Computer knows best: Self-supervised signal cleaning

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Slides:
tinyurl.com/deepclean-esicm

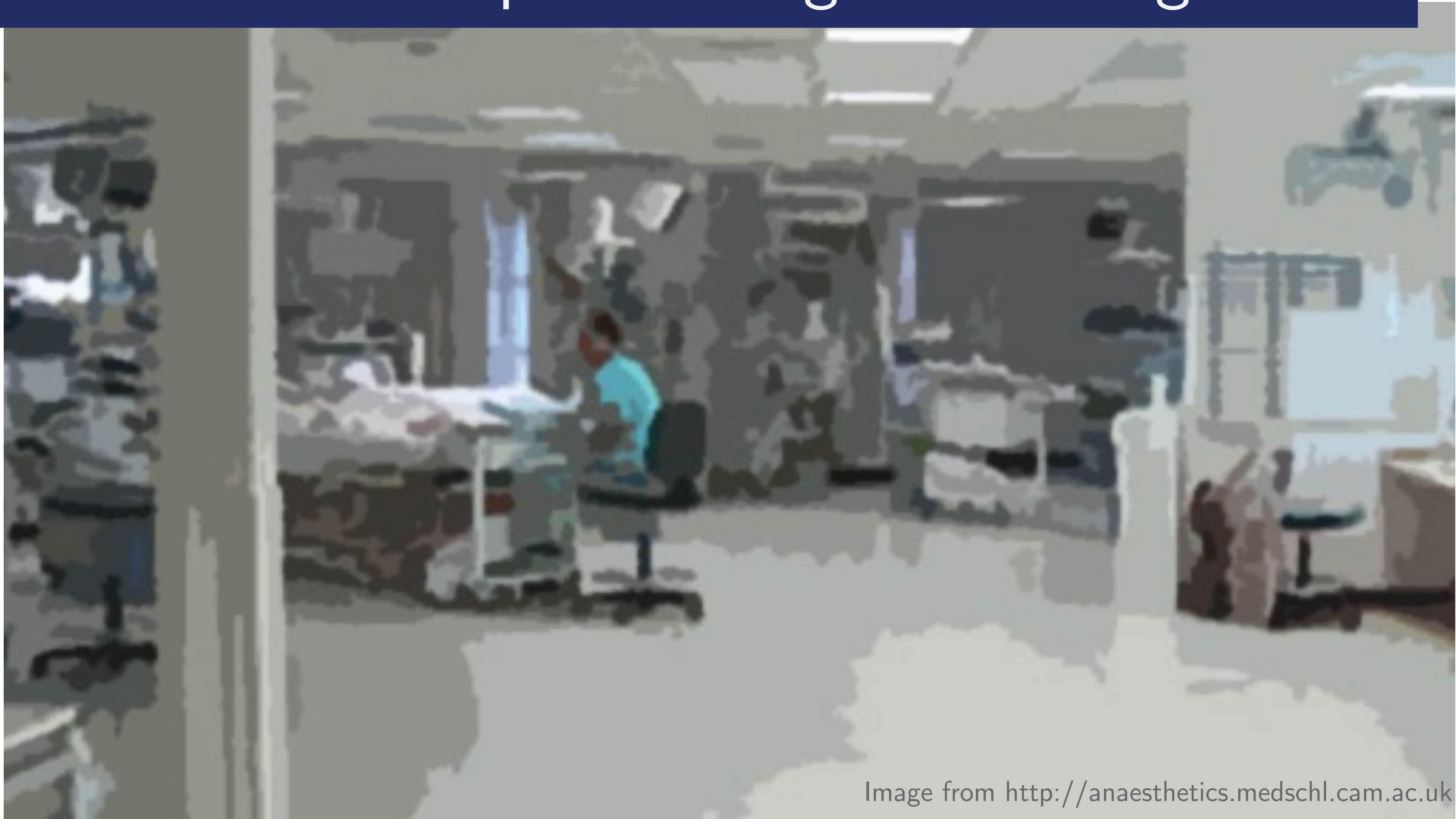

Image from http://anaesthetics.medschl.cam.ac.uk

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I have no conflict of interest in this work.

