UNCERTAINTY AND THE MEDICAL INTERVIEW

TOWARDS SELF-ASSESSMENT IN MACHINE LEARNING MODELS

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Department of Applied Mathematics and Computer Science

Thesis

Chapter 1-3	**Introduction, research questions, and background**
Chapter 4	**Hierarchical VAEs know what they don't know**
Chapter 5	**Model-agnostic out-of-distribution detection using combined statistical tests**
Chapter 6	**A brief overview of unsupervised speech representation learning**
Chapter 7	**Benchmarking latent variable models for speech**
Chapter 8	**Automated medical coding on MIMIC-III and MIMIC-IV: A critical review and replicability study**
Chapter 9	**A retrospective study on machine learning-assisted stroke recognition for medical helpline calls**
Chapter 10	**Discussion and conclusion**

Overview
Thesis

Background

Healthcare

Healthcare is the improvement of health via the prevention, diagnosis, treatment, amelioration or cure of disease, illness, injury, and other physical and mental impairments in people.

Medical dialogue

Medical dialogue

- General practitioner
- Nurse
- Midwife
- Emergency medical dispatcher
- Paramedic
- Emergency room
- Health insurance

Errors in medical dialogue

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- It is complex, involving multiple participants, different contexts, and different purposes.

- Adverse events: Failure of communication is a leading cause of medical error contributing to two out of three adverse events [51].
- Preventability: A considerable fraction of all hospital admissions have preventable adverse outcomes[a] [11].

[a] 9% to 16.6% in AU, NZ, UK, DK.

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- Time-consuming: Physicians spend 34-37% of their time on documentation [27, 50, 52][a].
- Varying quality: Discharge summaries almost never meet *all* timeline, transmission, and content criteria. [23][b]

[a] Ambulatory care across four specialties in four states and tertiary care at an academic medical center.
[b] Outpatient visits, Yale-New Haven Hospital.

How might machine learning help?

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- Improve decision-making.

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- Reduce the impact of medical errors and adverse events.
- Free up time spent on documentation for patient care.

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- Fairness in treatment of different groups of people.
- Robustness to noise, outliers, distribution shift, and adversarial attacks.

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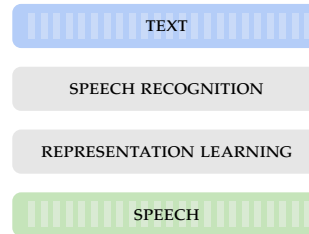

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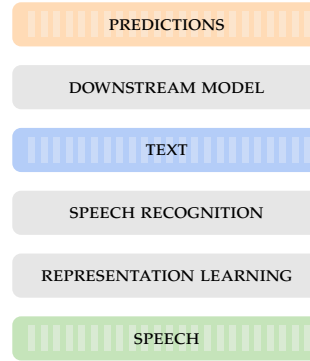

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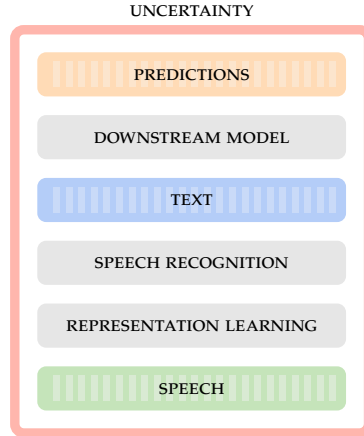
Modular approach:

- Source data: Speech or text (potentially images, video, electronic health records, etc.).
- Foundation modelling: Converting the input into representations useful for downstream tasks.
- Downstream tasks: Suggesting, summarizing, classifying, transcribing, translating, etc.
- Uncertainty: Estimating the reliability of data, representations, predictions.



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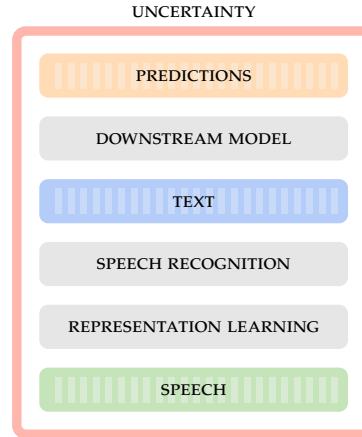

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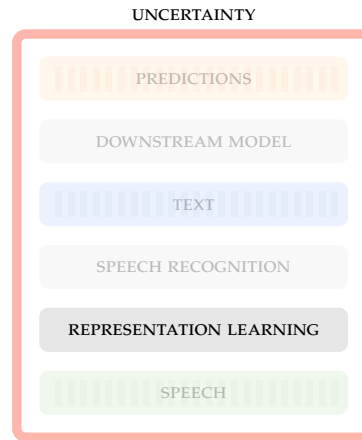

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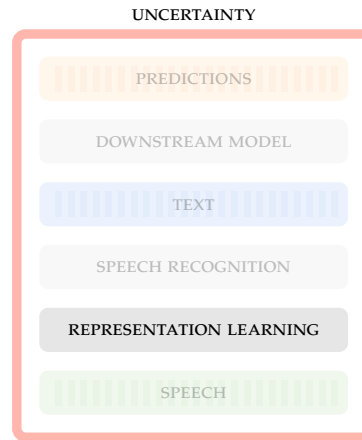

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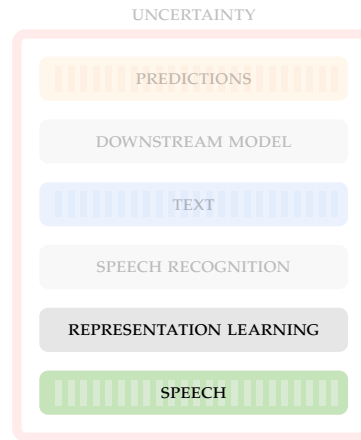

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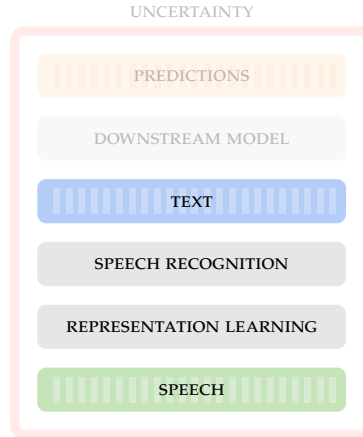

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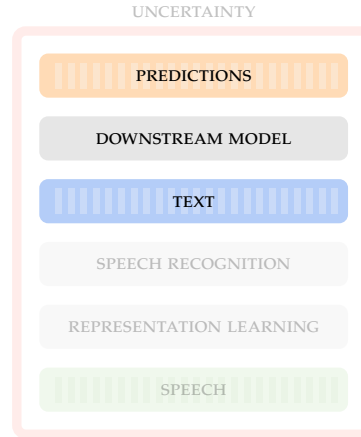

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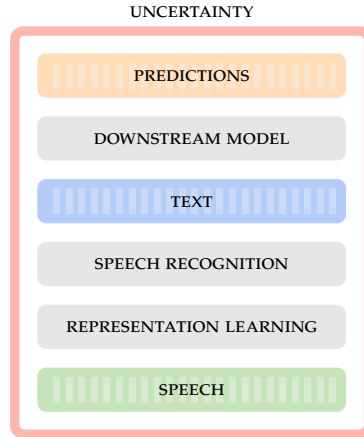
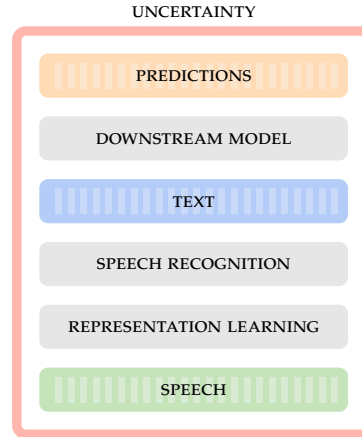


Presentation



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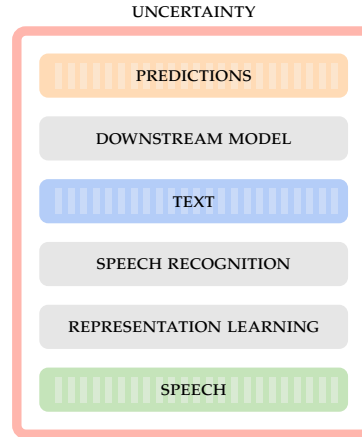

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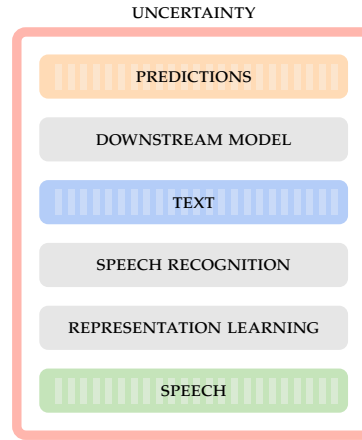

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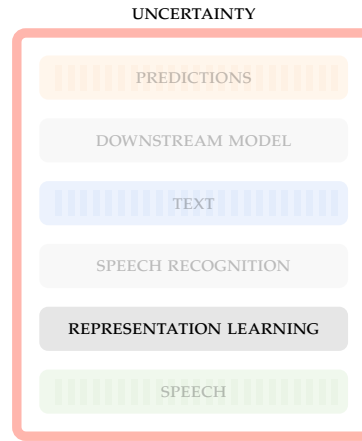
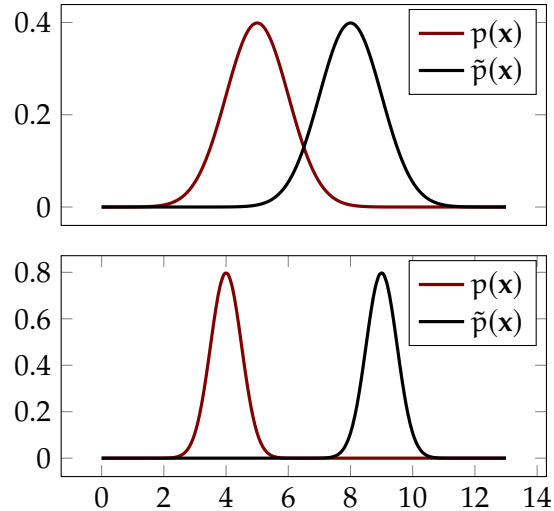


