Compressing Transformer-Based Self-Supervised Models for Speech Processing

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Abstract—Despite the success of Transformers in self-supervised learning with applications to various downstream tasks, the computational cost of training and inference remains a major challenge for applying these models to a wide spectrum of devices. Several isolated attempts have been made to compress Transformers, but the settings and metrics are different across studies. Trade-off at various compression rates are also largely missing in prior work, making it difficult to compare compression techniques. In this work, we aim to provide context for the isolated results, studying several commonly used compression techniques, including weight pruning, head pruning, low-rank approximation, and knowledge distillation. We report trade-off at various compression rate, including wall-clock time, the number of parameters, and the number of multiply-accumulate operations. Our results show that compared to recent approaches, basic compression techniques are strong baselines. We further present several applications of our results, revealing properties of Transformers, such as the significance of diagonal attention heads. In addition, our results lead to a simple combination of compression techniques that improves trade-off over recent approaches. We hope the results would promote more diverse comparisons among model compression techniques and promote the use of model compression as a tool for analyzing models. Our code of compressing speech self-supervised model is available at https://github.com/nervjack2/Speech-SSL-Compression/.

Index Terms—Compression, Self-supervised, Representation

I. INTRODUCTION

SELF-SUPERVISED learning for speech processing has had a great success in scaling up with the increasing amount of unlabeled data, achieving strong performance in various tasks, such as automatic speech recognition (ASR), and speaker verification [1]. To make use of the large amount of unlabeled data, self-supervised models are typically large, for example, with 12 or more layers of Transformers [2]–[5]. These large models are slow in runtime, requiring cutting-edge hardware, such as GPUs with sufficient memory. In this work, we focus on compressing Transformer-based self-supervised models, making them more efficient and suitable for a wide spectrum of devices and settings.

Common compression techniques, such as iterative pruning [6]–[8], low-rank approximation [9]–[11], and knowledge distillation [12], have little in common—a sign that the concept of model compression is broad, if not too broad. Model compression is typically defined as a function $C$ that takes in a model $m$ and returns a small model $C(m)$ (sometimes with additional training and data). The compression function $C$ can, in fact, return a small model, completely ignoring the input model $m$. For example, training a small model from random initialization and neural architecture search can both be treated as model compression, even though nothing is really compressed. Any approach that returns a small yet performant model contributes to the trade-off and should be considered in the opportunity cost of compression. In this work, we limit the study to iterative pruning, low-rank approximation, and knowledge distillation. Following this argument, we also provide simple baselines, where we simply take the early layers, i.e., stopping the forward process of the large model early. Stopping the forward process early not only reduces computation but also maintains satisfactory performance, because low layers are often already useful for several downstream tasks [13].

Comparing compression techniques involving self-supervised training is complicated. Some study compression for a particular downstream task [13]–[17], while some aim to obtain a model that can extract a general representation across different downstream tasks [18]–[27]. In addition to the common task accuracy, some compare the number of parameters [19], while some compare wall-clock time [21], [25] or the number of multiply-accumulate operations (MACs) [17]. Many have also failed to include simple baselines, making it difficult to compare approaches.

In this work, we focus on compressing self-supervised models with the self-supervised loss that the models are trained with. As a baseline, we choose MelHuBERT [28], a variant of HuBERT that takes Mel spectrograms as input and has a simplified training recipe. We train our own MelHuBERT from random initialization to obtain a complete training loss curve. Having a complete loss curve is essential because subsequent compression all rely on monitoring and maintaining the loss values.

To facilitate the comparison of compression techniques on self-supervised models, we provide a comprehensive study of theoretical and practical speed-up of different compression techniques, measuring wall-clock time, numbers of parameters, and numbers of MACs per one second speech, charting the landscape of compressing Transformer-based self-supervised models. Our results enable a fair and comprehensive comparison among prior work, such as DistilHuBERT [19], FitHuBERT [21], and LightHuBERT [20]. We also show that our simple baselines are strong contenders for these more involved approaches.

Our results suggest that pruning entire layers is the best for improving the runtime on GPUs, while head pruning and low-rank approximation are useful for reducing the number of parameters but not as effective in improving the runtime on GPUs. The results motivate us to chain these techniques
together, leveraging the strengths of each technique. These simple combinations provide better trade-off than prior work.

Finally, we conduct an in-depth analysis on the compression results. We attempt to answer to what degree we can maintain the self-supervised loss when compressing and to what degree maintaining the self-supervised loss leads to generalization of different downstream tasks. In addition, prior work compress various parts of a neural network without providing insights as to what are compressed. We will show what parts tend to be compressed more, e.g., what types of attention heads tend to be compressed. Compression, in general, is a valuable tool for understanding models, and, in our case, Transformers.

We summarize our contributions as follows.

