UNCERTAINTY AND THE MEDICAL INTERVIEW

TOWARDS SELF-ASSESSMENT IN MACHINE LEARNING MODELS

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Outline of Part

- Introduction

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

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General practitioner

Emergency room

Health insurance

Hospital

Specialist doctor

Psychiatrist

Physiotherapist

Emergency services

Errors in medical dialogue

- Communication is everywhere in healthcare.
- It is complex, involving multiple participants, different contexts, and different purposes.

Errors in medical dialogue

- Communication is everywhere in healthcare.
- It is complex, involving multiple participants, different contexts, and different purposes.
- Failure of communication is a leading cause of medical error contributing to two out of three adverse events [6].
- A considerable fraction of all hospital admissions had preventable adverse outcomes (9% to 16.6% in AU, NZ, UK, DK) [34].

Documenting medical encounters

- Documentation is a central part of healthcare.
- E.g. patient records, insurance claims, billing, research, training, legal purposes.

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

Documenting medical encounters

- Documentation is a central part of healthcare.
- E.g. patient records, insurance claims, billing, research, training, legal purposes.

- Time-consuming: Physicians spend 34-37% of their time on documentation [15, 2, 9][1].
- Varying quality: Discharge summaries rarely meet all timeline, transmission, and content criteria. [3][2]

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

How might machine learning help?

- Assist with documentation.
- Augment communication.
- Improve decision-making.

- Reduce errors.
- Save time.

Reliability of machine learning

- Data: Privacy, quality, quantity, diversity.
- Interpretability: Trust, ethics, regulation.
- Explainability: Transparency, accountability.
- Robustness: Adversarial attacks, distribution shift.
- Bias: Fairness, transparency.
- Complexity: Context, domain, language, culture.

Part I

Unsupervised Out-of-Distribution Detection

Outline of Part

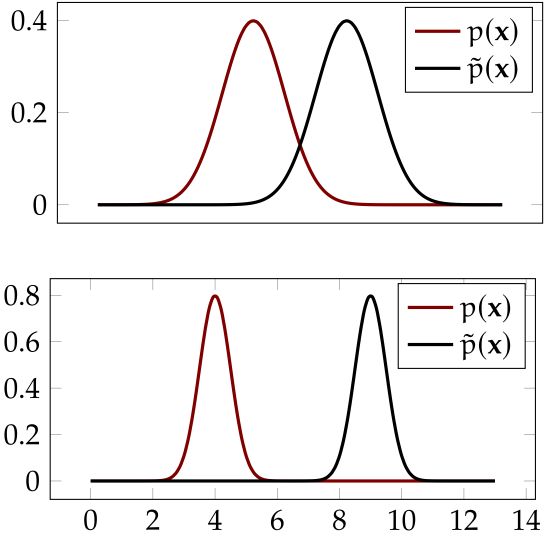
- Out-of-distribution detection
- Latent variable models
- Identifying the issue
- The $\mathcal{L}^{>k}$ likelihood bound
- Likelihood ratio

Defining OOD detection

Out-of-distribution (OOD) detection is about enabling models to distinguish the training data distribution $p(\mathbf{x})$ from any other distribution $\tilde{p}(\mathbf{x})$.

We are concerned with doing this on a per-observation basis, i.e. answering the question:

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

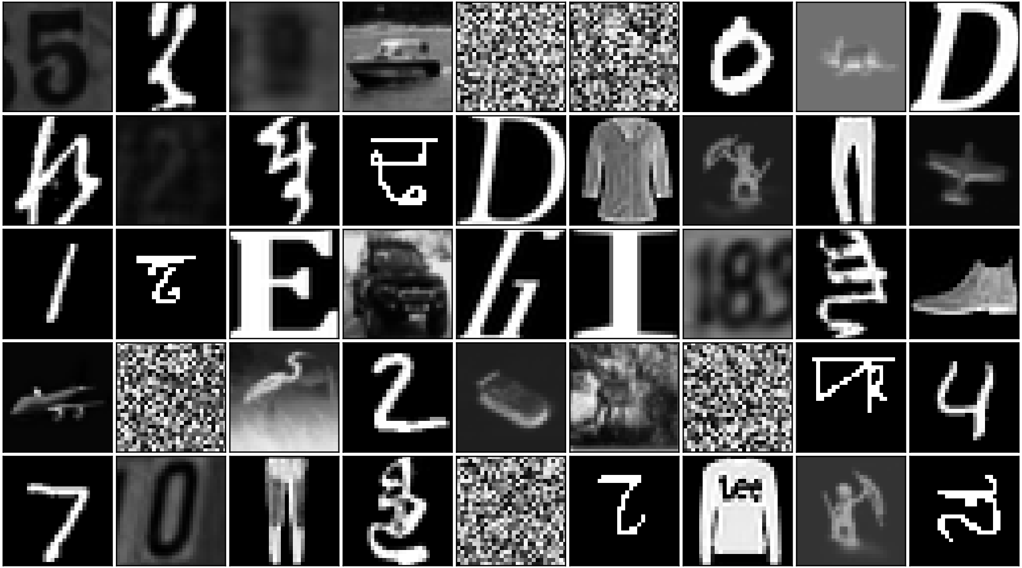


Problem and Contributions

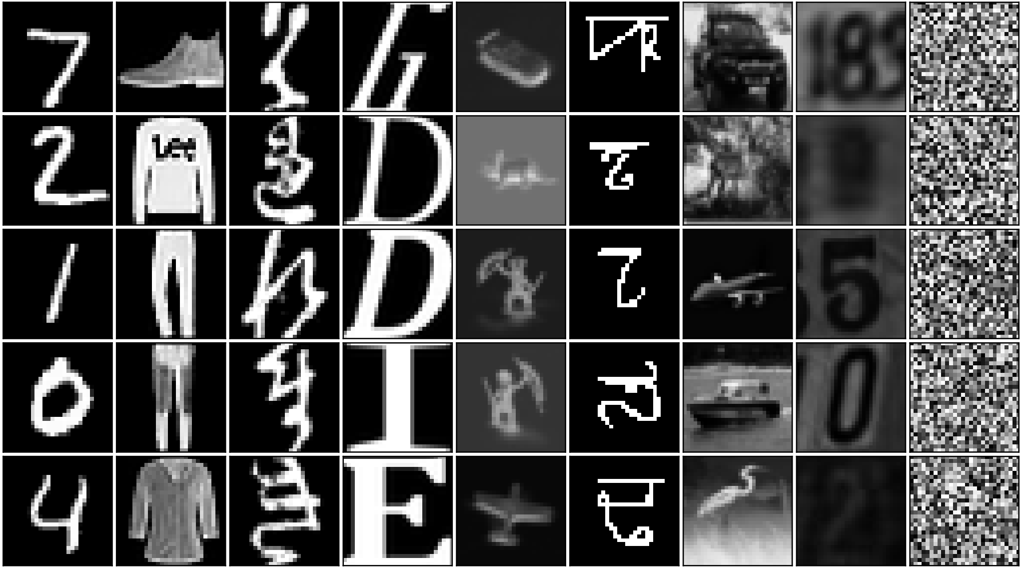
- Deep generative models often fail at OOD detection task when using their likelihood estimate as the score function [23] by, perhaps surprisingly, assigning **higher likelihoods** to the OOD data.
- Contributions:
  - We provide evidence that out-of-distribution detection fails due to learned low-level features that generalize across datasets.
  - We present a fast and fully unsupervised method for OOD detection competitive with the state-of-the-art

Out-of-distribution detection

In distribution?



Out of distribution?



Hierarchical VAE

We choose the hierarchical VAE as our model [4, 5].

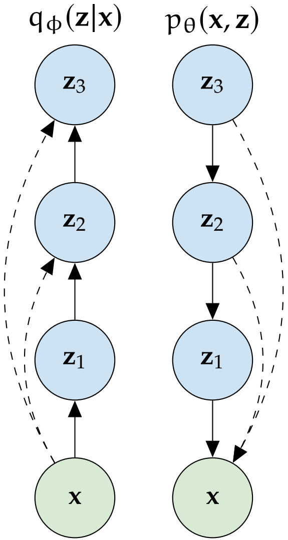
$$p_\theta(\mathbf{x}) = \int p_\theta(\mathbf{x}, \mathbf{z}) d\mathbf{z} = \int p_\theta(\mathbf{x}|\mathbf{z}) p_\theta(\mathbf{z}) d\mathbf{z}$$

Specifically we use

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

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

2. a ten-layered layered Bidirectional-Inference Variational Autoencoder (BIVA) [22].



