Compressing Self-Supervised Models

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Goal of the project

- Self-supervised models are large (and getting larger).
- There usually exists a much smaller network that can perform equally well as the large one.
- The goal is to **compress** self-supervised models for speech.

Model compression

- Common compression techniques have little in common.
  - Pruning
  - Knowledge distillation
  - Low-rank approximation

Model compression

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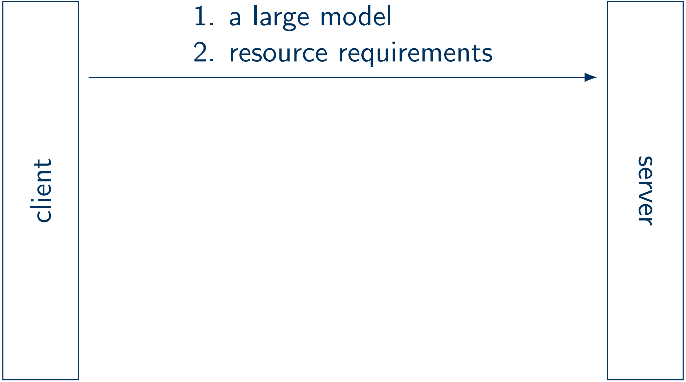

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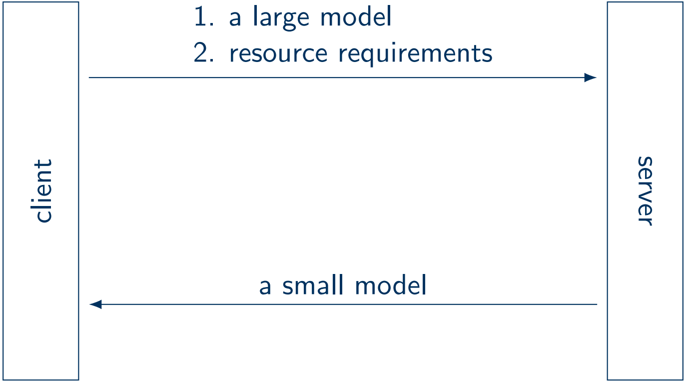

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- Any technique qualifies as model compression as long as a smaller model is returned.
  - Neural architecture search
  - Caching models of different sizes

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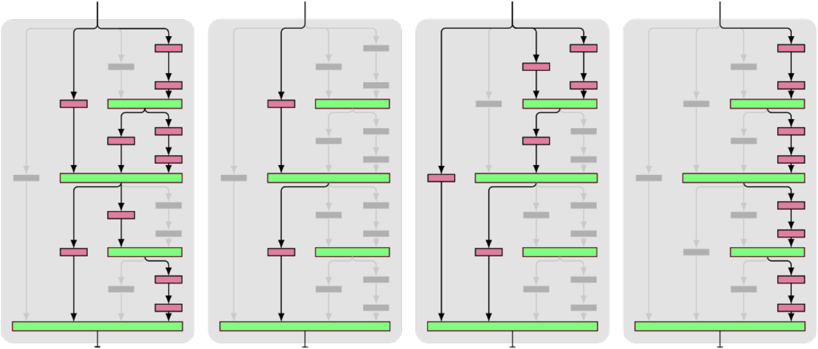
- Any technique qualifies as model compression as long as a smaller model is returned.
  - Neural architecture search
  - Caching models of different sizes
- It is a task of finding a model that satisfies a set of resource constraints.
  - Number of floating point operations
  - Number of compute cores
  - Memory consumption

Anytime Inference



(Larsson et al., 2017)

Scope of the project

- The landscape of compressing self-supervised models
- Anytime Transformers

Outline

- Desirable properties of self-supervised models
- Properties of common compression techniques
- Plans and experiments

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- Wide applicability through fine-tuning
  - ASR
  - speaker verifitication

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- Improved **accessibility** of high-level concepts
  - acoustic unit discovery
  - phone or word segmentation
  - discrete units for TTS

Representation of speech

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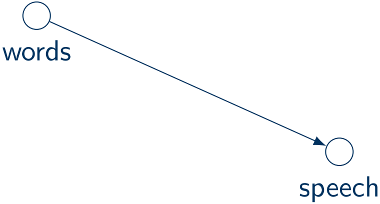