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Title – DeepClean: Self-Supervised Artefact Rejection for Intensive Care Waveform Data Using Deep Generative Learning.

Problem: artefact detection in physiological waveforms

Intensive care is data-dense and reliant on continuous multimodality monitoring.

High-frequency physiological waveforms (e.g. ABP, ICP, ECG) alert clinicians to changes in the patient state in real-time and allow computation of derived measures associated with outcome e.g. cerebral autoregulation.

Waveform artefacts arise from various sources e.g. patient movement, clinical intervention, arterial flushing, sensor noise.

Problem: artefact detection in physiological waveforms

Why are artefacts in physiological waveforms a problem?

Artefacts introduce bias and reduce reliability in estimation of derived parameters, creating uncertainty in clinical decision making.

Artefact detection can also help to reduce the likelihood of false positive ICU alarms. Alarm fatigue is unhelpful for clinical staff.

Motivation: artefact detection is tricky!

Manual annotation of artefacts is still the gold standard but is painstakingly time-consuming, can be subjective and is susceptible to bias/replicability issues.

Just identifying artefacts still leaves problems! Removal of artefacts creates problems with missing data, and simple imputation methods underestimate variability and may also be biased.

Motivation: artefact detection is tricky!

→ Artefact detection (and imputation) seems a good task to use automated/machine learning methods!

Other approaches include active learning (Megjhani *et al.*, 2019), SAX strings (Cabaleira *et al.*, 2021) or signal-specific feature engineering (Sun *et al.*, 2006).

Our approach using a machine learning method but we didn't ask the ML algorithm to try and identify artefacts in the waveform!

Brief aside: generative learning and variational autoencoders

Generative learning aims to learn a distribution $p_\theta(x)$ to approximate the true distribution P of the data X. We can sample from $p_\theta(x)$ to generate new example data (useful for imputation or synthetic data).

