**Deep Neural Compression Via Concurrent Pruning and Self-Distillation**

James O’ Neill  
Department of Computer Science,  
University of Liverpool  
Liverpool L69 3BX, UK  
james.o-neill@liverpool.ac.uk

Sourav Dutta & Haytham Assem  
Huawei Ireland Research Center  
Georges Court, Townsend St  
Dublin 2, D02 R156, Ireland  
{sourav.dutta2,haytham.assem}@huawei.com

**Abstract**

Pruning aims to reduce the number of parameters while maintaining performance close to the original network. This work proposes a novel self-distillation based pruning strategy, whereby the representational similarity between the pruned and unpruned versions of the same network is maximized. Unlike previous approaches that treat distillation and pruning separately, we use distillation to inform the pruning criteria, without requiring a separate student network as in knowledge distillation. We show that the proposed cross-correlation objective for self-distilled pruning implicitly encourages sparse solutions, naturally complementing magnitude-based pruning criteria. Experiments on the GLUE and XGLUE benchmarks show that self-distilled pruning increases mono- and cross-lingual language model performance. Self-distilled pruned models also outperform smaller Transformers with an equal number of parameters and are competitive against (6 times) larger distilled networks. We also observe that self-distillation (1) maximizes class separability, (2) increases the signal-to-noise ratio, and (3) converges faster after pruning steps, providing further insights into why self-distilled pruning improves generalization.

**1 Introduction**

Neural network pruning [Mozer & Smolensky, 1989; Karnin, 1990; Reed, 1993] zeros out weights of a pretrained model with the aim of reducing parameter count and storage requirements, while maintaining performance close to the original model. The criteria to choose which weights to prune has been an active research area over the past three decades [Karnin, 1990; LeCun et al., 1990; Han et al., 2015a; Anwar et al., 2017; Molchanov et al., 2017]. Lately, there has been a focus on pruning models in the transfer learning setting whereby a self-supervised pretrained model trained on a large amount of unlabelled data is fine-tuned to a downstream task while weights are simultaneously pruned. In this context, recent work proposes to learn important scores over weights with a continuous mask and prune away those that having the smallest scores [Mallya et al., 2018; Sanh et al., 2020].

However, these learned masks double the number of parameters in the network, requiring twice the number of gradient updates to tune the original parameters and their continuous masks [Sanh et al., 2020]. Ideally, we aim to perform task-dependent fine-pruning without adding more parameters to the network, or at least far lesser than twice the count. More generally, we desire pruning methods that can recover from performance degradation directly after pruning steps, faster than current pruning methods while encoding task-dependent information into the pruning process. To this end, we hypothesize self-distillation may recover performance faster after consecutive pruning steps, which becomes more important with larger performance degradation at higher compression regime.
Additionally, self-distillation has shown to encourage sparsity as the training error tends to 0 (Mobahi et al., 2020). This implicit sparse regularization effect complements magnitude-based pruning criteria.

Hence, this paper proposes to maximize the cross-correlation between output representations of the fine-tuned pretrained network and a pruned version of the same network – referred to as self-distilled pruning (SDP). Unlike typical knowledge distillation (KD) where the student is a separate network trained from random initialization, here the student is initially a masked version of the teacher. We focus on pruning fine-tuned monolingual and cross-lingual transformer models, namely BERT (Devlin et al., 2018) and XLM-RoBERTa (Conneau et al., 2019). To our knowledge, this is the first study that introduces the concept of self-distilled pruning and analyze iterative pruning in cross-lingual contexts. In a nutshell, our main contributions are as follows:

1. We propose self-distilled pruning, a novel pruning framework that improves the generalization of pruned networks without introducing any additional parameters, using only a set of soft targets.
2. Inspired by the recent success of correlation-based objectives for representation learning in computer vision (Zbontar et al., 2021), we propose the use of a cross-correlation objective for self-distillation pruning that reduces redundancy and encourages sparse solutions, naturally fitting with magnitude-based pruning. This sets state of the art results for magnitude-based pruning.
3. We provide three insights as to why self-distillation leads to more generalizable pruned networks. Namely, we observe that self-distilled pruning (1) recovers performance faster after pruning steps (i.e., improves convergence), (2) maximizes the signal-to-noise ratio (SNR), where pruned weights are considered as noise, and (3) improves the fidelity between pruned and unpruned representations as measured by mutual information of the respective penultimate layers.
4. A comprehensive study of iterative pruning for monolingual and cross-lingual pretrained models on GLUE and XGLUE benchmarks. To our knowledge, this is the only work to include an evaluation of pruned model performance in the cross-lingual transfer setting.

2 BACKGROUND AND RELATED WORK

Regularization-based pruning can be achieved by using a weight regularizer that encourages network sparsity. Three well-established regularizers are $L_1$, $L_2$ and $L_0$ weight regularization (Louizos et al., 2017; Liu et al., 2017; Ye et al., 2018) for weight sparsity (Han et al., 2015b,a). For structured pruning, Group-wise Brain Damage (Lebedev & Lempitsky, 2016) and SSL (Wen et al., 2016) propose to use Group LASSO (Yuan & Lin, 2006) to prune whole structures (e.g., convolution blocks or blocks within standard linear layers). Park et al. (2020) aim to avoid pruning small weights if they are connected to larger weights in consecutive layers and vice-versa, by constraining the Frobenius norm of the pruned layers to be close to unpruned network.

