

UNCERTAINTY AND THE MEDICAL INTERVIEW

TOWARDS SELF-ASSESSMENT IN MACHINE LEARNING MODELS

Jakob D. Havtorn

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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
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CHAPTER 9 **A RETROSPECTIVE STUDY ON MACHINE LEARNING-
ASSISTED STROKE RECOGNITION FOR MEDICAL HELPLINE CALLS**

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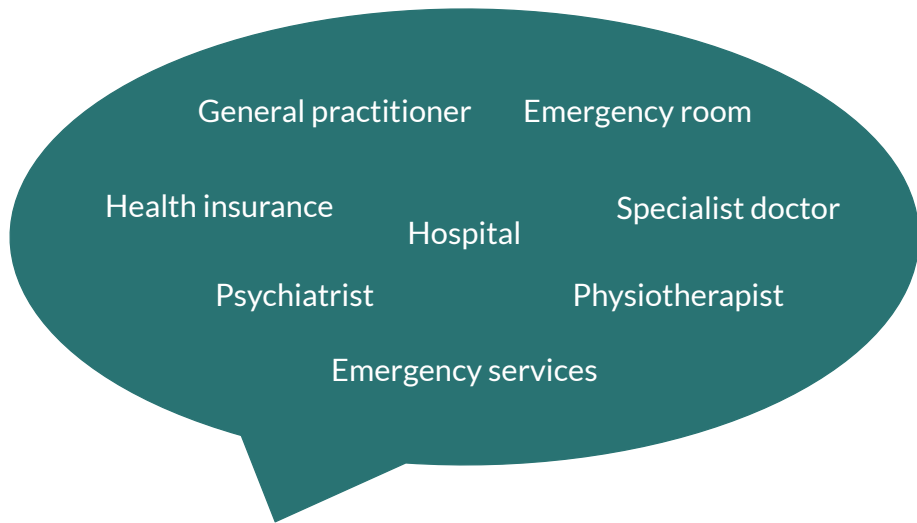
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- Introduction
- Out-of-distribution detection
- Latent variable models
- Identifying the issue
- The $\mathcal{L}^{>k}$ likelihood bound
- Likelihood ratio
- A Retrospective Study on Machine Learning-Assisted Stroke Recognition for Medical Helpline Calls

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.



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

- 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].

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

¹Ambulatory care across four specialties in four states and tertiary care at an academic medical center.

²Outpatient visits, Yale-New Haven Hospital.

- 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

¹Ambulatory care across four specialties in four states and tertiary care at an academic medical center.

²Outpatient visits, Yale-New Haven Hospital.

How might machine learning help?

- Assist with documentation.
- Augment communication.
- Improve decision-making.
- Reduce errors.
- Save time.

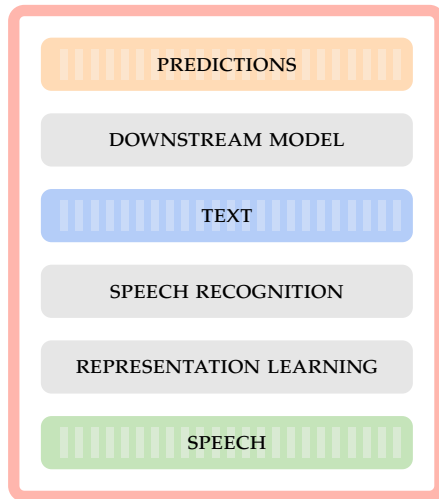
- **Data**: Privacy, quality, quantity, diversity.
- **Interpretability**: Trust, ethics, regulation.
- **Explainability**: Transparency, accountability.
- **Robustness**: Adversarial attacks, distribution shift.
- **Bias**: Fairness, transparency.
- **Complexity**: Context, domain, language, culture.

