Self-Supervised Learning for Speech

Hao Tang

Automatic Speech Recognition—ASR Lecture 16
12 March 2025

Outline

- How self-supervised learning came about
- What self-supervised learning is
- Examples of SSL on speech
    - Contrastive Predictive Coding
    - wav2vec 2.0
    - HuBERT
- How SSL models are used
    - Fine-tuning
    - Probing

Background

- Training on one task can sometimes help learn other tasks.

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- Two examples
  - Word embeddings (Mikolov *et al.*, 2013)
  - Supervised pre-training in computer vision (Girshick *et al.*, 2014)

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- Girshick *et al.* (2014) found that a pre-trained image classifier can be fine-tuned for object detection.
- They named the idea **supervised pre-training**.

	mAP
DPM	33.7
R-CNN pool_5	44.2
R-CNN fc_6	46.2
R-CNN fc_7	44.7
R-CNN fine-tuned pool_5	47.3
R-CNN fine-tuned fc_6	53.1
R-CNN fine-tuned fc_7	54.2

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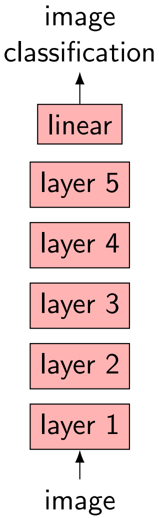

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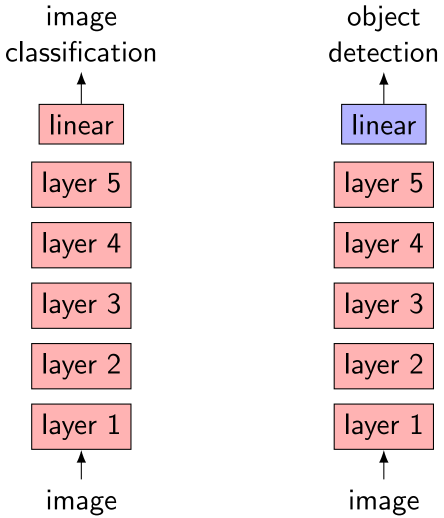

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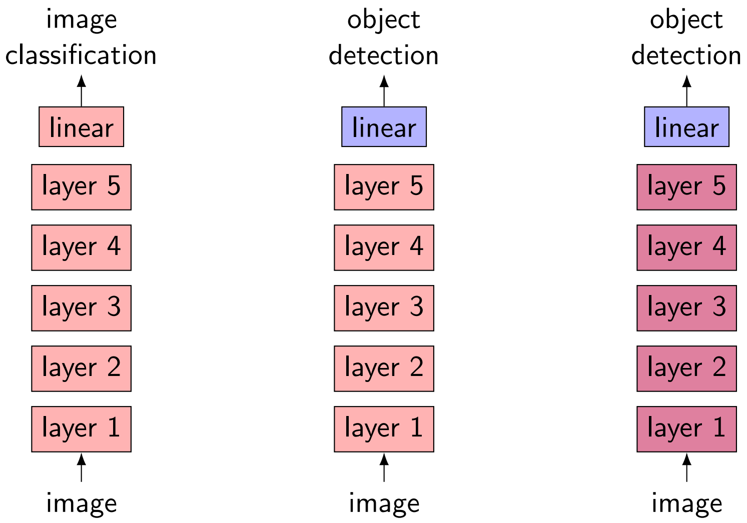
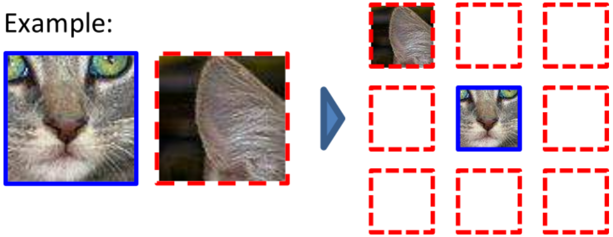


Supervised Pre-Training

- Training on one task can sometimes help learn other tasks.
- The tasks in pre-training is called the **pretext task**, while the other tasks that might benefit from pre-training are called **downstream tasks**.
- Does pre-training (i.e., the pretext task) needs to involve manual labels?