What is wrong with the ELBO for OOD detection?

We can split the ELBO into two terms

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

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

The second term we can rewrite as,

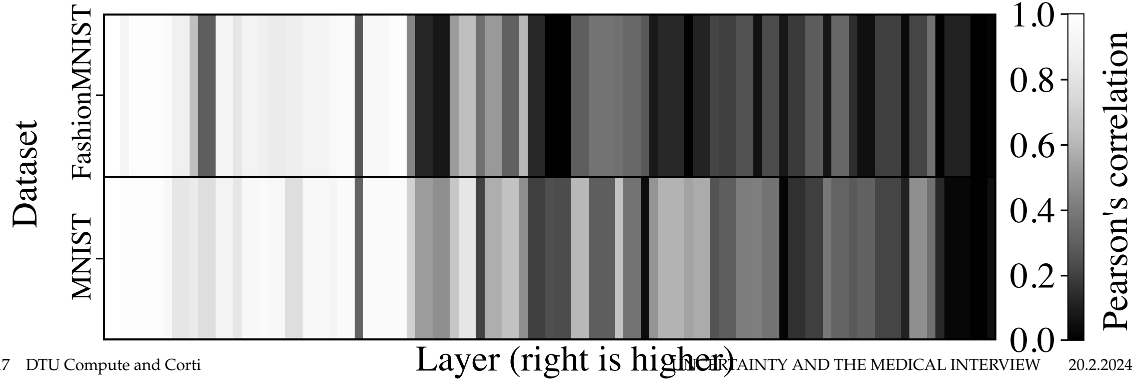
$$D_{KL}(q_\phi(\mathbf{z}|\mathbf{x})||p(\mathbf{z})) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}\left[\sum_{i=1}^{L-1} \log \frac{p_\theta(\mathbf{z}_i|\mathbf{z}_{i+1})}{q_\phi(\mathbf{z}_i|\mathbf{z}_{i-1})} + \log \frac{p_\theta(\mathbf{z}_L)}{q_\phi(\mathbf{z}_L|\mathbf{z}_{L-1})}\right] \,. \tag{2}$$

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 [22]

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

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 [1].

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

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, $S \to \infty$ [7],

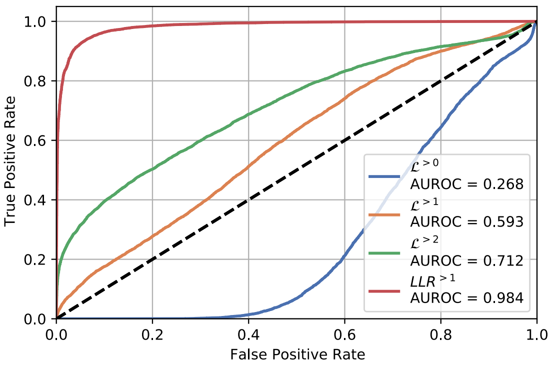
$$\mathcal{L}_S = \mathbb{E}_{q(\mathbf{z}|\mathbf{x})}\left[\log \frac{1}{N} \sum_{s=1}^{S} \frac{p(\mathbf{x}, \mathbf{z}^{(s)})}{q(\mathbf{z}^{(s)}|\mathbf{x})}\right] \leqslant \log p_\theta(\mathbf{x}) \,, \tag{7}$$