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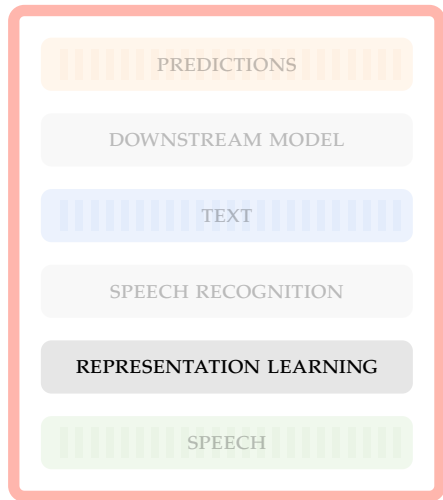
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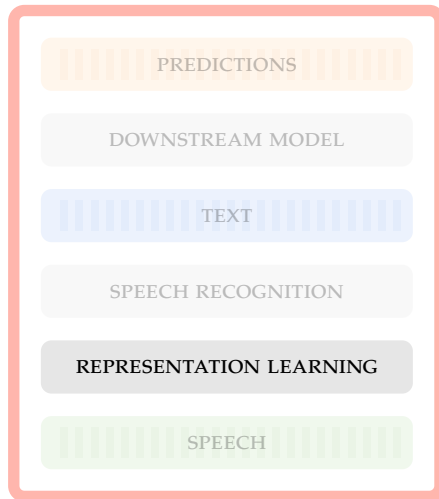
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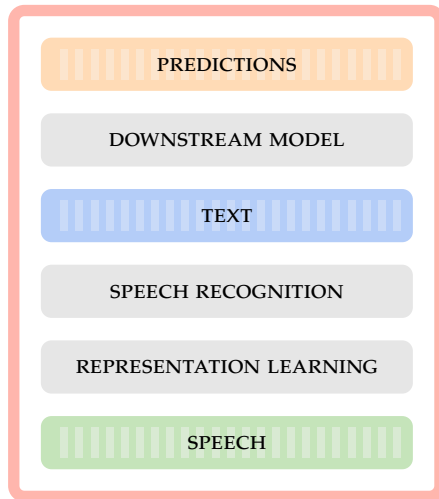
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Out-of-distribution detection
Overview: Presentation



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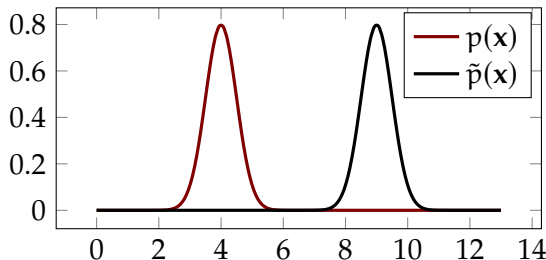
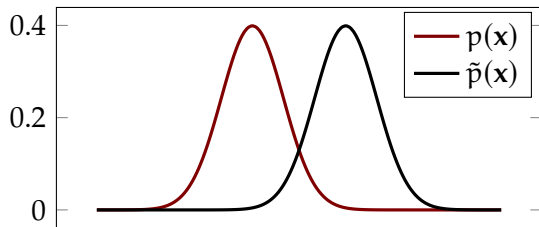
Out-of-distribution detection

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 $\tilde{p}(\mathbf{x})$.

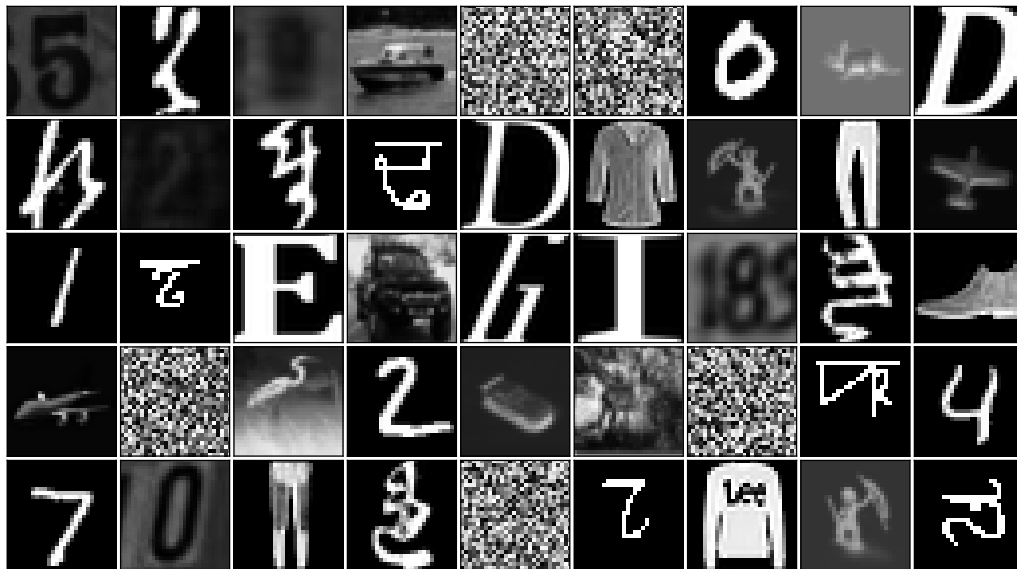
We are concerned with doing this on a per-observation basis, i.e. answering the question:

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



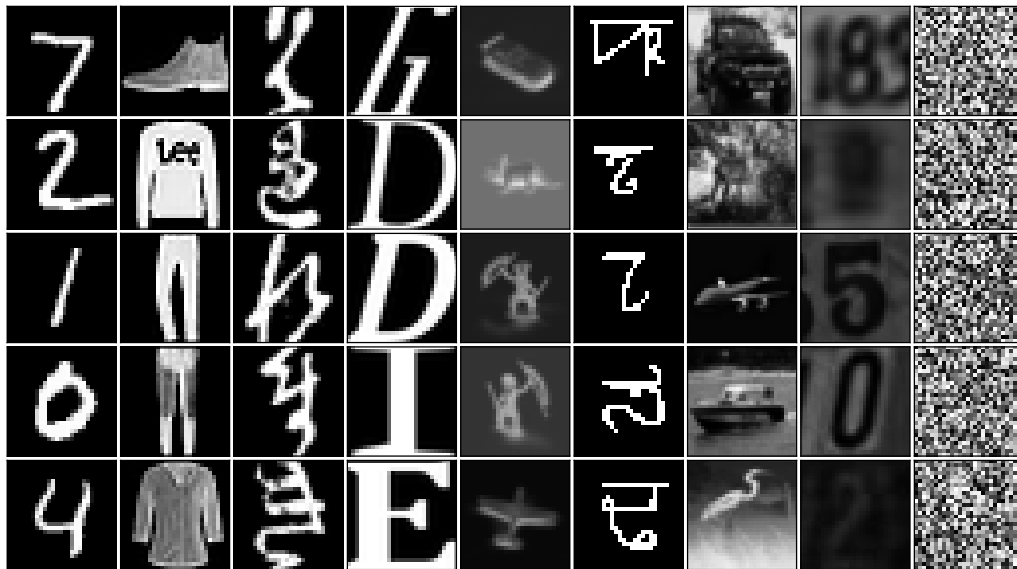
- Deep generative models often fail at OOD detection task when using their likelihood estimate as the score function [23] by, perhaps surprisingly, assigning **higher likelihoods** to the OOD data.
- Contributions:
 - We provide evidence that out-of-distribution detection fails due to learned low-level 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 detection

Out of distribution?



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

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

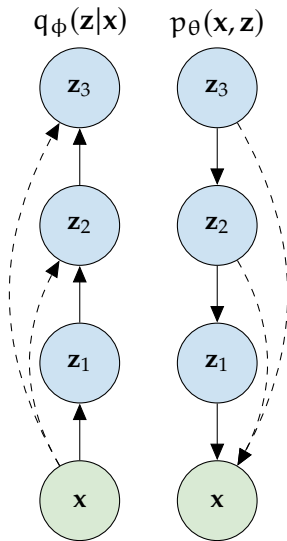
Specifically we use

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

Generative model: $p_{\theta}(\mathbf{x}|\mathbf{z}) = p_{\theta}(\mathbf{x}|\mathbf{z}_1)p_{\theta}(\mathbf{z}_1|\mathbf{z}_2)p(\mathbf{z}_3),$

Inference model: $q_{\phi}(\mathbf{z}|\mathbf{x}) = q_{\phi}(\mathbf{z}_1|\mathbf{x})q_{\phi}(\mathbf{z}_2|\mathbf{z}_1)q_{\phi}(\mathbf{z}_3|\mathbf{z}_2).$

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



What is wrong with the ELBO for OOD detection?

We can split the ELBO into two terms

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

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

The second term we can rewrite as,

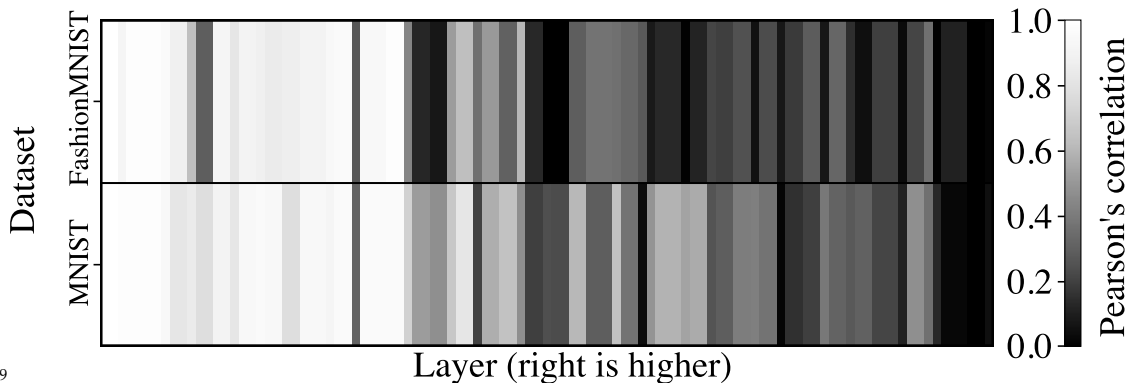
$$D_{\text{KL}}(q_{\phi}(\mathbf{z}|\mathbf{x})||p(\mathbf{z})) = \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})} \left[\sum_{i=1}^{L-1} \log \frac{p_{\theta}(\mathbf{z}_i|\mathbf{z}_{i+1})}{q_{\phi}(\mathbf{z}_i|\mathbf{z}_{i-1})} + \log \frac{p_{\theta}(\mathbf{z}_L)}{q_{\phi}(\mathbf{z}_L|\mathbf{z}_{L-1})}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