1) Different compression techniques have different strengths among MACs, numbers of parameters and real-time factors. We hope that this work will encourage others to evaluate compression methods from a more diverse and comprehensive perspective.

2) Mapping comprehensive trade-off allows us to compare several recent approaches, namely, DistilHuBERT [19], FitHuBERT [21], and LightHuBERT [20]. Our simple baselines are surprisingly strong compared to prior work.

3) We show that it is possible to provide better trade-off by simply chaining several compression techniques together.

4) We analyze what parts of Transformers are likely to be pruned, revealing various properties of self-supervised Transformers.

II. Model Compression

Since the training loss after compression typically becomes worse, it is common to have additional training on the compressed model to recover the training loss. To monitor and to assess how much training loss is recovered, we need to have access to the training curve prior to any compression.

We choose MelHuBERT [28] due to its strong performance and simple training recipe. The simple training recipe allows us to obtain the entire training curve from random initialization. We will briefly review MelHuBERT and its self-supervised loss function, as the loss function will be what we monitor and want to recover.

After reviewing MelHuBERT, we will detail the specifics of model compression techniques used in this work, including weight pruning, head pruning, low-rank approximation, knowledge distillation. Except knowledge distillation, the others can be seen as instances of iterative pruning. Iterative pruning performs the following two steps iteratively.

1) Prune a block of weights.

2) Train the pruned network until the loss (to be introduced next) converges.

What constitutes a block and how a block is chosen can be customized. If we choose individual weights as blocks, this algorithm becomes weight pruning [29]; If we instead choose attention heads as blocks, this algorithm becomes head pruning [8]. If we choose rows or columns as blocks, this algorithm becomes low-rank approximation [2]. As opposed to one-shot pruning, we perform pruning iteratively, because iterative pruning typically achieves better compression [30]. We avoid using more involved variants of pruning as our baselines, such as those in [17], [25], because pruning while training or additional terms in the optimization add confounding factors, complicating our analysis.

A. MelHuBERT

MelHuBERT [28] is a variant of HuBERT, with simplifications on both the model architecture and the training objective. MelHuBERT takes Mel spectrograms as input (hence the name), as opposed to wave samples in HuBERT. MelHuBERT excludes the seven convolution layers in HuBERT for producing 20-ms frames, saving about 33.3% of MACs and about 31.2% of pre-training time on a single 24GB RTX 3090 GPU. In addition to the model architecture, the training objective of MelHuBERT has been simplified as well. Instead of using the wav2vec 2.0 style loss function in HuBERT, MelHuBERT minimizes the cross entropy loss, which has been shown to accelerate training [31].

Since the loss will be used for subsequent compression, we formally define it as follows. Suppose we have a sequence of 10-ms log Mel frames $x_1 \ldots x_T$. We first quantize the sequence into a sequence of indices $c_1 \ldots c_T$ with k-means clustering. In particular, $c_t = \arg \min_{i=1, \ldots, k} \|x_t - m_i\|_2$, where $k$ is the number of clusters used in k-means clustering, and $m_i$ is $i$-th cluster centroid. The self-supervised loss function for training MelHuBERT is formulated as:

$$
\mathcal{L} = - \sum_{t=1}^{T} \log p(c_t|x),
$$

where

$$
p(c_t|x) = \frac{\exp(W_{c_t}^\top o_t)}{\sum_{i=1}^{K} \exp(W_i^\top o_t)}
$$

is the distribution of the centroids predicted by the Transformer, $W$ is a learnable projection matrix, $W_i$ is the $i$-th row of $W$, and $o_t$ is the model’s output representation at time step $t$.

Following [28], we train two variants, MelHuBERT-10ms and MelHuBERT-20ms. MelHuBERT-10ms takes the typical Mel spectrograms at a 10 ms frame period, while MelHuBERT-20ms takes the concatenation of every two frames to achieve a 20 ms frame period. For MelHuBERT-20ms, we select the cluster labels of odd Mel frames $c_1, c_3, \ldots, c_{2n+1}$, where $n = \lceil \frac{T}{2} \rceil - 1$, as predicting targets. Similar to [3], we train MelHuBERT in two stages. The first stage uses quantized Mel spectrograms as targets, while the second stage uses quantized MelHuBERT hidden vectors as targets. Note that in the second stage, the frame rate of hidden vectors is the same as the targets, so we do not subsample the targets as in the first stage for MelHuBERT-20ms.

MelHuBERT not only is competitive against HuBERT but also trains at a lower computational cost, offering a strong footing for subsequent compression.
B. Weight pruning

Weight pruning is one of the earliest pruning algorithms [29]. The idea is based on the finding that the increase in loss due to small changes to the weights of neural networks can be quickly recovered by a small amount of training. Weight pruning usually is an instance of iterative pruning, which converges faster and with lower training loss compared to one-shot pruning. In this work, we adopt one of the simplest criteria for pruning [7], [30], setting the weight to zero when the absolute value is below a threshold. We follow the usual implementation [7], using a binary mask to keep track of what weights are pruned. Weights that are pruned are never instantiated again.