Defining OOD detection

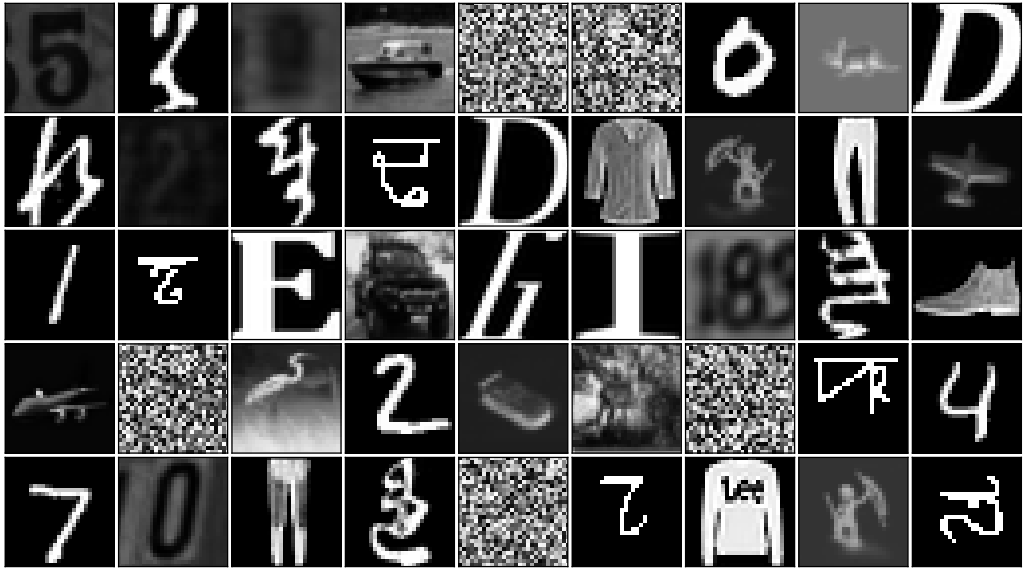
Enable models to distinguish the training data distribution $p(\mathbf{x})$ from any other distribution $\tilde{p}(\mathbf{x})$.

Do this for any given single observation, i.e. answer the question:

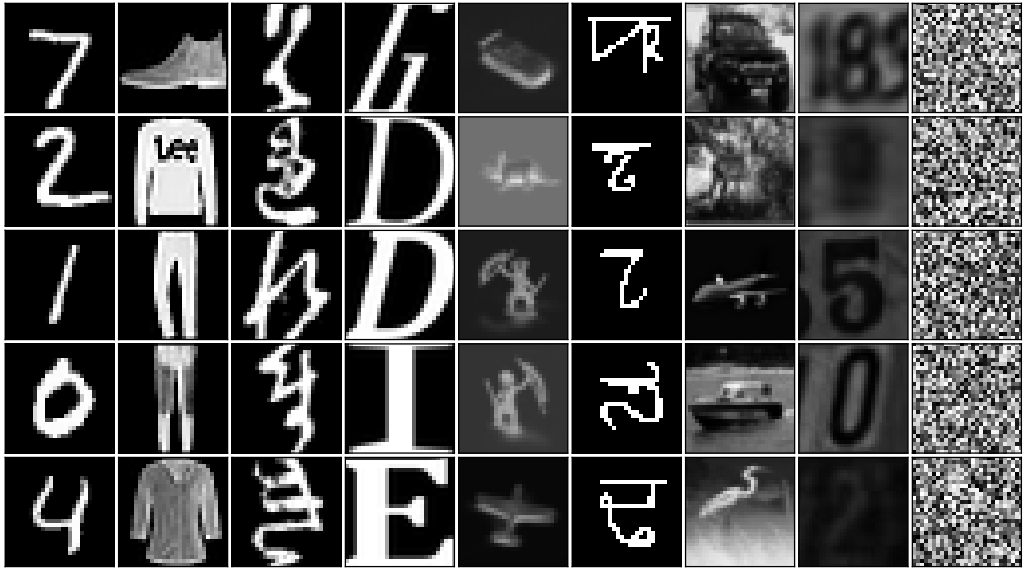
"Was $\mathbf{x}$ sampled from $p(\mathbf{x})$ or not?"



In distribution?



Out of distribution?



Problem and Contributions

- Deep generative models often fail at OOD detection task when using their likelihood estimate as the score function [40] by, perhaps surprisingly, assigning higher likelihoods to OOD data.
- Contributions:
  - We provide evidence that out-of-distribution detection fails due to learned low-level features that generalize across datasets.
  - We present a new score for OOD detection with hierarchical VAEs that alleviates this issue.

Hierarchical VAE

We choose the hierarchical VAE as our model [31, 47].

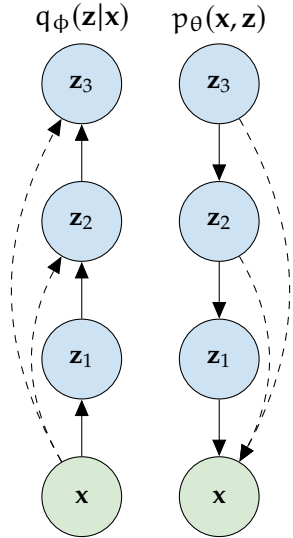
$$p_\theta(\mathbf{x}) = \int p_\theta(\mathbf{x}, \mathbf{z}) d\mathbf{z} = \int p_\theta(\mathbf{x}|\mathbf{z}) p_\theta(\mathbf{z}) d\mathbf{z}$$

Specifically we use

1. a three-layered hierarchical VAE with bottom-up inference and deterministic skip-connections for both inference and generation.

$$\text{Generative model:} \quad p_\theta(\mathbf{x}|\mathbf{z}) = p_\theta(\mathbf{x}|\mathbf{z}_1) p_\theta(\mathbf{z}_1|\mathbf{z}_2) p(\mathbf{z}_3),$$
$$\text{Inference model:} \quad q_\phi(\mathbf{z}|\mathbf{x}) = q_\phi(\mathbf{z}_1|\mathbf{x}) q_\phi(\mathbf{z}_2|\mathbf{z}_1) q_\phi(\mathbf{z}_3|\mathbf{z}_2).$$

2. a ten-layered layered Bidirectional-Inference Variational Autoencoder (BIVA) [39].



Out-of-distribution detection with hierarchical VAEs

- Generative models learn to approximate the **data distribution** $p(\mathbf{x})$.
- The likelihood of the model given a sample $\mathbf{x}$ is a measure of how well the model **explains the data**.
- **Model likelihood** has long been thought of as useful for OOD detection [6].

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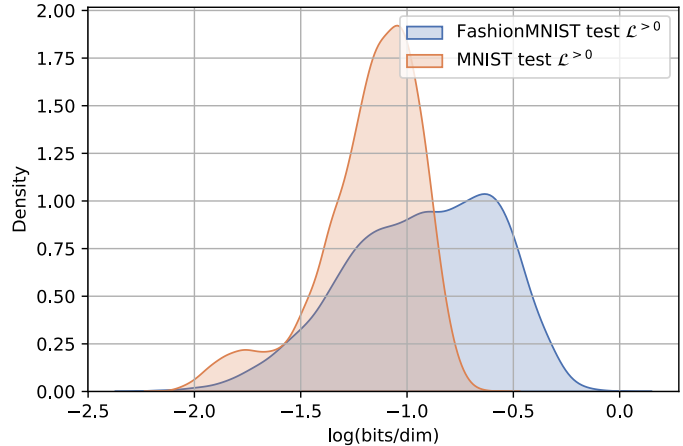


What is wrong with the ELBO for OOD detection?

We can split the ELBO into two terms

$$\mathcal{L}(\mathbf{x};\theta,\phi) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}\left[\log \frac{p_\theta(\mathbf{x},\mathbf{z})}{q_\phi(\mathbf{z}|\mathbf{x})}\right] = \underbrace{\mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z})]}_{\text{reconstruction likelihood}} - \underbrace{D_{KL}(q_\phi(\mathbf{z}|\mathbf{x})||p(\mathbf{z}))}_{\text{regularization penalty}} . \quad (1)$$

The first term is high if the data is well-explained by $\mathbf{z}$.

The second term we can rewrite as,

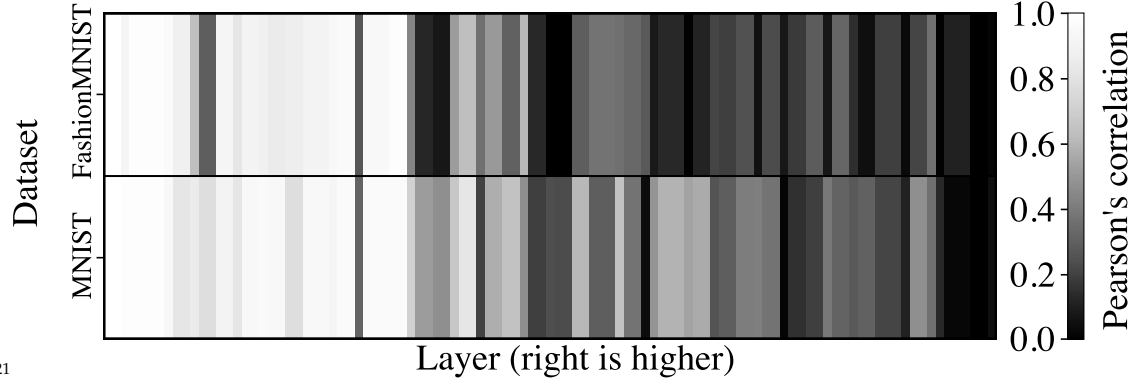
$$D_{KL}(q_\phi(\mathbf{z}|\mathbf{x})||p(\mathbf{z})) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}\left[\sum_{i=1}^{L-1} \log \frac{p_\theta(\mathbf{z}_i|\mathbf{z}_{i+1})}{q_\phi(\mathbf{z}_i|\mathbf{z}_{i-1})} + \log \frac{p_\theta(\mathbf{z}_L)}{q_\phi(\mathbf{z}_L|\mathbf{z}_{L-1})}\right] . \quad (2)$$

The absolute log-ratios grow with $\dim(\mathbf{z}_i)$ since the log probability terms are computed by summing over the dimensionality of $\mathbf{z}_i$.