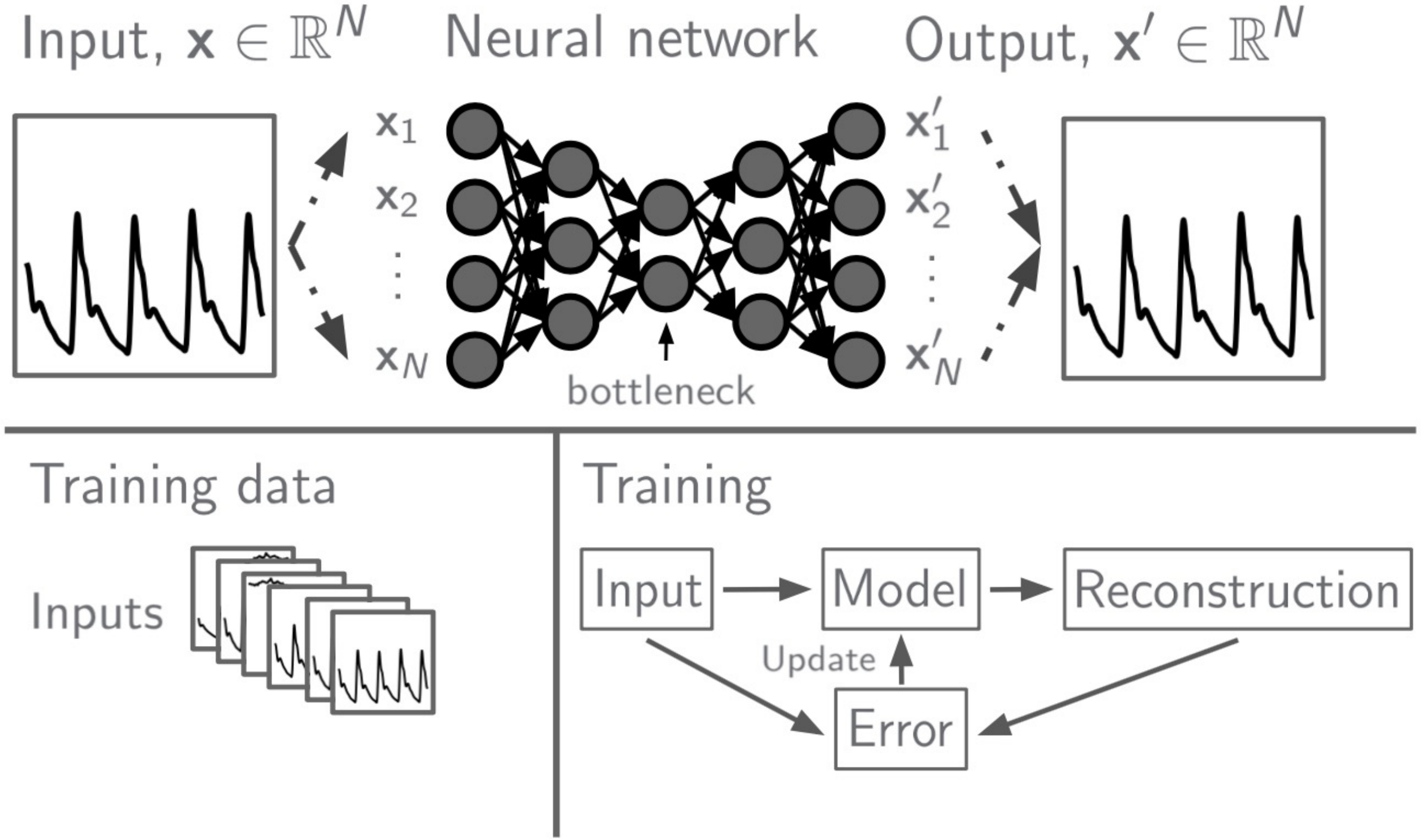
Latent variable models condition on (unobservable) latent features z. For a given x, the corresponding feature state z provides a lower-dimensional representation.

A variational autoencoder learns to encode each data point as a distribution in this latent representation space, and then from this generates new candidate waveform data that should accurately reconstruct the inputs from the underlying distribution P.