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 version of the ELBO that only partially uses the approximate posterior can be written as [22]

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

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

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

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

We can use our new bound to compute the score used in a standard likelihood ratio test [1].

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

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

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

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

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

The importance weighted autoencoder (IWAE) bound is tight with the true likelihood in the limit of infinite samples, $S \rightarrow \infty$ [7],

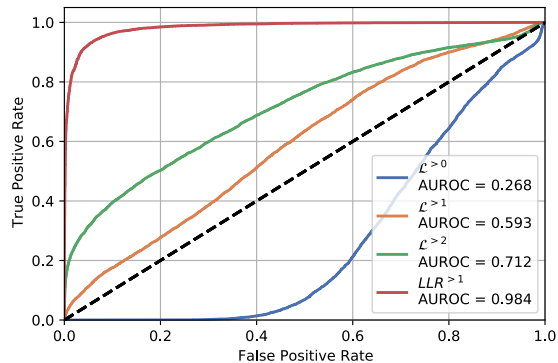
$$\mathcal{L}_S = \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{1}{N} \sum_{s=1}^S \frac{p(\mathbf{x}, \mathbf{z}^{(s)})}{q(\mathbf{z}^{(s)}|\mathbf{x})} \right] \leq \log p_{\theta}(\mathbf{x}) , \quad (7)$$

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

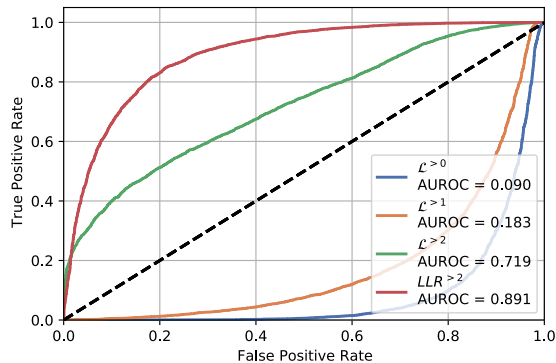
$$\text{LLR}_S^{>k}(\mathbf{x}) \rightarrow D_{\text{KL}}(p(\mathbf{z}_{\leq k}|\mathbf{z}_{>k})q(\mathbf{z}_{>k}|\mathbf{x})||p(\mathbf{z}|\mathbf{x})) . \quad (8)$$

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

Likelihood ratio
Results with $LLR > k$



(a) FashionMNIST HVAE evaluated on MNIST



(b) CIFAR10 BIVA evaluated on SVHN

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
$p(\hat{y} x)$ with OOD as noise class [24]	0.877	0.871	0.195
$p(\hat{y} x)$ 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			
$p(\hat{y} x)$ [24, 11]	0.734	0.702	0.506
Entropy of $p(y x)$ [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			
<i>- Ensembles</i>			
WAIC, 5 models, VAE [20]	0.766	-	-
WAIC, 5 models, PixelCNN [24]	0.221	0.401	0.911
<i>- Not ensembles</i>			
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
LLR $^{>1}$ + HVAE (ours)	0.964	0.961	0.036
LLR $_{250}^{>1}$ + HVAE (ours)	0.984	0.984	0.013

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			
<i>- Ensembles</i>			
WAIC, 5 models, Glow [20]	1.000	-	-
WAIC, 5 models, PixelCNN [24]	0.628	0.616	0.657
<i>- Not ensembles</i>			
Likelihood regret [27]	0.875	-	-
LLR ^{>2} + HVAE (ours)	0.811	0.837	0.394
LLR ^{>2} + BIVA (ours)	0.891	0.875	0.172