Importance-based pruning assigns a score for each weight in the network and removes weights with the lowest importance score. The simplest scoring criteria is magnitude-based pruning (MBP), which uses the lowest absolute value (LAV) as the criteria (Reed, 1993; Han et al., 2015b,a) or $L_1/L_2$-norm for structured pruning (Liu et al., 2017). MBP can be seen as a zero-th order pruning criteria. However higher order pruning methods approximate the difference in pruned and unpruned model loss using a Taylor series expansion up until 1st order (LeCun et al., 1990; Hassibi & Stork, 1993) or the 2nd order, which requires approximating the Hessian matrix (Martens & Grosse, 2015; Wang et al., 2019; Singh & Alistarh, 2020) for scalability. Lastly, the regularization-based pruning is commonly used with importance-based pruning e.g using $L_2$ weight regularization alongside MBP.

Knowledge Distillation (KD) transfers the logits of an already trained network (Hinton et al., 2015) and uses them as soft targets to optimize a student network. The student network is typically smaller than the teacher network and benefits from the additional information soft targets provide. There has been various extensions that involve distilling intermediate representations (Romero et al., 2014), distributions (Huang & Wang, 2017), maximizing mutual information between student and teacher representations (Ahn et al., 2019), using pairwise interactions for improved KD (Park et al., 2019) and contrastive representation distillation (Tian et al., 2019; Neill & Bollegala, 2021).

Self-Distillation is a special case of KD whereby the student and teacher networks have the same capacity. Interestingly, self-distilled students often generalize better than the teacher (Parlanello et al., 2018; Yang et al., 2019), however the mechanisms by which self-distillation leads to improved generalization remains somewhat unclear. Recent works have provided insightful observations of this...
We begin by defining a dataset \( D := \{(X_i, y_i)\}_{i=1}^{D} \) with single samples \( s_i = (X_i, y_i) \), where each \( X_i \) (in the \( D \) training samples) consists of a sequence of vectors \( X_i := (x_1, \ldots, x_N) \) and \( x_i \in \mathbb{R}^d \). For structured prediction (e.g., NER, POS) \( y_i \in \{0,1\}^{N \times C} \), and for single and pairwise sentence classification, \( y_i \in \{0,1\}^{C} \), where \( C \) is the number of classes. Let \( y^S = f_\theta(X_i) \) be the output prediction \( y^S \in \mathbb{R}^C \) from the student \( f_\theta(\cdot) \) with pretrained parameters \( \theta := \{W_l, b_l\}_{l=1}^{L} \) for \( L \) layers. The input to each subsequent layer is denoted as \( z_i \in \mathbb{R}^{n_l} \) where \( x := z_0 \) for \( n_l \) number of units in layer \( l \) and the corresponding output activation as \( A_l = g(z_l) \). The loss function for standard classification fine-tuning is defined as the cross-entropy loss \( \ell_{CE}(y^S, y) := -\frac{1}{n} \sum_{i=1}^{n} y_i \log(p_i^S) \).

For self-distilled pruning, we also require an already fine-tuned teacher network \( f_\Omega \), that has been tuned from the pretrained state \( f_\theta \), to retrieve the soft teacher labels \( y^T := f_\Omega(x) \), where \( y^T \in \mathbb{R}^C \) and \( \sum_{c} y_i^T = 1 \). The soft label \( y^T \) can be more informative than the one-hot targets \( y \) used for standard classification as they implicitly approximate pairwise class similarities through logit probabilities. The Kullback-Leibler divergence \( \ell_{KLD} \) is then used with the main task cross-entropy loss \( \ell_{CE} \) to express \( \ell_{SDP-KLD} \) as shown in Equation 1,

\[
\ell_{SDP-KLD} = (1 - \alpha)\ell_{CE}(y^S, y) + \alpha \tau^2 D_{KLD}(y^S, y^T)
\]

where \( D_{KLD}(y^S, y^T) = \mathbb{H}(y^T) - y^T \log(y^S), \mathbb{H}(y^T) = y^T \log(y^T) \) is the entropy of the teacher distribution and \( \tau \) is the softmax temperature. Following [Hinton et al., 2015], the weighted sum of cross-entropy loss and KLD loss shown in Equation 1 is used as our main SDP-based KD loss baseline, where \( \alpha \in [0,1] \). After each pruning step during iterative pruning, we aim to recover the immediate performance degradation by minimizing \( \ell_{SDP-KLD} \). In our experiments, we use weight magnitude-based pruning as the criteria for SDP given MBP’s flexibility, scalability and miniscule computation overhead (only requires a binary tensor multiplication to be applied for each linear layer at each pruning step). However, \( D_{KLD} \) only distills the knowledge from the soft targets which may not propagate enough information about the intermediate dynamics of the teacher, nor does it penalize representational redundancy. This brings us to our proposed cross-correlation SDP objective.

