ABSTRACT

This paper is a study of performance-efficiency trade-offs in pre-trained models for automatic speech recognition (ASR). We focus on wav2vec 2.0, and formalize several architecture designs that influence both the model performance and its efficiency. Putting together all our observations, we introduce SEW (Squeezed and Efficient Wav2vec), a pre-trained model architecture with significant improvements along both performance and efficiency dimensions across a variety of training setups. For example, under the 100h-960h semi-supervised setup on LibriSpeech, SEW achieves a 1.9x inference speedup compared to wav2vec 2.0, with a 13.5% relative reduction in word error rate. With a similar inference time, SEW reduces word error rate by 25–50% across different model sizes.

1 INTRODUCTION

Recently, there is significant interest in self-supervised pre-training using unlabeled audio data to learn versatile feature representations, that are subsequently fine-tuned on task-specific annotated audio (Zhang et al., 2020b; Wang et al., 2021b; Xu et al., 2020a; Pepino et al., 2021). This follows similar trends in natural language processing (NLP; Devlin et al., 2018; Liu et al., 2019; He et al., 2020) and computer vision (CV; He et al., 2019; Chen et al., 2020; Grill et al., 2020). Maybe the most prominent example of this class of models is wav2vec 2.0 (W2V2; Baevski et al., 2020b), which achieves competitive word error rate (WER) following fine-tuning on only ten minutes of transcribed (labeled) data, when prior supervised approaches often require nearly a thousand hours. If recent developments in NLP and CV are any indication, the importance of such pre-trained audio models that are fine-tuned on expert tasks will only increase. Indeed, W2V2 has already been studied with focus on the impact of pre-training data (Conneau et al., 2020; Hsu et al., 2021), pre-training task (Hsu et al., 2020), or combination with pseudo labelling (Xu et al., 2020a; Zhang et al., 2020b).

In this paper, we study W2V2’s model design, and possible trade-offs between its components. Our focus is on efficiency for practical applications, rather than extending the model. As W2V2-type models become increasingly common, understanding their efficiency trade-offs is critical for transferring their benefits from the lab to the real world, where any increase in efficiency can substantially reduce the inference costs and energy footprints across a plethora of real world applications.

We study several aspects of the W2V2 model. We focus on automatic speech recognition (ASR), while retaining the standard pre-training and few-sample fine-tuning setup. First, we study how

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1While pre-training time can be considered a secondary metric for efficiency, it is not our primary goal.
the temporal resolution of the network trades-off performance and efficiency, and show that using different resolutions for computing pre-trained representations and ASR decoding significantly reduces inference time, while retaining similar performance. Second, we propose an efficient family of waveform feature extractors, which achieves similar performance with half the inference time as the original W2V2 extractor. Finally, we study the impact of shifting model expressivity between different parts of the network. We observe that it is better to assign more parameters to later parts in the pre-trained network, compared to increasing capacity closer to the input waveform. We also see that increasing the expressivity of the pre-training predictor heads increases performance, while not influencing downstream-task computation as these heads are discarded.

We combine our observations to propose two models: SEW (Squeezed and Efficient Wav2vec) and SEW-D (SEW with disentangled attention [He et al. 2020]). We pre-train SEW and SEW-D on 960 hours of unlabeled audio from the LibriSpeech dataset (Panayotov et al. 2015), and fine-tune with multiple ASR tasks. SEW yields a significantly better performance-efficiency trade-off than the original W2V2. For example, with 100h labeled data, compared to a W2V2-tiny model, SEW reduces the LibriSpeech test-clean WER from 22.8% to 10.6% while being slightly faster, even outperforming a larger W2V2 model with 12.8% WER. Compared to the official W2V2-large release, our best SEW-D-base+ achieves 2.7× and 3.2× speed-ups for inference and pre-training with comparable WER using half of the number of parameters. Compared to W2V2-base, our SEW-D-mid achieves 1.9× inference speed-up with a 13.5% relative reduction in WER. Fig. 1 shows the performance-efficiency trade-offs with various model size. SEW-D outperforms W2V2 in most pre-training settings, when experimenting with LibriSpeech (Panayotov et al. 2015), Ted-lium 3 (Hernandez et al. 2018), VoxPopuli (Wang et al. 2021a), and Switchboard (Godfrey and Holliman 1993) datasets. Pre-trained models and code are available at https://github.com/asappresearch/sew.

2 RELATED WORK

Unsupervised Audio Representation Learning Contrastive predictive coding (CPC) is a general unsupervised learning method for speech, vision, text, and reinforcement learning [van den Oord et al. 2018]. When applied to speech, it uses past audio to predict the future audio, similar to language modeling [Mikolov et al. 2010; Dauphin et al. 2017; Kaplan et al. 2020] but with contrastive loss. Wav2vec (Schneider et al. 2019) further improves the CPC model architecture design and focuses on unsupervised pre-training for end-to-end automatic speech recognition. Roughly speaking, wav2vec includes a feature extractor that generates a sequence of vectors from raw waveform audio, and a context network that encodes the features from the recent past to predict the features in the immediate future. This context network is only used to learn useful feature representations, and is typically discarded after pre-training. Recently, [Baevski et al. 2020a] introduced vq-wav2vec and a combination of vq-wav2vec with a discrete BERT-like model (Devlin et al. 2019; Baevski et al. 2019). W2V2 [Baevski et al. 2020b] combines vq-wav2vec and the BERT-like model into an end-to-end setup, where the BERT portion functions as the context network, but not discarded. More recently, [Hsu et al. 2020] propose HuBERT and show that W2V2 can be pre-trained with clustered targets instead of contrastive objectives. Besides ASR-focused works, there is significant interest in learning representations for other speech tasks (Synnaeve and Dupoux 2016; Chung et al. 2018; Chuang et al. 2019; Song et al. 2019), music (Yang et al. 2021; Zhao and Guo 2021), and general audio (Saeed et al. 2021; Gong et al. 2021; Nizumi et al. 2021; Wang et al. 2021c).