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

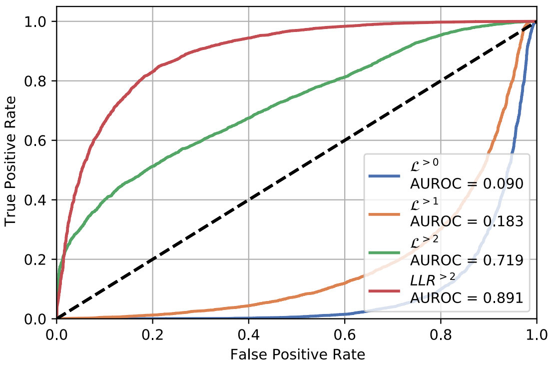
$$\mathrm{LLR}_S^{>k}(\mathbf{x}) \to D_{\mathrm{KL}}(p(\mathbf{z}_{\leqslant}|\mathbf{z}_{>k})q(\mathbf{z}_{>k}|\mathbf{x})||p(\mathbf{z}|\mathbf{x})) \,. \tag{8}$$

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

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



(a) FashionMNIST HVAE evaluated on MNIST



(b) CIFAR10 BIVA evaluated on SVHN

Results on FashionMNIST/MNIST

Method	AUROC↑	AUPRC↑	FPR80↓
FashionMNIST (in) / MNIST (out)			
Use prior knowledge of OOD			
Backgr. contrast. LR (PixelCNN) [24]	0.994	0.993	0.001
Backgr. contrast. LR (VAE) [20]	0.924	-	-
Binary classifier [24]	0.455	0.505	0.886
$p(\hat{y}\|\mathbf{x})$ with OOD as noise class [24]	0.877	0.871	0.195
$p(\hat{y}\|\mathbf{x})$ with calibration on OOD [24]	0.904	0.895	0.139
Input complexity (S, Glow) [21]	0.998	-	-
Input complexity (S, PixelCNN++) [21]	0.967	-	-
Use in-distribution data labels y			
$p(\hat{y}\|\mathbf{x})$ [24, 11]	0.734	0.702	0.506
Entropy of $p(y\|\mathbf{x})$ [24]	0.746	0.726	0.448
ODIN [24, 19]	0.752	0.763	0.432
VIB [13, 20]	0.941	-	-
Mahalanobis distance, CNN [24]	0.942	0.928	0.088
Mahalanobis distance, DenseNet [18]	0.986	-	-
Ensemble, 20 classifiers [24, 12]	0.857	0.849	0.240
No OOD-specific assumptions			
- Ensembles			
WAIC, 5 models, VAE [20]	0.766	-	-
WAIC, 5 models, PixelCNN [24]	0.221	0.401	0.911
- Not ensembles			
Likelihood regret [27]	**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
$\mathrm{LLR}^{>1}$ + HVAE (ours)	0.964	0.961	0.036
$\mathrm{LLR}^{>1}_{250}$ + 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) [24]	0.930	0.881	0.066
Backgr. contrast. LR (VAE) [27]	0.265	-	-
Outlier exposure [21]	0.984	-	-
Input complexity (S, Glow) [26]	0.950	-	-
Input complexity (S, PixelCNN++) [26]	0.929	-	-
Input complexity (S, HVAE) (Ours) [26]**??**	0.833	0.855	0.344
Use in-distribution data labels y			
Mahalanobis distance [18]	0.991	-	-
No OOD-specific assumptions			
- *Ensembles*			
WAIC, 5 models, Glow [20]	1.000	-	-
WAIC, 5 models, PixelCNN [24]	0.628	0.616	0.657
- *Not ensembles*			
Likelihood regret [27]	0.875	-	-
$\text{LLR}^{>2}$ + HVAE (ours)	0.811	0.837	0.394
$\text{LLR}^{>2}$ + 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

Part II

Medical Applications

Outline of Part

- A Retrospective Study on Machine Learning-Assisted Stroke Recognition for Medical Helpline Calls

