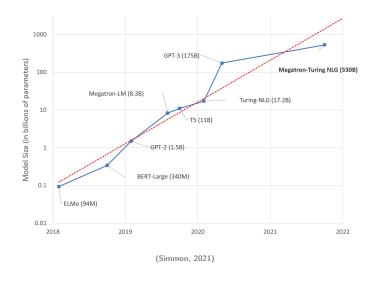
Compressing Self-Supervised Models

Jack Lin¹, Hao Tang², Hung-yi Lee¹

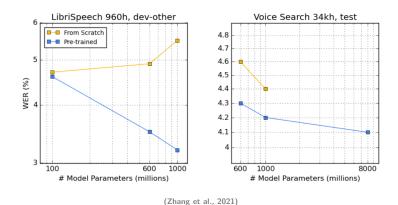
¹National Taiwan University, ²The University of Edinburgh

Self-supervised models are getting bigger.



Similar things are happening in speech.

CPC	2M
APC	4M
wav2vec	33M
12-layer Transformer	
wav2vec 2.0 Base	95M
HuBERT Base	95M
WavLM Base	95M
24-layer Transformer	
wav2vec 2.0 Large	317M
HuBERT Large	317M
WavLM Large	317M
36-layer Transformer	
ConformerG	8000M

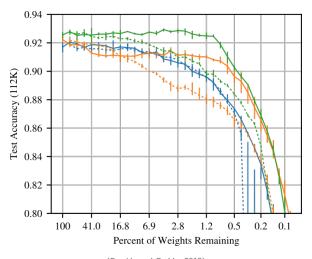


Large neural networks can be compressed.

Network	Top-1 Error	Top-5 Error	Parameters	Compression Rate
LeNet-300-100 Ref	1.64%	-	267K	
LeNet-300-100 Pruned	1.59%	-	22K	12 imes
LeNet-5 Ref	0.80%	-	431K	
LeNet-5 Pruned	0.77%	-	36K	$12\times$
AlexNet Ref	42.78%	19.73%	61M	
AlexNet Pruned	42.77%	19.67%	6.7M	9×
VGG-16 Ref	31.50%	11.32%	138M	
VGG-16 Pruned	31.34%	10.88%	10.3M	13×

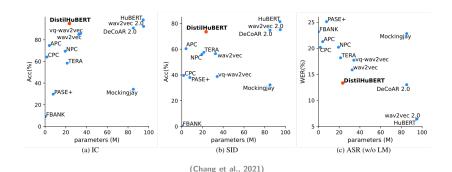
(Han et al., 2015)

Large neural networks can be compressed.



(Frankle and Carbin, 2019)

Large self-supervised models can be compressed.

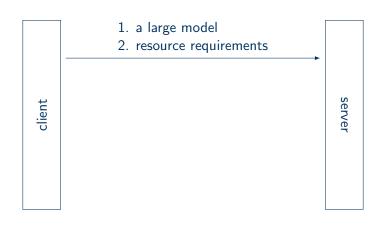


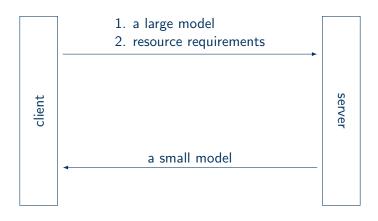
Common Compression Techniques

- Pruning
- Knowledge distillation
- Low-rank approximation
- Quantization (Low-precision floating points)

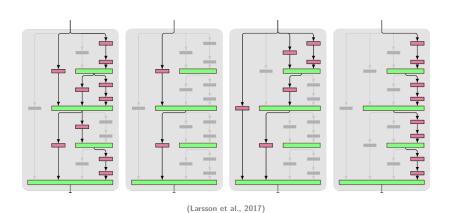
client

server





Anytime Inference



Goal

- Understanding the landscape and limit of compressing self-supervised models
- Build anytime transformer

Plan

Mar-Jun

- Train and compress 12-layer transformers on the Librispeech 360-hour subset
- Analyze the impact of compression
- Build an anytime transformer on the Librispeech 360-hour subset

Jun-Aug

- Scale up to Librispeech 960-hour subset
- Scale up analysis to many tasks

Aug-Oct

- Complete analysis
- Summarize findings