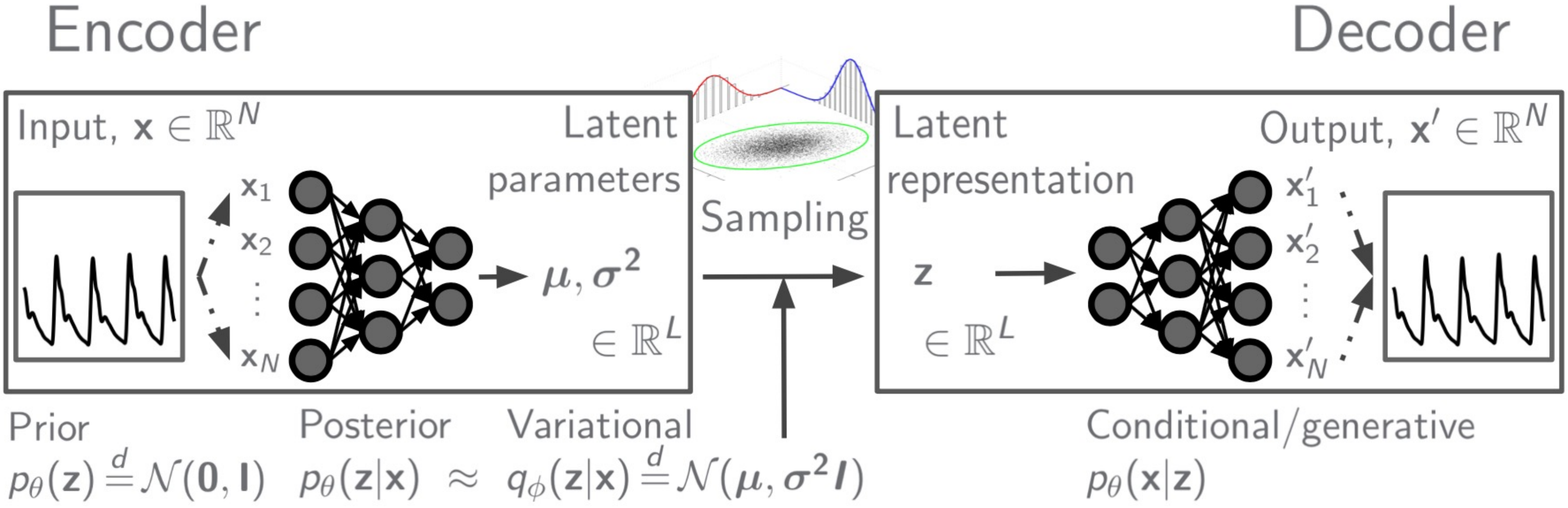
An autoencoder

The network maps inputs to themselves, through a lower dimensional ‘information bottleneck’.

This bottleneck (hopefully) learns some salient features, from which the full waveform is reconstructed.



Variational autoencoder: some technical details



A solution, via variational autoencoders: DeepClean