To be more precise, suppose \( f \) is the forward function, \( x \) is the input, and \( \theta \) is the model parameter. To compute the forward results of a pruned model, instead of computing \( f(x; \theta) \), we compute \( f(x; m \odot \theta) \), where \( m \in \{0, 1\}^{\mid \theta \mid} \) is a binary mask. The value of the mask \( m \) is determined by:

\[
m_i = \begin{cases} 
0 & \text{if } |\theta_i| < \delta \\
1 & \text{otherwise}
\end{cases}
\]

where \( \delta \) is the threshold determined based on a target density. We will have a schedule for the amounts to be pruned in the experiments.

Since the mask does not exhibit any structure, speed-up of weight pruning can only come from sparse parallel computations or dedicated hardware [6]. In this work, we do not explore these options and only report theoretical speed-up.

C. Head pruning

Head pruning is an iterative pruning technique specific to Transformers [8], where the unit of a block being pruned is a set of key, query, and value weights for computing self-attention. Previous studies have discovered that it is sufficient to perform well with only few attention heads [32], [33]. We are interested in to what extent this statement holds for self-supervised Transformers. If it holds, pruning heads can lead to significant reduction in memory and computation, considering the \( O(T^2) \) memory and computation for a sequence of length \( T \) to compute the self-attention.

Similar to weight pruning, we compute a score for each head and prune heads of low scores to a target density. There are several options to compute the score of an attention head. The first is simply using the \( \ell_1 \) norm for each head \( H_i \), where \( J_i \) is the attention map multiplied by the forward result of the value matrix \( V_i \), and \( \frac{\partial C}{\partial J_i} \) is the gradient to that particular computation node. This quantity considers the \( \ell_1 \) of both the attention map and its gradient. If the \( \ell_1 \) norm of the forward result is small, then the head is a good candidate to prune. If the \( \ell_1 \) norm of the gradient is small, changing the attention map has little effect on the loss, also meaning that the head is a good candidate to prune.

Contrary to weight pruning, the computation of self-attention can be avoided entirely when pruned, so the approach can lead to actual runtime speed-up without sparse operations or dedicated hardware.

D. Low-rank approximation

Weight matrices in fully connected layers often turn out to be low-rank after training [9]. In this case, the low-rank matrices can be approximated by matrix factorization, for example, with singular value decomposition [34]. Transformers have two feed-forward layers after self-attentions, and the dimension after the first feed-forward layer is typically large (e.g., 3072). Most of the computation is due to the large dimensionality of this hidden layer. Given the high dimensionality, we suspect the weight matrices before and after the 3072-dimensional vector are low-rank. Instead of doing matrix factorization, we prune the 3072-dimensional hidden layers. This amounts to pruning the columns of the first feed-forward layer and the corresponding rows of the second feed-forward layer based on the sum of their weight magnitudes.

Formally, assume that \( U \in \mathbb{R}^{d \times 3072} \) and \( V \in \mathbb{R}^{3072 \times d} \) to be the projection matrix of the first feed-forward layer and the second feed-forward layer of a Transformers layer respectively, where \( d \) is the hidden dimension of the model. For each dimension \( i \), we compute a score

\[
s_i = \sum_{k=1}^{d} (|U_{ki}| + |V_{ik}|). \tag{6}
\]

We then prune the rows and columns of low scores to a target density. If \( U \) and \( V \) are low-rank, pruning the columns of \( U \) and the rows of \( V \) would likely not reduce their rank.

Note that our approach differs from the usual low-rank approximation. Low-rank approximation as used in [9] maintains the input and output dimensions, and offers speed-up by factorizing one large matrix into two matrices with a low-dimension bottleneck. In contrast, our approach involves two matrices, and offers speed-up by pruning rows and columns.

E. Knowledge distillation

Knowledge distillation is often used to compress a model, training a smaller neural network (a student) to match parts of the other, larger neural network (a teacher) [35]. Matching the output of a teacher is the most common, while matching the hidden layers are also a viable option [36]–[38]. In terms of the losses, KL divergence is often used to match probability outputs, while \( \ell_2 \) norm is often used to match the hidden vectors [38]. In this work, since MelHuBERT uses cross entropy for training, we simply use KL divergence as the
distillation loss. Specifically, suppose the output representation of the student at the timestamp \( t \) is \( o_t \). We minimize the loss

\[
\frac{1}{T} \sum_{t=1}^{T} \text{KL}[\hat{p}(c_t|x)\|\hat{p}(c_t|x)]
\]

where \( \hat{p}(c_t|x) \) is the distribution predicted by the teacher defined in (2).

\[
\hat{p}(c_t|x) = \frac{\exp(\hat{W}_t^T o_t)}{\sum_{i=1}^{K} \exp(\hat{W}_i^T o_t)}
\]

is the distribution of centroids predicted by the student, and \( \hat{W} \) is a trainable projection matrix of the student. All the parameters of the teacher are frozen during distillation.