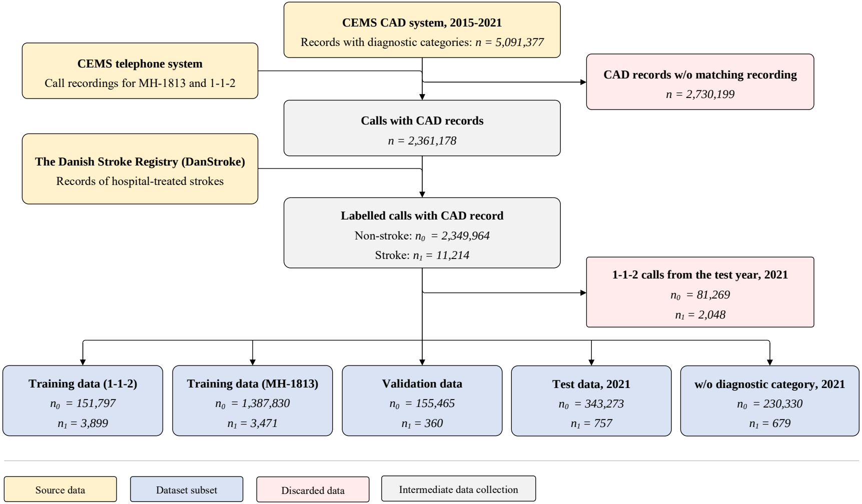
Stroke

- Stroke is a leading cause of disability and death worldwide [30, 17, 16].
- Effective treatment is very time-sensitive. [28, 25].
- 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 [31, 32].
- The effectiveness of mobile stroke units hinges on call-taker recognition of stroke [31, 32].
- But stroke

The study

- Collaboration between Corti and the Copenhagen Emergency Medical Services (CEMS) ("Akutberedskabet").
- 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, 10, 14].
- We wanted to investigate if a machine learning model could assist call-takers of 1813 in recognizing stroke.

Population selection and datasets

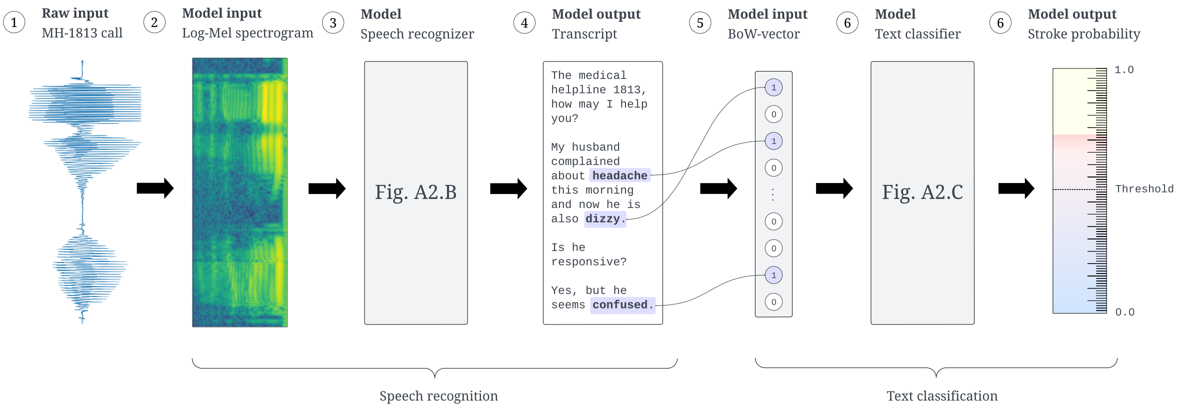


Population characteristics

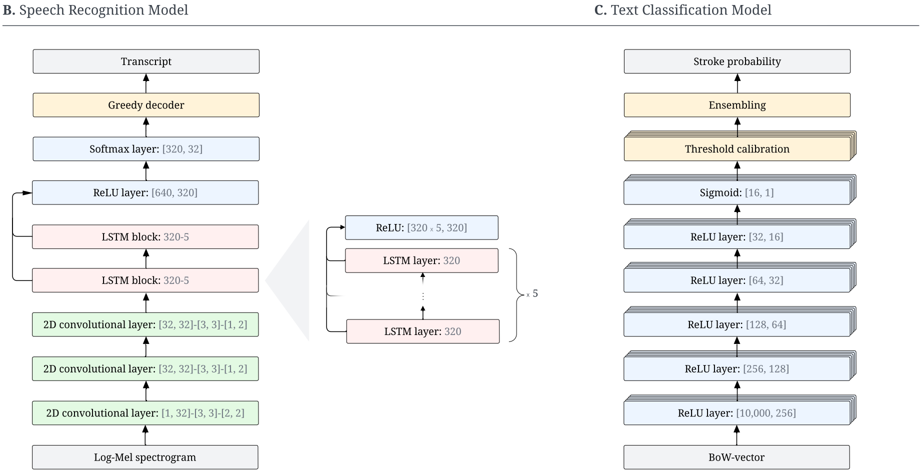
	Training (112)	Training (MH-1813)	Validation	Test	2021 w/o category
All calls					
Num. calls	155,696	1,391,301	155,825	344,030	231,009
Female	74,640 (47.94%)	792,783 (56.98%)	86,959 (55.81%)	190,974 (55.51%)	134,324 (58.14%)
Male	79,564 (51.10%)	596,760 (42.89%)	68,866 (44.19%)	153,050 (44.49%)	96,258 (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 calls					
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