We approached this from a slightly different standpoint, originally being interested in using machine learning methods to learn latent representations of physiological signals.

(i) Train a variational autoencoder on some ‘good’ waveform data.

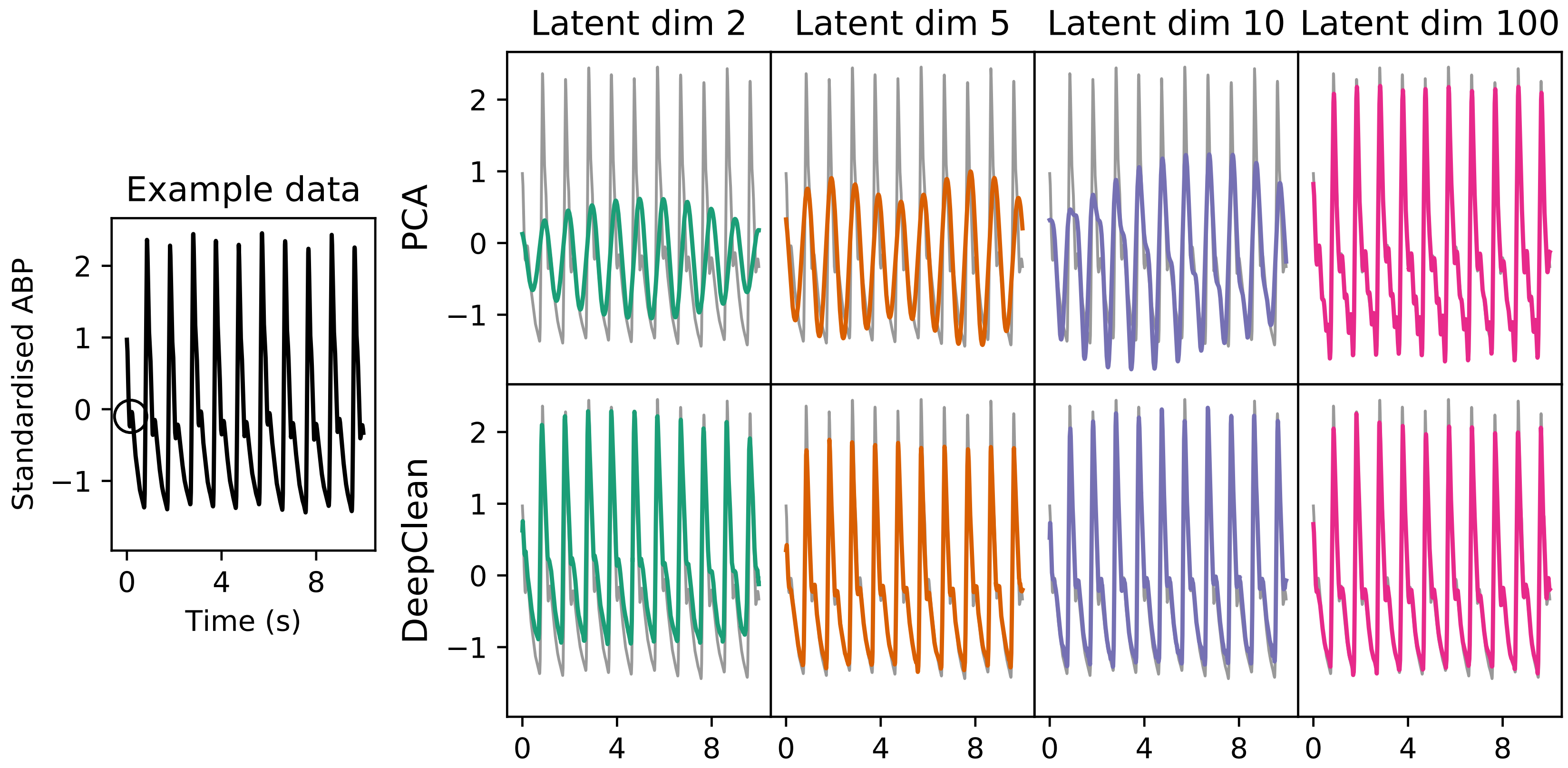
- This doesn’t require previously annotated samples (i.e. we don’t tell it what an artefact looks like).