What do the lowest latent variables code for?

Absolute Pearson correlations between data representations in all layers of the inference network of a hierarchical VAE trained on FashionMNIST and of another trained on MNIST.

Correlation computed between the representations of the two different models given the same data, FashionMNIST (top) and MNIST (bottom).



An alternative likelihood bound, $\mathcal{L}^{>k}$

An alternative version of the ELBO that only partially uses the approximate posterior can be written as [39]

$$\mathcal{L}^{>k}(\mathbf{x};\theta,\phi) = \mathbb{E}_{p_\theta(\mathbf{z}_{\leqslant k}|\mathbf{z}_{>k})q_\phi(\mathbf{z}_{>k}|\mathbf{x})}\left[\log \frac{p_\theta(\mathbf{x}|\mathbf{z})p_\theta(\mathbf{z}_{>k})}{q_\phi(\mathbf{z}_{>k}|\mathbf{x})}\right] \tag{3}$$

Here, we have replaced the approximate posterior $q_\phi(\mathbf{z}|\mathbf{x})$ with a different proposal distribution that combines part of the approximate posterior with the conditional prior, namely

$$p_\theta(\mathbf{z}_{\leqslant k}|\mathbf{z}_{>k})q_\phi(\mathbf{z}_{>k}|\mathbf{x})$$

This bound uses the conditional prior for the lowest latent variables in the hierarchy.

Likelihood ratios

We can use our new bound to compute the score used in a standard likelihood ratio test [10].

$$\mathrm{LLR}^{>k}(\mathbf{x}) \equiv \mathcal{L}(\mathbf{x}) - \mathcal{L}^{>k}(\mathbf{x}) \,. \tag{4}$$

We can inspect what this likelihood-ratio measures by considering the exact form of our bounds.

$$\begin{aligned} \mathcal{L} &= \log p_\theta(\mathbf{x}) - D_{\mathrm{KL}}\left(q_\phi(\mathbf{z}|\mathbf{x})||p_\theta(\mathbf{z}|\mathbf{x})\right), \\ \mathcal{L}^{>k} &= \log p_\theta(\mathbf{x}) - D_{\mathrm{KL}}\left(p_\theta(\mathbf{z}_{\leqslant}|\mathbf{z}_{>k})q_\phi(\mathbf{z}_{>k}|\mathbf{x})||p_\theta(\mathbf{z}|\mathbf{x})\right) \,. \end{aligned} \tag{5}$$

In the likelihood ratio the reconstruction terms cancel out and only the KL-divergences from the approximate to the true posterior remain.

$$\begin{aligned} \mathrm{LLR}^{>k}(\mathbf{x}) = &-D_{\mathrm{KL}}\left(q_\phi(\mathbf{z}|\mathbf{x})||p_\theta(\mathbf{z}|\mathbf{x})\right) \\ &+ D_{\mathrm{KL}}\left(p_\theta(\mathbf{z}_{\leqslant}|\mathbf{z}_{>k})q_\phi(\mathbf{z}_{>k}|\mathbf{x})||p_\theta(\mathbf{z}|\mathbf{x})\right) \,. \end{aligned} \tag{6}$$

Importance sampling the ELBO

The importance weighted autoencoder (IWAE) bound is tight with the true likelihood in the limit of infinite samples, $S \to \infty$ [9],

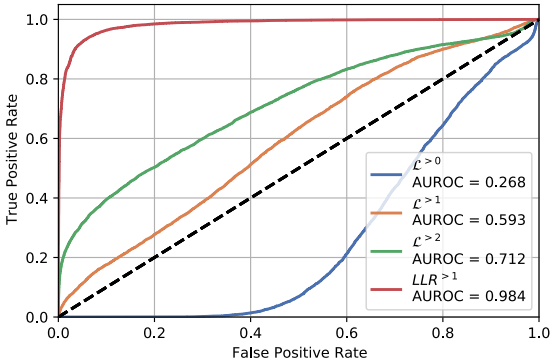
$$\mathcal{L}_S = \mathbb{E}_{q(\mathbf{z}|\mathbf{x})}\left[\log \frac{1}{N}\sum_{s=1}^{S}\frac{p(\mathbf{x},\mathbf{z}^{(s)})}{q(\mathbf{z}^{(s)}|\mathbf{x})}\right] \leqslant \log p_\theta(\mathbf{x})\,, \tag{7}$$

Consequently, by importance sampling the ELBO, the associated KL-divergence vanishes and our likelihood ratio reduces to the KL-divergence of $\mathcal{L}^{>k}$.

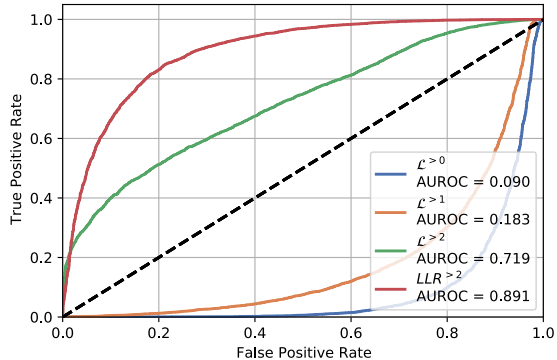
$$\mathrm{LLR}_S^{>k}(\mathbf{x}) \to \mathrm{D}_{\mathrm{KL}}(p(\mathbf{z}_{\leqslant}|\mathbf{z}_{>k})q(\mathbf{z}_{>k}|\mathbf{x})||p(\mathbf{z}|\mathbf{x}))\,. \tag{8}$$

$\mathrm{LLR}_S^{>k}(\mathbf{x})$ performs KL-divergence-based OOD detection using top-most latent variables.

Results with $\text{LLR}^{>k}$



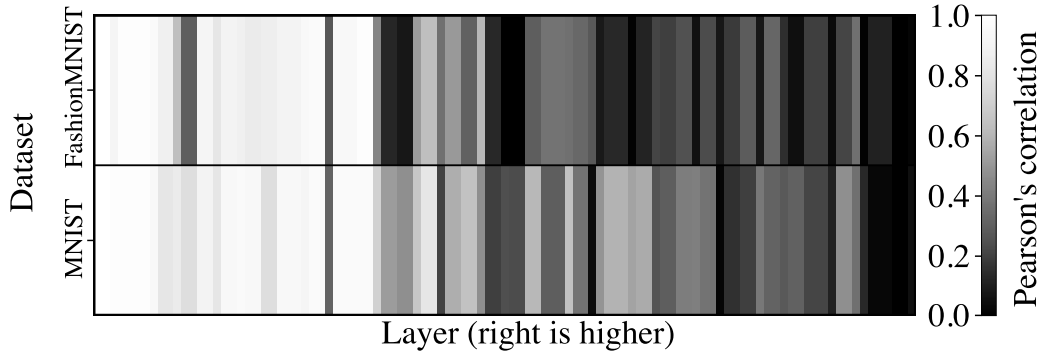
(a) FashionMNIST HVAE evaluated on MNIST



(b) CIFAR10 BIVA evaluated on SVHN

Selecting the value of k

- Use validation OOD dataset(s).
- Compute $\text{LLR}^{>k}$ for different values of k and select the one that maximizes the AUROC.
- Compute feature correlations for different values of k and select k at the drop.



Results on FashionMNIST/MNIST

Method	AUROC↑	AUPRC↑	FPR80↓
FashionMNIST (in) / MNIST (out)			
Use prior knowledge of OOD			
Backgr. contrast. LR (PixelCNN) [46]	0.994	0.993	0.001
Backgr. contrast. LR (VAE) [12]	0.924	-	-
Binary classifier [46]	0.455	0.505	0.886
$p(\hat{y}\|\mathbf{x})$ with OOD as noise class [46]	0.877	0.871	0.195
$p(\hat{y}\|\mathbf{x})$ with calibration on OOD [46]	0.904	0.895	0.139
Input complexity (S, Glow) [22]	0.998	-	-
Input complexity (S, PixelCNN++) [22]	0.967	-	-
Use in-distribution data labels $\mathbf{y}$			
$p(\hat{y}\|\mathbf{x})$ [21, 46]	0.734	0.702	0.506
Entropy of $p(\mathbf{y}\|\mathbf{x})$ [46]	0.746	0.726	0.448
ODIN [35, 46]	0.752	0.763	0.432
VIB [2, 12]	0.941	-	-
Mahalanobis distance, CNN [46]	0.942	0.928	0.088
Mahalanobis distance, DenseNet [34]	0.986	-	-
Ensemble, 20 classifiers [33, 46]	0.857	0.849	0.240
No OOD-specific assumptions			
- Ensembles			
WAIC, 5 models, VAE [12]	0.766	-	-
WAIC, 5 models, PixelCNN [46]	0.221	0.401	0.911
- Not ensembles			
Likelihood regret [56]	**0.988**	-	-
$\mathcal{L}^{>0}$ + HVAE (ours)	0.268	0.363	0.882
$\mathcal{L}^{>1}$ + HVAE (ours)	0.593	0.591	0.658
$\mathcal{L}^{>2}$ + HVAE (ours)	0.712	0.750	0.548
$\text{LLR}^{>1}$ + HVAE (ours)	0.964	0.961	0.036
$\text{LLR}^{>1}_{250}$ + HVAE (ours)	0.984	**0.984**	**0.013**

Results on CIFAR10/SVHN

Method	AUROC↑	AUPRC↑	FPR80↓
CIFAR10 (in) / SVHN (out)			
Use prior knowledge of OOD			
Backgr. contrast. LR (PixelCNN) [46]	0.930	0.881	0.066
Backgr. contrast. LR (VAE) [56]	0.265	-	-
Outlier exposure [22]	0.984	-	-
Input complexity (S, Glow) [49]	0.950	-	-
Input complexity (S, PixelCNN++) [49]	0.929	-	-
Input complexity (S, HVAE) (Ours) [49]	0.833	0.855	0.344
Use in-distribution data labels y			
Mahalanobis distance [34]	0.991	-	-
No OOD-specific assumptions			
- Ensembles			
WAIC, 5 models, Glow [12]	1.000	-	-
WAIC, 5 models, PixelCNN [46]	0.628	0.616	0.657
- Not ensembles			
Likelihood regret [56]	0.875	-	-
$LLR^{>2}$ + HVAE (ours)	0.811	0.837	0.394
$LLR^{>2}$ + BIVA (ours)	**0.891**	**0.875**	**0.172**