Table 1: Overall performance on MH-1813 test data, performance without 1-1-2 training data, and performance on data from 2021 without diagnostic categories as well as performance on MH-1813 based on demographic subgroups (age/sex) [mean (95% CI)]. NPV: negative predictive value, PPV: positive predictive value, FOR: false omission rate, CI: confidence interval.

	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)
Without 112 training data					
Model	32.4 (31.8-33.1)	60.4 (59.3-61.4)	22.2 (21.6-22.7)	0.088 (0.085-0.091)	0.467 (0.460-0.474)
On MH-1813 data without diagnostic category					
Model	32.6 (31.9-33.4)	48.3 (47.2-49.4)	24.7 (23.9-25.3)	0.153 (0.148-0.158)	0.435 (0.427-0.443)
18-64 years					
Call-takers	15.9 (13.1-18.5)	50.5 (43.6-57.2)	9.40 (7.61-11.18)	0.036 (0.028-0.043)	0.353 (0.331-0.375)

Model performance

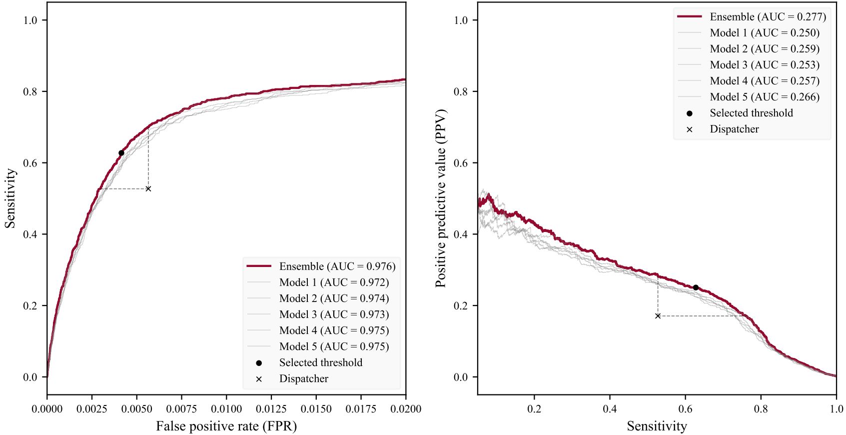


Figure 2: Left, the ROC curve and, right, PPV-sensitivity curve (precision-recall curve). Models 1-5 are the individual models that make up the ensemble model.

Model performance

Figure 3: 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:

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

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

Which features are important?

	Positive ranking score, $r^{(w)}$		Negative ranking score, $r^{(w)}$	
	Stroke predictions, $D = 1,897$		Non-stroke predictions, $D = 342,133$	
	Word, w *(translated)*	Occurrences, $D^{(w)}$	Word, w *(translated)*	Occurrences, $D^{(w)}$
1.	Ambulance	1,680	Tetanus	4,378
2.	Blood clot	895	Pregnant	8,749
3.	Left	1,108	Cut	7,592
4.	Right	1,050	Bandage	4,561
5.	Double vision	84	Amager (a location)	23,776
6.	The words	344	O'clock	94,436
7.	Suddenly	783	The emergency room	42,809
8.	Arm	709	The police	2,903
9.	Side	1,139	Swollen	60,559
10.	Stroke	117	Over the counter (OTC)	4,641
11.	Double	113	The neck	30,151
12.	Control	134	Fever	112,586
13.	Call	39	Prescription	5,450

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 [29].

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

	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

- Self-supervised learning directly from audio data.
- Investigate learning to defer to predict methods [33].

Thank you for your attention

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