Context Prediction



(Doersch *et al.*, 2015)

Context Prediction

- The pretext task in this case is to predict the relative position of patches.

	mAP
R-CNN w/o pre-training	39.8
R-CNN self-supervised pre-training	46.3
R-CNN supervised pre-training	54.2

- Inspired by word2vec, Doersch *et al.* (2015) coins the approach **self-supervised learning**.
- Why does this work?

Context Prediction

- If the models knows ____________________, then it should be able do well on _______________.

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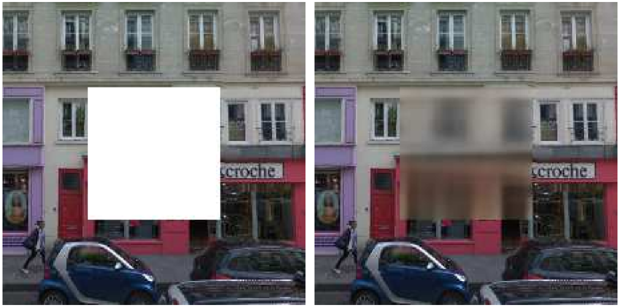
Context Prediction

- If the models knows ____________________, then it should be able do well on ______________.
- If the models knows something about images, then it should be able do well on context prediction.
- We train a model to do context prediction and hope that the model can know something about images.

More Exapmles



(Pathak *et al.*, 2016)

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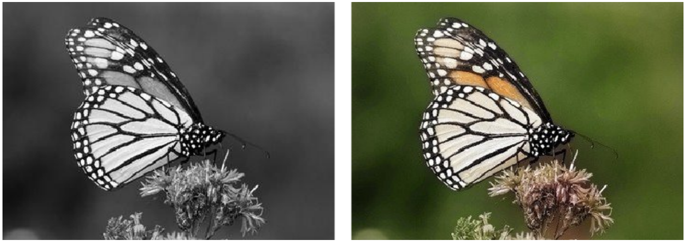
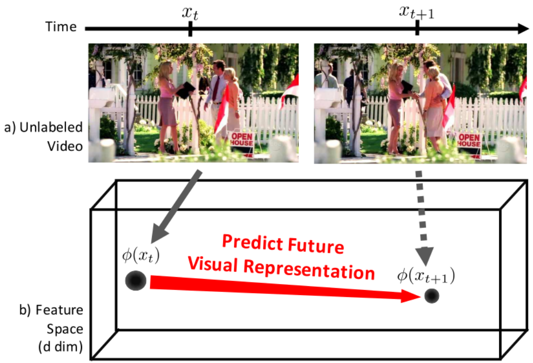

(Larsson *et al.*, 2016)

Prediction Features in the Future



(Vondrick *et al.*, 2016)

Prediction Features in the Future

- Predicting the future in the feature space seems like a reasonable pretext task for self-supervised learning.
- To formalize this, we want to train f to predict $\phi(x_{t+1})$ from $\phi(x_t)$, where $\phi(x_t)$ is the feature of x_t.
- The objective is simply

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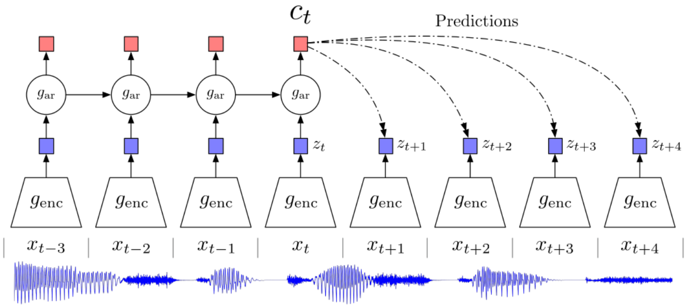
- However, if we train both f and ϕ to minimize the objective, there are trivial solutions where $\phi(x) = c\mathrm{I}$ for any constant c.
- Vondrick *et al.* (2016) use a pre-trained network for ϕ and only trains f while holding ϕ fixed.

Contrastive Predictive Coding (CPC)



(van den Oord *et al.*, 2018)

Contrastive Predictive Coding (CPC)

- The goal of CPC is to predict the future in the feature space.
- It suffers from the same problem, having trivial solutions.
- Instead of predicting the future with mean-squared error, van den Oord *et al.* (2018) adopt a contrastive approach, to distinguish the correct one from others.