### 3.1 Maximizing Cross-Correlation Between Pruned and Unpruned Embeddings

Iterative pruning can be viewed as progressively adding noise \( M_l \in \{0,1\}^{n_l-1 \times n_l} \) to the weights \( W_l \in \mathbb{R}^{n_l-1 \times n_l} \). Thus, as the pruning steps increase, the outputs become noisier and the relationship between the inputs and outputs becomes weaker. Hence, a correlation measure is a natural choice for dealing with such pruning-induced noise. To this end, we use a cross-correlation loss to maximize the correlation between the output representations of the last hidden state of the pruned network and the unpruned network to reduce the effects of this pruning noise. The proposed cross-correlation SDP loss function, \( \ell_{CC} \), is expressed in Equation 2, where \( \lambda \) controls the importance of minimizing the non-adjacent pairwise correlations between \( z^S \) and \( z^T \) in the correlation matrix \( C \). Here, \( m \) denotes the sample index in a mini-batch of \( M \) samples. Unlike \( \ell_{KLD} \), this loss is applied to the outputs of the last hidden layer as opposed to the classification logit outputs. Thus, we have,

\[
\ell_{CC} := \sum_{i} (1 - C_{ii})^2 + \lambda \sum_{i} \sum_{j \neq i} C_{ij}^2 \ s.t. \ C_{ij} := \frac{\sum_{m} z_{m,i}^S z_{m,j}^T}{\sqrt{\sum_{m} (z_{m,i}^S)^2} \sqrt{\sum_{m} (z_{m,j}^T)^2}}
\]

Maximizing correlation along the diagonal of \( C \) makes the representations invariant to pruning noise, while minimizing the off-diagonal term decorrelates the components of the representations that are batch normalized. To reiterate, \( z^S \) is obtained from the pruned version of the network \( (f_\theta) \) and \( z^T \) is obtained from the unpruned version \( (f_\Omega) \).
Since the learned output representations should be similar if their inputs are similar, we aim to address the problem where a correlation measure may produce representations that are instead proportional to their inputs. To address this, we use batch normalization across mini-batches to stabilize the optimization when using the cross-correlation loss, essentially avoiding local optima that correspond to degenerate representations that do not distinguish proportionality. In our experiments, this is used with the classification loss and KL divergence distillation loss as shown in Equation 3.

\[
\ell_{SDP-CC} = (1 - \alpha)\ell_{CE}(y^S, y) + \alpha^2\ell_{KLD}(y^S, y^T) + \beta\ell_{CC}(z^T, z^F)
\] (3)

To bring it all together, in Figure 1, we show the proposed framework of Self-Distilled Pruning with cross-correlation loss (SDP-CC), where \(I\) is the identity matrix. Additionally, we provide a PyTorch based pseudo-code for SDP-CC in Figure 1 for a single epoch, in the general case. We see that the inner training loop requires little additional overhead, only requiring the extra computation (compared to normal pruning) to compute distil_loss and cross_corr_loss.

### 3.2 A Frobenius Distortion Perspective of Self-Distilled Pruning

To formalize the objective being minimized when using MBP with self-distillation, we take the view of Frobenius distortion minimization (FDM; Dong et al., 2017) which says that layer-wise MBP is equivalent to minimizing the Frobenius distortions of a single layer. This can be described as \(\min_{M} \|W - M \odot W\|_F\), where \(\odot\) is the Hadamard product and \(p\) is a constraint of the number of weights to remove as a percentage of the total number of weights for a layer. Therefore, the output distortion is approximately the product of single layer Frobenius distortions. However, this minimization only defines a 1st order approximation of pruning induced Frobenius distortions which is a loose approximation for deep networks. In contrast, the \(y^T\) targets provide higher-order information outside of the \(l\)-th layer being pruned in this FDM framework because \(\Theta\) encodes information of all neighboring layers. Hence, we reformulate the FDM problem for SDP as an approximately higher-order MBP method as in Equation 4 where \(W^T\) are the weights in \(f_\theta\).

\[
\min_{M: \|M\|_F = p} \left(\|W - M \odot W\|_F + \lambda\|W^T - M \odot W\|_F\right)
\] (4)

As described in Dong et al. (2017); Hassibi & Stork (1993), the error function can be approximated with a Taylor Series (TS) expansion as \(\mathcal{E}(Z^T) - \mathcal{E}(Z) = \delta E = \frac{\partial^2 \mathcal{E}}{\partial \theta^2} \delta \theta + \frac{1}{2} \delta \theta^T H \delta \theta + O(\|\delta \theta\|^3)\). Since, MBP corresponds to the 1st order term of this TS expansion, we can express the TS approximation of the error function \(\mathcal{E}(\cdot)\) with self-distilled pruning as shown in Equation 5, where
\( Z^*_t \) is the true latent representation of the input.

\[
2\mathcal{E}(Z_t) - \mathcal{E}(Z^*_t) - \mathcal{E}(Z^*_t) = \delta \mathcal{E}_t \approx \left( \frac{\partial \mathcal{E}_t}{\partial \theta_t} \right)^\top \delta \theta_t + \lambda \left( \frac{\partial \mathcal{E}_t^T}{\partial \theta_t} \right)^\top \delta \theta_t
\]  

(5)

3.3 How Does Self-Distillation Improve Pruned Model Generalization?

We put forth the following insights as to the advantages provided by self-distillation for better model generalization, and later experimentally demonstrate their validity.

Recovering Faster From Performance Degradation After Pruning Steps. The first explanation for why self-distillation leads to better generalization in iterative pruning is that the soft targets bias the optimization and smoothen the loss surface through implicit similarities between the classes encoded in the logits. We posit this too holds true for performance recovery after pruning steps, as the classification boundaries become distorted due to the removal of weights. Faster convergence is particularly important for high compression rates where the performance drops become larger.