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

Stroke

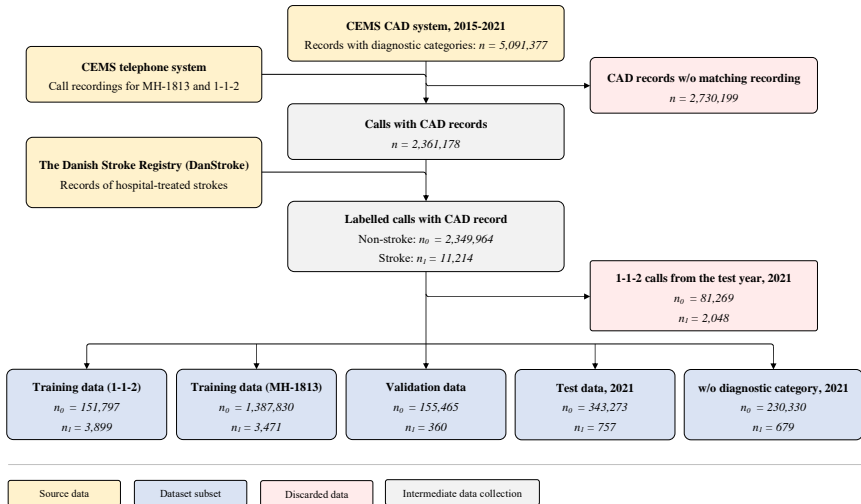
- Stroke is a leading cause of **disability and death** worldwide [30, 17, 16].
- Effective treatment is very **time-sensitive**. [28, 25].
- The gateway to **ambulance transport and hospital admittance** is through **prehospital telehealth services**.
- **Mobile stroke units** has made it possible to 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.

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

Population selection and datasets



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



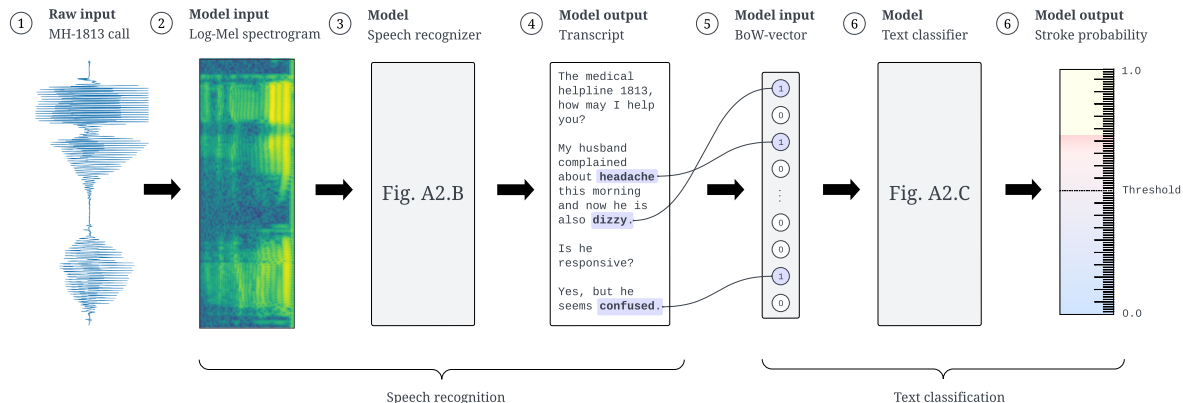
Population characteristics

	Training (112)	Training (MH-1813)	Validation	Test	2021 w/o category
<i>All calls</i>					
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 \pm std.)	59.47 \pm 21.24	47.12 \pm 21.38	44.63 \pm 20.08	44.31 \pm 20.10	50.36 \pm 22.77
<i>Stroke calls</i>					
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 \pm std.)	72.91 \pm 12.77	70.68 \pm 13.85	70.93 \pm 13.83	71.51 \pm 13.41	73.41 \pm 14.11
<i>Non-stroke calls</i>					
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 \pm std.)	59.12 \pm 21.30	47.06 \pm 21.36	44.57 \pm 20.05	44.25 \pm 20.08	50.29 \pm 22.76

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

Model design

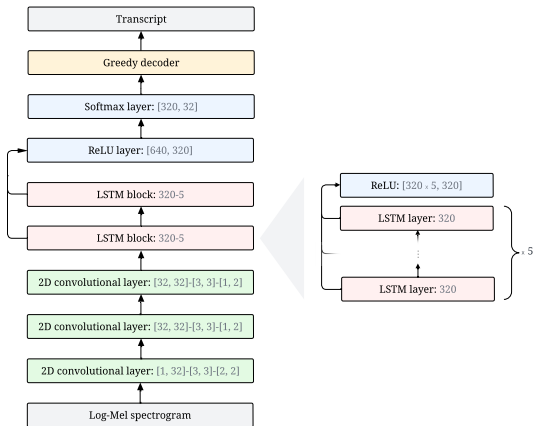
A. Schematic Overview of Stroke Classification Pipeline