Knowledge distillation is fundamentally different from other pruning approaches, in that a small, student model is trained from random initialization. This approach does not attempt to preserve the structure of the teacher model, nor does it preserve the weights of the teacher model. This approach does not even rely on the training loss that the teacher model is trained on; hence the popularity among recent compression approaches, such as DistilHuBERT [19], FitHuBERT [21], and LightHuBERT [20].

### III. RELATED WORK

There are many attempts to compress self-supervised models in text and vision applications, and we broadly mention a few that are based on Transformers. Some of them [39–42] apply knowledge distillation to transfer knowledge from the teacher model. Others [43, 45, 44] decide to prune parts of the network by either weight pruning or head pruning. Additionally, some [45] use the concept of low-rank approximation to factorize weight matrices. Some [46–48] choose to quantize the network to a low-precision version. Another way to speed up a model is to stop the forward process midway [49, 50]. Other than the low-precision approaches, these studies inspire our choice of approaches and design of experiments to be detailed in later sections.

In speech processing, many studies focus on producing a compressed model from a pre-trained self-supervised model for a particular downstream task. This approach differs from regular compression in that models are simultaneously fine-tuned for a particular task and compressed. Examples along this line include [14–17].

Other studies that do not focus on a specific downstream task, instead, compress models at the pre-training stage. These approaches either require access to the pre-training loss (like what is done in this paper) or have to resort to knowledge distillation [19–27]. These types of compressed models are capable of extracting representations that can generalize to multiple downstream tasks.

DistilHuBERT [19] is one of the first attempts to study distillation on speech self-supervised model. They introduce three prediction heads after the final layer of the student model to match the hidden representations of the fourth, eighth, and twelfth layers of the teacher model. Cosine similarity and \( \ell_1 \) norm are combined as their loss function. They use the weight of the first two layers of the teacher model to initialize the student model. Their result, DistilHuBERT, is a 2-layer Transformer, demonstrating the viability of distilling a self-supervised speech model.

FitHuBERT [21] is also a model based on distillation. Compared to DistilHuBERT, they choose to keep the model depth at 12 layers while reducing the dimensions of self-attention and feedforward layers. Additionally, they decrease the number of channels in the lower layers of the convolutional feature extractor, significantly reducing the computational cost.

LightHuBERT [20] involves a two-stage training, where a HuBERT-sized supernet is trained by distillation in the first stage. Then, they apply once-for-all training in the second stage. In particular, they divide the Transformer into several parts, such as the embedding dimension, the number of attention heads, the width of the feedforward network, and the depth of the Transformer. They then randomly sample a subnet from the student model according to the predefined structure during each forwarding pass. Their smallest model, LightHuBERT small, is a 12-layer Transformers with reduced embedding dimension, reduced feedforward layer hidden dimension, and a reduced number of self-attention heads. LightHuBERT small achieves strong performance, but requires an additional distillation to a HuBERT-sized network, a stringent requirement without many industrial-scale GPUs.

Peng et al. [17] propose an approach to simultaneously fine-tuned a self-supervised model particularly for ASR while compressing heads and feedforward layers in Transformers. Wang et al. [25] extend their methods to a task-agnostic version by replacing the objective for ASR with knowledge distillation. Their compressed model is able to extract general representation across different downstream tasks, and can be seen as a combination of knowledge distillation and pruning.

In this work, we will compare our approach to DistilHuBERT, FitHuBERT, and LightHuBERT. We do not compare to Wang et al. [25] because of two reasons. They use knowledge distillation, while we use the pre-training loss for pruning, more faithful to the pruning objectives in the supervised setting. They prune both feedforward layers and attention heads together, confusing the sources of improvements. We, instead, offer a clean comparison among approaches and identify their strengths and weaknesses. We also offer, as an application of our results, a simple approach to combining compression techniques.

### IV. DESIGN OF EXPERIMENTS

Compressing self-supervised models inherits the same goal of self-supervised learning, i.e., to provide representations for downstream tasks. To measure the trade-off between compression and downstream performance, we pre-train and compress 12-layer Transformers with the entire LibriSpeech, a data set consisting of 960 hours of read speech. For the downstream tasks, we conduct phone recognition on the 100-hour subset of LibriSpeech, and speaker identification on VoxCeleb 1. All the experiments follow default SUPERB settings [1], where the pre-trained models are frozen after pre-training and are not fine-tuned. Before making predictions, a downstream classifier learns a weighted sum of all 12 layers in a Transformer. The weights are learned together with the downstream models.
When measuring the amount of compression, we define density as the amount pruned relative to the total amount that can be pruned. For example, the density in head pruning is the amount of heads pruned over the total number of heads.