(ii) The machine learning part is done. Now we feed in waveform samples to the trained VAE and use the output reconstructions to discriminate artefacts.

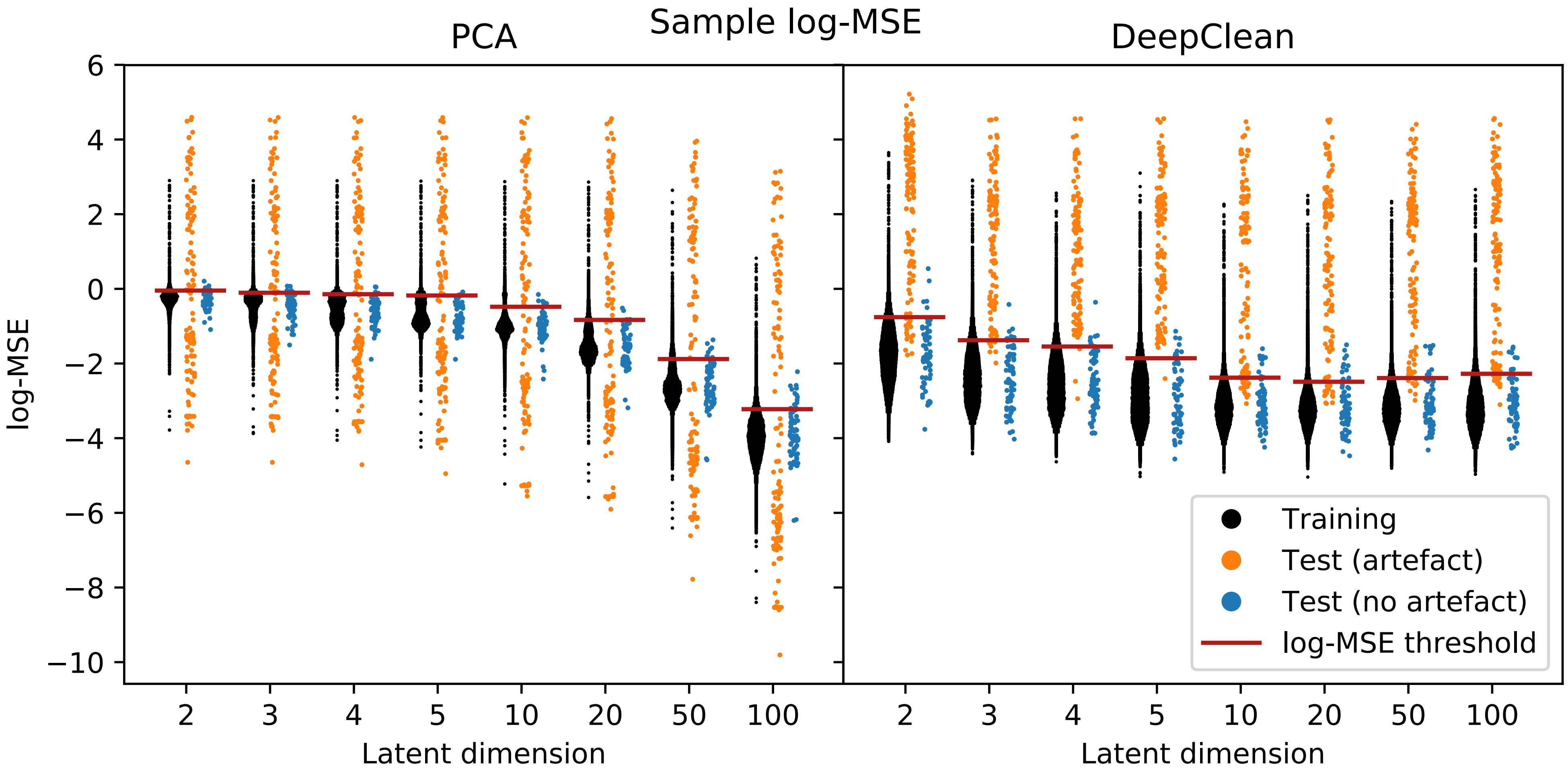
- Artefacts have low ‘reconstruction probability’ and high MSE compared to model output.
- The trained model is useful not only for artefact detection but also for imputation!