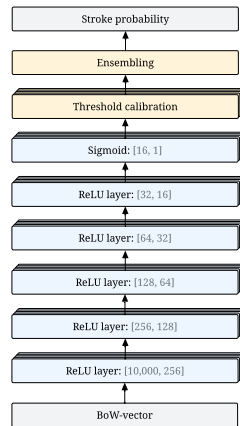
A Retrospective Study on Machine Learning-Assisted Stroke Recognition for Medical Helpline Calls

Model design

B. Speech Recognition Model



C. Text Classification Model



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)
<i>Overall</i>					
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)
<i>Without 112 training data</i>					
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)
<i>On MH-1813 data without diagnostic category</i>					
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)
<i>18-64 years</i>					
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

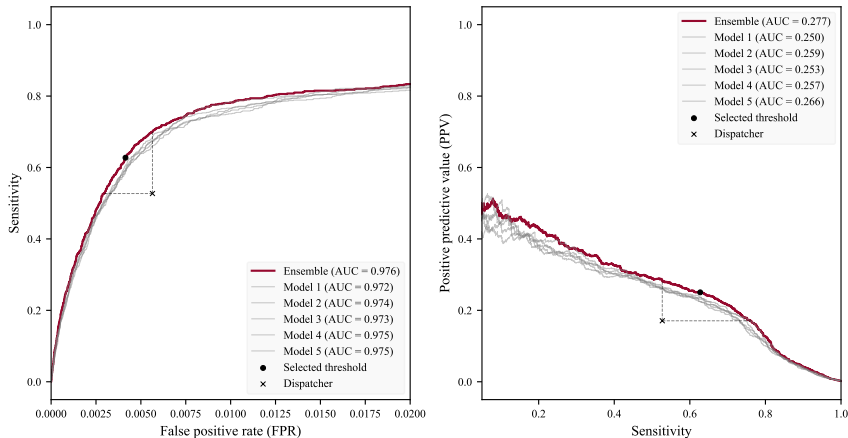


Figure 2: Left, the ROC curve and, right, PPV-sensitivity curve (precision-recall curve). Models 1-5 are the individual models that make up the ensemble model.

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 positives 1,938
	Negatives	False negatives 358	True negatives 341,335

		Ground truth labels	
		Positives	Negatives
Model predictions	Positives	True positives 477	False positives 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.

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

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

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

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

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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 (<i>translated</i>)	Occurrences, $D^{(w)}$	Word, w (<i>translated</i>)	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].

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

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)
	<i>Overall</i>				
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

Bibliography I

- [1] Adolf Buse. “The Likelihood Ratio, Wald, and Lagrange Multiplier Tests: An Expository Note”. In: *The American Statistician* 36 (3a 1982), pp. 153–157.
- [2] Matthew D. Tipping et al. “Where Did the Day Go?—A Time-Motion Study of Hospitalists”. In: *Journal of Hospital Medicine* 5.6 (2010), pp. 323–328. ISSN: 1553-5606. DOI: 10.1002/jhm.790. pmid: 20803669.
- [3] Leora I. Horwitz et al. “Comprehensive Quality of Discharge Summaries at an Academic Medical Center”. In: *Journal of hospital medicine : an official publication of the Society of Hospital Medicine* 8.8 (Aug. 2013), pp. 436–443. ISSN: 1553-5592. DOI: 10.1002/jhm.2021. pmid: 23526813. URL: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3695055/> (visited on 02/15/2024).

Bibliography II

- [4] Diederik P Kingma and Max Welling. “Auto-Encoding Variational Bayes”. In: *Proceedings of the 2nd International Conference on Learning Representations (ICLR)*. International Conference on Learning Representations. Banff, AB, Canada, 2014. arXiv: 1312.6114. URL: <http://arxiv.org/abs/1312.6114>.
- [5] Danilo Jimenez Rezende, Shakir Mohamed, and Daan Wierstra. “Stochastic Backpropagation and Approximate Inference in Deep Generative Models”. In: *Proceedings of the 31st International Conference on Machine Learning (ICML)*. International Conference on Machine Learning. Vol. 32. Beijing, China: PMLR, Jan. 16, 2014, pp. 1278–1286. URL: <http://proceedings.mlr.press/v32/rezende14.pdf> (visited on 08/12/2018).
- [6] Amy J Starmer et al. “Changes in Medical Errors after Implementation of a Handoff Program”. In: *New England Journal of Medicine* 371.19 (2014), pp. 1803–1812.