Results on diverse datasets

OOD dataset	Metric	AUROC↑	AUPRC↑	FPR80↓
Trained on CIFAR10				
SVHN	$LLR^{>2}$	0.811	0.837	0.394
CIFAR10	$LLR^{>1}$	0.469	0.479	0.835
Trained on SVHN				
CIFAR10	$LLR^{>1}$	0.939	0.950	0.052
SVHN	$LLR^{>1}$	0.489	0.484	0.799

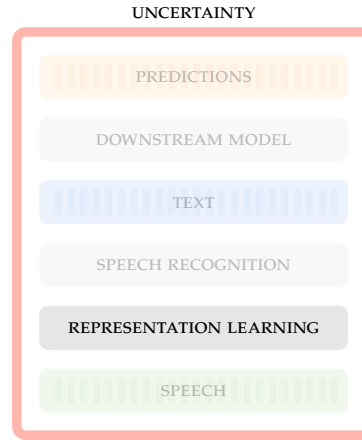
OOD dataset	Metric	AUROC↑	AUPRC↑	FPR80↓
Trained on FashionMNIST				
MNIST	$LLR^{>1}$	0.986	0.987	0.011
notMNIST	$LLR^{>1}$	0.998	0.998	0.000
KMNIST	$LLR^{>1}$	0.974	0.977	0.017
Omniglot28x28	$LLR^{>2}$	1.000	1.000	0.000
Omniglot28x28Inverted	$LLR^{>1}$	0.954	0.954	0.050
SmallNORB28x28	$LLR^{>2}$	0.999	0.999	0.002
SmallNORB28x28Inverted	$LLR^{>2}$	0.941	0.946	0.069
FashionMNIST	$LLR^{>1}$	0.488	0.496	0.811
Trained on MNIST				
FashionMNIST	$LLR^{>1}$	0.999	0.999	0.000
notMNIST	$LLR^{>1}$	1.000	0.999	0.000
KMNIST	$LLR^{>1}$	0.999	0.999	0.000
Omniglot28x28	$LLR^{>1}$	1.000	1.000	0.000
Omniglot28x28Inverted	$LLR^{>1}$	0.944	0.953	0.057
SmallNORB28x28	$LLR^{>1}$	1.000	1.000	0.000
SmallNORB28x28Inverted	$LLR^{>1}$	0.985	0.987	0.000
MNIST	$LLR^{>2}$	0.515	0.507	0.792

Conclusions

- Key observations:
  - The likelihood of a generative model is not a good score for OOD detection [40].
  - Strong correlations between some latent variables for different datasets.
  - Reconstructions of OOD data are good when using full approximate posterior.

→ Proposed a new score, $\text{LLR}^{>k}$, that uses the conditional prior for the top-most latent variables in the hierarchy.

Presentation



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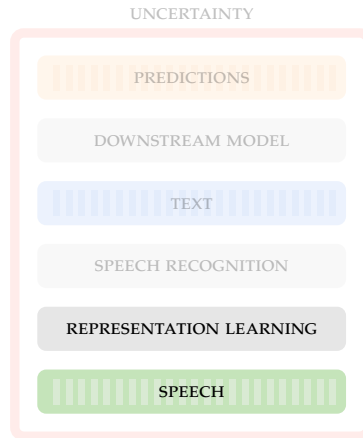

Overview: Representation Learning for Speech

- We focus on two primary categories:
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  - Probabilistic latent variable models (LVMs)
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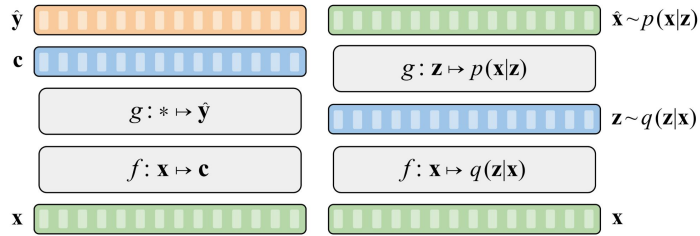

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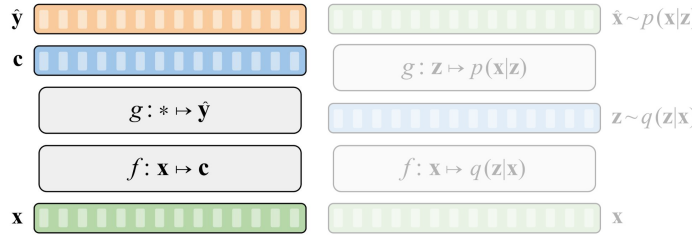
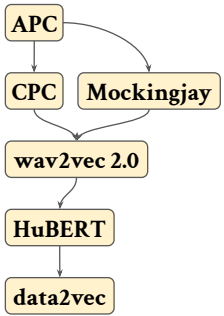
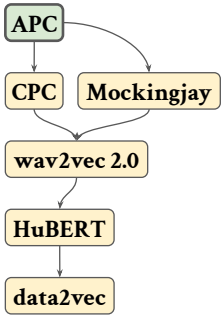


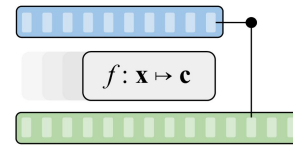
Development of SSL for speech



Autoregressive Predictive Coding (APC)



- **Task**: Predict future inputs.
- **Input/target**: Log-mel spectrogram.
- **Architecture**: RNN/Transformer decoder.
- **Slow features**: Predict k steps ahead.



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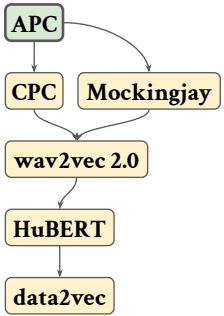
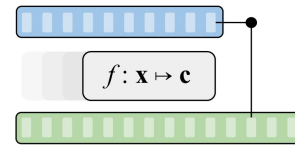
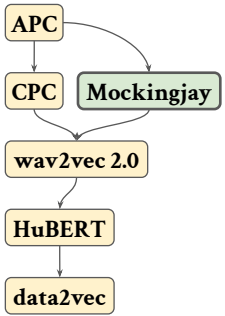


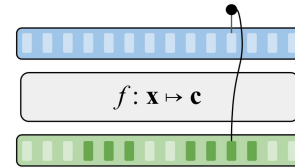
- **Challenges**:
  - Encodes only past inputs ✗
  - Uses the input as target ✗



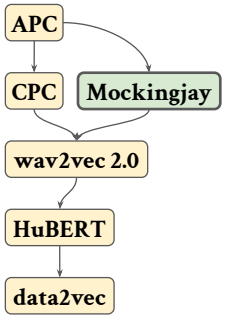
Mockingjay



- **Task**: Reconstruct masked inputs.
- **Architecture**: Transformer encoder.
- **Masking**:
  - X% at random. (Mockingjay)
  - X% + N consecutive (wav2vec 2.0)
  - SpecAugment (Masked RNN)



Mockingjay



- **Challenges**:
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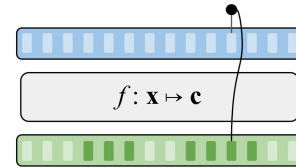
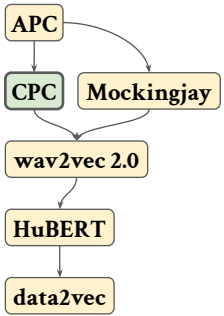
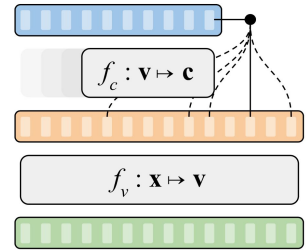


Contrastive Predictive Coding (CPC)



- **Contrastive models**: Distinguish target samples from negative samples.
- **Learned target**: Discard details.
- **Sampling negatives**:
  - Sample sequence?
  - Same speaker?



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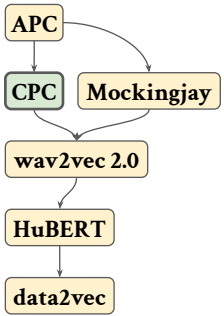

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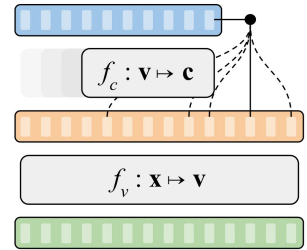

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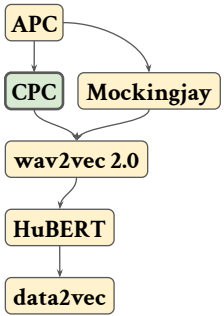

- **Challenges**:
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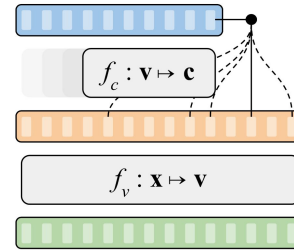
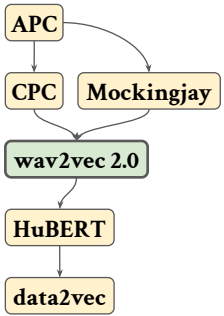
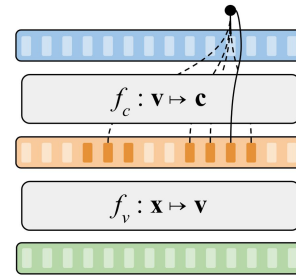


wav2vec 2.0



- Masking + contrastive learning.
- **Quantisation**: Better negative samples.
- **Results**:
  - 960 hours: **2.0%** WER.
  - 10 mimutes: **4.8%** WER.



