Bleeding Detection by Multi-View Correlation Clustering of Central Venous Pressure

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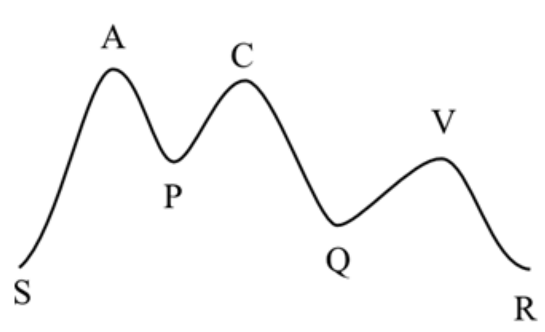
Exploiting Vital Sign Correlations Between Inspiration and Expiration Phases of Breathing

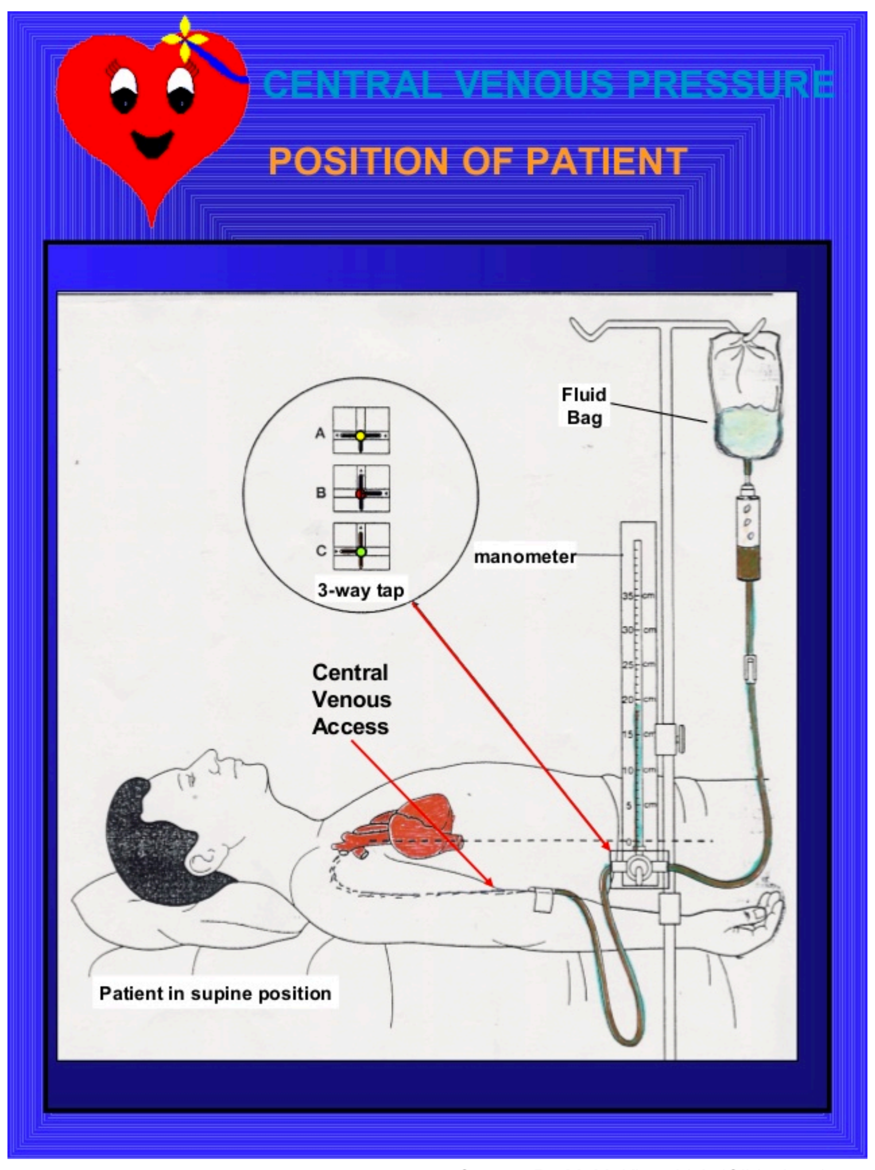
Introduction

- One question in medicine is whether the presence of bleeding is correlated with **central venous pressure** (CVP), the blood pressure in an area of the heart.
- Several studies argue that CVP has no clinical utility even though it is used in practice (Fig. B) because patient movements induce noise.
- The problem of filtering noise is separate from the intrinsic utility of CVP. We investigate CVP within a laboratory setting that restricts noise, which has rarely been studied.
- A CVP waveform has several peaks and troughs (Fig. A). The differences in amplitude are thought to be significant, such as the difference *CQ*.