In this section, we will detail the training hyperparameters and show a few results that shape our design decisions. A more comprehensive comparison among all approaches will follow in the next section.

A. MelHuBERT

We train MelHuBERT-10ms and MelHuBERT-20ms with masked prediction [3], [4] for two pre-training stages. For the first stage, we first run k-means with 512 clusters on log Mel features extracted from the 960-hour subset of LibriSpeech. We then train a 12-layer Transformer to predict the cluster labels of each frame for MelHuBERT-10ms or to predict every other frame for MelHuBERT-20ms. For the second stage, we run k-means with 512 clusters on the ninth layer hidden representations of the first stage model. We predict each frame for both MelHuBERT-10ms and MelHuBERT-20ms in the second stage. We choose a masking strategy based on [28], using a 7% masking probability with a mask of 10 frames (100 ms) for MelHuBERT-10ms and a 14% masking probability with a mask of 5 frames (100 ms) for MelHuBERT-20ms. To compare, HuBERT uses 8% of masking probability with a mask of 10 frames (200 ms) [5]. For the first stage, both MelHuBERT-10ms and MelHuBERT-20ms are trained on 8 V100 GPUs with Adam for 200 epochs. For the second stage, we train MelHuBERT-10ms for 200 epochs and MelHuBERT-20ms for 100 epochs. We use an effective batch size of 32 and a learning rate of $10^{-4}$ for both stages. It requires about 32 days to train MelHuBERT-10ms in total, and about 15 days for MelHuBERT-20ms. Dropout of 10% is applied after the multiplication of matrices, such as query, key, and value matrices, and after FC1 and FC2.

B. Weight Pruning

For weight pruning, we iteratively prune individual weights based on their $\ell_1$ for all weights and biases in linear layers of Transformers. We keep track the exponential moving average of the loss with a decay of 0.9998, and if the loss does not change much (within 0.001) compared to the one 15,000 steps before, pruning is triggered. We use a pruning schedule that is aggressive when the network is dense, and mild when the network is sparse. In particular, we prune 20% until 80% density, 10% until 50% density, 5% until 35% density, 2.5% until 30% density, 1% until 10% density, and 0.5% until 5% density. We use a batch size of 4 and a learning rate of $10^{-5}$. The pruning schedule follows [7], [18] with minor modifications.

Initial results of pruning MelHuBERT-10ms are shown in Figure 1. As the weights are pruned (reading from high density to low density), the pre-training loss first improves and later degrades. The improvement of the loss suggests that lightly pruning a pre-trained model has a regularization effect, and this finding will come up again in other experiments. We also find that the loss is indicative of the downstream performance. The density when the loss starts to degrade too much is also the point where the downstream performance starts to degrade. These results, though intuitive, are largely missing in prior work in the context of pruning self-supervised models with the pre-training loss.

C. Head Pruning

For head pruning, recall that we have two approaches, one based on the $\ell_1$ norm of head weights, and the other based on the $\ell_1$ norm of gradients. For the weight-based approach, we prune a fixed amount of heads for each layer, because higher layers tend to have larger $\ell_1$ norm. If we compare heads across layers, an entire layer would be pruned before we prune others. For the gradient-based approach, we use a 25% of the training data to compute the scores of each head. Similarly, since the $\ell_1$ norm varies across layers, as opposed to pruning a fixed number for each layer, we normalize the scores of heads within each layer and prune the heads by comparing them altogether. As for all iterative pruning approaches, we train the model for a fixed 25,000 steps after pruning, with learning rate $10^{-5}$ and a batch size of 4.

Performance on downstream tasks behave similarly to weight pruning, and we defer the comparison until the next section. Results of comparing the two approaches of head pruning are shown in Figure 2. We find that the gradient-based approach is better than the weight-based approach, and will focus on the gradient-based approach for the rest of the paper.

D. Low-Rank Approximation

For low-rank approximation, recall that we target the 3072-dimensional output of the FC1 layer. Reducing the dimension amounts to pruning the rows of FC1 and the columns of FC2 based on the sum of their $\ell_1$ norm. The input and output dimensions (in our case 768) are seldom larger than the dimension in the middle (in this case 3072).

Before any pruning, we first inspect whether these matrices are low-rank after pre-training. Figure 3 shows the singular values of FC1 and FC2. From the sharp drop in values after the first few dimensions, it is clear that nearly all matrices in
weight-based head pruning
gradient-based head pruning

Fig. 2. Phoneme recognition and speaker identification performance comparing weight-based and gradient-based head pruning on MelHuBERT-10ms. The dashed line is the performance of the unpruned MelHuBERT-10ms.

(a) phoneme recognition  (b) speaker identification

Fig. 3. Singular values of the FC1 and FC2 weight matrices in MelHuBERT-10ms. In each figure, the x-axis is the number of dimension (in this case 768) and the y-axis is the value itself.