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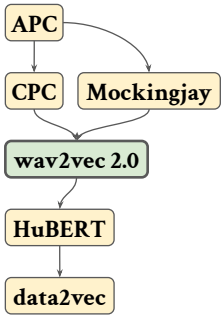

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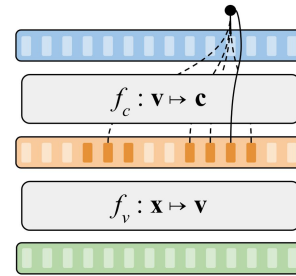
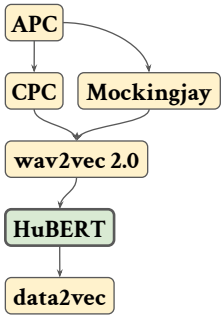
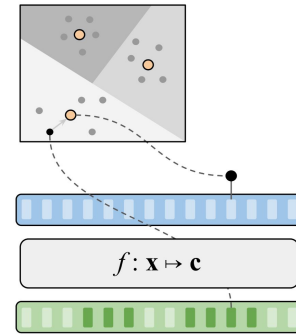


Hidden-unit BERT (HuBERT)



- **Target**: K-means teacher.
- **Training**: Simple cross-entropy loss.
- **1st iteration**: K-means on inputs.



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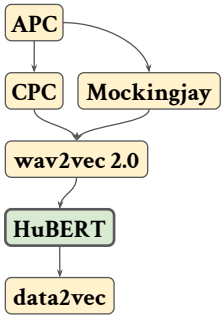

- **Target**: K-means teacher.
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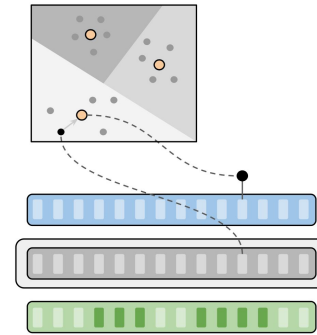
- **1st iteration**: K-means on inputs.
- **2nd iteration**: K-means on hidden layers.



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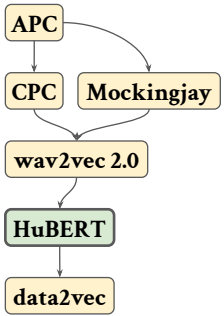

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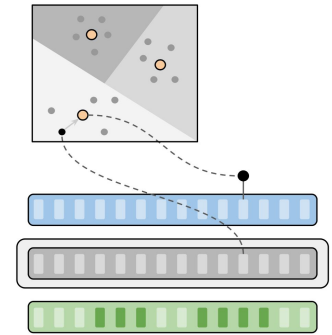
  - No need for negative samples ✓



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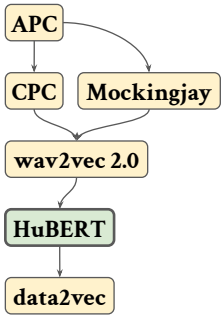

- **Challenges**:
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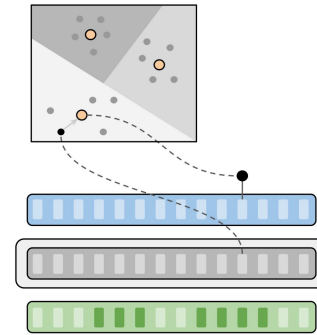
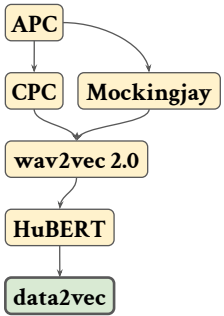
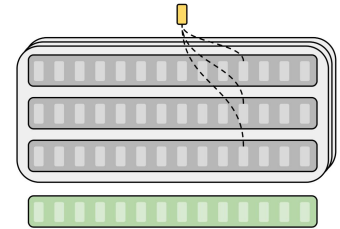
  - No need for negative samples ✓
  - Targets updated infrequently ✗
  - Quantized targets ✗



data2vec



- Uses a teacher-student framework.
- **Teacher**:
  - EMA of student (online) ✓
  - Target is average of top K layers ✓



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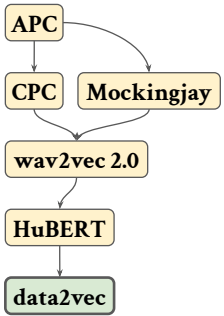

- Uses a teacher-student framework.
- **Teacher**:
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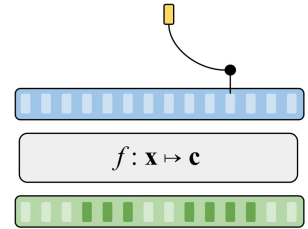
- **Student training**: Smooth $_1$ loss.



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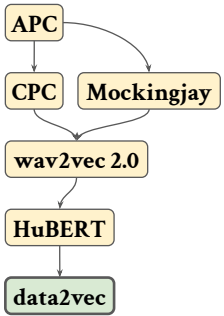

- **Challenges**:
  - Encodes the entire input ✓
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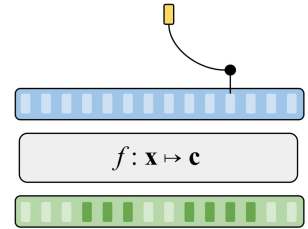
  - No need for negative samples ✓
  - Targets updated continuously ✓
  - Continuous-valued targets ✓



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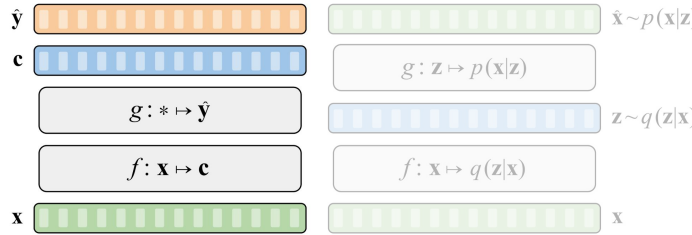

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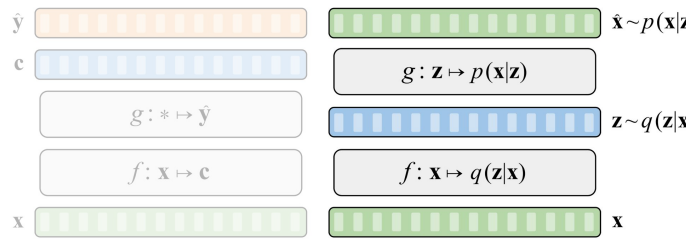
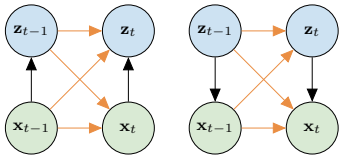
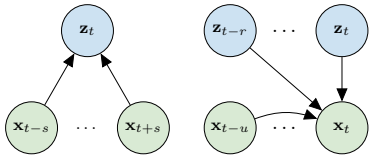


Graphical models for LVMs

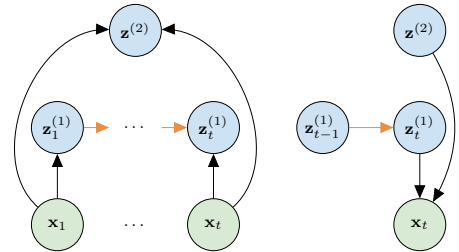
VRNN



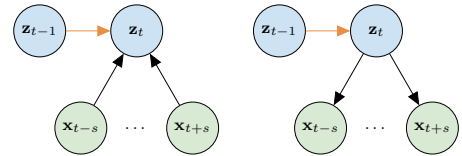
VQ-VAE



FDMM



ConvDMM



Orange edges indicate parameters shared between inference and generative models.

Overview of LVM probabilistic components

Type		Form
	Observation model	
ARX	Autoregressive on $\mathbf{x}_t$	$p(\mathbf{x}_t \vert \mathbf{x}_{1:t-1})$
LOC	Local latent variable	$p(\mathbf{x}_t \vert \mathbf{z}_{1:t})$
GLB	Global latent variable	$p(\mathbf{x}_t \vert \mathbf{z})$
	Prior	
ARX	Autoregressive on $\mathbf{x}_t$	$p(\mathbf{z}_t \vert \mathbf{x}_{1:t-1})$
ARZ	Autoregressive on $\mathbf{z}_t$	$p(\mathbf{z}_t \vert \mathbf{z}_{1:t-1})$
IND	Locally independent $\mathbf{z}_t$	$p(\mathbf{z}_t)$
GLB	Global latent variable	$p(\mathbf{z})$
	Inference model	
ARZ	Autoregressive on $\mathbf{z}_t$	$q(\mathbf{z}_t \vert \mathbf{z}_{1:t-1})$
FLT	Filtering	$q(\mathbf{z}_t \vert \mathbf{x}_{1:t})$
LSM	Local smoothing	$q(\mathbf{z}_t \vert \mathbf{x}_{t-r:t+r})$
GSM	Global smoothing	$q(\mathbf{z}_t \vert \mathbf{x}_{1:T})$
GLB	Global latent variable	$q(\mathbf{z} \vert \mathbf{x}_{1:T})$

Classification of selected LVMs for speech

	Observation			Prior				Inference					
Model	**ARX**	**LOC**	**GLB**	**ARX**	**ARZ**	**IND**	**GLB**	**ARZ**	**FLT**	**LSM**	**GSM**	**GLB**	**HIE**
VRNN [14]	✓	✓	✗	✓	✓	✗	✗	✓	✓	✗	✗	✗	✗
SRNN [17]	✓	✓	✗	✓	✓	✗	✗	✓	✗	✗	✓	✗	✗
HMM-VAE [16]	✗	✓	✗	✗	✓	✗	✗	✓	✓	✗	✗	✗	✓
ConvVAE [25]	✗	✗	✓	✗	✗	✗	✓	✗	✗	✗	✓	✓	✗
FHVAE [26]	✗	✓	✓	✗	✗	✓	✓	✗	✗	✗	✓	✓	✓
VQ-VAE [43]	✓	✓	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗	✗
BHMM-VAE [19]	✗	✓	✗	✗	✓	✗	✗	✓	✓	✗	✗	✗	✗
STCN [1]	✗	✓	✗	✓	✗	✗	✗	✗	✓	✗	✗	✗	✓
FDMM [29]	✗	✓	✓	✗	✓	✗	✓	✓	✓	✗	✗	✓	✓
ConvDMM [30]	✗	✓	✗	✗	✓	✗	✗	✓	✗	✓	✗	✗	✗

