# Estimating Dynamics and Data Assimilation to Detect Obstructive Sleep Apnea

Andrew M. Fraser

SIAM DS25

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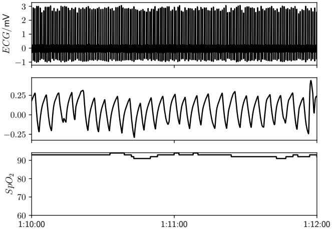
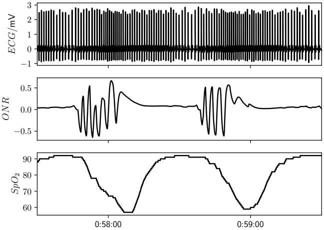
# Goal of CINC 2000: Use ECG to Detect Apnea

Computers in Cardiology 2000 Challenge: Classify EKG

Normal



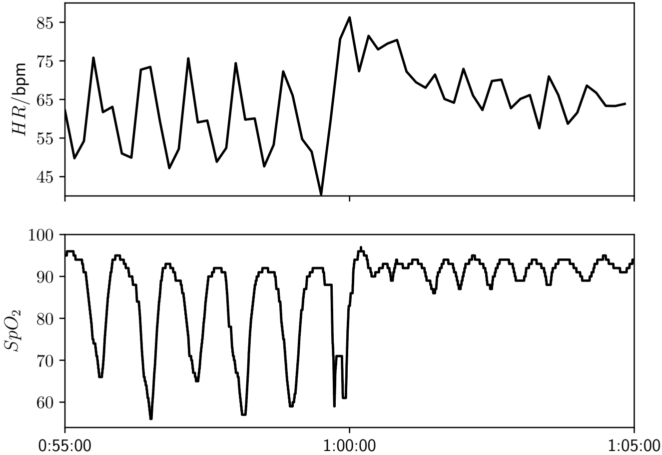

Apnea



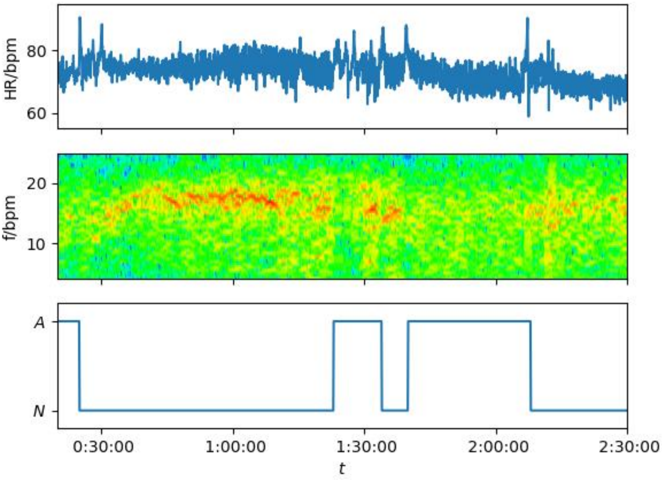

Intermediate Objectives:

Detect QRS Pattern $\rightarrow$ Estimate Heart Rate

# See Apnea in Heart Rate

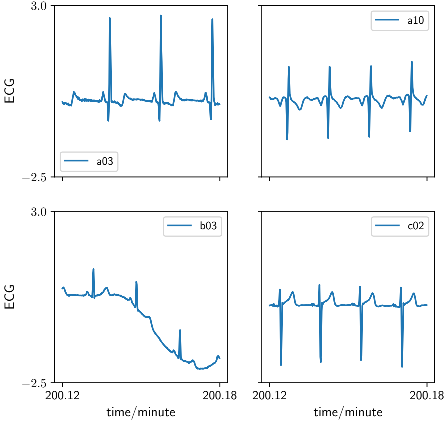


# Respiration in Spectrogram



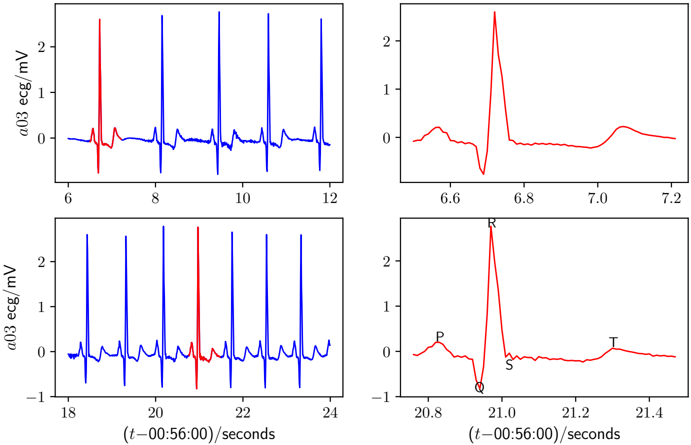

James McNames saw respiration between 10 and 20 cpm.

# Different Strokes



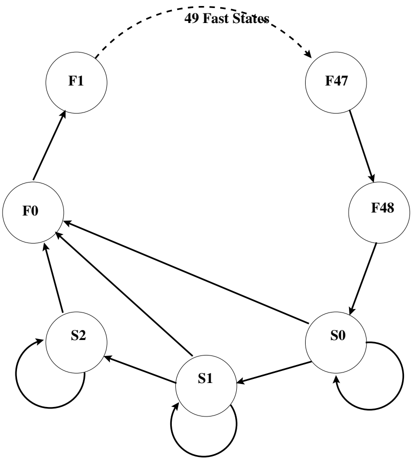

The waveforms differ between records.

# Unvarying PQRST Duration



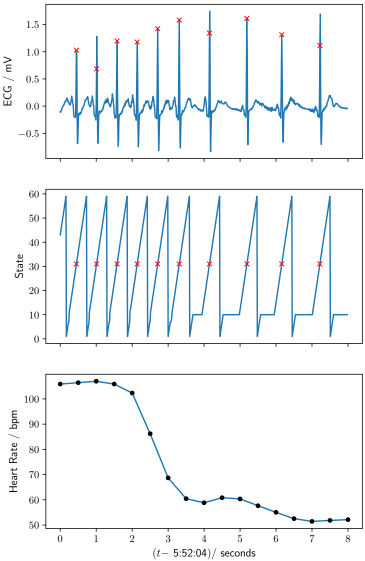

At different heart rates the shape and duration of the PQRST pattern doesn't change. Only the delay between the sequences changes.

# HMM State Structure

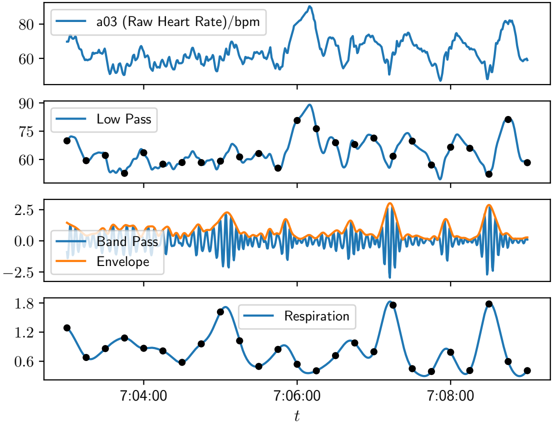



Code fits deterministic chain of 49 states to unvarying PQRST data. Variable residence time in states $s_0, s_1$ and $s_2$ accommodates delay between PQRST sequences.