A



- We apply a classification method based on multi-view correlation clustering to detect bleeding from CVP.
- We reveal how the relationship between CVP during inspiration and expiration changes depending on whether bleeding exists.



B

Source: Dr. M. M. Kharabish (*Slideshare*)

Data

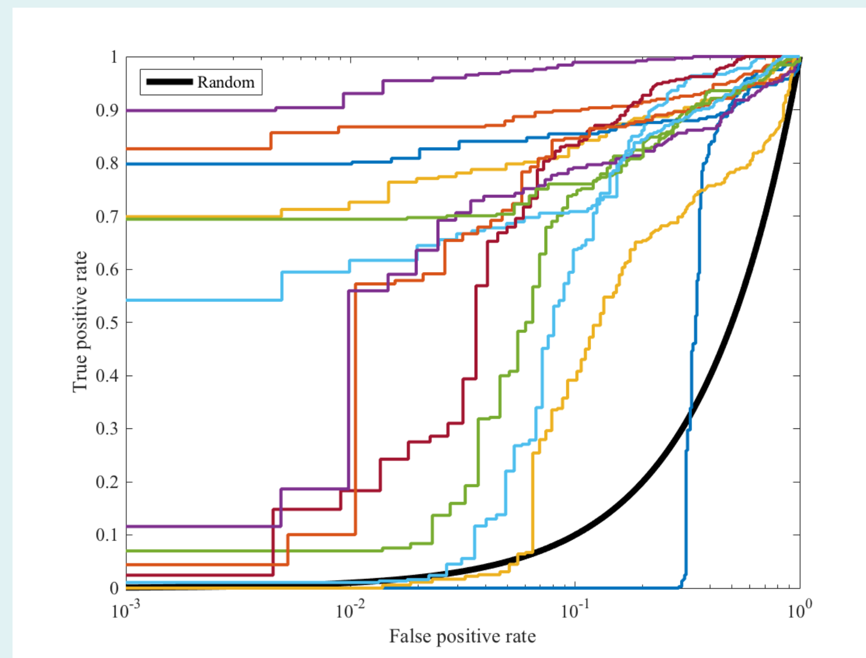
- The data were collected from an experiment in which 38 sedated pigs were subjected to controlled bleeding at a constant rate of 20mL/min.
- A pair of CVP waveforms was measured from each pair of inspiration and expiration phases.
- The dataset covers 20 minutes before and 30 minutes after the onset of bleeding, for an average of 556 observations per pig.
- Twenty-one features were extracted from each waveform as averages and ratios between different points.

Experiments

Bleeding Detection as Classification

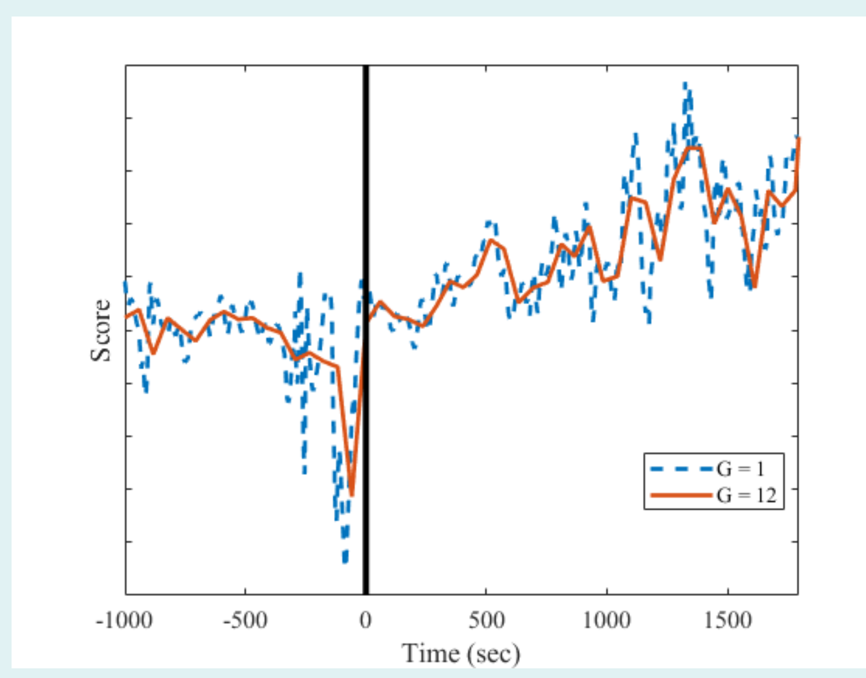
- We tried classifying individual points as well as consecutive windows.