Implicit Maximization of the Signal-to-Noise Ratio. One explanation for faster convergence is that optimizing for soft targets translates to maximizing the margin of class boundaries given by the implicit class similarities provided by teacher logits. Intuitively, task provided one-hot targets do not inform SGD of how similar incorrect predictions are to the correct class, whereas the teacher logits do, to the extent they have learned on the same task. To measure this, we use a formulation of the signal-to-noise ratio (SNR) to measure the class separability and compactness differences between pruned model representations trained with and without self-distillation. We formulate SNR as

\[
\text{SNR}(Z) = \frac{1}{N(C-1)^2} \sum_{c=1}^{N} \sum_{c \neq c}^{C} \sum_{i,j=1}^{C} || \sqrt{Z_{c,n}} - \sqrt{Z_{i,n}} ||_2
\]

(6)

This estimation is \( C - 1 \) in the number of pairwise distances to be computed between the inter-class distances for the classes. For large output spaces (e.g., language modeling) we recommend defining the top \( k \)-NN classes for each class and estimate their distances on samples from them.

Quantifying Fidelity Between Pruned Models Trained With and Without Self-Distillation. A natural question to ask is how much generalization power does the distilled soft targets provide when compared to the task provided one-hot targets? If best generalization is achieved when \( \alpha = 1 \) in Equation 1 this implies that the pruned network should have as high fidelity as possible with the unpruned network. However, as we will see there is a bias-variance trade-off between fidelity and generalization performance, i.e., \( \alpha = 1 \) is not optimal in most cases. To measure fidelity between SDP representations and standard fine-tuned representations, we compute their mutual information (MI) and compare this to the MI between representations of pruned models without self-distillation and standard fine-tuned models. The MI between continuous variables can be expressed as

\[
\hat{I}(Z^T; Z^S) = \text{H}(Z^T) - \text{H}(Z^T|Z^S) = -\mathbb{E}_{Z^T} [\log p(Z^T)] + \mathbb{E}_{Z^T, Z^S} [\log p(Z^T|Z^S)]
\]

(7)

where \( \text{H}(Z^T) \) is the entropy of the teacher representation and \( \text{H}(Z^T|Z^S) \) is the conditional entropy that is derived from the joint distribution \( p(Z^T, Z^S) \). This can also be expressed as the KL divergence between the joint probabilities and product of marginals as

\[
I(Z^T; Z^S) = D_{\text{KL}}(p(Z^T, Z^S)||p(Z^T)p(Z^S))
\]

However, these theoretical quantities have to be estimated from test sample representations. We use a \( k \)-NN based MI estimator (Kraskov et al., 2004; Evans, 2008; Ver Steeg & Galstyan, 2013; Ver Steeg, 2000) which partitions the supports into a finite number of bins of equal size, forming a histogram that can be used to estimate \( \hat{I}(Z^S; Z^T) \) based on discrete counts in each bin. This MI estimator is given as

\[
\hat{I}(z^S; z^T) \approx \epsilon \left( \log \frac{\phi(z^S)(i, k[z^S]) \phi(z^T)(i, k[z^T])}{\phi_z(i, k)} \right)
\]

(8)

\text{A measure typically used in signal processing to evaluate signal quality.}
where \( \phi_z(i, k_{z, j}) \) is the probability measure of the \( k \)-th nearest neighbour ball of \( z^S \in \mathbb{R}^{n_z} \) and \( \omega_{z,t}(i, k_{z, j}) \) is the probability measure of the \( k_{z, j} \)-th nearest neighbour ball of \( z^T \in \mathbb{R}^{n_t} \) where \( n_L \) is the dimension of the penultimate layer. In our experiments, we use 256 bins for the histogram with Gaussian smoothing and \( k = 5 \) (see Kraskov et al. (2004) for further details).

4 EXPERIMENTAL SETUP

Datasets. We perform experiments on monolingual tasks within the GLUE (Wang et al., 2018) benchmark with pretrained BERT\textsubscript{Base} and multilingual tasks from the XGLUE benchmark (Liang et al., 2020) with pretrained XLM\textsubscript{R}\textsubscript{Base}. In total, this covers 18 different datasets, covering pairwise classification, sentence classification, structured prediction and question answering. To our knowledge, this work is the first to analyse iterative pruning in the context of cross-lingual models and their application on multilingual datasets.

Iterative Pruning Baselines. For XGLUE tasks, we perform 15 pruning steps on XLM-RoBERTA\textsubscript{Base}, one per 15 epochs, while for the GLUE tasks, we perform 32 pruning steps on BERT\textsubscript{Base}. The compression rate and number of pruning steps is higher for GLUE tasks compared to XGLUE, because GLUE tasks involve evaluation in the supervised classification setting; whereas in XGLUE we report in the more challenging zero-shot cross-lingual transfer setting with only a single language used for training (i.e., English). At each pruning step, we uniformly pruning 10% of the parameters for both the models. Although prior work suggests non-uniform pruning schedules (e.g., cubic schedule (Zhu & Gupta, 2017)), we did not see any major differences to uniform pruning. We compare the performance of the proposed SDP-CC method against the following baselines:

- **Random Pruning (MBP-Random)** - prunes weights uniformly at random across all layers. Random pruning can be considered as a lower bound on iterative pruning performance.
- **Layer-wise Magnitude Based Pruning (MBP)** - for each layer, prunes weights with LAV.
- **Global Magnitude Pruning (Global-MBP)** - prunes LAV weights anywhere in the network.
- **Layer-wise Gradient Magnitude Pruning (Gradient-MBP)** - for each layer, prunes the weights with LAV of the accumulated gradients evaluated on a batch of inputs.
- **1\textsuperscript{st} Taylor Series Pruning (TS)** - prunes weights based on the LAV of \(|\text{gradient} \times \text{weight}|\).
- **\( L_0 \) norm MBP** (Louizos et al., 2017) - uses non-negative stochastic gates that choose which weights are set to zero as a smooth approximation to the non-differentiable \( L_0 \)-norm.
- **\( L_1 \) norm MBP** (Li et al., 2016) - applies \( L_1 \) weight regularization and uses MBP.
- **Lookahead pruning (LAP)** (Park et al., 2020) - prunes weight paths that have the smallest magnitude across blocks of layers, unlike MBP that does not consider neighboring layers.
- **Layer-Adaptive MBP (LAMP)** (Lee et al., 2020) - adaptively compute the pruning ratio per layer.

For all above pruning methods we exclude weight pruning of the embeddings, layer normalization parameters and the last classification layer, as they play an important role for generalization and account for less than 1% of weights in both BERT and XLM-R\textsubscript{Base}.

- **Knowledge Distillation** – We also compare against a class of smaller knowledge distilled versions of BERT model with varying parameter sizes on the GLUE benchmark. We report prior results of DistilBERT (Sanh et al., 2019) and also mini-BERT models including TinyBERT (Jiao et al., 2019), BERT-small (Ture et al., 2019) and BERT-medium (Ture et al., 2019).

- **Self-Distilled Pruning Variant** – In addition, we consider maximizing the cosine similarity between pruned and unpruned representations in the SDP loss, as \( \ell_{\text{SDP-COS}} := \alpha \ell_{\text{CE}}(\hat{y}, \hat{y}) + \beta (1 - \frac{\langle \hat{y}^S, z^T \rangle}{||\hat{y}^S|| ||z^T||}) \). Unlike cross-correlation, there is no decorrelation of non-adjacent features in both representations for SDP-COS. This helps identify whether the redundancy reduction in cross-correlation is beneficial compared to the correlation loss that does not directly optimize this.

Hyperparameter Settings. For SDP-KLD, we tested \( \alpha = [0.1, 0.2, 0.5, 0.8, 1] \) on three tasks for GLUE and XGLUE and extrapolate the best performing setting for the remaining tasks of both benchmarks with a fixed \( \tau = 0.9 \). We find \( \alpha = 0.5 \) to perform the best in all cases. For SDP-CC, we perform tests with \( \beta = [10^{-6}, 2 \times 10^{-5}, 5 \times 10^{-5}, 10^{-4}] \), finding that \( \beta = 2 \times 10^{-5} \) results in the best average performance. For SDP-COS, we set \( \beta = 0.05 \).

\(^2\)WNLI is excluded for known issues, see the Q. 12 on the GLUE benchmark FAQ.
### Empirical Results

#### Pruning Results on GLUE

Table 1 shows the test performance across all GLUE tasks of the different models with varying pruning ratios, up to 10% remaining weights of original BERT$_{Base}$ along with mini-BERT models (Sanh et al., 2019; Jiao et al., 2019; Turc et al., 2019) of varying size. However, for the CoLA dataset, we report at 20% pruning as nearly all compression methods have an MCC score of 0, making the compressed method performance indistinguishable. For this reason, the GLUE score (Score) is computed for all tasks and methods @10% apart from CoLA. The best performing compression method per task is marked in bold. We find that our proposed SDP approaches (all three variants) outperform against baseline pruning methods, with SDP-CC performing the best across all tasks. We note that for the tasks with fewer training samples (e.g., CoLA has 8.5k samples, STS-B has 7k samples and RTE has 3k samples), the performance gap is larger compared to BERT$_{Base}$, as the pruning step interval is shorter and less training data allows lesser time for the model to recover from pruning losses and also less data for teacher model to distil in the case of using SDP.

Smaller dense versions of BERT require more labelled data in order to compete with unstructured MBP and higher-order pruning methods such as 1$^{st}$ order Taylor series and Lookahead pruning. For example, we see BERT-Mini (@10%) shows competitive test accuracy with our proposed SDP-CC on QNLI, MNLI and QQP, the three datasets with the most training samples (105k, 393k and 364k respectively). Overall, $L_2$-MBP + SDP-CC achieves the highest GLUE score for all models at 10% remaining weights when compared to BERT-Base parameter count. Moreover, we find that $L_2$-MBP + SDP-CC achieves best performance for 5 of the 8 tasks, with 1 of the remaining 3 being from $L_2$-MBP+SDP-KLD. This suggests that redundancy reduction via a cross-correlation objective is useful for SDP and clearly improve over SDP-COS which does not minimize correlations between off-diagonal terms. Figure 2 shows the performance across all pruning steps. Interestingly, for QNLI we observe the performance notably improves between 30-70% for SDP-CC and SDP-KLD. For SST-2, we observe a significant gap between SDP-KLD and SDP-CC compared to the pruning baselines and smaller versions of BERT, while TinyBERT becomes competitive at extreme compression rates (<4%).