End-to-end Automatic Speech Recognition (ASR) As large datasets and fast compute become available, end-to-end ASR models [Amodei et al. 2016; Zhang et al. 2020a] increasingly achieve state-of-the-art results, outperforming HMM-DNN hybrid systems [Abdel-Hamid et al. 2012; Hinton et al. 2012]. End-to-end ASR models can be roughly categorized into three main types: connectionist temporal classification (CTC; Graves et al. 2013), RNN transducers (RNN-T; Graves 2012; Han et al. 2020; Gultati et al. 2020), and sequence-to-sequence (a.k.a. Listen, Attend and Spell models) (Seq2seq; Chan et al. 2016; Dong et al. 2018; Watanabe et al. 2018). CTC models are extremely fast for batch decoding; RNN-T variants are often used in real-time systems; Seq2seq models are more popular in offline settings. Recently, and following success on NLP tasks, there is a transition in speech processing towards the Transformer architecture (Vaswani et al. 2017; Dong et al. 2018) and its variants (Zhang et al. 2020a; Baevski et al. 2020b; Gultati et al. 2020; Zhang et al. 2020b; Yeh et al. 2019).
3 Technical Background: Wav2Vec 2.0 (W2V2)

W2V2 is made of a waveform feature extractor that generates a sequence of continuous feature vectors, each encoding a small segment of audio, and a context network that maps these vectors to context-dependent representations.

During pre-training, some of the features are masked out, and are not seen by the context network. In parallel, the pre-masking features are discretized as prediction targets. The context network aims to discriminate the discretized version of the original features at the masked positions from a pool of negative samples using the InfoNCE loss (van den Oord et al., 2018).

Fig. 2 shows the W2V2 framework, including (a) a feature extractor, (b) a context network, (c) an optional quantization module, and (d) two projection heads.

Wave Feature Extractor (WFE) The wave feature extractor \( f(\cdot) \) encodes and downsamples the raw waveform audio inputs \( X = (x_1, \ldots, x_{T_{\text{input}}}) \in \mathbb{R}^{T_{\text{input}} \times d_{\text{input}}} \) (\( d_{\text{input}} = 1 \) for single-channel audio) into an array of feature vectors \( Z = f(X) = (z_1, \ldots, z_T) \in \mathbb{R}^{T \times d_{\text{feat}}} \).

For example, W2V2 maps 16KHz audio sequences to 50Hz frames using a convolutional WFE with receptive field size of 400 and stride size of 320. Each feature vector encodes the raw signals within a sequence length is \( T = T_{\text{feat}} - 400 + 1 = T_{\text{feat}} - 80 \).

Context Network The context network \( g(\cdot) \) follows a similar principle as masked language models in NLP (e.g., BERT [Devlin et al., 2018] or RoBERTa [Liu et al., 2019]). During pre-training, each \( z_t \) is masked and replaced with a trainable mask vector \( m \) with a predefined probability \( p \).

To illustrate, \( Z = (z_1, z_2, z_3, z_4, z_5, z_6, \ldots, z_T) \) can become \( Z' = (z_{1,c}, m, m, m, \ldots, z_{c-1}, z_T) \). The context network maps this masked sequence to a sequence of contextual representations \( C = g(Z') = (c_1, \ldots, c_T) \in \mathbb{R}^{T \times d_{\text{context}}} \) to incorporate context information. Even if \( z_t \) is masked and replaced with \( m \), we anticipate that \( c_t \) can recover the information in \( z_t \) because it contains information from surrounding, not-masked input vectors. The context network is usually implemented with a Transformer architecture [Vaswani et al., 2017; Gulati et al., 2020].

Quantization Module The quantization module \( q(\cdot) \) maps each unmasked vector \( z_t \) into a quantized form \( q_t = q(z_t) \in \mathbb{R}^{d_{\text{context}}} \) for each masked position \( t \). Quantized \( q_t \)'s are the prediction targets.

The quantization module is based on Gumbel softmax with straight-through estimator (Gumbel [1954], Jang et al., 2016, Maddison et al., 2014). There are \( G \) codebooks and each codebook has \( V \) entries, giving \( G \times V \) vectors \( e_{g,v} \in \mathbb{R}^{d_{\text{context}}} \) where \( g \in \{1, \ldots, G\}, v \in \{1, \ldots, V\} \).

For each group \( g \), the probability of assigning \( z_t \) to the \( v \)-th entry is
\[
p_{g,v} = \frac{\exp(W^g z_t / \tau_Q)}{\sum_{v' \in V} \exp(W^g z_t / \tau_Q)},
\]
where \( W^g \in \mathbb{R}^{V \times d_{\text{context}}} \) is a trainable matrix and \( \tau_Q \) is the quantization temperature. For each group \( g \), \( z_t \) is assigned to the \( v^* \)-th entry where \( v^* = \arg \max_v p_{g,v} \).

The corresponding embedding vectors \( (e_{1,v_1}, \ldots, e_{G,v_G}) \) are concatenated to a single vector \( q_t \in \mathbb{R}^{d_{\text{context}}} \), and constitutes a quantized feature sequence \( Q = (q_1, \ldots, q_T) \in \mathbb{R}^{T \times d_{\text{context}}} \).

Projection Heads Two linear projection heads \( p_1(\cdot) \) and \( p_2(\cdot) \) reduce the dimensionality of \( C \) and \( Q \).

For a \( z_t \) that is masked and replaced with \( m \), we want \( p_1(c_t) \in \mathbb{R}^{d_{\text{proj}}} \) to be similar to \( p_2(q_t) \in \mathbb{R}^{d_{\text{proj}}} \). Baevski et al. (2020b) do not separate between \( p_1 \) and \( p_2 \) or \( g \) in their original notations. However, we keep the distinctions, as they serve different roles and are discarded before downstream fine-tuning.