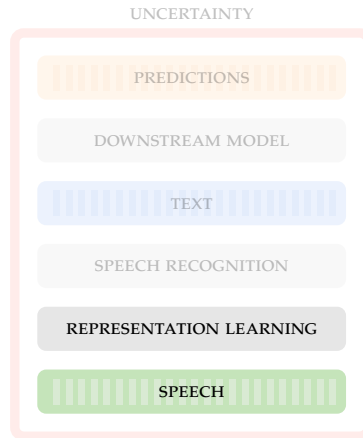
Comparison of LVMs and SSL methods

		MODEL AND TASK DESIGN						RESOLUTION			USAGE	
	MODEL	MSK	PRD	CON	REC	QTZ	GEN	LOC	GLB	VAR	FRZ	FTN
SELF-SUPERVISED MODELS	**CPC** [42]	✗	✓	✓	✗	✗	✗	✓	✗	✗	✓	✗
	APC [13]	✗	✓	✗	✓	✗	✗	✓	✗	✗	✓	✗
	wav2vec [48]	✗	✓	✓	✗	✗	✗	✓	✗	✗	✓	✗
	Mockingjay [38]	✓	✗	✗	✓	✗	✗	✓	✗	✗	✓	✓
	wav2vec 2.0 [4]	✓	✗	✓	✗	✓	✗	✓	✗	✗	✗	✓
	NPC [37]	✓	✗	✗	✓	✓	✗	✓	✗	✗	✓	✗
	DeCoAR 2.0 [36]	✓	✗	✗	✓	✓	✗	✓	✗	✗	✓	✗
	HuBERT [24]	✓	✗	✗	✗	✓	✗	✓	✗	✗	✗	✓
	data2vec [3]	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓
LATENT VARIABLE MODELS	**VRNN** [14]	✗	✗	✗	✓	✗	✓	✓	✗	✗	✓	✗
	SRNN [17]	✗	✗	✗	✓	✗	✓	✓	✗	✗	✓	✗
	ConvVAE [25]	✗	✗	✗	✓	✗	✓	✗	✓	✗	✓	✗
	FHVAE [26]	✗	✗	✗	✓	✗	✓	✓	✓	✗	✓	✗
	VQ-VAE [43]	✗	✗	✗	✓	✓	✓	✓	✗	✗	✓	✗
	STCN [1]	✗	✗	✗	✓	✗	✓	✓	✗	✗	✓	✗
	FDMM [29]	✗	✗	✗	✓	✗	✓	✓	✓	✗	✓	✗
	ConvDMM [30]	✗	✗	✗	✓	✗	✓	✓	✗	✗	✓	✗

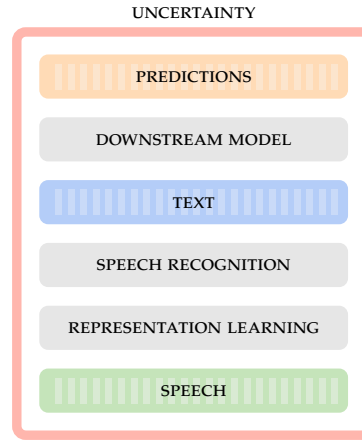
Conclusions

- **Main conclusions**:
  - The most popular self-supervised speech models can be compactly described by a few core design choices.
  - Many of these design choices are mirrored in earlier work on speech embedding models.
- **Open questions and limitations**:
  - Which design choices benefit which downstream tasks?
  - It is difficult to compare methods as model size and evaluation procedures differ widely between papers.

Presentation



Presentation



Stroke

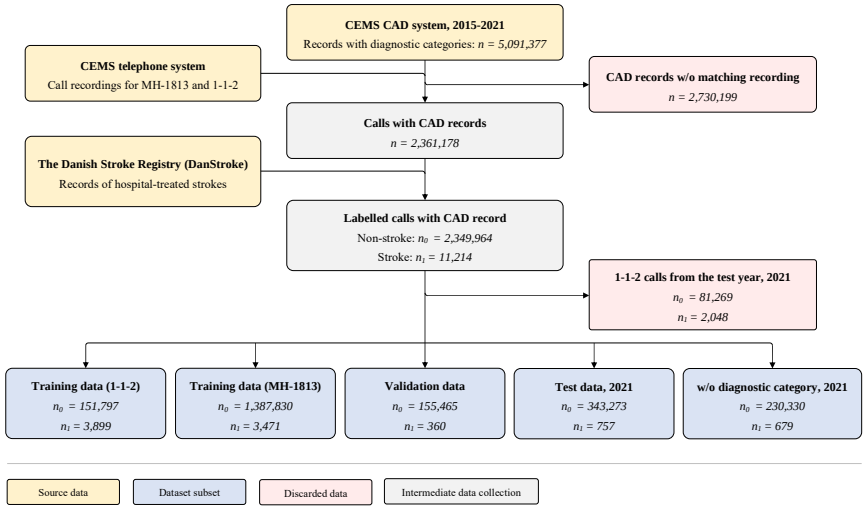
- Stroke is a leading cause of disability and death worldwide [18, 28, 32].
- Effective treatment is very time-sensitive. [5, 53].
- The gateway to ambulance transport and hospital admittance is through prehospital telehealth services.
- Mobile stroke units has made it possible to deliver advanced treatment faster [20, 41].
- The effectiveness of mobile stroke units hinges on call-taker recognition of stroke [20, 41].
- But stroke

The study

- Collaboration between Corti and the Copenhagen Emergency Medical Services (CEMS) ("Region Hovedstadens Akutberedskab").
- CEMS provides prehospital telehealth services in the Capital Region of Denmark (1.9M people).
- CEMS operates the 1-1-2 emergency line (similar to 9-1-1) and the 1813 medical helpline (non-life-threatening conditions when general practitioner is unavailable).
- Approximately half of all patients with stroke do not receive the correct triage for their condition from call-takers [8, 44, 55].

- We wanted to investigate if a machine learning model could assist call-takers of 1813 in recognizing stroke.

Population selection and datasets

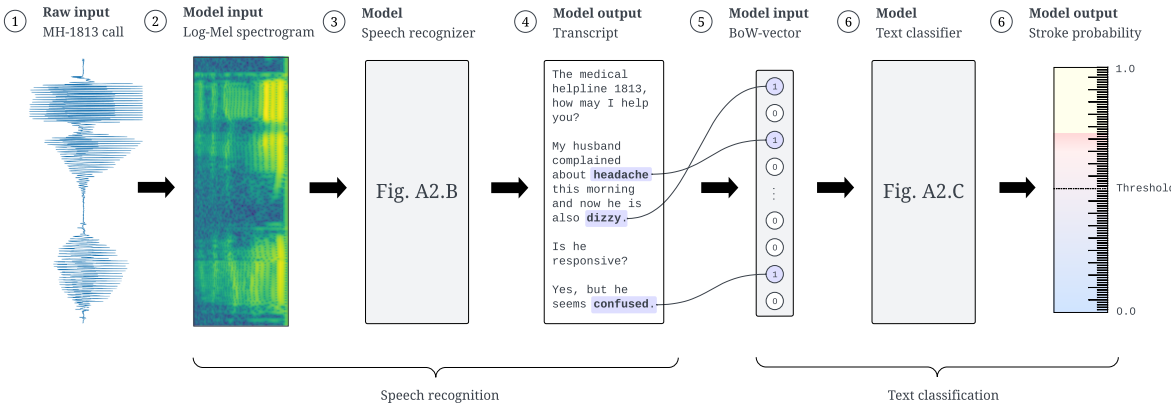


Population characteristics

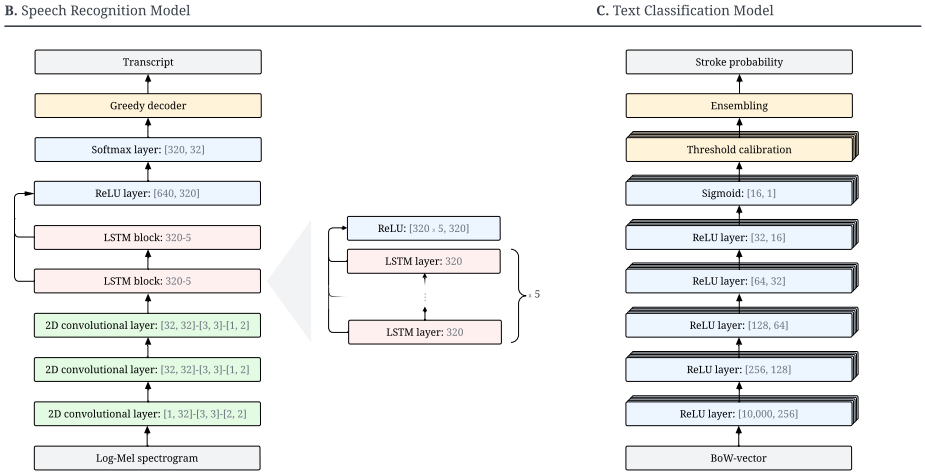
		Training (112)	Training (MH-1813)	Validation	Test	2021 w/o category
All calls	**Num. calls**	155,696	1,391,301	155,825	344,030	231,009
	Female	74,640 (47.94%)	792,783 (56.98%)	86,959 (55.81%)	190,974 (55.51%)	134,324 (58.14%)
	Male	79,564 (51.10%)	596,760 (42.89%)	68,866 (44.19%)	153,050 (44.49%)	96,258 (41.67%)
	65+ years	72,930 (46.84%)	335,146 (24.09%)	30,313 (19.45%)	65,652 (19.08%)	81,488 (35.27%)
	Age (mean ± std.)	59.47 ± 21.24	47.12 ± 21.38	44.63 ± 20.08	44.31 ± 20.10	50.36 ± 22.77
Stroke calls	**Num. calls**	3,899	3,471	360	757	679
	Female	1,784 (45.76%)	1,654 (47.65%)	161 (44.72%)	349 (46.10%)	366 (53.90%)
	Male	2,115 (54.24%)	1,815 (52.29%)	199 (55.28%)	408 (53.90%)	313 (46.10%)
	65+ years	2,968 (76.12%)	2,421 (69.75%)	250 (69.44%)	555 (73.32%)	567 (83.51%)
	Age (mean ± std.)	72.91 ± 12.77	70.68 ± 13.85	70.93 ± 13.83	71.51 ± 13.41	73.41 ± 14.11
Non-stroke	**Num. calls**	151,797	1,387,830	155,465	343,273	230,330
	Female	72,856 (48.00%)	791,129 (57.00%)	86,798 (55.83%)	190,625 (55.53%)	133,958 (58.16%)
	Male	77,449 (51.02%)	594,945 (42.87%)	68,667 (44.17%)	152,642 (44.47%)	95,945 (41.66%)
	65+ years	69,962 (46.09%)	332,725 (23.97%)	30,063 (19.34%)	65,097 (18.96%)	80,921 (35.13%)
	Age (mean ± std.)	59.12 ± 21.30	47.06 ± 21.36	44.57 ± 20.05	44.25 ± 20.08	50.29 ± 22.76