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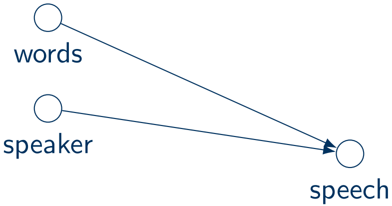

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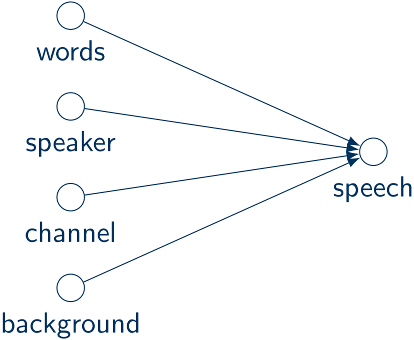

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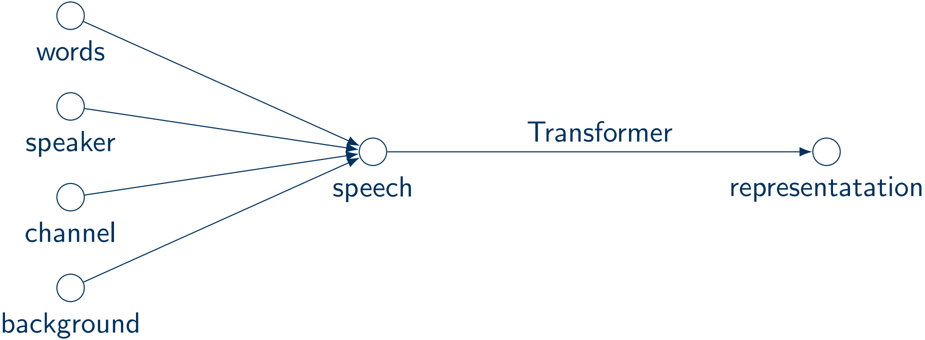
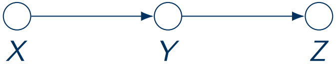
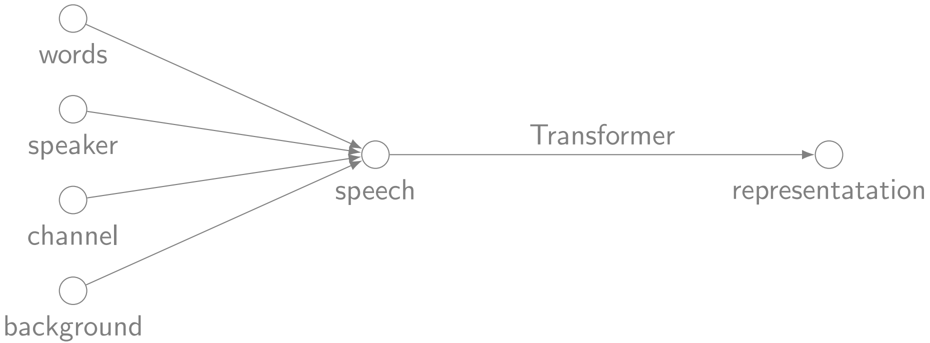


Data processing inequality



$$I(X, Y) \geq I(X, Z)$$

Representation of speech



$$I(\{\text{words}, \text{speaker}, \ldots\}, \log \text{Mel}) \geq I(\{\text{words}, \text{speaker}, \ldots\}, \text{representation})$$

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- Nothing is richer than the input log Mel spectrograms themselves.
- High-level concepts, such as phonetic information, prosodic information, speaker characteristics, are more **accessible**.
- Typically, accessibility is measured by a linear probing model.

Desirable properties of self-supervised models

- Wide applicability through fine-tuning
  - ASR
  - speaker verifitication
- Improved **accessibility** of high-level concepts
  - acoustic unit discovery
  - phone or word segmentation
  - discrete units for TTS

Research questions

- Are the returned small models still susceptible to fine-tuning?
- Do the returned small models preserve accessibility of high-level concepts?