Pre-training Objective W2V2 combines contrastive and diversity losses in the pre-training loss:
\[
L = L_m + \alpha L_d.
\]
The goal of the contrastive loss $L_m$ is to make the projected outputs $p_c(c_t)$ close to $p_q(q_t)$ and far away from any other $p_q(q_{t'})$, where $z_t$ is masked and $t'$ is any other position in the same sequence. W2V2 uses an InfoNCE loss (van den Oord et al., 2018):

$$L_m = E_{t \text{ is masked}} \left[ -\log \frac{\exp(\text{sim}(p_c(c_t), p_q(q_t))/\kappa)}{\sum_{q_{t'} \in Q} \exp(\text{sim}(p_c(c_t), p_q(q_{t'}))/\kappa)} \right].$$

(2)

with $\text{sim}(a, b) = \frac{a^\top b}{\|a\|\|b\|}$, $Q$ is a set containing the positive sample $q_t$ and $K$ negative samples, and $\kappa$ is the temperature. The expectation is computed over masked positions only. The diversity loss $L_d$ prevents the quantization module from collapsing to a trivial mapping (e.g., by collapsing all inputs to a single discrete code). It encourages the quantization probability $p_{g,v}$ to be evenly distributed:

$$L_d = E_t \left[ 1 - \frac{1}{G^2} \sum_{g=1}^G \exp \left( - \sum_{v=1}^V p_{g,v} \log p_{g,v} \right) \right].$$

(3)

4 EXPLORING MODEL DESIGN TRADE-OFFS

4.1 EXPERIMENTAL SETUP

We use the official W2V2 implementation in fairseq (Ott et al., 2019), with the hyper-parameters of W2V2-base (Baevski et al., 2020b). We describe key hyper-parameters; the linked configuration files provide the full details.

**Pre-training** We use the LibriSpeech (CC BY 4.0) (Panayotov et al., 2015) 960h training data for unsupervised pre-training, leaving 1% as validation set for pre-training. We use the same hyperparameters as W2V2-base (Appendix B). To speed up and reduce the cost of our experiments, we pre-train all models for 100K updates similar to Hsu et al. (2020). All experiments use an AWS p3.16xlarge instance with 8 NVIDIA V100 GPUs and 64 Intel Xeon 2.30GHz CPU cores. Because Baevski et al. (2020b) use 64 GPUs, we set gradient accumulation steps to 8 to simulate their 64-GPU pre-training with 8 GPUs.

**Fine-tuning** We add a linear classifier to the top of the context network and fine-tune the model using a CTC objective on LibriSpeech train-clean 100h set for 80K updates using the same set of hyper-parameters as W2V2-base (Appendix B).

**Evaluation** We use CTC greedy decoding (Graves et al., 2006) for all experiments because it is faster than Viterbi decoding (Viterbi, 1967) and we do not find any WER differences between the two using baseline W2V2 models (Appendix D). We use LibriSpeech dev-other for validation, and hold out test-clean and test-other as test sets. We consider three metrics to evaluate model efficiency and performance: pre-training time, inference time, and WER (word error rate). All evaluation is done on a NVIDIA V100 GPU with FP32 operations, unless specified otherwise. When decoding with a language model (LM), we use the official 4-gram LM and wav2letter (Collobert et al., 2016) decoder with the default LM weight 2, word score -1, and beam size 50. Reducing the inference time with LM is an important direction for future work, as the wav2letter decoder is the bottleneck and is at least 3× slower than W2V2-base (Appendix D).

4.2 DEPTH VS. WIDTH

The smallest W2V2 model is W2V2-base with 94M parameters and is already relatively large compared to other ASR models (Han et al., 2020; Gulati et al., 2020). We study two strategies of changing the context network Transformer to reduce the model size and speed up the model, potentially at cost to performance: reducing model depth by using fewer Transformer layers or reducing model width by using smaller hidden state size in the Transformer. When reducing the hidden size, we fix the head dimension to 64. For example, a 12-head 768d Transformer would be

https://github.com/pytorch/fairseq/blob/master/examples/wav2vec/config/pretraining/wav2vec2_base_librispeech.yaml
https://github.com/pytorch/fairseq/blob/master/examples/wav2vec/config/finetuning/base_100h.yaml
https://www.openslr.org/resources/11/4-gram.arpa.gz
https://github.com/flashlight/wav2letter/tree/v0.2/bindings/python
Fig. 3 shows the performance-efficiency trade-offs of scaling down the depth or width of the model. Scaling down the width achieves better performance-efficiency compared to scaling down the depth; a deep and narrow model is more favorable than a shallow and wide model. These narrow models serve as the baselines for our following experiments.

4.3 TEMPORAL RESOLUTION VS. MODEL SIZE

The wave feature extractor of W2V2 down-samples the raw audio to 50Hz frames with a stride size of 20ms, reducing the sequence length by a factor of 320 (Sec. 3). However, even lower resolutions are common in prior end-to-end ASR approaches. For example, several methods (Han et al., 2020; Gulati et al., 2020) use log-mel filterbank features with a stride of 10ms (100Hz) and down-sample them to 40ms (25Hz) with two layers of strided convolutions. The result is halving the sequence length, and reducing the computation and memory footprint of the context network. Reducing the sequence length may allow increasing the model size with the same computation costs.

Table 1 shows the performance-efficiency trade-off of models with different temporal resolutions at context encoding, mask prediction, and CTC decoding. Reducing the temporal resolution while increasing the model size (first vs. second rows) effectively reduces the WER while maintaining the inference time. However, compared to a model with similar size but higher resolution (last row) there...
Table 2: WFE-O-c512 vs. WFE-C-c128-l0 in terms of FLOPs and encoding time for a batch of twenty 10-second inputs. We show the number of channels (c), kernel size (k), and stride size (s) of each conv layer. WFE-C-c128-l0 allocates the FLOPs and processing time more evenly across layers.

is a noticeable gap in WER. Increasing the output resolution to 50Hz while keeping the encoding resolution the same (25Hz) (third row) reduces this gap. We added a transposed 1d convolution layer to the output of the context network during fine-tuning, which allows each frame (25Hz) to generate two predictions (50Hz).

Squeezed Context Networks To further close the gap, we propose to encode the features at a low resolution (e.g., 25Hz) while keeping contrastive learning at a high resolution (e.g., 50Hz). We add a down-sampling layer and an up-sampling layer around the original context network. Because there is already a convolution layer at the bottom of the W2V2 context network, we simply change its stride size from 1 to s to avoid additional computation, where s is the squeezing factor. The up-sample layer is a transposed 1d convolution with kernel size s and stride size s (s = 2 in our experiments). Fig. 4 illustrates the context network squeezing. The fourth row in Table 1 shows that using a squeezed context network further reduces the WER with similar inference time.