#### Pruning Results on XGLUE

We show the per task test performance and the average task understanding score on XGLUE for pruning baselines and our proposed SDP approaches in Table 2. Our proposed cross-task-relevance objective for SDP again achieves the best average (Avg.) score and achieves the best task performance in 6 out of 8 tasks, while standard SDP-KLD achieves best performance on one (news classification) of the remaining two. Most notably, we outperform methods which use higher order gradient information (1$^{st}$-order Taylor) at 30% remaining weights, which tends to be a point at which XLM-R$_{Base}$ begins to degrade performance below 10% of the original fine-tuned test performance for SDP methods and competitive baselines. In Figure 3 we can observe
Figure 2: Iterative Pruning Test Performance on GLUE tasks.

Table 2: XGLUE Iterative Pruning @ 30% Remaining Weights of XLM-R<sub>Base</sub> - Zero Shot Cross-Lingual Performance Per Task and Overall Average Score (Avg).

| Prune Method                      | XNLI | NC   | NER  | PAWSX | POS  | QAM  | QADSM | WPR  | Avg  |
|-----------------------------------|------|------|------|-------|------|------|-------|------|------|
| XLM-R<sub>Base</sub>              | 73.48| 80.10| 82.60| 89.24 | 80.34| 68.56| 68.06 | 73.32| 76.96|
| Random                            | 51.22| 70.19| 38.19| 57.37 | 52.57| 53.85| 52.34 | 70.69| 55.80|
| Global-Random                     | 50.97| 69.88| 38.30| 56.74 | 53.02| 54.02| 53.49 | 69.11| 55.69|
| L<sub>2</sub>-MBP                 | 64.75| 78.98| 56.22| 72.09 | 71.38| 59.31| 53.35 | 71.70| 65.97|
| L<sub>2</sub>-MBP Global          | 64.30| 78.79| 54.43| 77.99 | 70.68| 59.24| 60.33 | 71.52| 67.16|
| Lookahead                         | 65.12| 78.64| 54.47| 79.13 | 71.37| 59.26| 60.61 | 71.80| 67.55|
| 1<sup>st</sup>-order Taylor       | 61.11| 73.77| 53.25| 79.56 | 65.89| 57.35| 59.33 | 71.59| 65.23|
| LAMP                              | 64.26| 79.34| 63.60| 82.83 | 68.94| 61.69| 62.42 | 72.28| 69.09|
| L<sub>2</sub>-MBP + SDP-COS       | 60.84| 79.18| 54.44| 71.05 | 68.76| 55.94| 53.41 | 71.26| 64.36|
| L<sub>2</sub>-MBP + SDP-KLD       | 58.04| 63.64| 51.92| 66.05 | 67.43| 55.36| 52.42 | 71.09| 60.74|
| L<sub>2</sub>-MBP + SDP-CC        | 64.96| 79.02| 62.77| 78.70 | 72.88| 60.21| 60.94 | 72.04| 68.94|
| L<sub>2</sub>-MBP Global + SDP-COS| 65.94| 80.72| 64.50| 79.25 | 73.18| 61.66| 61.09 | 71.84| 69.77|
| L<sub>2</sub>-MBP Global + SDP-CC | 64.47| 79.73| 66.34| 80.03 | 73.45| 63.73| 62.78 | 72.59| 70.76|

this trend from the various tasks within XGLUE. We note that the number of training samples used for retraining plays an important role in the rate of performance degradation. For example, of the 6 presented XGLUE tasks, NER has the lowest number of training samples (15k) of all XGLUE tasks and also degrades the fastest in performance (from 90% to 50% Test F1 at 30% remaining weights). In comparison, XNLI has the most training samples for retraining (433k) and maintains performance relatively well, keeping within 10% of the original fine-tuned model at 30% remaining weights.

Summary of Results. From our experiments on GLUE and XGLUE task, we find that SDP consistently outperforms pruning, KD and smaller BERT baselines. SDP-KLD and SDP-CC both outperform larger sized BERT models (BERT-Small), somewhat surprisingly, given that BERT-Small (and the remaining BERT models) have the advantage of large-scale self-supervised pretraining, while pruning only has supervision from the downstream task. For NER in XGLUE, higher order pruning methods such as Taylor-Series pruning have an advantage at high compression rates mainly.
due to lack of training samples (only 15k). Apart from this low training sample regime, SDP with MBP dominates at high compression rates both in standard and zero-shot settings.

**Measuring Fidelity To The Fine-Tuned Model.** We now analyse the empirical evidence that soft targets used in SDP may force higher fidelity with the representations of the fine-tuned model when compared to using MBP without self-distillation. As described in subsection 3.3, we measure mutual dependencies between both representations of models with the best performing hyperparameter settings of $\alpha$, $\beta$ and the softmax temperature $\tau$. We note that increasing the temperature $\tau$ translates to "peakier" teacher logits distributions, encouraging SGD to learn a student with high fidelity to the teacher. From the LHS of Figure 4, we can see that SDP models have higher mutual information (MI) with the teacher compared to MBP, which performs worse for PAWS-X (similar on remaining tasks, not shown for brevity). In fact, the rank order of the best performing pruned models at each pruning step has a direct correlation with MI, e.g., SDP-COS-MBP maintains highest MI and the highest test accuracy for PAWS-X for the same step has a direct correlation with MI, e.g., SDP-COS-MBP maintains highest MI and the highest test accuracy for PAWS-X for the same

**Self-Distilled Pruning Increases Class Separability and The Signal-To-Noise Ratio (SNR).** We also find that the SNR is increased at each pruning step as formulated in subsection 3.3. From this observation, we find that SDP-COS-MBP using cross-correlation loss does particularly well in the 30%-50% remaining weights range. More generally, all 3 SDP losses clearly lead to better class separability and class compactness across all pruning steps compared to MBP (i.e., no self-distillation).