How good is the reconstruction?

Comparing principal component analysis (PCA) and DeepClean (our VAE model)

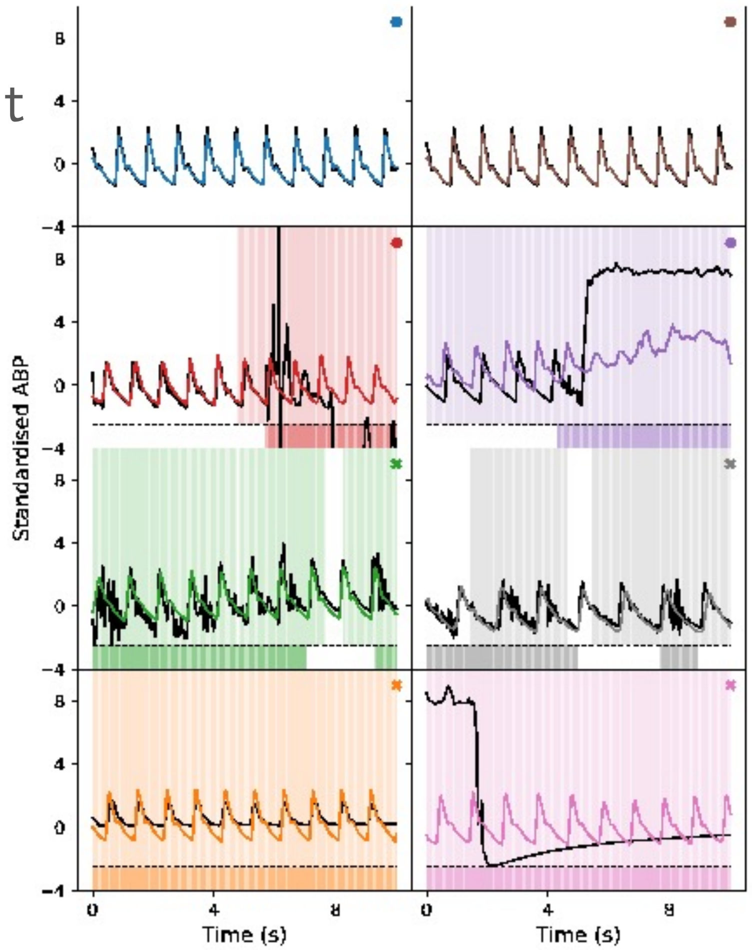


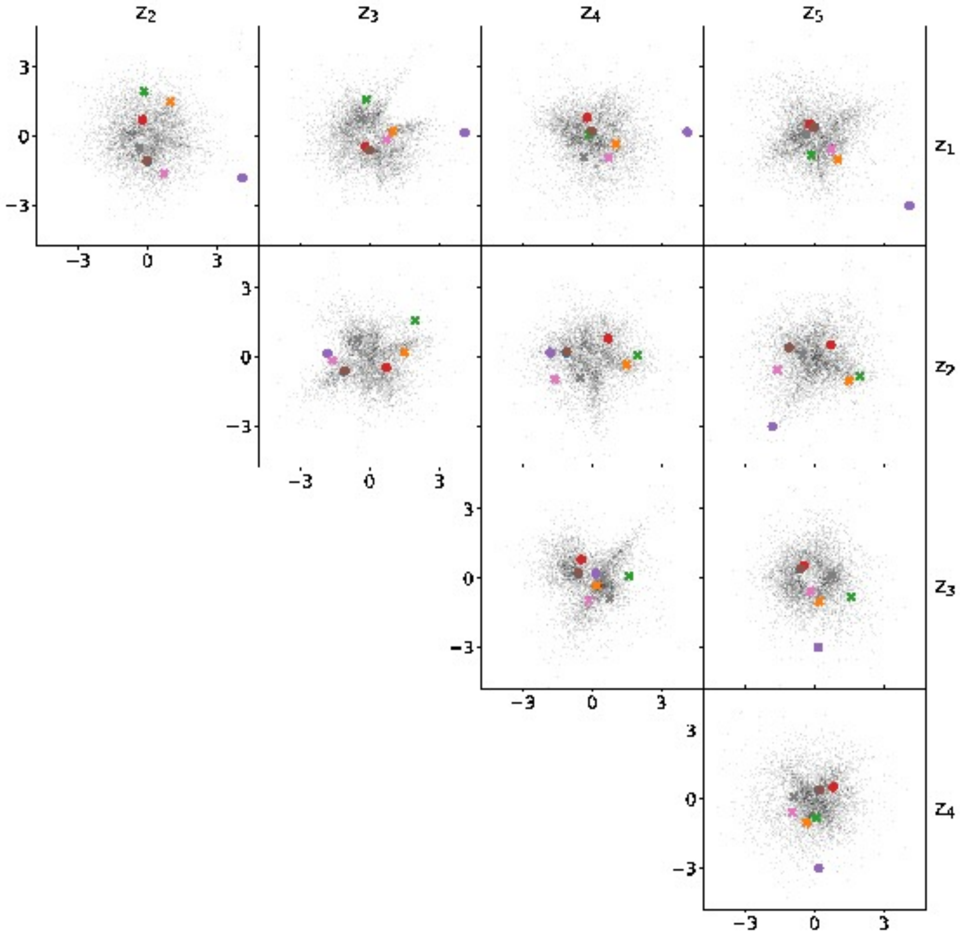
Sensitivity and specificity: trade-off



When can we impute using the model output?