4.4 WAVE FEATURE EXTRACTORS DESIGN

W2V2 has the same number of channels in all layers of its convolutional wave feature extractor (WFE-O; “O” stands for original). Table 2 (left) shows FLOPs and inference time of a WFE-O with width 512. The first few layers consume much of the computation time, while the last three consume less than 10% of the total computation. We hypothesize that the first few layers are unnecessarily large, and that the computation can be more evenly distributed across layers.

Compact Wave Feature Extractors (WFE-C) We introduce a compact wave feature extractor (WFE-C) which doubles the number of channel when the sequence length is downscaled by 4 times. The progression of channel dimensionality is (c, 2c, 2c, 4c, 4c, 8c, 8c) across its 7 conv layers where c is a hyper-parameter. We keep the kernel sizes (7, 3, 3, 3, 2, 2, 2, 2, 2, 2) and strides (5, 2, 2, 2, 2, 2, 2, 2) of WFE-O. Table 2 (right) shows the FLOPs and inference time of a WFE-C-c128-l0 (i.e., c = 128) feature extractor. The inference time is distributed more evenly across layers. Table 3 presents the inference time and WER of a Squeezed wav2vec with different WFEs. WFE-C-c128-l0 achieves a similar performance as WFE-O-c512 while being much faster.

WFEs Depth vs. Width We study scaling up WFE-C by adding a point-wise (kernel size 1) convolutional layer after each original convolutional layer except for the first layer, which creates a 13-layers convolutional network with kernel sizes (7, 3, 1, 3, 1, 3, 1, 2, 1, 2, 1, 2, 1) and strides (5, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1). We refer this model as WFE-C-c128-l1, where “l1” denotes one additional intermediate layer between every two original layers. The last two rows of Table 3 show the performance of increasing the width (WFE-C-c160-l0) and increasing the depth (WFE-C-c128-l1).

6We use a Linear layer instead of a ConvTranspose1d in PyTorch (Paszke et al., 2019) for efficiency.
7There is a shortcut connection in W2V2—it adds the inputs of the convolution to its outputs and passes it to the Transformer. We apply average pooling with kernel and stride sizes s in this shortcut path which averages every two steps into one so that it can be added to the outputs of the strided convolution.
Table 3: An E512L12 W2V2 with squeezed context network with different WFEs. WFE-C-c128-l0 performs similar to WFE-O-c512 while reducing overall model inference time by 37%. With a similar inference time, depth increase (WFE-C-c128-l1) is better than width increase (WFE-C-c160-l0).

Table 4: Ablation study with a controlled inference time. Rows 2 → 3: using a squeezed context network. Rows 3 → 4: replace WFE-O with WFE-C. Rows 4 → 5: Smaller WFE and larger Transformer. Rows 5 → 6: Smaller conv kernel size in the context network and wider WFE. Rows 6 → 7: using MLP predictor heads. Rows 7 → 8: using 80D filter bank features (FBFE-c160, i.e. Filter Bank Feature Extractor with two 2D convolutional layers and 160 channels followed by a linear projection layer) instead of raw waveform (WFE-C).

4.5 Feature Extractor vs. Context Network

We study where to allocate computation budgets: the feature extractor or the context network. Table 4 shows this study with a controlled inference time. The third row is a model with a squeezed context network as we show in Subsec. 4.3. The fourth row replaces WFE-O-c256 with WFE-C-c96-l1 and achieves better WER. The fifth row reduces the size of the WFE and increases the size of its context network. It outperforms the fourth row significantly in WER even as it shows a slightly lower inference time. Moreover, we observe that W2V2 has a convolution layer with a particularly large kernel size of 128 at the bottom of the context network. The sixth row shows a reduction of the size of this kernel to 31, which allows using a larger WFE-C. It achieves similar WER as the fifth row while having lower pre-training and inference time. We provide an additional ablation study of the kernel size in Appendix E.

4.6 MLP Predictor Heads

Chen et al. (2020) use MLP predictor heads instead of linear ones for unsupervised image representation learning, leading to better pre-trained features with little overhead during pre-training. We replace the linear projection of W2V2 with a two-layer MLP with hidden size 4096, a ReLu activation in between, and BatchNorm [Ioffe and Szegedy, 2015] after each linear layer. Because the predictor heads are discarded following pre-training, there is no inference overhead. The seventh row in Table 4 shows the performance of using such an MLP predictor. Compared to the sixth row, using such an MLP predictor leads to better performance without any additional inference time. Appendix C provides a more detailed ablation study on MLP predictor heads.

4.7 Raw Waveform vs. Filter Bank Features Inputs

Zhang et al. (2020b) propose a variant wav2vec 2.0 which removes the wave feature extractor and uses 80-dimensional log-mel filterbank (frame length 25ms and frame shift 10ms) and achieves superior
Table 5: Model hyper-parameters, categorized by inference time. We focus on performance-efficiency trade-off, and therefore we do not control for model size within each time category. O': W2V2-large removes the InstanceNorm layer after the first convolution and adds LayerNorm after each convolution.

We combine our observations from Sec. 4 to propose SEW (Squeezed and Efficient Wav2vec), an efficient pre-trained model architecture. SEW differs from W2V2 in: (a) using a squeezed context network, (b) replacing WFE-O with WFE-C, (c) reallocating computing across different components, and (d) using MLP predictor heads with BatchNorm. Table 5 shows the hyper-parameters of W2V2 and SEW with different inference budgets, and Table 6 shows model performance.

5 SEW (SQUEEZED AND EFFICIENT WAV2VEC)

We adopt a simple scaling up recipe, leaving finding more optimal scaled-up configurations, an open research problem (Tan and Le, 2019; Dollár et al., 2021), for future work. We take the row 7 in Table 4 as SEW-tiny, which has similar inference times to W2V2 with width 256. We increase the width by 1.5 to create SEW-small, which has the same Transformer size as W2V2-base. Based on our observation that deep models are favorable (Subsec. 4.2), we create SEW-mid by making the model twice as deep.