Contrastive Predictive Coding (CPC)

- Suppose we want to use c_t to predict z_{t+3}.
- We know that minimizing $\|z_{t+3} - Wc_t\|_2^2$ leads to a degenerate solution.
- Instead, we want $z_{t+3}^\top Wc_t$ to be high, and $z^\top Wc_t$ to be low for any other z.
- The correct sample, in this case z_{t+3}, is typically called the **positive example**, while the others are called **negative examples**.

Contrastive Predictive Coding (CPC)

- We want $z_{t+3}^\top W c_t$ to be high, and $z^\top W c_t$ to be low for any other z.
- In other words, we want

$$\log \frac{\exp(z_{t+3}^\top W c_t)}{\sum_{z \in N \cup \{z_{t+3}\}} \exp(z^\top W c_t)} \tag{2}$$

  to be high, where N is the set of negative samples.
- The negative samples can be other frames of the same utterance, frames from other utterances of the same speaker, or frames from other utterances of different speakers.

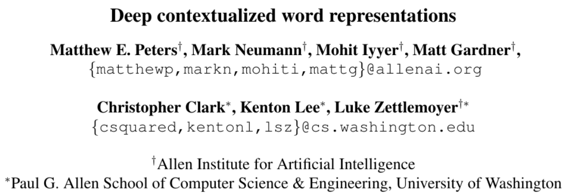
Contrastive Predictive Coding (CPC)

- The final objective is

$$\sum_{t=1}^{T-3} \log \frac{\exp(z_{t+3}^\top W c_t)}{\sum_{z \in N \cup \{z_{t+3}\}} \exp(z^\top W c_t)}. \quad (3)$$

- The number of frames into the future (3 in z_{t+3}) is a *necessary* hyperparameter.
- The negative examples are typically just all the frames in the batch.

In 2018 ...



Deep contextualized word representations

Matthew E. Peters[†], **Mark Neumann**[†], **Mohit Iyyer**[†], **Matt Gardner**[†],
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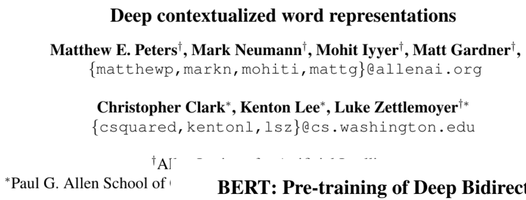
[†]Allen Institute for Artificial Intelligence
[*]Paul G. Allen School of Computer Science & Engineering, University of Washington

In 2018 ...



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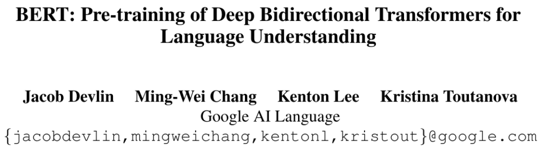
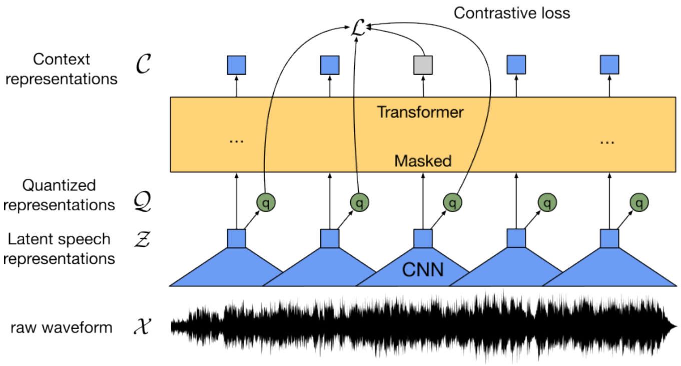


BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin Ming-Wei Chang Kenton Lee Kristina Toutanova
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

wav2vec 2.0



(Baevski *et al.*, 2020)

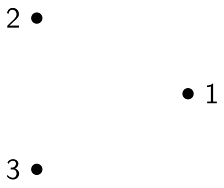
wav2vec 2.0

- The model architecture is a 12-layer Transformer.
- Instead of future prediction, wav2vec 2.0 uses masked prediction.
- The design is heavily inspired by BERT (Devlin *et al.*, 2019).
- There is a quantization layer after the CNN.