Window Size	AUC	TPR@10FPR	FPR@50TPR
1	87.9 ± 5.3	72.8 ± 14.4	5.5 ± 5.5
12	89.4 ± 6.0	76.5 ± 16.9	4.7 ± 5.6
All observations	92.3 ± 15.4	-	-



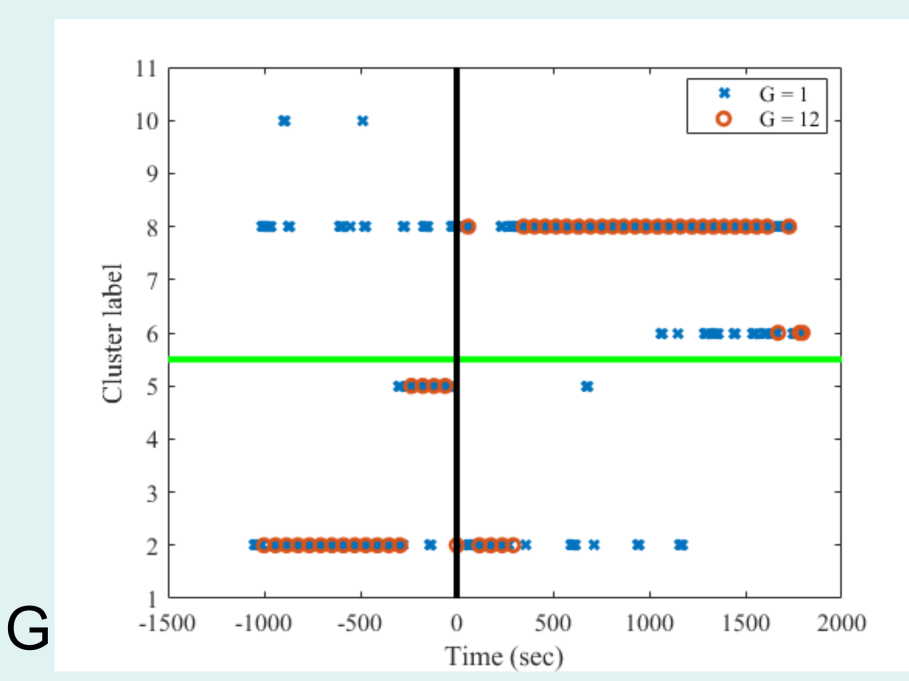
E

- Fig. E shows the ROCs of pigs in the test set.
- Some pigs have high TPR at low FPR and the rest do not.



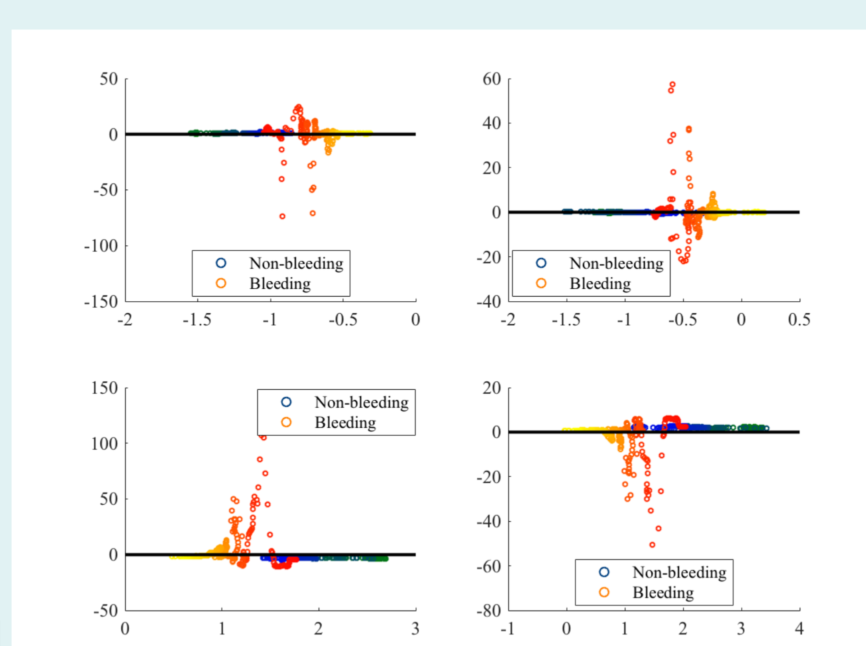
F

- Fig. F shows the classification score over time on a particular pig at window sizes *G* = 1 and *G* = 12.
- The score increases after bleeding starts.