SEW-D (SEW with Disentangled Attention) Disentangled attention (He et al., 2020) is a variant of self-attention with relative position representations (Shaw et al., 2018), which outperforms Transformer’s multi-head attention (Vaswani et al., 2017) on various NLP tasks. Unlike Transformer which adds absolute positional embeddings to the content embeddings at the beginning, disentangled attention keeps the positional embeddings and content embeddings separate and has 3 components in its attention weight computation: (a) content-to-content, (b) content-to-position, and (c) position-to-content attentions (Appendix G). The disentangled computation requires more matrix multiplication operations compared to conventional self-attention, and is slower with a similar number of parameters.

Because Zhang et al. (2020b) do not provide implementation details, we borrow the publicly available implementation from ESPNet (Watanabe et al., 2018), set the stride of the second convolution to 1 to match the encoding resolution, and reduce the number of channels to 160 to ensure the inference time is within the constraint.
To retain similar computation costs, we reduce the Transformer width to reduce its parameters by half. SEW-D benefits from the advanced attention mechanism, while overall it displays faster inference time. In Sec. 6, we show that SEW-D outperforms a 2x larger SEW counterpart. To have a model with comparable inference time as W2V2-base, we further increase the width of the context network of SEW-D by 1.5 to create SEW-D-base. Because it is still slightly faster than W2V2-base, we further scale up the width of the WFE by 1.5 leading to a SEW-D-base+.

### Table 6: Libri-Speech 100h-960h semi-supervised setup pretrained for 100K updates.

| Model       | # Param. | PT (h)  | Infer. (s) | dev-clean | dev-other | test-clean | test-other |
|-------------|----------|---------|------------|-----------|-----------|------------|------------|
| W2V2-tiny   | 11.1     | 24.7    | 7.5 ±0.04  | 22.0 / 7.7 | 40.7 / 23.4 | 22.8 / 8.3  | 42.1 / 25.6 |
| SEW-tiny    | 40.7     | 19.8    | 6.7 ±0.02  | 10.6 / 4.6 | 23.7 / 14.4 | 10.6 / 5.1  | 23.7 / 14.5 |
| SEW-D-tiny  | 24.1     | 23.8    | 7.5 ±0.02  | 10.1 / 4.4 | 22.3 / 13.4 | 10.4 / 4.9  | 22.8 / 13.9 |
| W2V2-small  | 40.7     | 19.8    | 6.7 ±0.02  | 10.6 / 4.6 | 23.7 / 14.4 | 10.6 / 5.1  | 23.7 / 14.5 |
| SEW-small   | 89.6     | 32.3    | 7.6 ±0.02  | 17.1 / 10.9| 37.8 / 24.4 | 17.8 / 11.4 | 38.4 / 25.4 |
| SEW-D-small | 41.0     | 38.1    | 9.6 ±0.04  | 17.9 / 11.1| 37.8 / 24.4 | 17.8 / 11.4 | 38.4 / 25.4 |
| W2V2-mid    | 44.1     | 40.3    | 19.9 ±0.04 | 9.3 / 4.1  | 21.9 / 13.2 | 9.6 / 4.8   | 22.2 / 13.5 |
| SEW-mid     | 174.7    | 41.7    | 19.1 ±0.03 | 6.5 / 3.4  | 17.4 / 9.7  | 6.7 / 3.9   | 14.9 / 10.0 |
| SEW-D-mid   | 78.8     | 51.7    | 16.5 ±0.03 | 6.3 / 3.2  | 14.0 / 9.3  | 6.4 / 3.8   | 14.2 / 9.5  |
| W2V2-base   | 94.4     | 55.2    | 30.8 ±0.05 | 6.9 / 3.4  | 16.6 / 10.4 | 7.1 / 4.0   | 16.4 / 10.4 |
| SEW-D-base  | 175.1    | 59.1    | 26.3 ±0.06 | 5.8 / 3.2  | 12.6 / 8.6  | 5.8 / 3.6   | 13.2 / 9.3  |
| SEW-D-base+ | 177.0    | 68.4    | 27.8 ±0.05 | 5.3 / 3.0  | 12.4 / 8.7  | 5.3 / 3.5   | 12.6 / 9.0  |

6 Further Experiments

We compare SEW and SEW-D to W2V2 using a variety of fine-tuning setups.

**SEW vs. SEW-D vs. W2V2 on LibriSpeech 100h-960h** We pre-train W2V2, SEW, and SEW-D on 960h LibriSpeech audios for 100K updates and fine-tune them on 100h labelled data. We follow the setup of Subsec. 4.1. Table 6 shows pre-training times, inference times, and WERs with and without an LM. Without an LM, compared with the W2V2-tiny, SEW-tiny reduces the WER by 53.5% (22.8% to 10.6%) and 43.7% (41.1% to 23.7%) on test-clean and test-other, while being faster. With an LM, WER improves by 38.6% and 43.4% on test-clean and test-other. Compared with the W2V2-mid, SEW-mid reduces WER by 30.2% (9.6% to 6.7%) and 32.9% (22.2% to 14.9%) with similar inference times. SEW does incur slight increase in training time compared to W2V2 with similar inference times. However, SEW has lower WER even compared to a slower W2V2 which takes longer to train (e.g., SEW-small vs. W2V2-mid or SEW-mid vs. W2V2-base).

SEW-D has lower WER compared to SEW even with smaller width and half of the parameters. With large models, SEW-D is also more efficient. However, SEW-D-tiny is slower than SEW-tiny, due to the implementation difference.