Baseline preparation

$$
\begin{tikzcd}
\begin{array}{c}\text{APC}\\ \text{LSTM}\end{array} \arrow[r] \arrow[d] & \begin{array}{c}\text{APC}\\ \text{Causal Transformer}\end{array} & \\
\begin{array}{c}\text{Target-quantized APC}\\ \text{LSTM}\end{array} \arrow[r] & \begin{array}{c}\text{Target-quantized APC}\\ \text{Causal Transformer}\end{array} \arrow[r] & \text{HuBERT}
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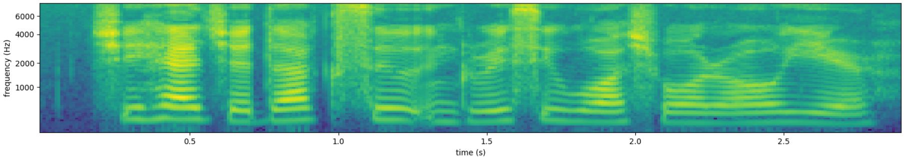
Autoregressive predictive coding (APC) (Chung et al., 2019)



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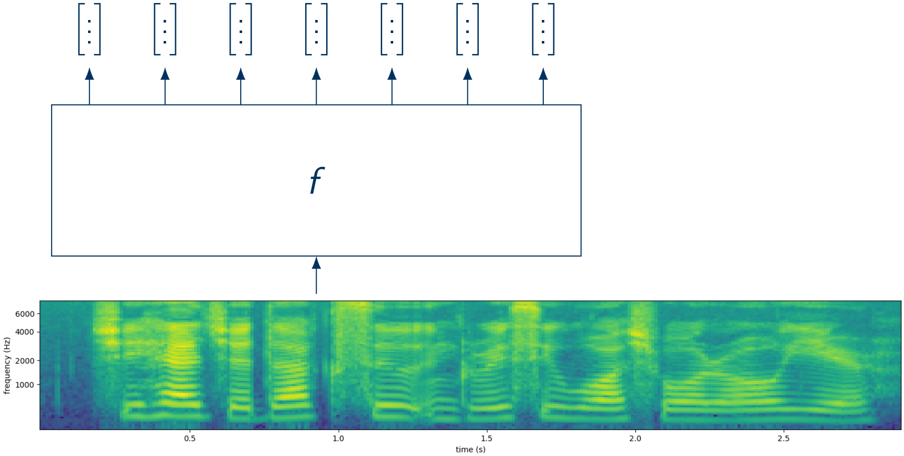

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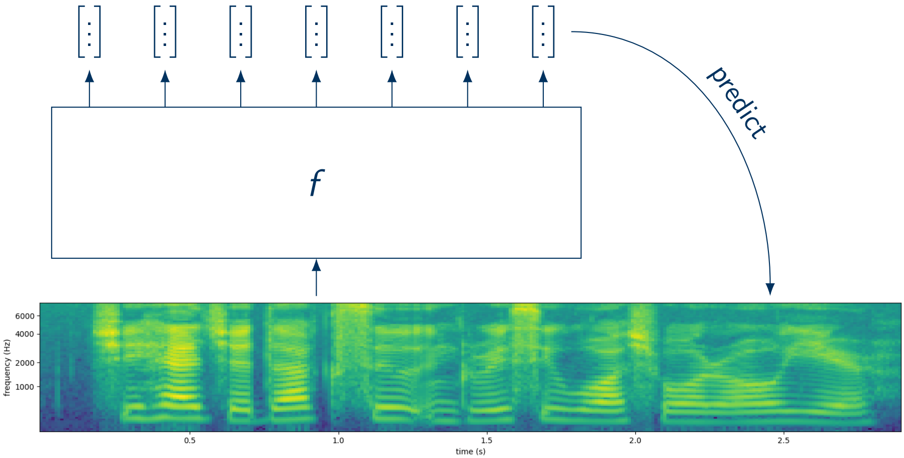

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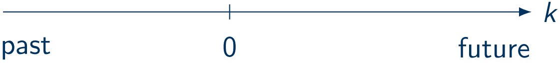