Vector Quantization

- Vector quantization is a procedure that converts a vectors into an integer.
- The integer is called a **code**, and every integer corresponds to a **code vector**.
- The set of integers and their corresponding vectors comprise a **codebook**.
- Given a vector, vector quantization finds the closest code vector in the codebook and returns the code.

Vector Quantization



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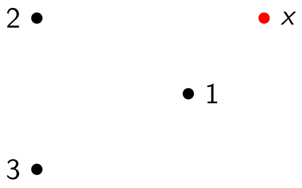

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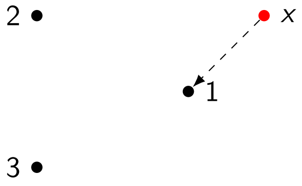


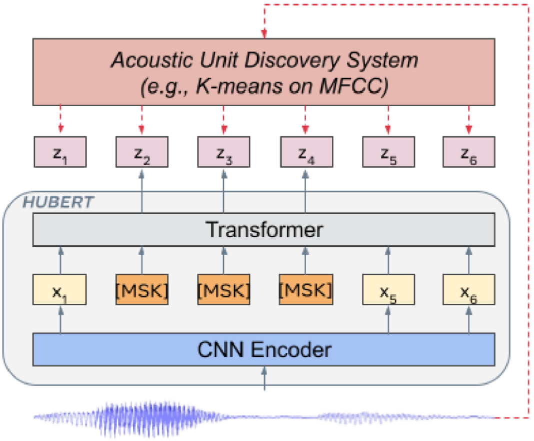
wav2vec 2.0

- wav2vec 2.0 still uses the contrastive objective

$$\sum_{t \in M} \log \frac{\exp(\cos(q_t, c_t))}{\sum_{q \in N \cup \{q_t\}} \exp(\cos(q, c_t))}, \tag{4}$$

where M is the indices of the masked frames and N is the set of negative samples.

HuBERT



(Hsu *et al.*, 2021)

HuBERT

- HuBERT uses a slightly different loss

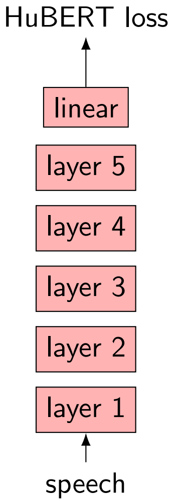
$$\sum_{t \in M} \log \frac{\exp(\cos(q_t, c_t))}{\sum_{q \in V} \exp(\cos(q, c_t))}, \tag{5}$$

where M is the indices of the masked frames and V is the codebook.

After Pre-Training ...

- A pre-trained model can serve as an initialization of another model on a new task. This approach is often called **fine-tuning**.
- A pre-trained model can also be used as a feature extractor.

Fine-Tuning


HuBERT loss
linear
layer 5
layer 4
layer 3
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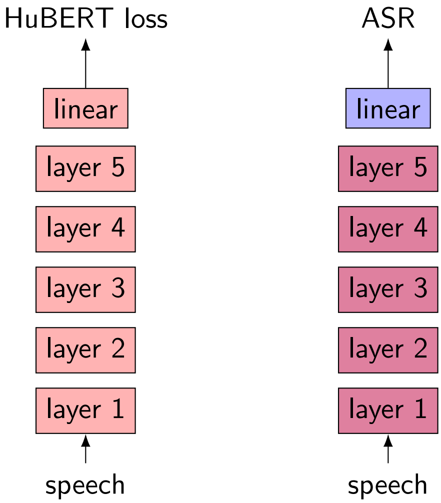
speech

Fine-Tuning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wav2vec 2.0 Results