**Self-Distilled Pruning Recovers Faster Performance Degradation Directly After Pruning Steps.**
Figure 5 shows how SDP with Magnitude pruning (SDP-MBP) recovers during training in between pruning steps. The top of each vertical bar is the recovery development accuracy and the bottom is the initial performance degradation prior to retraining. We see that SDP pruned models degrade in performance more than magnitude pruning without self-distillation. This suggests that SDP-MBP may force weights to be closer, as there is more initial performance degradation if weights are not driven to zero. However, the recovery is faster. This may be explained by recent work that suggests the stability generalization tradeoff (Bartoldson et al., 2019).

6 Conclusion

In this paper, we proposed a novel self-distillation based pruning technique based on a cross-correlation objective. We extensively studied the confluence between pruning and self-distillation for masked language models and its enhanced utility on downstream tasks in both monolingual and multi-lingual settings. We find that self-distillation aids in recovering directly after pruning in iterative magnitude-based pruning, increases representational fidelity with the unpruned model and implicitly maximize the signal-to-noise ratio. Additionally, we find our cross-correlation based self-distillation pruning objective minimizes neuronal redundancy and achieves state-of-the-art in magnitude-based pruning baselines, and even outperforms KD based smaller BERT models with more parameters.

References

Sungsoo Ahn, Shell Xu Hu, Andreas Damianou, Neil D Lawrence, and Zhenwen Dai. Variational information distillation for knowledge transfer. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 9163–9171, 2019.

Zeyuan Allen-Zhu and Yuanzhi Li. Towards understanding ensemble, knowledge distillation and self-distillation in deep learning. arXiv preprint arXiv:2012.09816, 2020.

Sajid Anwar, Kyuyeon Hwang, and Wonyong Sung. Structured pruning of deep convolutional neural networks. ACM Journal on Emerging Technologies in Computing Systems (JETC), 13(3):1–18, 2017.

Brian R Bartoldson, Ari S Morcos, Adrian Barbu, and Gordon Erlebacher. The generalization-stability tradeoff in neural network pruning. arXiv preprint arXiv:1906.03728, 2019.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. Unsupervised cross-lingual representation learning at scale. arXiv preprint arXiv:1911.02116, 2019.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018.

Xin Dong, Shangyu Chen, and Sinno Jialin Pan. Learning to prune deep neural networks via layer-wise optimal brain surgeon. arXiv preprint arXiv:1705.07565, 2017.

Dafydd Evans. A computationally efficient estimator for mutual information. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 464(2093):1203–1215, 2008.

Tommaso Furlanello, Zachary Lipton, Michael Tschannen, Laurent Itti, and Anima Anandkumar. Born again neural networks. In International Conference on Machine Learning, pp. 1607–1616. PMLR, 2018.

S Han, H Mao, and WJ Dally. Compressing deep neural networks with pruning, trained quantization and huffman coding. arXiv preprint, 2015a.
Song Han, Jeff Pool, John Tran, and William J Dally. Learning both weights and connections for efficient neural networks. *arXiv preprint arXiv:1506.02626*, 2015b.

Babak Hassibi and David G Stork. *Second order derivatives for network pruning: Optimal brain surgeon*. Morgan Kaufmann, 1993.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2015.

Zehao Huang and Naiyan Wang. Like what you like: Knowledge distill via neuron selectivity transfer. *arXiv preprint arXiv:1707.01219*, 2017.

Xiaoqi Jiao, Yichun Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang, and Qun Liu. Tinybert: Distilling bert for natural language understanding. *arXiv preprint arXiv:1909.10351*, 2019.

Ehud D Karnin. A simple procedure for pruning back-propagation trained neural networks. *IEEE transactions on neural networks*, 1(2):239–242, 1990.

Alexander Kraskov, Harald Stögbauer, and Peter Grassberger. Estimating mutual information. *Physical review E*, 69(6):066138, 2004.

Vadim Lebedev and Victor Lempitsky. Fast convnets using group-wise brain damage. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2554–2564, 2016.

Yann LeCun, John S Denker, and Sara A Solla. Optimal brain damage. In *Advances in neural information processing systems*, pp. 598–605, 1990.

Jaeho Lee, Sejun Park, Sangwoo Mo, Sungsoo Ahn, and Jinwoo Shin. Layer-adaptive sparsity for the magnitude-based pruning. In *International Conference on Learning Representations*, 2020.

Hao Li, Asim Kadav, Igor Durjanovic, Hanan Samet, and Hans Peter Graf. Pruning filters for efficient convnets. *arXiv preprint arXiv:1608.08710*, 2016.

