Detecting Physiological State Changes During Blood Loss via Deep Unsupervised Learning

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Introduction

- Internal bleeding is a common symptom from physical traumas, but it is difficult to analyze due to its complexity
- Previous work mostly uses supervised learning to predict clearly delineated outcomes e.g bleeding vs not bleeding
- Lei et al's work demonstrated that interesting patterns could be found from the clusters [1]
- We demonstrate a modern deep unsupervised encoder model in the application of finding embeddings from continuous data of 6 health metrics

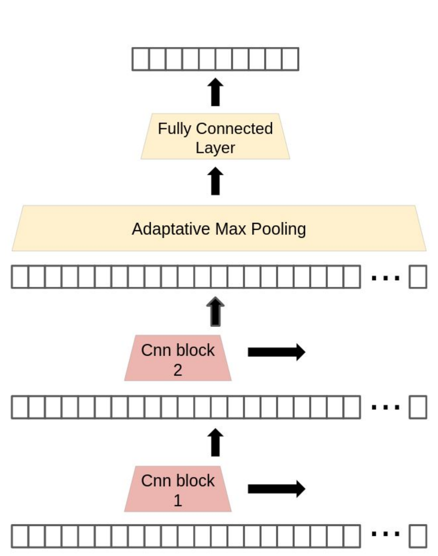
Methodology

- Time series health data (prebleed to crash) from 16 pigs total, bled at 5 ml per min
- Use dilated causal convolutional encoder as proposed by Franceschi et al. [2]
- Train with triplet loss - similar data are close together and unsimilar data are further apart

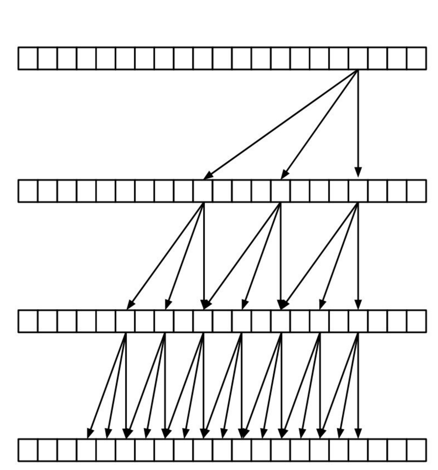
$$L = -log(\sigma(f(x)^T f(x^{pos}))) - \sum_{k=1}^{K} log(\sigma(-f(x)^T f(x_k^{neg})))$$