Bibliography III

- [7] Yuri Burda, Roger Grosse, and Ruslan R. Salakhutdinov. “Importance Weighted Autoencoders”. In: *Proceedings of the 4th International Conference on Learning Representations (ICLR)*. International Conference on Learning Representations. San Juan, Puerto Rico, 2016, p. 8. URL: <https://arxiv.org/abs/1509.00519> (visited on 10/04/2017).
- [8] John Adam Oostema et al. “Dispatcher Stroke Recognition Using a Stroke Screening Tool: A Systematic Review”. In: *Cerebrovascular Diseases* 42.5-6 (2016), pp. 370–377.
- [9] Christine Sinsky et al. “Allocation of Physician Time in Ambulatory Practice: A Time and Motion Study in 4 Specialties”. In: *Annals of Internal Medicine* 165.11 (Dec. 6, 2016), pp. 753–760. ISSN: 1539-3704. DOI: 10.7326/M16-0961. pmid: 27595430.

Bibliography IV

- [10] Søren Viereck et al. “Medical Dispatchers Recognise Substantial Amount of Acute Stroke during Emergency Calls”. In: *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine* 24 (2016), pp. 1–7.
- [11] Dan Hendrycks and Kevin Gimpel. “A Baseline for Detecting Misclassified and Out-of-Distribution Examples in Neural Networks”. In: *Proceedings of the 5th International Conference on Learning Representations (ICRL)*. International Conference on Learning Representations. Toulon, France, 2017. URL: <http://arxiv.org/abs/1610.02136> (visited on 01/23/2021).
- [12] Balaji Lakshminarayanan, Alexander Pritzel, and Charles Blundell. “Simple and Scalable Predictive Uncertainty Estimation Using Deep Ensembles”. In: *Proceedings of the 31st Conference on Neural Information Processing Systems (NeurIPS)*. Conference on Neural Information Processing Systems. Long Beach, CA, USA, 2017. URL: <http://arxiv.org/abs/1612.01474> (visited on 10/31/2018).

Bibliography V

- [13] Alexander A. Alemi, Ian Fischer, and Joshua V. Dillon. *Uncertainty in the Variational Information Bottleneck*. July 2, 2018. arXiv: 1807.00906. URL: <http://arxiv.org/abs/1807.00906> (visited on 01/23/2021).
- [14] K Bohm and Lisa Kurland. “The Accuracy of Medical Dispatch - A Systematic Review”. In: *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine* 26 (2018), pp. 1–10.
- [15] Erik Joukes et al. “Time Spent on Dedicated Patient Care and Documentation Tasks Before and After the Introduction of a Structured and Standardized Electronic Health Record”. In: *Applied Clinical Informatics* 09.01 (Jan. 2018), pp. 046–053. ISSN: 1869-0327. DOI: 10.1055/s-0037-1615747. URL: <http://www.thieme-connect.de/DOI/DOI?10.1055/s-0037-1615747> (visited on 02/15/2024).

Bibliography VI

- [16] Mira Katan and Andreas Luft. “Global Burden of Stroke”. In: *Seminars in Neurology*. Vol. 38. 02. Thieme Medical Publishers, 2018, pp. 208–211.
- [17] Hmwe Hmwe Kyu et al. “Global, Regional, and National Disability-Adjusted Life-Years (DALYs) for 359 Diseases and Injuries and Healthy Life Expectancy (HALE) for 195 Countries and Territories, 1990–2017: A Systematic Analysis for the Global Burden of Disease Study 2017”. In: *The Lancet* 392.10159 (2018), pp. 1859–1922.
- [18] Kimin Lee et al. “A Simple Unified Framework for Detecting Out-of-Distribution Samples and Adversarial Attacks”. In: *Proceedings of the 32nd Conference on Neural Information Processing Systems (NeurIPS)*. Conference on Neural Information Processing Systems. Montréal, Quebec, Canada, 2018, p. 11. URL: <https://papers.nips.cc/paper/2018/file/abdeb6f575ac5c6676b747bca8d09cc2-Paper.pdf>.

Bibliography VII

- [19] Shiyu Liang, Yixuan Li, and R. Srikant. “Enhancing the Reliability of Out-of-Distribution Image Detection in Neural Networks”. In: *Proceedings of the 6th International Conference on Learning Representations (ICLR)*. International Conference on Learning Representations. Vancouver, Canada, 2018. URL: <https://openreview.net/forum?id=H1VGkIxRZ>.
- [20] Hyunsun Choi, Eric Jang, and Alexander A. Alemi. *WAIC, but Why? Generative Ensembles for Robust Anomaly Detection*. May 23, 2019. arXiv: 1810.01392. URL: <http://arxiv.org/abs/1810.01392> (visited on 01/19/2021).
- [21] Dan Hendrycks, Mantas Mazeika, and Thomas G. Dietterich. “Deep Anomaly Detection with Outlier Exposure”. In: *Proceedings of the 7th International Conference on Learning Representations (ICLR)*. International Conference on Learning Representations. New Orleans, LA, USA, 2019. URL: <https://openreview.net/forum?id=HyxCxhRcY7>.