FC1 and FC2 are low-rank. We would expect that a lot of the rows and columns can be pruned. We prune 128 dimensions every 25,000 steps, and use a learning rate of $10^{-5}$ and a batch size of 4 to train the model after every pruning step. Performance on downstream tasks and comparison to other approaches are deferred to the next section.

E. Knowledge Distillation

For knowledge distillation, we explore a 2-layer and a 6-layer student network. Prior work [20], [26] has suggested that some masking of the input would be beneficial for distillation as opposed to not masking. The same study also suggest initializing student networks with middle layers taken directly from teacher networks. The temperature of the teacher distribution is also encouraged to be higher than 1, because the output distribution tends to be peaky [12]. Setting the temperature high would make the values of the tail larger. Given these reasons, we study several design decisions, including changing the masking strategy, initializing with MelHuBERT layers, and the temperature when training with KL divergence. Based on our study, neither applying masking on the input nor initializing with MelHuBERT layers lead to improvement. Hence, we simply minimize KL divergence as our distillation loss without masking and initializing.

Results of compressing MelHuBERT for both 10 ms and 20 ms frame periods are shown in Figure 4. We find that both the 2-layer and 6-layer students are able to retain the performance of teachers on speaker identification, with the 6-layer ones performing even better than the teachers. Both students are not able to match the teachers’ performance on phone recognition, with the 2-layer one lacking significantly behind. The worse performance seems to suggest that knowledge distillation might not be an effective compression approach. However, as we will see in later sections, once we put all the results in context, knowledge distillation actually performs favorably compared to others.

V. MAIN RESULTS

Given the design of individual compression approaches, in this section, we present a comprehensive comparison across approaches. Since each individual approach comes with its own strengths and weaknesses, it is likely difficult to conclude definitively which approach is the best under all conditions. Instead, we evaluate them with several metrics to showcase their strengths and weaknesses.

A. Downstream performance

We first study downstream performance, specifically phone recognition and speaker identification, along the pruning process, i.e., at different densities. Note that density is measured relative to the total amount that can be pruned. For example, in head pruning, density is the number of attention heads left over the total number of heads in the unpruned Transformer. We are interested in to what extent downstream performance is maintained while we prune models with the pre-training loss. We compare approaches that belong to the iterative pruning family, namely, weight pruning, head pruning, and low-rank approximation. Knowledge distillation will be compared in the next section. Results are shown in Figure 5.

With weight pruning, we can prune the model to at least 40% density while maintaining phone recognition performance under both 10ms and 20ms frame rates. Similarly, we can prune the model to 20% density while maintaining speaker identification performance under both frame rates. As we have shown in the last section, as pruning proceeds, there is a period where the pre-training loss and the downstream performance both improve over the unpruned model.

With head pruning, we can prune the model to at least 33% density while maintaining the phone recognition and speaker...
identification performance under both 10ms and 20ms frame rates. Similar to weight pruning, as pruning proceeds, there is a period where the downstream performance is better than the unpruned model.

For low-rank approximation however, the results are different from weight pruning and head pruning—downstream performance starts to degrade, as soon as pruning starts. For phone recognition, we can prune the rows and columns in the feed-forward layers to at least 50% density while keeping the degradation within 0.5% PER. However, the impact of low-rank approximation on speaker identification is much stronger than on phone recognition. We only focus on pruning with $\ell_1$ norm, so there might exist better pruning approaches for the feed-forward layers. Regardless, this suggests that the feed-forward layers in Transformers are particularly important for speaker identification.

B. MACs, parameters, and runtime

While Figure 5 shows how well each approach maintains performance along the pruning process, it does not show the benefit of compression. Density is a relative measure, making it difficult to compare across approaches. To evaluate the benefit of compression across approaches, we decide to use three metrics, the number of multiply-accumulation operations (MACs) per one second speech, the number of parameters, and the runtime measured on a single GPU. The three metrics are related. Reduction in MACs represents the theoretical speed-up of inference when parallel computation is not available. In the presence of a GPU, the reduction in MACs does not always translate to faster runtime, as it depends on the structure of the pruned networks. Reduction in model parameters usually leads to a reduction in MACs and can improve generalization. As we have seen in weight pruning and head pruning (Figure 5), there is a period along the pruning process where the pre-trained loss and downstream performance both improve. Results of all approaches evaluated on the three metrics are shown in Figure 6. We only focus on phone recognition, but it shows a similar trend for speaker identification.

First, we find that weight pruning has a significant effect on reducing MACs per one second speech and the number of parameters, without affecting phone recognition much. However, the resulting networks are sparse, and it is difficult to parallelize computation unless dedicated hardware is designed for the pruned network. As a result, we do not measure runtime on the GPU for weight pruning. For serial computation, weight pruning is the best choice among all approaches.