**Less Supervision** To further test the performance of SEW-D, we experiment with only 10min, 1h, and 10h of supervised data (see Appendix B). Table 7 shows the WER of W2V2 and SEW-D. SEW-D-mid outperforms W2V2-base in the 1h and 10h scenarios while being more efficient. SEW-D-mid is worse than W2V2-base in the extreme 10m scenario; however, we did not tune the fine-tuning hyper-parameters and use the ones tuned for W2V2-base. SEW-D-base+ achieves significantly better performance than W2V2-base in most of the setups except for using 10 minutes supervision and decoded with LM. Potentially due to a large model size, we observe that SEW-D-base+ is unstable to fine-tune; therefore, instead of using W2V2’s tuned hyperparameters, we reduce the learning rate by 5 times to $10^{-5}$, set the dropout rates as the pre-training (W2V2 uses different sets of dropouts

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9 We use the official PyTorch (Paszke et al., 2019) implementation of disentangled attention (https://github.com/microsoft/DeBERTa) for SEW-D, which uses BTC tensor format instead of a more efficient TBC tensor format used in fairseq (Ott et al., 2019). Moreover, fairseq uses a dedicated CUDA implementation of self-attention which is more efficient.
Table 7: LibriSpeech results with 10m, 1h, or 10h supervised data. All the models are pre-trained for 100K updates on LibriSpeech 960h. We report inference times on dev-clean and WERs without LM and with 4-gram LM (beam size 50). The mean and standard deviations are calculated from three random runs. Similar to BERT-large (Phang et al., 2018), we observe that our SEW-D-base+ is unstable during fine-tuning. We run five random runs and stop two degenerate runs after 3K updates.

Table 8: LibriSpeech 100h-960h semi-supervised setup pretrained for 400K updates. We use the public W2V2s (Baevski et al., 2020b) as the baselines. Notably, W2V2-base is reported as taking 102.4 GPU-days to pre-train on 64 GPUs, but from our estimation it only takes 73.5 GPU-days on 8 GPUs. Unlike Baevski et al. (2020b), we neither tune the decoding hyper-parameters nor use a huge beam size 1500.

Comparison to Published Results: We continue training our best SEW-D-mid model to 400K updates and compare it with the official W2V2-base\textsuperscript{10} and W2V2-large\textsuperscript{11} checkpoints (Baevski et al., 2020b). Table 8 shows inference times and WERs with or without an LM. Compared to W2V2-base, SEW-D-mid reduces inference time by 46.4% (a 1.9× speed-up) and WER by 19.7% and 13.5% on both test sets without an LM; SEW-D-base+ reduces inference time by 9.7% and WER by 27.9% and 30.8%. Compared to W2V2-large, SEW-D-base+ achieves 2.7× and 3.2× speed-ups for inference and pre-training with comparable WER and half of the number of parameters.

Transferring to Out-of-domain Data: We evaluate W2V2 and SEW-D pre-trained models on three additional ASR datasets: TED-LIUM 3 (CC BY-NC-ND 3.0) (Hernandez et al., 2018), VoxPopuli (CC0, CC BY-NC 4.0) (Wang et al., 2021a), and Fisher+Switchboard (LDC200{4,5}S13, LDC200{4,5}T19, LDC97S62) (Godfrey and Holliman, 1993; Cieri et al., 2004, 2005a)\textsuperscript{12} with a similar setup to Hsu et al. (2021) (see Appendix B). We use only 10h of supervised audio to stress test low resource domain transfer. Table 9 shows the inference times and WERs. SEW-D-mid consistently reduces inference times by about 30% while providing lower WERs on TED-LIUM 3, similar WERs on VoxPopuli, and slightly higher WERs on Fisher+Switchboard. SEW-D-base+ consistently outperforms W2V2-base by a large margin while being only 10% slower.

\textsuperscript{10}https://dl.fbaipublicfiles.com/fairseq/wav2vec/wav2vec_small_100h.pt
\textsuperscript{11}https://dl.fbaipublicfiles.com/fairseq/wav2vec/wav2vec_big_100h.pt
\textsuperscript{12}https://dl.fbaipublicfiles.com/fairseq/wav2vec/wav2vec_small_100h.pt
Table 9: Inference time and WER of LibriSpeech pre-trained models (400K updates) transferred to TED-LIUM 3, VoxPopuli, and Fisher+Switchboard datasets with only 10h labels. SEW-D mid outperforms W2V2 base on all settings while being at least 30% faster. We report the inference time on the dev sets. The mean and standard deviations are computed over three random runs.

7 Conclusion

Our study is a detailed analysis of the architecture of W2V2, an influential pre-training method for spoken language tasks. Through careful consideration of both compute time and model expressivity we achieve better ASR performance with faster inference times. Aggregating our observations, we propose SEW, a family of pre-trained models, with significantly better performance-efficiency trade-off than the existing W2V2 architecture. SEW models can function as direct replacement of W2V2 models, including in recent work (Hsu et al., 2020; 2021; Xu et al., 2020a).

In general, our approach outlines a recipe and set of considerations to apply when studying complex network architectures with the goal of finding better balance of performance and efficiency. While model performance is commonly prioritized in research, the economics of inference times are often as critical for model deployment in the real world. This study will inform practitioners optimizing complex models for deployment beyond this specific instance of W2V2.

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A Limitation

We focus on model inference time, without considering LM computation times. As discussed in Appendix D, we perform beam-search decoding with LM on CPU using W2V2’s implementation. This results in significant slowdown of tiny models. How to speed it up is an important direction for future work. Additionally, different hardware devices require different optimized models. All our ablation studies are done on GPUs. Our observation may change on other types of hardware, such as embedded systems or CPUs. As we discuss in ??, there remain a need to study ASR across more diverse types of data (e.g., across languages, domains, ethnic groups, etc.). Similar to existing work, which we compare with, different data may lead to different performance observations. However, we do not expect significant changes in computation speedups, the main focus of our work.

B Experimental Setup Details

B.1 LibriSpeech

LibriSpeech (CC BY 4.0) (Panayotov et al., 2015) is a corpus of 16kHz read-English speech. The data are derived from read audiobooks from the LibriVox project. LibriSpeech includes a 960h training set (including three subsets: train-clean-100, train-clean-360, and train-other-500), two development sets, dev-clean (5.4h) and dev-other (5.3h), and two test sets, test-clean (5.4h) and test-other (5.1h). The data is designed to provide more challenging evaluation with the dev-other and test-other splits. We use train-clean-100 as the 100h supervised data. For 10min, 1h, and 10h subset of labelled data, we use splits provided by Libri-Light (Kahn et al., 2020).