Model Architecture

- An illustration of our model running on sequence data

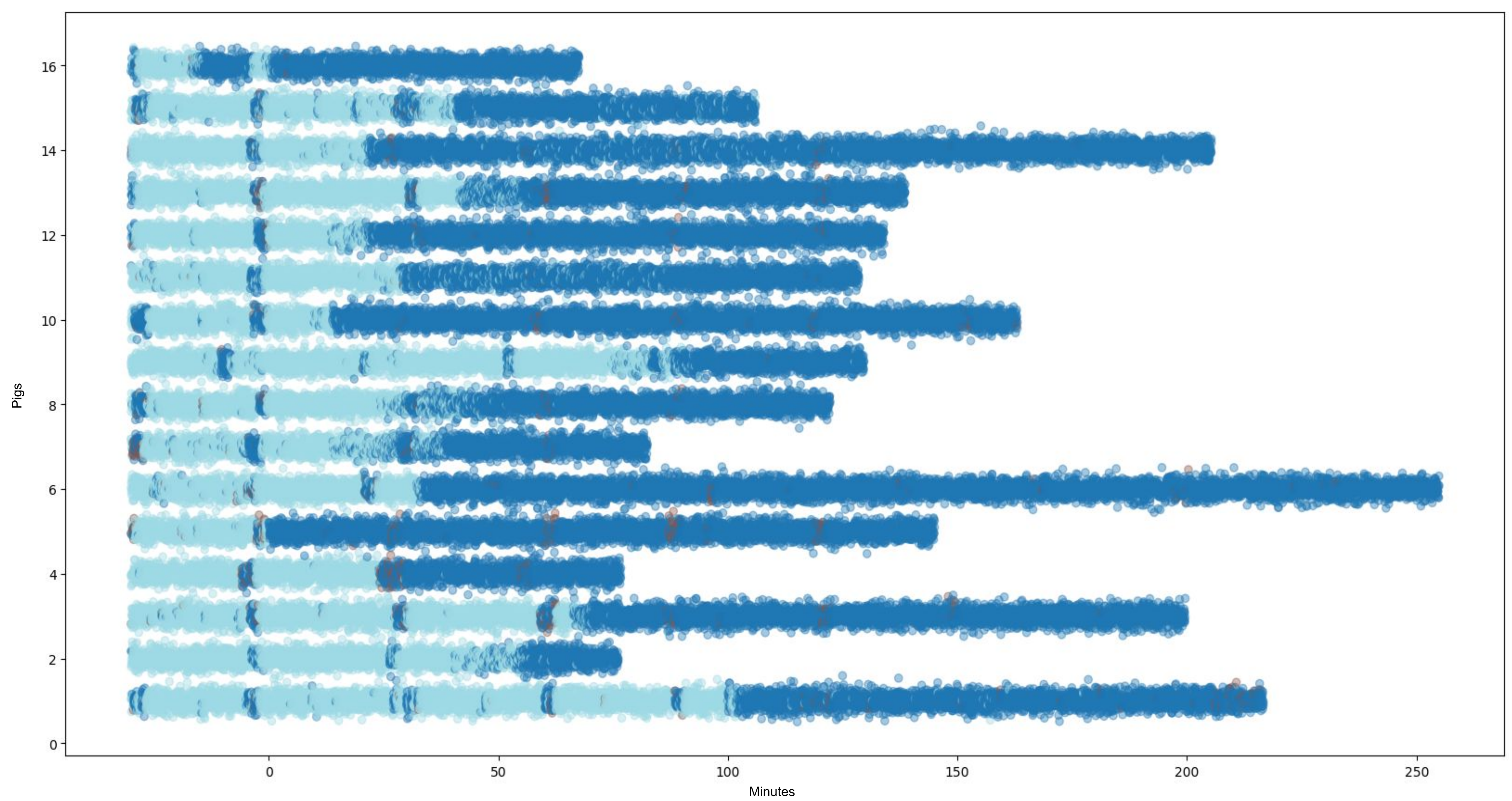


- An illustration of our model running on sequence data

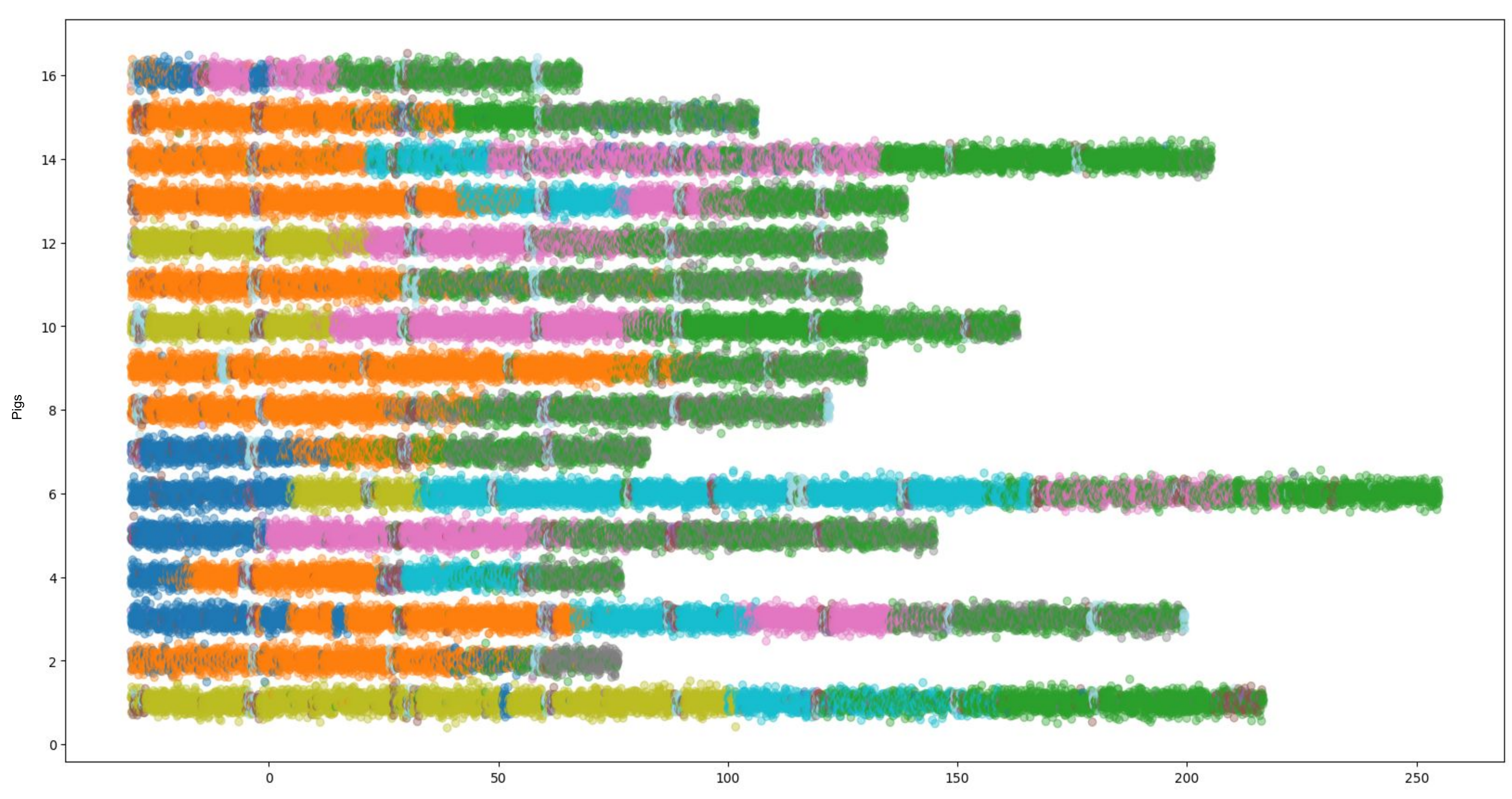


Results

Time vs 3 clusters



Time vs 11 clusters



Discussion

- Various colors may be different physiological reactions
- There is a lot of noise from blood draws
- We can find patterns corresponding to early and late stages of bleed
- Individual pigs may have different responses to internal bleeding
- There are groups of pigs that behave similarly
- All pigs end up in green cluster, which corresponds to a crash

Future Work

- Automatically classify time series of a new patient
- Verify class predictions with validation data
- Check with physicians for validity of clusters

References

- Lei, K. Miller, and A. Dubrawski, "Learning mixtures of multi-output regression models by correlation clustering for multi-view data,"arXiv preprint arXiv:1709.05602, 2017.
- J.-Y. Franceschi, A. Dieuleveut, and M. Jaggi, "Unsupervised scalable representation learning for multivariate time series,"arXiv preprint arXiv:1901.10738, 2019.

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