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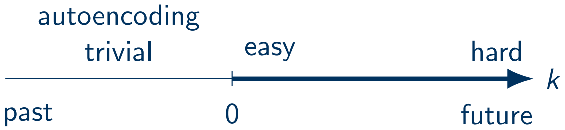

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APC
LSTM

$\downarrow$

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Baseline preparation

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APC
Causal Transformer

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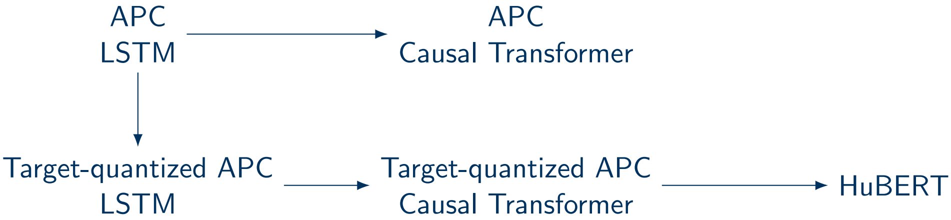

More baselines

- Small models (fewer heads, fewer layers)
- Lottery ticket hypothesis
- Knowledge distillation
- Low-rank approximation

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- Not GPU-friendly
- Great for network architecture search
- Sensitive to re-initialization

Knowledge distillation (Ba and Caruana, 2014)

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- Related to learning data geometry (Phuong and Lampert, 2019)
- Leading to drastically different student models (Stanton et al., 2021)

Low-rank approximation (Sainath et al., 2013)

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$$
\begin{aligned}
\min_{U,V} \quad & \|W - UV\|_2^2 \\
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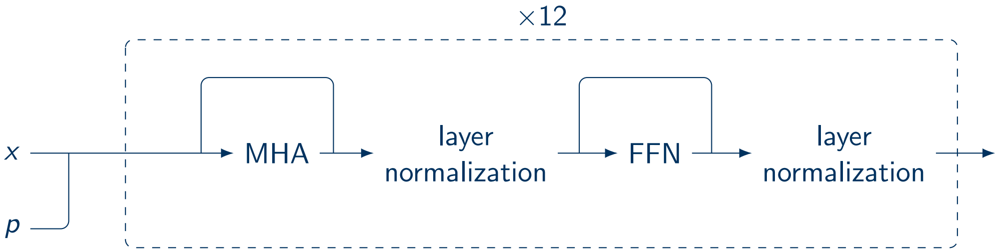

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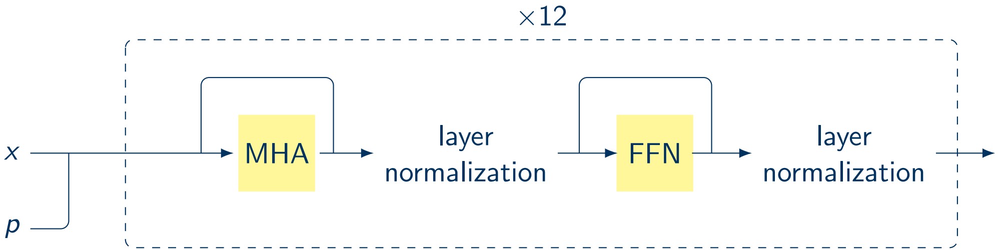

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- FFN typically occupies a significant amount of memory.
- The approach can be training-free.

Research questions

- Are the returned small models still susceptible to fine-tuning?
- Do the returned small models preserve accessibility of high-level concepts?
- Do we allow re-training at compression time?
- Do we have access to a large pre-trained model at compression time?

Where we are

$$
\begin{tikzcd}
\text{APC LSTM} \arrow[r] \arrow[d] & \text{APC Causal Transformer} & \\
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Timeline

Apr–Jun Baselines

- Reproducing HuBERT
- Implement lottery ticket hypothesis
- Implement knowledge distillation
- Implement low-rank approximation
- Pilot experiments on LibriSpeech 360 hours

Jun–Aug Workshop period

- Scaling up to LibriSpeech 960 hours
- Analyses

Aug–Oct Wrap-up

- ICASSP submission