- [22] Lars Maaløe et al. “BIVA: A Very Deep Hierarchy of Latent Variables for Generative Modeling”. In: *Proceedings of the 32nd Conference on Neural Information Processing Systems (NeurIPS)*. Conference on Neural Information Processing Systems. Vancouver, Canada, Feb. 6, 2019, pp. 6548–6558. URL: <http://arxiv.org/abs/1902.02102> (visited on 03/19/2019).
- [23] Eric Nalisnick et al. “Do Deep Generative Models Know What They Don’t Know?”. In: *Proceedings of the 7th International Conference on Learning Representations (ICLR)*. International Conference on Learning Representations. New Orleans, LA, USA, 2019. arXiv: 1810.09136. URL: <http://arxiv.org/abs/1810.09136> (visited on 10/02/2019).

Bibliography IX

- [24] Jie Ren et al. “Likelihood Ratios for Out-of-Distribution Detection”. In: *Proceedings of the 33rd International Conference on Neural Information Processing Systems (NeurIPS)*. International Conference on Neural Information Processing Systems. Vancouver, Canada, 2019, p. 12. URL: <https://papers.nips.cc/paper/2019/file/1e79596878b2320cac26dd792a6c51c9-Paper.pdf>.
- [25] Guillaume Turc et al. “European Stroke Organisation (ESO)-European Society for Minimally Invasive Neurological Therapy (ESMINT) Guidelines on Mechanical Thrombectomy in Acute Ischemic Stroke”. In: *Journal of Neurointerventional Surgery* 11.8 (2019), pp. 535–538.

Bibliography X

- [26] Joan Serrà et al. “Input Complexity and Out-of-Distribution Detection with Likelihood-Based Generative Models”. In: *Proceedings of the 8th International Conference on Learning Representations (ICLR)*. International Conference on Learning Representations. Addis Ababa, Ethiopia, 2020. URL: <https://openreview.net/forum?id=SyxIWpVYvr>.
- [27] Zhisheng Xiao, Qing Yan, and Yali Amit. “Likelihood Regret: An Out-of-Distribution Detection Score for Variational Auto-Encoder”. In: *Proceedings of the 33rd Conference on Neural Information Processing Systems (NeurIPS)*. Conference on Neural Information Processing Systems. Virtual, 2020. URL: <https://proceedings.neurips.cc/paper/2020/hash/eddea82ad2755b24c4e168c5fc2ebd40-Abstract.html>.

Bibliography XI

- [28] Eivind Berge et al. “European Stroke Organisation (ESO) Guidelines on Intravenous Thrombolysis for Acute Ischaemic Stroke”. In: *European Stroke Journal* 6.1 (2021), pp. I–LXII.
- [29] Stig Nikolaj Blomberg et al. “Effect of Machine Learning on Dispatcher Recognition of Out-of-Hospital Cardiac Arrest during Calls to Emergency Medical Services: A Randomized Clinical Trial”. In: *JAMA Network Open* 4.1 (2021), e2032320–e2032320.
- [30] GBD 2019 Stroke Collaborators et al. “Global, Regional, and National Burden of Stroke and Its Risk Factors, 1990–2019: A Systematic Analysis for the Global Burden of Disease Study 2019”. In: *The Lancet Neurology* 20.10 (2021), pp. 795–820. ISSN: 1474-4422. DOI: 10.1016/S1474-4422(21)00252-0.
- [31] Praveen Hariharan et al. “Mobile Stroke Units: Current Evidence and Impact”. In: *Current Neurology and Neuroscience Reports* 22.1 (2022), pp. 71–81.

- [32] Babak B Navi et al. “Mobile Stroke Units: Evidence, Gaps, and next Steps”. In: *Stroke* 53.6 (2022), pp. 2103–2113.
- [33] Rajeev Verma and Eric Nalisnick. “Calibrated Learning to Defer with One-vs-All Classifiers”. In: *International Conference on Machine Learning*. PMLR, 2022, pp. 22184–22202.
- [34] Niki Carver, Vikas Gupta, and John E. Hippskind. “Medical Errors”. In: *StatPearls*. Treasure Island (FL): StatPearls Publishing, 2024. pmid: 28613514. URL: <http://www.ncbi.nlm.nih.gov/books/NBK430763/> (visited on 02/13/2024).