Pre-training We use W2V2’s official codebase as provided in fairseq (Ott et al., 2019) for all experiments. Following the provided configuration\[13\] we use the Adam (Kingma and Ba, 2015) optimizer with learning rate 0.0005, betas (0.9, 0.98), weight decay 0.01, and 32K linear warm-up steps (Goyal et al., 2017). We apply Layerdrop [Huang et al., 2016; Fan et al., 2020] of 0.05. We use layerdrop rate of 0.1 and 0.2 for SEW and SEW-D. Otherwise, the models diverge. This follows the configuration of W2V2-large which also has 24 Transformer layers. The learning rate is decayed linearly to 0 from 32K steps to 400K steps. Time masking probability is set to 0.065 with mask length 10. Audio examples are batched by length to ensure that the total batch (across 64 GPUs) contains at most 5, 600 = 64 × 1, 400, 000/16, 000 seconds of audios. We apply 8 gradient accumulation steps to simulate 64-GPU training with 8 GPUs. Each GPU processes at most 87.5 = 1, 400, 000/16, 000 seconds of audio in each forward-backward pass. For tiny models, the memory usage is lower, so we double this number to 175 seconds and half the gradient accumulation steps to 4, which makes GPUs less underutilized and shortens the pre-training time. This modification does not change the maximum size of the total batch size. We use half-precision (FP16) training.

Fine-tuning on 10m or 1h Supervised Labels We use the Adam optimizer with learning rate $3 \times 10^{-5}$, betas (0.9, 0.98) and tri-stage learning rate scheduler (Zhang et al., 2020a) (10% warm-up, 40% constant, 50% exponential decay to 5% of the peak learning rate) for 13K updates. The models are fine-tuned for 13K updates. In the first 10K updates, the context network is frozen and only the additional linear layer is trained. The WFE is always frozen. The audios are batched by length to ensure that the total batch (across 8 GPUs) contains at most 1, 600 = 8 × 3, 200, 000/16, 000 seconds of audio in each forward-backward pass. For tiny models, the memory usage is lower, so we double this number to 175 seconds and half the gradient accumulation steps to 4, which makes GPUs less underutilized and shortens the fine-tuning time. This modification does not change the maximum size of the total batch size. We use half-precision (FP16) training.

Fine-tuning on 10h Supervised Labels The models are fine-tuned for 20K updates. In the first 10K updates, the context network is frozen and only the additional linear layer is trained. The WFE is always frozen. The rest of the settings are the same as the 10-minute scenario.

Fine-tuning on 100h Supervised Labels The models are fine-tuned for 80K updates. The context network is fine-tuned from the beginning (i.e., not frozen). The WFE is frozen all the time. The rest of the settings are the same as the 10-minute scenario. To speed up the experiment, we set gradient accumulation steps to 2 to simulate fine-tuning with 4 GPUs.

\[12\] https://dl.fbaipublicfiles.com/librilight/data/librispeech_finetuning.tgz
\[13\] https://github.com/pytorch/fairseq/blob/master/examples/wav2vec/config/pretraining/wav2vec2_base_librispeech.yaml
Inference Without an LM, we decode the models with a CTC greedy decoding (a.k.a. best path decoding) algorithm, which takes the most likely token at each timestep, collapses the duplicated tokens, and removes all blank tokens. When using an LM, we use the wav2letter lexicon decoder (Collobert et al., 2016) which uses beam search. We set the beam size to 50, LM weight to 2, and word score to -1. We use the official lexicon and a 4-gram LM.[14] During decoding the audio examples are sorted by length and batched with at most 250 = 4,000,000/16,000 seconds in a batch. All these hyper-parameters are the default values in W2V2’s official inference code. The inference time is estimated on an AWS p3.2xlarge instance with 1 NVIDIA V100-SXM2-16GB GPU and 8 Intel(R) Xeon(R) CPU E5-2686 v4 @ 2.30GHz. We run 5 trials and report the mean and standard deviation of the inference time.

B.2 TED-LIUM 3

TED-LIUM 3 (CC BY-NC-ND 3.0) (Hernandez et al., 2018) is an English speech recognition corpus extracted from the public TED talks. It includes a 452h training set, a 1.6h development set, and a 2.6h test set. We follow the Kaldi (Povey et al., 2011) data preparation recipe.[15] We randomly sample the 10h labelled data from the training set.

Fine-tuning on 10h Supervised Labels We following the same fine-tuning hyperparameters as the LibriSpeech 10h setup.

Inference We follow [Hsu et al., 2021] to create a 5-gram LM. Otherwise, we use the same inference setup for LibriSpeech.

B.3 VoxPopuli

VoxPopuli (CC0, CC BY-NC 4.0) (Wang et al., 2021a) is a large-scale multilingual speech corpus collected from 2009–2020 European Parliament event recordings. We use the transcribed English corpus which consists of a 522h training set, a 5h development set, and a 5h test set. We randomly sample the 10h labelled data from the training set.

Fine-tuning on 10h Supervised Labels We follow the same fine-tuning hyperparameters as the LibriSpeech 10h setup.

Inference We use the official lexicon and 5-gram LM.[16] Otherwise, we use the same inference setup for LibriSpeech.

B.4 Fisher+Switchboard

Fisher (LDC200{4,5}S13, LDC200{4,5}T19) (Cieri et al., 2004,2005a,) and Switchboard (LDC97S62) (Godfrey and Holliman, 1993) are conversational telephone speech corpora recorded in 8kHz. We combine them to create a 2250h training set. RT-03S (LDC2007S10, 6.3h) (Fiscus, 2007) and Hub5 Eval2000 (LDC2002S09, 3.6h) (Consortium, 2002) are used as a development set and a test set. We preprocess the data according to [Hsu et al., 2021] including re-sampling 8kHz data to 16kHz. We use the Kaldi [Povey et al., 2011] data preparation and evaluation recipe.[17] We randomly sample the 10h labelled data from the training set.

Fine-tuning on 10h Supervised Labels We use the same fine-tuning hyperparameters as the LibriSpeech 10h setup.

