to be comparable in terms of accuracy but significantly better in efficiency, we therefore persisted with it to carry this study. Table 3 presents the results.

In RFE, we repeatedly build a logistic regression classifier, starting with all the features and pruning the least important features in every run. The weights of the logistic regression classifier at each run are used as a proxy for the importance of each input feature, removing a set number of features in every run. We can see that the overall results are very comparable, however, because of the iterative nature of RFE, the ElasticNet-based selection is much faster. The model training happens just once in the latter, while RFE trains one model per iteration, where the number of iterations depends on the number of layers selected by the LayerSelector module.

### 5.5 Correlation Clustering

We perform a qualitative analysis on the clusters created by correlation clustering. Firstly, we visualize neurons within a cluster across a few sentences (examples in Figure 4) and see the similarities of activation values across words. The neurons within a cluster are quite similar in their behavior, though not identical. Hence, we tune the clustering algorithm to not cluster very aggressively (by setting the maximum distance threshold to a smaller value, in our case 0.3).

We also analyze the general makeup of the clusters formed by correlation clustering. Figure 5 shows the percentage of clusters (accumulated over all sequence classification tasks) that contain features from the same layer (window size 1), neighboring layers (window sizes 2 and 3) and from layers further apart. We can see that the vast majority of clusters (≈95%) either contain features from the same layer or from adjacent layers. This reflects that the main source of redundancy is among the individual representation units in the same layer or neighbouring layers of the network. The finding motivates pruning of models by compressing layers as oppose to reducing the depth in a distilled version of a model.

### 6 Related Work

#### Contextualized Embeddings

Contextual representations have shown to achieve state-of-the-art results in a wide range of NLP tasks. Researchers have extracted context-sensitive features from bilingual LSTMs trained on the task of language modeling (Peters et al., 2018) or machine translation (McCann et al., 2017). A typical approach involves extracting activations from the entire network, or just the final layer (Peters et al., 2017) and using them as static features to train a classifier for the downstream task. More recently there has been a shift from LSTMs towards Transformer language models (Radford et al., 2019; Devlin et al., 2019; Yang et al., 2019), for pre-training; and from feature-based approach towards tuning (Dai and Le, 2015; Radford et al., 2019) the entire pre-trained network towards a downstream task. Howard and Ruder (2018) found fine-tuning an entire pre-trained model superior to the feature-based approach, although recent research (Peters et al., 2019) demonstrated that the feature-based method is preferable when the target task is dissimilar to the source task used to train the pre-trained model. Feature selection is handy in a scenario where a task cannot be easily represented by the underlying architecture and requires task-specific model architecture to be added (Devlin et al., 2019).

#### Deeper Models and Distillation

Given the performance gains achieved using large networks, there has been an active area of research to distill these models down to fit in real-world applications. Dehghani et al. (2019) applied cross-layer parameter sharing in their Universal Transformer. Dabre and Fujita (2019) applied the idea in a recurrently stacked sequence-to-sequence model. Lan et al. (2019) showed an impressive reduction in BERT-xlarge parameters through weight sharing and embedding factorization, while improving performance on several benchmarks. An-
other approach that has been successfully applied is the student-teacher-based knowledge distillation framework (Hinton et al., 2015). Hu et al. (2018) adapted this framework to distill knowledge from BERT into a single-layer BiLSTM model. Other task specific distillation works include Turc et al. (2019), Chatterjee (2019) and You et al. (2019) using multi-task knowledge distillation, to mention a few. Sanh et al. (2019) proposed a triple loss combining language modeling, distillation and cosine-distance losses to reduce task-agnostic BERT model by 40% while retaining 97% of its accuracy. Tsai et al. (2019) applied a similar approach but using multilingual model. Different from distilling pre-trained model, we carry task-specific feature-based reduction. We proposed novel methods to speed up the feature-based pipeline by limiting the forward pass and selecting the most relevant features for the task in hand.

7 Conclusion

Feature-based transfer learning is expensive for two reasons: i) extracting large contextualized embeddings requires a lot of computational power and ii) building a classifier on a large number of features is cumbersome and inefficient. In this work, we presented a novel method that makes the feature-based transfer learning pipeline efficient. We introduced LayerSelector, an algorithm that limits the forward pass to fewer layers and reduces the number of forward pass parameters up to 47%. We then presented CCFS, a multivariate feature selection method, which reduces the feature set by removing redundant and irrelevant features. Our method reduced the feature set to 4% of the original network size for sequence labeling tasks and less than 1% for the sequence classification tasks while maintaining at least 97% of the original performance.

Our findings illuminate interesting observations about BERT and XLNet models. Compared to BERT, XLNet learns both word-level and sequence-level information much earlier in the network. This enabled our algorithm to select fewer layers, resulting in greater reduction in the case of XLNet. Additionally, we show that representation units within a layer are more redundant than across layers. This leads towards an interesting research direction of pruning models by layer compression as opposed to making models shallower.

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