Model design

A. Schematic Overview of Stroke Classification Pipeline



Model design



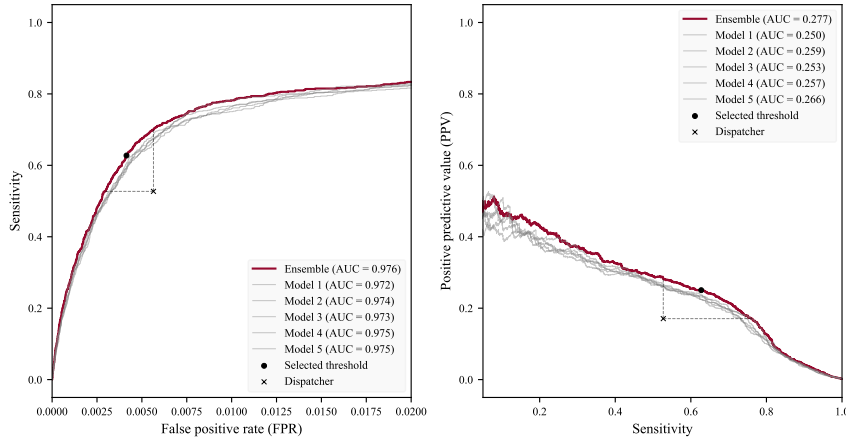
Main results

MH-1813 test set performance in demographic subgroups (age/sex) [mean (95% CI)].

Subset	Predictor	F1-score [%] ↑	Sensitivity [%] ↑	PPV [%] ↑	FOR [%] ↓ (1 - specificity)	FPR [%] ↓ (1 - NPV)
Overall	**Call-takers**	25.8 (23.7-27.9)	52.7 (49.2-56.4)	17.1 (15.5-18.6)	0.105 (0.094-0.116)	0.565 (0.539-0.590)
	Model	35.7 (35.0-36.4)	63.0 (62.0-64.1)	24.9 (24.3-25.5)	0.082 (0.079-0.085)	0.419 (0.413-0.426)
18-64 years	**Call-takers**	15.9 (13.1-18.5)	50.5 (43.6-57.2)	9.40 (7.61-11.2)	0.036 (0.028-0.043)	0.353 (0.331-0.375)
	Model	22.9 (21.8-24.0)	54.1 (52.1-56.3)	14.5 (13.8-15.3)	0.033 (0.031-0.035)	0.231 (0.226-0.236)
65+ years	**Call-takers**	32.9 (30.1-35.7)	53.5 (49.4-57.6)	23.7 (21.4-26.0)	0.401 (0.352-0.449)	1.467 (1.373-1.560)
	Model	42.8 (41.9-43.7)	66.3 (65.1-67.5)	31.6 (30.8-32.4)	0.290 (0.278-0.303)	1.224 (1.198-1.249)
Male	**Call-takers**	30.2 (27.2-33.3)	53.9 (49.1-58.9)	21.0 (18.5-23.5)	0.124 (0.105-0.141)	0.542 (0.506-0.580)
	Model	39.0 (38.0-40.1)	63.7 (62.3-65.2)	28.1 (27.3-29.0)	0.097 (0.093-0.102)	0.435 (0.425-0.445)
Female	**Call-takers**	21.9 (19.1-24.6)	51.3 (46.0-56.6)	13.9 (12.0-15.8)	0.090 (0.076-0.103)	0.582 (0.547-0.616)
	Model	32.4 (31.4-33.4)	62.3 (60.7-63.8)	21.9 (21.1-22.7)	0.069 (0.066-0.073)	0.407 (0.399-0.416)

Main results

ROC curve and PPV-sensitivity curve (precision-recall curve). Models 1-5 are the individual models that make up the ensemble model.



Main results

Confusion matrices of predictions for call takers and the model on the test set. Numbers for the model are given as the rounded mean over eleven runs.

		Ground truth labels	
		Positives	Negatives
Call taker predictions	Positives	True positives 399	False positves 1,938
	Negatives	False negatives 358	True negatives 341,335

		Ground truth labels	
		Positives	Negatives
Model predictions	Positives	True positives 477	False positves 1,440
	Negatives	False negatives 280	True negatives 341,833

Which features are important?

Let $z^{(n,d,w)}$ be the logit output of model n in the ensemble for transcript d when the word w is occluded. For transcript d, we computed the word impact score $i^{(d,w)}$ as the mean difference between the logit before and after occlusion.

$$i^{(d,w)} = \frac{1}{N_d} \sum_{n=1}^{N_d} \left(z^{(n,d)} - z^{(n,d,w)} \right) \quad . \tag{9}$$

To select words for inspection, we computed a word-rank score, $r^{(w)}$, as the sum of the signed squares of the impact:

$$r^{(w)} = \sum_{d=1}^{N} \text{sign}\left(i^{(d,w)} \right) \left(i^{(d,w)} \right)^2 \quad . \tag{10}$$

Squaring $i^{(d,w)}$ favors rare features with a high impact over common features with a low impact.

Which features are important?

"Features with positive ranking score ($r^{(w)} > 0$) computed on stroke positive predictions (D = 1,897)					
Rank	Word, *w (translated)*	Occurrences, $D^{(w)}$	Rank	Word, *w (translated)*	Occurrences, $D^{(w)}$
1.	Ambulance	1,680	16.	Difficulties speaking	44
2.	Blood clot	895	17.	Hemorrhagic stroke	133
3.	Left	1,108	18.	Hand	297
4.	Right	1,050	19.	The ambulance	521
5.	Double vision	84	20.	Slurred speech	58
6.	The words	344	21.	Blood clots	224
7.	Suddenly	783	22.	Fast	663
8.	Arm	709	23.	Express	44
9.	Side	1,139	24.	Blood thinner	259
10.	Stroke	117	25.	Incoherent	15
11.	Double	113	26.	Lopsided	211
12.	Control	134	27.	Reduced	528
13.	Call	39	28.	Hangs	628
14.	Numb	94	29.	Transient	48
15.	Minutes	763	30.	Not making sense	14

[Recognition, Symptom, Urgency/Time]

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[Recognition, Symptom, Urgency/Time]

Which features are important?

Features with negative ranking score ($r^{(w)} < 0$) **computed on stroke-negative predictions** (D = 342, 133)					
Rank	Word, *w (translated)*	Occurrences, $D^{(w)}$	Rank	Word, *w (translated)*	Occurrences, $D^{(w)}$
1.	Tetanus	4,378	16.	The pharmacy	10,085
2.	Pregnant	8,749	17.	The stomach	42,105
3.	Cut	7,592	18.	Psychiatric	3,688
4.	Bandage	4,561	19.	Pneumonia	7,597
5.	Amager (a location)	23,776	20.	Stomach pain	10,551
6.	O'clock	94,436	21.	Stool	19,155
7.	The emergency room	42,809	22.	The ribs	3,928
8.	The police	2,903	23.	Bleed	10,501
9.	Swollen	60,559	24.	Bleeding	24,313
10.	Over the counter (OTC)	4,641	25.	Ribs	2,941
11.	The neck	30,151	26.	Broken	19,415
12.	Fever	112,586	27.	Inflammation	10,050
13.	Prescription	5,450	28.	Common cold	8,127
14.	Centimeter	12,026	29.	Morning or morrow	78,558
15.	The knee	8,875	30.	Swelling	17,762

[Recognition, Symptom, Urgency/Time]

Which features are important?

Features with negative ranking score ($r^{(w)} < 0$) **computed on stroke-negative predictions** ($D = 342,133$)					
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8.	The police	2,903	23.	Bleed	10,501
9.	Swollen	60,559	24.	Bleeding	24,313
10.	Over the counter (OTC)	4,641	25.	Ribs	2,941
11.	The neck	30,151	26.	Broken	19,415
12.	Fever	112,586	27.	Inflammation	10,050
13.	Prescription	5,450	28.	Common cold	8,127
14.	Centimeter	12,026	29.	Morning or morrow	78,558
15.	The knee	8,875	30.	Swelling	17,762

[Recognition, Symptom, Urgency/Time]

Which features are important?

Features with negative ranking score ($r^{(w)} < 0$) **computed on stroke-negative predictions** ($D = 342,133$)

Rank	Word, w *(translated)*	Occurrences, $D^{(w)}$	Rank	Word, w *(translated)*	Occurrences, $D^{(w)}$
1.	Tetanus	4,378	16.	The pharmacy	10,085
2.	Pregnant	8,749	17.	The stomach	42,105
3.	Cut	7,592	18.	Psychiatric	3,688
4.	Bandage	4,561	19.	Pneumonia	7,597
5.	Amager (a location)	23,776	20.	Stomach pain	10,551
6.	O'clock	94,436	21.	Stool	19,155
7.	The emergency room	42,809	22.	The ribs	3,928
8.	The police	2,903	23.	Bleed	10,501
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[Recognition, Symptom, Urgency/Time]

Simulated prospective study

I. When is the model prediction presented to the call-taker?

1. Notify the call-taker after the call ends.
2. Notify the call-taker during the call.

II. How does prediction influence the diagnostic code the call-taker assigns to the call?

A. Call-takers mirror model positives.
B. Call-takers mirror model negatives.
C. Call-takers mirror model predictions (corresponds to main results of the model itself).