G

- Fig. G shows the predicted cluster membership of the pig.
- Non-bleeding clusters are below the green line.
- There are 3 to 4 predicted phenotypes for this pig's behavior.



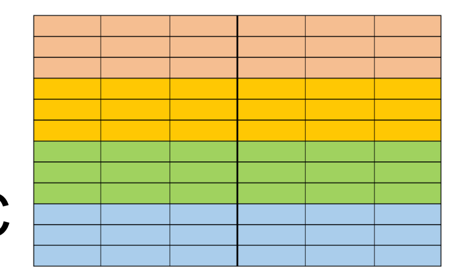
H

- Fig. H shows latent variable residuals from Cluster 2.
- The residuals diverge from 0 after bleeding starts.

Multi-View Correlation Clustering

- **Multi-view data** have features that are partitioned into two views or sets: inspiration and expiration in this case.
- In **multi-view correlation clustering**, observations can be clustered based on the relationship between views (Fig. C).

C



Method

- We apply a novel EM-like algorithm to estimate multi-view correlation clusters.
- The correlations are found by a technique called **Canonical Least Squares** (CLS), which resembles **Canonical Correlation Analysis** (CCA):

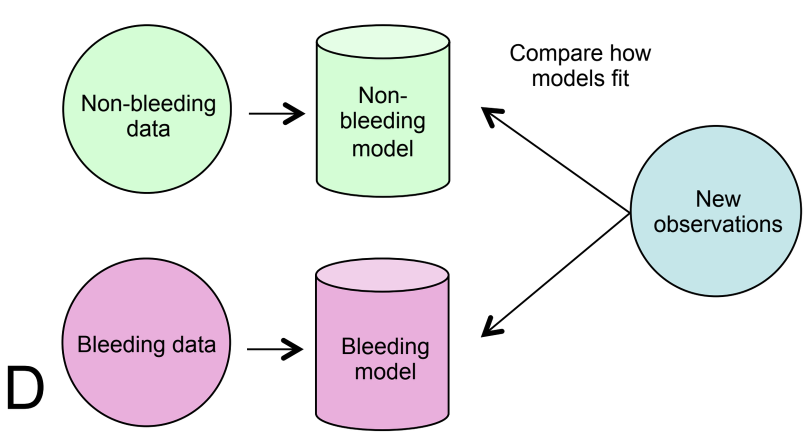
$$\sum_i \min_{U^{(i)},V^{(i)}} \|R^{(i)}(XU^{(i)} - YV^{(i)})\|_{\mathcal{F}}^2$$

$$V^{(i)\top}V^{(i)} = I,\ i = 1, \ldots, k$$

- CLS clustering alternates between an update phase, solving CLS for each cluster, and assignment phase.
- CLS clusters are fitted separately on data from each class to get parameters U_0, V_0, U_1, V_1.
- A set of points $(\tilde{X}, \tilde{Y})$ is scored by comparing the best fitting cluster from each class (Fig. D):

$$\arg\min_i \|\tilde{X}U_1^{(i)} - \tilde{Y}V_1^{(i)}\|_{\mathcal{F}}^2 - \arg\min_j \|\tilde{X}U_0^{(j)} - \tilde{Y}V_0^{(j)}\|_{\mathcal{F}}^2$$

- The score is averaged over multiple initializations of clusters.



D

Procedure

- The problem was framed as a binary classification between bleeding and non-bleeding.
- Data from all pigs were pooled.
- Points from the same pig were constrained to the same cluster.
- Using LOOCV over pigs, hyperparameters were selected as 5 clusters for pre-bleeding and 6 for post-bleeding to maximize AUC.
- The final model was evaluated on a hold-out set of 13 pigs.

Summary

- CVP waveforms can help predict bleeding when the level of noise is controlled.
- The presence of bleeding can change the correlation between waveforms during inspiration and expiration.
- In the future, we will investigate whether noise in CVP can be filtered.

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