Yaobo Liang, Nan Duan, Yeyun Gong, Ning Wu, Fenfei Guo, Weizhen Qi, Ming Gong, Linjun Shou, Daxin Jiang, Guihong Cao, et al. Xglue: A new benchmark dataset for cross-lingual pre-training, understanding and generation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 6008–6018, 2020.

Zhuang Liu, Jianguo Li, Zhiqiang Shen, Gao Huang, Shoumeng Yan, and Changshui Zhang. Learning efficient convolutional networks through network slimming. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 2736–2744, 2017.

Christos Louizos, Max Welling, and Diederik P Kingma. Learning sparse neural networks through l0 regularization. *arXiv preprint arXiv:1712.01312*, 2017.

Arun Mallya, Dillon Davis, and Svetlana Lazebnik. Piggyback: Adapting a single network to multiple tasks by learning to mask weights. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pp. 67–82, 2018.

James Martens and Roger Grosse. Optimizing neural networks with kronecker-factored approximate curvature. In *International conference on machine learning*, pp. 2408–2417. PMLR, 2015.

Hossein Mobahi, Mehrdad Farajtabar, and Peter L Bartlett. Self-distillation amplifies regularization in hilbert space. *arXiv preprint arXiv:2002.05715*, 2020.

Dmytro Molchanov, Arsenii Ashukha, and Dmitry Vetrov. Variational dropout sparsifies deep neural networks. In *International Conference on Machine Learning*, pp. 2498–2507. PMLR, 2017.

Michael C Mozer and Paul Smolensky. Skeletonization: A technique for trimming the fat from a network via relevance assessment. In *Advances in neural information processing systems*, pp. 107–115, 1989.

James O’Neill and Danushka Bollegala. Semantically-conditioned negative samples for efficient contrastive learning. *arXiv preprint arXiv:2102.06603*, 2021.
Sejun Park, Jaeho Lee, Sangwoo Mo, and Jinwoo Shin. Lookahead: A far-sighted alternative of magnitude-based pruning. *arXiv preprint arXiv:2002.04809*, 2020.

Wonpyo Park, Dongju Kim, Yan Lu, and Minsu Cho. Relational knowledge distillation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 3967–3976, 2019.

Russell Reed. Pruning algorithms-a survey. *IEEE transactions on Neural Networks*, 4(5):740–747, 1993.

Adriana Romero, Nicolas Ballas, Samira Ebrahimi Kahou, Antoine Chassang, Carlo Gatta, and Yoshua Bengio. Fitnets: Hints for thin deep nets. *arXiv preprint arXiv:1412.6550*, 2014.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. *arXiv preprint arXiv:1910.01108*, 2019.

Victor Sanh, Thomas Wolf, and Alexander M Rush. Movement pruning: Adaptive sparsity by fine-tuning. *arXiv preprint arXiv:2005.07683*, 2020.

Sidak Pal Singh and Dan Alistarh. Woodfisher: Efficient second-order approximations for model compression. *arXiv preprint arXiv:2004.14340*, 2020.

Samuel Stanton, Pavel Izmailov, Polina Kirichenko, Alexander A Alemi, and Andrew Gordon Wilson. Does knowledge distillation really work? *arXiv preprint arXiv:2106.05945*, 2021.

Yonglong Tian, Dilip Krishnan, and Phillip Isola. Contrastive representation distillation. *arXiv preprint arXiv:1910.10699*, 2019.

Iulia Turc, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Well-read students learn better: On the importance of pre-training compact models. *arXiv preprint arXiv:1908.08962*, 2019.

Greg Ver Steeg. Non-parametric entropy estimation toolbox (npeet). Technical report, Technical Report. 2000. Available online: https://www. isi. edu/˜ gregv . . . , 2000.

Greg Ver Steeg and Aram Galstyan. Information-theoretic measures of influence based on content dynamics. In *Proceedings of the sixth ACM international conference on Web search and data mining*, pp. 3–12, 2013.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. Glue: A multi-task benchmark and analysis platform for natural language understanding. *arXiv preprint arXiv:1804.07461*, 2018.

Chaoqi Wang, Roger Grosse, Sanja Fidler, and Guodong Zhang. Eigendamage: Structured pruning in the kronecker-factored eigenbasis. In *International Conference on Machine Learning*, pp. 6566–6575. PMLR, 2019.

Wei Wen, Chunpeng Wu, Yandan Wang, Yiran Chen, and Hai Li. Learning structured sparsity in deep neural networks. *arXiv preprint arXiv:1608.03665*, 2016.

Chenglin Yang, Lingxi Xie, Siyuan Qiao, and Alan L Yuille. Training deep neural networks in generations: A more tolerant teacher educates better students. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pp. 5628–5635, 2019.

Jianbo Ye, Xin Lu, Zhe Lin, and James Z Wang. Rethinking the smaller-norm-less-informative assumption in channel pruning of convolution layers. *arXiv preprint arXiv:1802.00124*, 2018.

Ming Yuan and Yi Lin. Model selection and estimation in regression with grouped variables. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 68(1):49–67, 2006.

Jure Zbontar, Li Jing, Ishan Misra, Yann LeCun, and Stéphane Deny. Barlow twins: Self-supervised learning via redundancy reduction. *arXiv preprint arXiv:2103.03230*, 2021.

Michael Zhu and Suyog Gupta. To prune, or not to prune: exploring the efficacy of pruning for model compression. *arXiv preprint arXiv:1710.01878*, 2017.