To simulate the online scenario (2.), we stream the transcript to the model and make predictions every 50 words. A stroke positive is triggered only when three consecutive positive predictions are made. This is similar to the strategy implemented for a previous RCT on cardiac arrest [7].

Simulated prospective study

Predictor	Call-taker	Model		Call-taker supported by the model (simulated)			
When	**During call**	**After call**	**During call**	**After call**	**During call**	**After call**	**During call**
Method	-	-	-	**neg → pos**	**neg → pos**	**pos → neg**	**pos → neg**
F1-score [%] ↑	25.8 (23.7-27.9)	35.7 (35.0-36.4)	33.1 (32.4-33.7)	28.9 (28.3-29.5)	27.6 (27.0-28.1)	33.3 (32.5-34.1)	32.7 (31.8-33.5)
Sensitivity [%] ↑	52.7 (49.2-56.4)	63.0 (62.0-64.1)	58.7 (57.7-59.8)	72.4 (71.5-73.3)	72.3 (71.4-73.3)	43.4 (42.3-44.5)	39.1 (38.1-40.1)
PPV [%] ↑	17.1 (15.5-18.6)	24.9 (24.3-25.5)	23.0 (22.5-23.6)	18.0 (17.6-18.4)	17.0 (16.7-17.4)	27.0 (26.3-27.8)	28.1 (27.3-28.9)
FOR [%] ↓ (1 - NPV)	0.105 (0.094-0.116)	0.082 (0.079-0.085)	0.091 (0.088-0.094)	0.061 (0.059-0.064)	0.061 (0.059-0.064)	0.125 (0.121-0.129)	0.134 (0.131-0.138)
FPR [%] ↓ (1 - specificity)	0.565 (0.539-0.590)	0.419 (0.413-0.426)	0.432 (0.426-0.439)	0.726 (0.717-0.735)	0.776 (0.767-0.786)	0.258 (0.253-0.263)	0.221 (0.216-0.226)

Fine-tuning a large language model

- Large language models are effective in a wide range of NLP tasks [15, 45].
- Might BERT be useful for recognizing stroke?

Fine-tuning a large language model

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Subset	Predictor	F1-score [%] ↑	Sensitivity [%] ↑	PPV [%] ↑	FOR [%] ↓ (1 - NPV)	FPR [%] ↓ (1 - specificity)
Overall	**Call-takers**	25.8 (23.7-27.9)	52.7 (49.2-56.4)	17.1 (15.5-18.6)	0.105 (0.094-0.116)	0.565 (0.539-0.590)
	MLP	35.7 (35.0-36.4)	63.0 (62.0-64.1)	24.9 (24.3-25.5)	0.082 (0.079-0.085)	0.419 (0.413-0.426)
	BERT (fine-tuned)	33.8 (31.5-36.2)	57.5 (53.9-60.9)	23.9 (21.9-25.9)	0.094 (0.084-0.104)	0.403 (0.381-0.424)

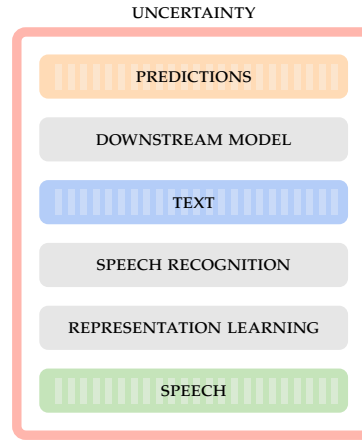
Future work

- Machine learning
  - Learning to predict directly from audio data (SSL).
  - Investigate learning to defer to predict methods [54].

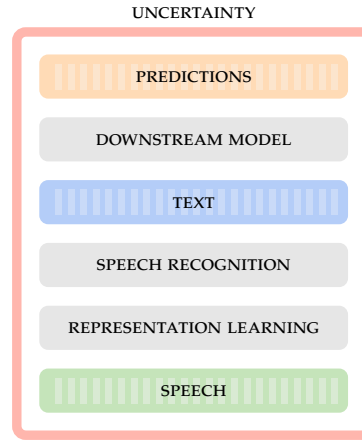
Future work

- Machine learning
  - Learning to predict directly from audio data (SSL).
  - Investigate learning to defer to predict methods [54].
- Clinical applications
  - Mental health (Screening for suicide risk in emergency and medical helpline calls).
  - Maternity ward (Screening for serious pregnancy complications.)

Presentation



Presentation



DISCUSSION

First slide for discussion

Building an operational decision support system

- Do we need true uncertainty estimates? Bayesian methods versus pragmatic methods.

From global to local In table 1, we see that work on global representations within self-supervised learning pre- cedes work on local representations. However, we find that the core ideas underlying the recent successes in learning lo- cal representation models have also been used for global rep- resentation learning; masking (Chung et al. 2016), context prediction (Chung and Glass 2018), and contrastive train- ing (Milde and Biemann 2018) have been applied in both settings. Furthermore, where work on global representation learning has taken inspiration from Word2vec (Mikolov et al. 2013), the techniques used for learning local repre- sentations are inspired by contextualized word embeddings (Devlin et al. 2019). Thus, the gap between these two model classes is largely a product of the developments in related fields and the general increase in computational resources.

Representations beyond inference Predictive tasks are commonly used for self-supervised models, but they are not directly compatible with LVM training. However, an LVM prior with an autoregressive parameterization, $p(z_t \mid z_{1:t-1})$ or $p(z_t \mid x_{1:t-1})$, can be seen as predictive in the sense that it tries to match the approximate posterior. Hence, the prior might be considered for feature extraction. Jones and Moore (2020) examine the importance of the prior in the VQ-VAE and show that the ability of this model to estimate

den- sities p(x1:T) lies solely in its prior. Other work has also explored representations beyond the latent variable such as hidden units of the observation model (Khurana et al. 2020; Chorowski et al. 2019b).

Masking and missing data Masking may also improve representations learned with VAEs. Masking in VAEs has already been explored in the literature in the context of missing data imputation. Here, x is only partially observed, and often represented as a segmentation into observed and miss- ing parts and a mask m indicating where the data is missing. The model is then trained to infer the latent variable from the observed data. Reconstruction also deals only with the ob- served data. Previous work has largely focused on the abil- ity of these models to yield high-quality imputations within the tabular and image data domains, without probing for the effects on the learned latent representation (Mattei and Frellsen 2019; Ipsen, Mattei, and Frellsen 2021). The idea of using VAEs to impute missing data was already examined in the seminal paper by Rezende, Mohamed, and Wierstra (2014). Here the model was trained with fully observed data and used to impute data in an iterative sampling approach post hoc leaving the learned representations unchanged.

Evaluating representations Although this review has a primarily methodological focus, we should briefly touch upon evaluation procedures. Training metrics for self- supervised tasks and the likelihood of LVMs offer little guid- ance as to the quality of the learned representations (Huszár 2017). Thus, a common approach is to evaluate the representations in terms of their usefulness for downstream tasks. Such tasks may be chosen to target specific attributes of the representation (e.g. semantic or speaker information).
The SUPERB benchmark (Yang et al. 2021) gathers mul- tiple tasks grouped into categories such as recognition, de- tection, semantics, speaker, paralinguistics and generation. The recently proposed SLUE benchmark focuses on spo- ken language understanding (Shon et al. 2021). The long- standing zero resource speech challenge (ZeroSpeech) offers a new set of tasks for each edition (Versteegh et al. 2015; Dunbar et al. 2017, 2019, 2020, 2021) usually featuring a minimal-pair ABX task (Schatz et al. 2013, 2014).
Tasks that evaluate representations in terms of speaker- related information include speaker verification (Hsu, Zhang, and Glass 2017b; Khurana et al. 2019; Milde and Biemann 2018), speaker identification (van den Oord, Li, and Vinyals 2018; Jati and

Georgiou 2019; Chung et al. 2019; Liu, Chung, and Glass 2021), dialect classification (Khurana et al. 2019), emotion recognition (Pascual et al. 2019; Yang et al. 2021) and gender classification (Lee et al. 2009). The semantic content of representations are evaluated using tasks such as intent classification (Morais et al. 2021; Yang et al. 2021), slot filling (Lai et al. 2021; Yang et al. 2021), sentiment analysis (Liu et al. 2020), question answer- ing (Chung, Zhu, and Zeng 2020), named entity recogni- tion (Shon et al. 2021; Borgholt et al. 2021a; Pasad et al. 2021) and speech translation (Bansal et al. 2017; Chung and Glass 2020a). Cardiac arrest detection for emergency calls has also been used to evaluate speech representations (Borgholt et al. 2021a). For local representations, phoneme classification is very common (Lee et al. 2009; Hsu, Zhang, and Glass 2017a; Chorowski et al. 2019b; Chung et al. 2019; Liu, Li, and Lee 2021). However, automatic speech recogni- tion has become the de facto standard benchmark task (Ling and Liu 2020; Chung and Glass 2020a; Hsu et al. 2021).

Moving forward Most of the seminal work has focused on improving speech recognition (Schneider et al. 2019; Baevski et al. 2020). This focus has gained traction over the last couple of years, as computational resources have be- come more accessible and

end-to-end models (Graves et al. 2006; Chan et al. 2016) have been established as the dominant approach to speech recognition (Gulati et al. 2020). It is important to stress that self-supervised models, such as wav2vec 2.0 (Baevski et al. 2020), represent a breakthrough, and recent successful approaches build upon this method. That is, deep self-attention models combined with masking (Hsu et al. 2021; Wang et al. 2021; Chen et al. 2021). This development mirrors years of rapid progress in masked lan- guage modeling within natural language processing (Devlin et al. 2019; Clark et al. 2020) and we expect this to continue for unsupervised neural speech representation learning.

Thank you for your attention

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Types of self-supervised speech representation learning methods

Schematic of self-supervised methods. Each subfigure illustrates the loss computation for a single time-step. The temporal subscript has been left out for simplicity.