In Transformers, the pairs of feed-forward layers constitute a significant number of parameters, so the reduction in the number of parameters achieved through head pruning is relatively limited compared to the other three approaches. However, head pruning provides a significant runtime speed-up on GPU, due to the expensive computation involved in self-attention. The improvement is particularly pronounced in the 10 ms case, as the input in the 10 ms case is twice as long as the 20 ms one.

Because the parameters are concentrated in the pairs of feed-forward layers, low-rank approximation provides a favorable reduction in the number of parameters. However, the feed-forward layers are significantly faster to compute on a GPU than self-attention. Even though low-rank approximation might achieve a lower MACs per one second speech compared to head pruning, the reduction in runtime is limited.

Knowledge distillation (with a 2-layer and a 6-layer student) achieves a significant reduction on all three metrics. In fact, knowledge distillation provides the best trade-off among all approaches. We attribute this to the the number of GPU kernel calls. Each GPU kernel call has a significant overhead, and computing with fewer layers not only reduces MACs per one
second speech, but also saves the overhead. For example, a model pruned with low-rank approximation can have a similar MACs per one second speech compared to a 6-layer student, but the runtime of the pruned model is significantly slower than the 6-layer student.

Finally, inspired by the results of knowledge distillation, we provide a baseline that only takes the first two layers and the first six layers of the pre-trained Transformers. This amounts to stopping the forward process at the second and the sixth layer. As we have argued, stopping the forward process can be seen as a form of compression. This approach involves no additional training and is arguably the simplest baseline. Combined with other approaches in Figure 6, we now have a better picture what the worst and the best are able to achieve. These results enable a wide range of applications, and we will explore a few in subsequent sections.

VI. APPLICATIONS

In the previous section, we have shown the trade-off of four model compression approaches, namely, weight pruning, head pruning, low-rank approximation, and knowledge distillation on three different metrics, MACs per one second speech, numbers of parameters, and real-time factors. In this section, we will showcase a few applications of our findings, including contextualizing prior work, designing new compression techniques, and analyzing Transformers.

A. Contextualizing prior work

There have been several attempts compressing self-supervised Transformers, such as wav2vec 2.0 and HuBERT. However, most studies focus on the breadth of tasks that can be maintained after compression, rather than the trade-off discussed in the previous section. To fill in this gap, we choose three approaches based on compressing HuBERT, i.e., DistilHuBERT [19], FitHuBERT [21], and LightHuBERT [20]. Given our findings, we can not only discuss their strengths and weaknesses, but also explain why.

Figure 7 shows how DistilHuBERT, FitHuBERT, and LightHuBERT (small) compare against our compression approaches on phone recognition. First, we note that LightHuBERT has the best PER. In fact, LightHuBERT has better PER before compressing, due to an initial round of self-distillation. DistilHuBERT and LightHuBERT both consumes significantly more MACs per one second speech, as they both retain the convolutional layers from HuBERT. In LightHuBERT for example, the convolutional layers accounts for about 64% of MACs while only constituting 4.4% of the parameters. On the other hand, the convolutional layers in FitHuBERT are optimized; hence consuming significantly fewer MACs per one second speech.

The three have similar numbers of parameters but significantly different performance on phone recognition. Since DistilHuBERT has 2 layers while FitHuBERT and LightHuBERT have 12, the result suggests that, for phone recognition, the depth of Transformers is more critical than the number of heads and the dimensions in the feed-forward layers.

In terms of the actual runtime however, LightHuBERT is the worst while FitHuBERT is not better than simply taking the first six layers of MelHuBERT. As we have argued in the previous section, using more layers leads to more GPU kernel calls. The overhead of GPU kernel calls dominates especially when each kernel is cheap to compute.

In sum, our results provide context for DistilHuBERT, FitHuBERT, and LightHuBERT, and can explain their strengths and weaknesses. In addition, simple baselines are strong compared to these recent approaches.
B. Combining compression techniques

Given our findings, we can combine compression techniques to make use of the strengths of each technique. We first use knowledge distillation to learn a 6-layer student from a 12-layer MelHuBERT-20ms. Six layers strike the right balance between reducing the overhead of GPU kernel calls and downstream performance. We then perform two iterations of head pruning, reducing the number of heads from 72 to 36. We further perform five iterations of low-rank approximation, reducing the dimension from 3072 to 512.

Both head pruning and low-rank approximation are effective at reducing MACs per one second speech, numbers of parameters, and real-time factors. All hyperparameters remain the same as introduced in early sections.

The results of combining compression techniques are shown in Figure 7. The combined approach is strictly better than knowledge distillation alone, and is close to weight pruning on MACs per one second speech and numbers of parameters. In addition, the resulting models are also strictly better than DistilHuBERT and FitHuBERT. Compared to dedicated approaches, simple combination of compression techniques is able to produce strong results.