Model	Unlabeled data	LM	dev		test	
			clean	other	clean	other
10 min labeled						
Discrete BERT [4]	LS-960	4-gram	15.7	24.1	16.3	25.2
BASE	LS-960	4-gram	8.9	15.7	9.1	15.6
		Transf.	6.6	13.2	6.9	12.9
LARGE	LS-960	Transf.	6.6	10.6	6.8	10.8
	LV-60k	Transf.	4.6	7.9	4.8	8.2
1h labeled						
Discrete BERT [4]	LS-960	4-gram	8.5	16.4	9.0	17.6
BASE	LS-960	4-gram	5.0	10.8	5.5	11.3
		Transf.	3.8	9.0	4.0	9.3
LARGE	LS-960	Transf.	3.8	7.1	3.9	7.6
	LV-60k	Transf.	2.9	5.4	2.9	5.8
10h labeled						
Discrete BERT [4]	LS-960	4-gram	5.3	13.2	5.9	14.1
Iter. pseudo-labeling [58]	LS-960	4-gram+Transf.	23.51	25.48	24.37	26.02
	LV-60k	4-gram+Transf.	17.00	19.34	18.03	19.92
BASE	LS-960	4-gram	3.8	9.1	4.3	9.5
		Transf.	2.9	7.4	3.2	7.8
LARGE	LS-960	Transf.	2.9	5.7	3.2	6.1
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100h labeled						
Hybrid DNN/HMM [34]	-	4-gram	5.0	19.5	5.8	18.6
TTS data augm. [30]	-	LSTM			4.3	13.5
Discrete BERT [4]	LS-960	4-gram	4.0	10.9	4.5	12.1
Iter. pseudo-labeling [58]	LS-860	4-gram+Transf.	4.98	7.97	5.59	8.95
	LV-60k	4-gram+Transf.	3.19	6.14	3.72	7.11
Noisy student [42]	LS-860	LSTM	3.9	8.8	4.2	8.6
BASE	LS-960	4-gram	2.7	7.9	3.4	8.0
		Transf.	2.2	6.3	2.6	6.3
LARGE	LS-960	Transf.	2.1	4.8	2.3	5.0
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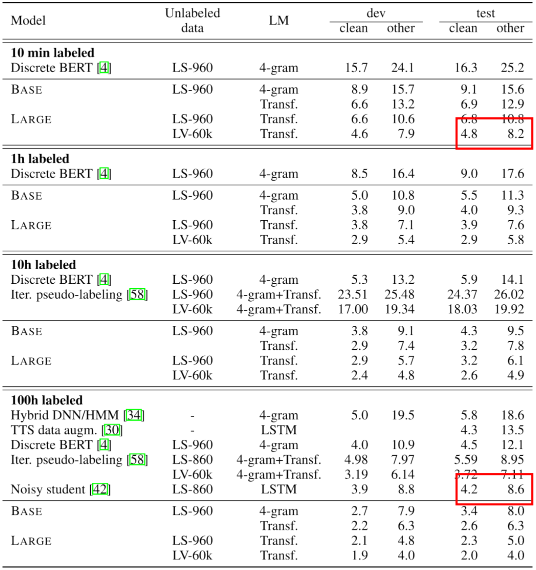
wav2vec 2.0 Results



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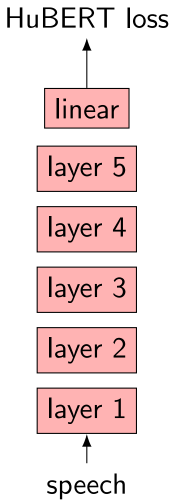
Feature Extractor



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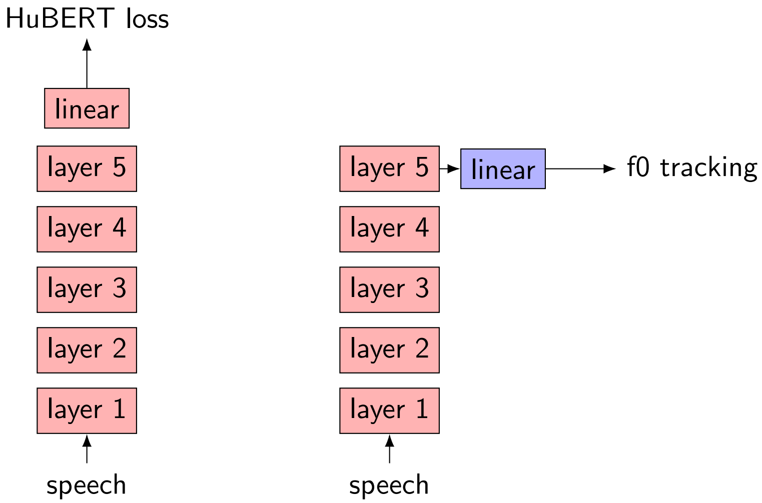