# Heart Rate from Viterbi Algorithm



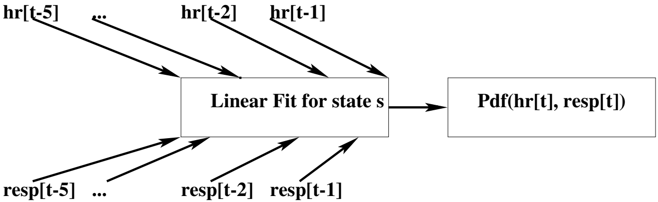
# 2-d Vector Observations




Observation at $t$ is

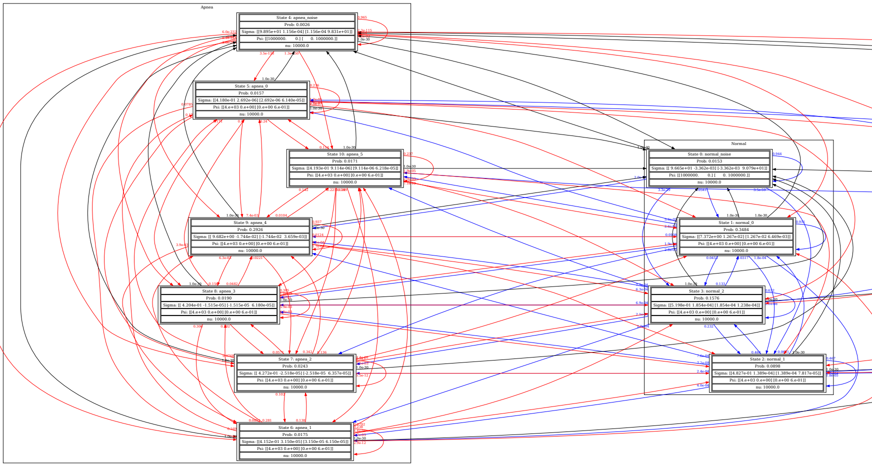
$$\boldsymbol{y}[t] \equiv (\text{Low Pass}[t], \text{Respiration}[t])$$

# Observation Model Given $s[t] = s$




$$\left[ \begin{matrix} \text{hr} \\ \text{resp} \end{matrix} \right] [t] \Bigg| s \sim \mathcal{N}\left(\boldsymbol{\mu}_{s,t}, \Sigma_s\right) \text{ with } \boldsymbol{\mu}_{s,t} = L_s(\text{past 5 observations})$$

# Schematic of HMM from Graphviz




7 apnea states and 4 normal states.

# Training and Classification

Choose maximum likelihood parameters given the training data, $y_{\text{training}}$

$$\hat{\boldsymbol{\theta}} = \operatorname*{argmax}_{\theta} P(y_{\text{training}}|\theta).$$

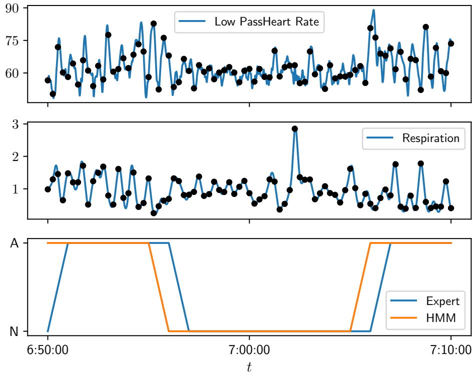
For each testing record consider all of the data, $y[0:T]$, and for each state, $s_i$, and each time, $t$, calculate the probability of being in that state at that time,

$$w_{t,i} \equiv P\left(s[t] = s_i | y[0:T], \hat{\boldsymbol{\theta}}\right).$$

Finally classify each time using the ratio

$$R[t] \equiv \frac{\sum_{i \in \text{Apnea}} w_{t,i}}{\sum_{i \in \text{Normal}} w_{t,i}}.$$

# Classification Performance




Error rates:

| | |
|---|---|
| 14% | On training data |
| 15% | On testing data |
| 7.5% | Classification by eye won in 2000 |

# Multi-Level Modeling?

Here, I have used separate dynamical models of these three aspects of physiology:

- Dynamics of single heart beat
- Dynamics of respiration
- Dynamics of apnea

Separating those aspects seems appropriate and useful in a way that I would like to quantify.

# The End

Questions?