C. Analyzing weights pruned

Model compression not only is an approach for reducing model size, but also an approach to understand the internals of Transformers. In this section, we analyze where the weights are pruned during weight pruning. Given that different layers have different downstream performance [13] or certain Transformer heads [32] are specialized, it is likely that weight pruning would help us identify parts of Transformer that are redundant or not useful for maintaining the pre-training loss. First, Figure 8(a) shows the density of layers along the process of weight pruning. To our surprise, the layers are equally pruned along the process of weight pruning, with the last layer pruned slightly more compared to others. We then measure the density for different weight matrices, including the matrices for computing queries, keys, and values, and the matrices in FC1 and FC2. As shown in Figure 8(b), again, to our surprise, weight matrices are mostly equally pruned throughout the pruning process, with the matrix for computing the values slightly more pruned than others.

Our results suggest several new research directions. Recall that we can maintain the pre-training loss with weight pruning until at least a density of 40%. Weight pruning is able to find a Transformer that is sparse uniformly compared to the unpruned one. It would be interesting to know whether the uniformity is due to the pruning algorithm. Given the strong performance of weight pruning, it’s also interesting to know whether the uniformity is necessary or even optimal for pruning.

D. Analyzing heads pruned

In addition to analyzing weight pruning, we similarly use model compression to analyze head pruning. Several studies have observed that attention maps tend to be diagonal after training [51–53]. If the attention maps are exactly diagonal, then self-attention is nothing but a feedforward layer and can be replaced with a feedforward layer to save computation [51]. In fact, if there exist many diagonal attention heads, they might be redundant and potentially be pruned during head pruning.

To study what attention heads are deemed more important and its relationship to diagonality, we follow [51] and measure diagonality of attention heads in each pruning iteration. Specifically, for a position $i$, the attention weight $a_{ij}$ to
position $j$ is scaled by $|i - j|$ to measure the weight that is off diagonal. The scaled attention is then normalized by the largest number of positions possible on either side of $i$, i.e., $\max(|i - 1|, \ldots, |i - T|)$, where $T$ is the sequence length. The diagonality is defined as

$$\frac{1 - \frac{1}{T} \sum_{i=1}^{T} \sum_{j=1}^{T} a_{ij}|i - j|}{\max(|i - 1|, \ldots, |i - T|)}.$$  \hfill (9)

We calculate diagonality for each attention head and average over all attention heads. We then average the diagonality of a pruned model over 100 utterances. Results are shown in the left of Figure 9. The diagonality of the unpruned Transformer is about 0.64, a high number consistent with the findings of others. However, to our surprise, the diagonality increases when more heads are being pruned. The increase in diagonality is due to the fine-tuning in between pruning. Attention heads that are less diagonal becomes more diagonal after fine-tuning. This suggests that diagonal attention heads have their significance in Transformers.

Given that many attention maps become diagonal, a potential approach to compress attention heads is to replace the highly diagonal ones with identity matrices. In particular, if

$$\text{softmax} \left( \frac{QK^\top}{\sqrt{d}} \right) \approx I$$  \hfill (10)

we can skip the computation of the query $Q$ and the key $K$ and directly output the value matrix $V$. Similar to regular head pruning, we iteratively replace highly diagonal attention heads with identity matrices according to diagonality in equation (9) and fine-tune the rest. We refer to this as the skip-ahead approach. The skip-ahead approach might be too crude an approximation. A weighted sum that centers around the diagonal can be approximated with a 1-D convolution. Instead of replacing a head with identity matrix, we replace it with a 1-D convolution.

Results on phone recognition for both the skip-ahead and 1-D convolution approaches are shown in the center and the right of Figure 9. The skip-ahead approach is indeed worse than regular head pruning. However, the performance is only about 2 to 3% worse, showing that the approximation does in fact align well with our findings. For the 1-D convolution, we experiment several filter sizes and find that a filter of size 21 (i.e., 10 frames on each side) performs the best. The 1-D convolution approach is on par with regular head pruning.

In conclusion, we observe that head pruning leads to an increase in diagonality during the pruning process, motivating the two approaches for pruning diagonal attention heads. Both the skip-ahead and 1-D convolution approaches successfully prune diagonal attention heads without much performance degradation. These findings could potentially inspire novel head pruning approaches.

VII. Conclusion

In this paper, we explore several simple and effective approaches for pruning self-supervised Transformers, including weight pruning, head pruning, low-rank approximation, and knowledge distillation. We report MACs per one second speech, numbers of parameters, and real-time factors, and recommend others to study compression from multiple aspects, as different approaches have different strengths and weaknesses. We present several applications of our results, contextualizing recent approaches, chaining several compression techniques, discussing the redundant parts of the architecture in Transformers, and suggesting novel head pruning approaches. Model compression is not just an approach to get small and efficient models, and we hope this work will spawn more use of model compression as a tool for analyzing models.

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