Inference We follow [Hsu et al., 2021] to create a 4-gram LM using all the texts in the training set. Otherwise, we use the same inference setup for LibriSpeech.

[14] https://www.openslr.org/11/
[15] https://github.com/kaldi-asr/kaldi/tree/master/egs/tedlium/s5_r3
[16] https://github.com/facebookresearch/voxpopuli
[17] https://github.com/kaldi-asr/kaldi/tree/master/egs/fisher_swbd/s5
Table 10: LibriSpeech test-other results using different MLP predictor heads. For simplicity, we use a W2V2 E512L12 (pre-trained on 960h, fine-tuned on 100h) as baseline. All models have the same inference time and number of parameters (44.1M) because the predictor heads are discarded during fine-tuning on the downstream tasks. Using a 2-layer MLP with BatchNorm performs the best while adding only 7% to the pre-training (PT) time.

| Predictor Heads      | # Param. (PT) | PT time (hr) | WER   | WER (+ LM) |
|----------------------|---------------|--------------|-------|------------|
| Linear (baseline)   | 44.7M         | 40.3         | 21.9  | 13.2       |
| 2-layer MLP          | 49.8M         | 42.0         | 20.4  | 12.4       |
| 2-layer MLP + BN     | 49.8M         | 42.9         | 20.0  | 12.2       |
| 3-layer MLP + BN     | 83.4M         | 45.3         | 20.0  | 12.3       |

Table 11: Best path decoding vs. Viterbi decoding using official W2V2 ASR models. We show a higher precision of WER to emphasize performance is identical.

C Ablation Study on MLP Predictor Heads

Table 10 shows LibriSpeech 100h performance with various prediction heads. Similar to vision models, batch normalization in the prediction heads improves W2V2 performance. Unlike vision models where the prediction head is applied to merely a single pooled vector for each example, in W2V2, the prediction heads are applied to all timesteps, which leads to higher pre-training overheads, but still no overhead during fine-tuning or inference where the prediction heads are dropped.

D CTC Decoding

Best-path (greedy) Decoding vs. Viterbi Decoding

Best path decoding finds the most likely decoding path. Viterbi decoding (Viterbi, 1967) finds the most likely collapsed token sequence by summing up all possible paths. Since the outputs of a CTC model at different timesteps are independent, the best path can be generated by taking the most likely token at each timestep. This makes decoding parallelizable and efficient on GPUs. The Viterbi decoding algorithm is a dynamic programming algorithm, which processes the model outputs sequentially and is implemented on CPUs in W2V2’s implementation. Table 11 shows the WER and inference time using best-path (greedy) and Viterbi decoding methods using four official W2V2 ASR models. Two method achieve exactly the same WER while the best path decoding is faster. Although the difference is only about one second, it is significant when using tiny models. It implies that all models are very confident in their predictions.

Inference Time with Language Models

Table 12 shows W2V2’s inference time with or without LM. Decoding with LM improves the WER significantly, but inference time is also increased dramatically. It is likely that the beam search implementation is sequential and CPU-bound which slows down decoding. Reducing the inference time with LM is an important direction for future work. Alternatively, recent work (Xu et al., 2020b) shows pseudo-labeling can improve the model performance and close the gap between with and without LM. This can also solve the slow inference time with LM. We use W2V2’s official inference script in these experiments. The slowdown depends on the CPU type. We observe smaller inference time overhead when decoding on faster CPUs, but for consistency, we use the same type of hardware as our pre-training setup.

E Additional Experiments on the Kernel Size of Downsampling

While in Subsec. 4.5 we show that with small inference budget reducing the kernel size of the downsampling layer allows us to increase the size of WFE and leads to better performance. We
## Table 12: W2V2’s inference time and WER with or without an LM. Decoding with an LM increases the inference time significantly.

|                      | WER (%)          |                      | WER (%)          |
|----------------------|------------------|----------------------|------------------|
| No LM                | LM (beam=5)      | LM (beam=50)         | No LM            |
|                      |                  |                      |                  |
| W2V2-tiny 100h (100K) | 7.5 ±0.04        | 20.1 ±0.10           | 119.0 ±0.81      |
| W2V2-base 100h (400K) | 30.8 ±0.05       | 42.7 ±0.28           | 128.5 ±0.82      |

Table 12 shows additional results of transferring LibriSpeech pre-trained models to three out-of-domain datasets. We share the performance of the models with trained with only 100K updates enable future works for quick comparison.

### Table 16: Disentangled Attention

He et al. (2020) introduced disentangled attention as a component of their DeBERTa model. Unlike Transformer which adds absolute positional embeddings to the content embeddings at the beginning, disentangled attention keeps the positional embeddings and content embeddings separate and has three attention components in its attention weight computation: (a) content-to-content, (b) content-to-position, and (c) position-to-content. Given the content embeddings $C \in \mathbb{R}^{T \times d}$ and position
where slower to compute than the conventional self-attention. Unlike conventional self-attention which only has content-to-content and four matrix multiplication embeddings $P \in \mathbb{R}^{(2k+1) \times d}$, where $k$ is the maximum relative position, the output embeddings $O \in \mathbb{R}^{d \times d}$ are:

$$O = \text{softmax} \left( \frac{1}{\sqrt{d}} \bar{A}^c \right) V^c, \quad \bar{A}_{i,j} = \left( Q^c K^c \right)_{i,j} + \left( Q^p K^p \right)_{i,j} \delta(i,j) + \left( Q^c \tilde{V}^c \right)_{i,j},$$

(4)

where $Q^c = CW^q c, K^c = CW^k c, V^c = CW^v c, Q^p = PW^{q,p}, K^p = PW^{k,p},$ and $W^{q,c}, W^{k,c}, W^{v,c}, W^{q,p}, W^{k,p} \in \mathbb{R}^{d \times d}$ are trainable projection weights. $\delta(i,j)$ is the relative position of $i, j$ clamped to $[-k, k]$ and is used to index the corresponding row of $P$ or its products.

Unlike conventional self-attention which only has content-to-content and four matrix multiplication operations in total, disentangled attention has nine multiplication operations in total and is much slower to compute than the conventional self-attention.