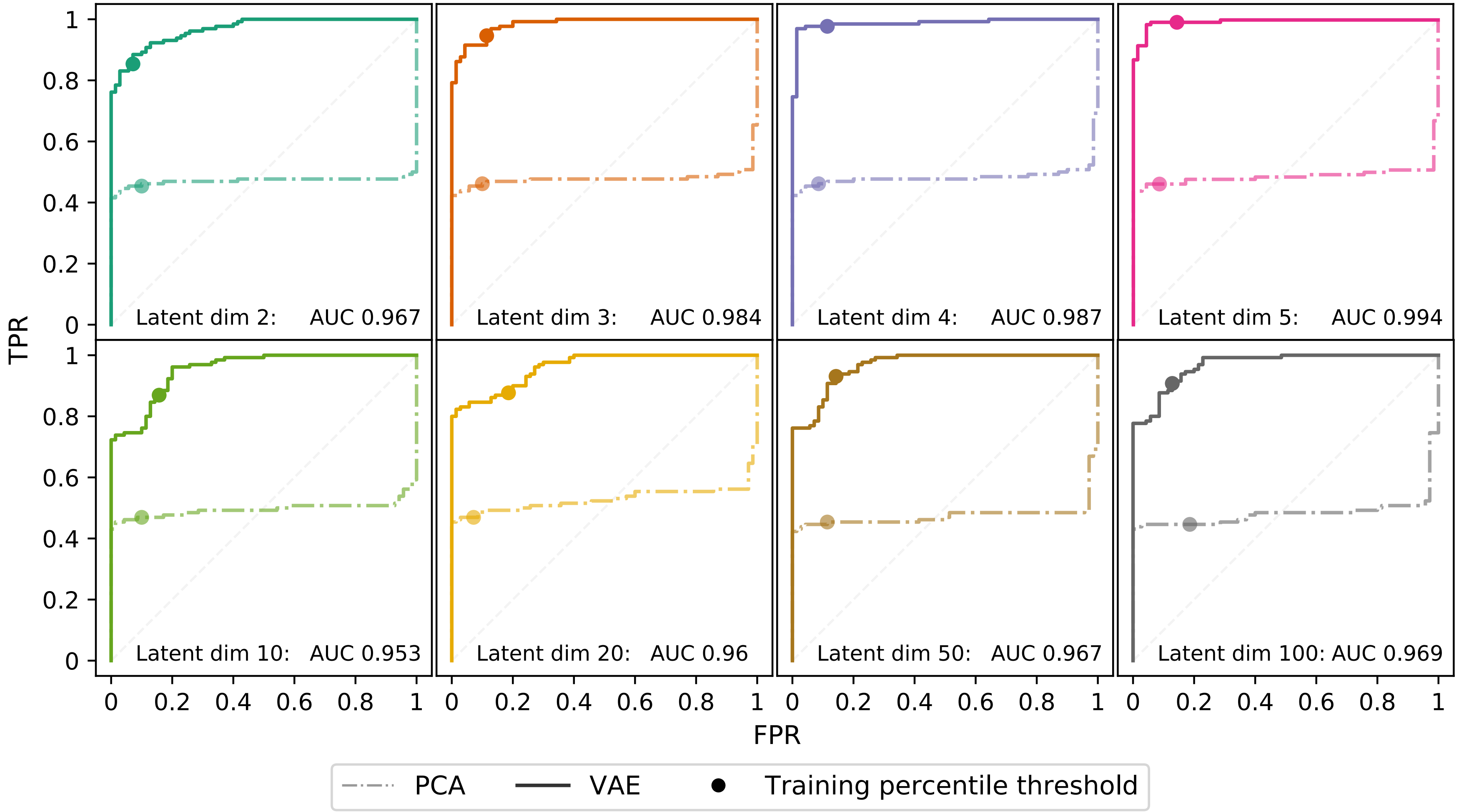
Input/output





Latent representation

Model performance: ROC AUC



Transfer learning

This can be generalised to new patients almost in real-time.

- Train on randomly selected 'good' waveforms from multiple patients for a baseline model.
- For a given patient, a small amount of extra training on this baseline model makes the model specific to that patient (transfer learning).
- After the model has finished training, identification of artefacts is almost instantaneous.

This approach is particularly well-suited to highly structured quasi-periodic signals (e.g. ABP).

Summary and conclusions

Key points:

- DeepClean can identify artefacts without the machine learning element being explicitly asked to do so.
- We have a generative model and we can use that for imputation when we discard artefacts within the waveform.
- Once the machine learning element is finished (and we can pre-train it on a mixed cohort of patients), identification of artefacts is near instantaneous.

Do computers know best? That's up for debate.

Acknowledgements

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