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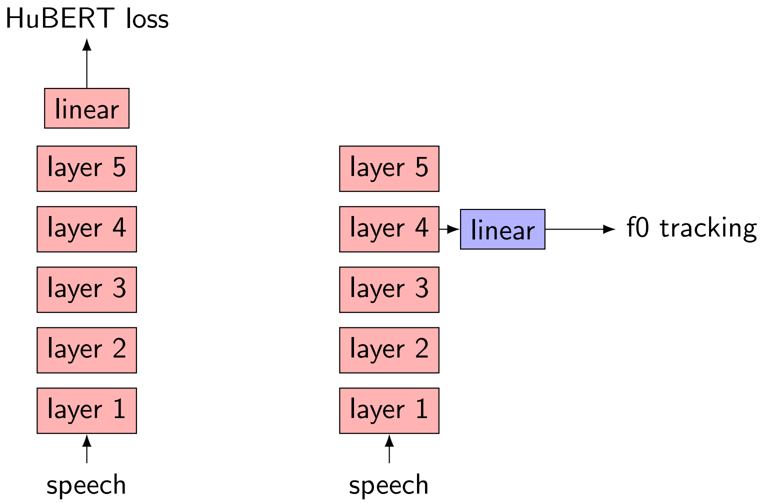

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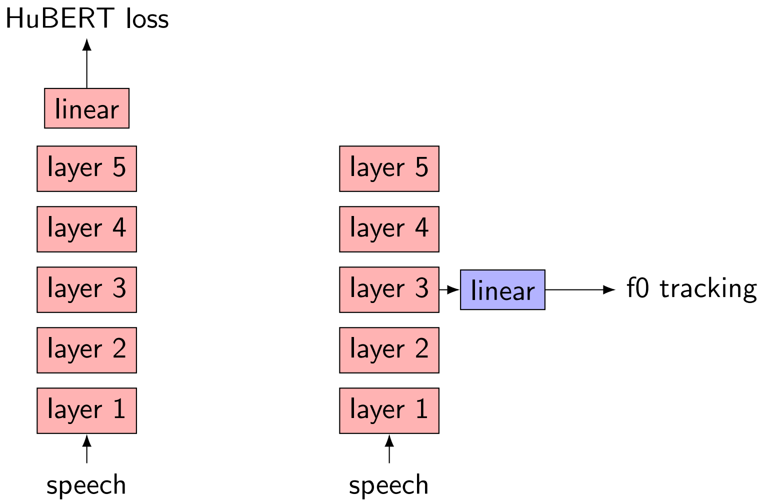

Speech Representations

- The hidden vectors are often better representations than the input at solving tasks. (Yang *et al.*, 2021)
- Don't forget that wave samples and Mel spectrograms are also speech representations.
- What aspects of speech are the hidden vectors "representing"?

Probing

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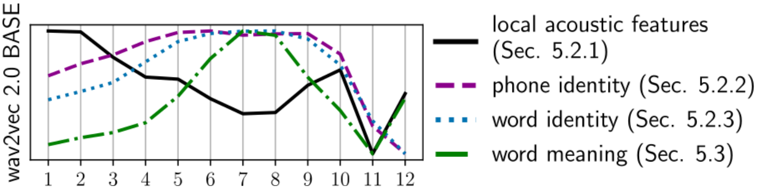
- A non-trivial accuracy tells us to what extent we can decode phones from a given representation.
- The act is usually called phone probing, and the classifier is called a probing classifier.
- There are no particular restrictions on what a probing classifier should be, but they are typically just a linear classifier.

Layer-Wise Analysis



(Pasad *et al.*, 2021)

Summary

- Pre-training followed by fine-tuning is a simple approach to leveraging data from different tasks.
- In particular, self-supervised learning makes it possible to leverage unlabeled data.
- Speech representations learned from self-supervision have found their way to many different applications.

Reference

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