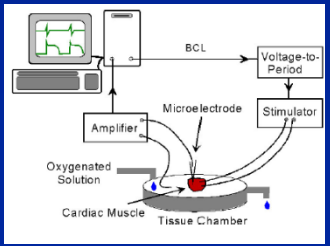
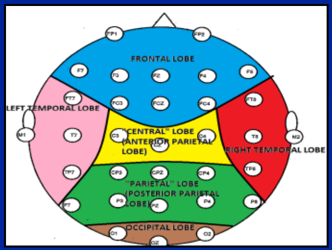
Signal Processing and Machine Learning for Intelligent Patient Monitoring

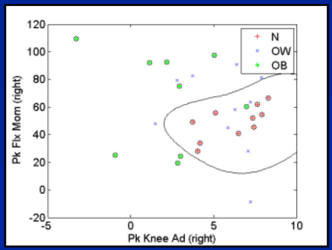
Xiaopeng Zhao

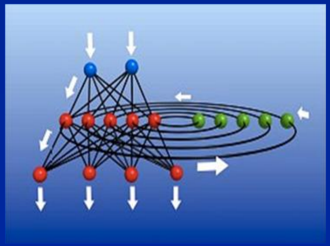
Department of MABE

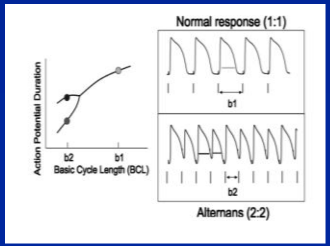
National Institute for Mathematical and Biological Synthesis
University of Tennessee, Knoxville
xzhao9@utk.edu











Challenges in Patient Monitoring

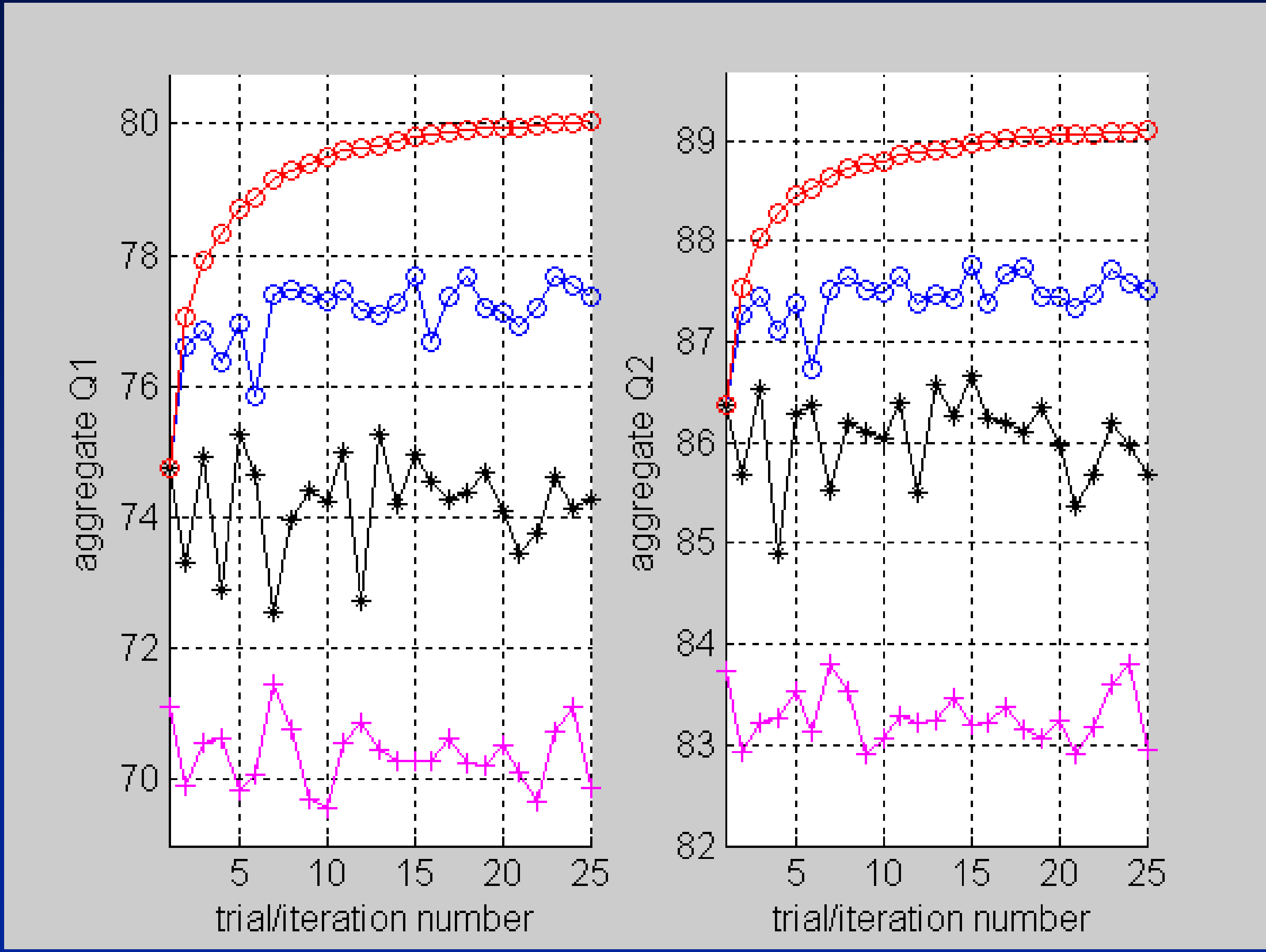
- Heterogeneities in data
  differences between patients, devices, hospitals, …
- Noise and errors
- Gaps in data
- Desired signals not unavailable
- Nonlinear and nonstationary physiological conditions

Need signal processing and machine learning techniques to predict, estimate, and diagnose, …

Problem Statement: Mind the Gap in Medical Signals

Constant monitoring of multiple physiological signals is essential for clinical diagnosis, treatment, and research. However, disruption or loss of signals can frequently happen, either due to errors in sensors or due to external disturbances.

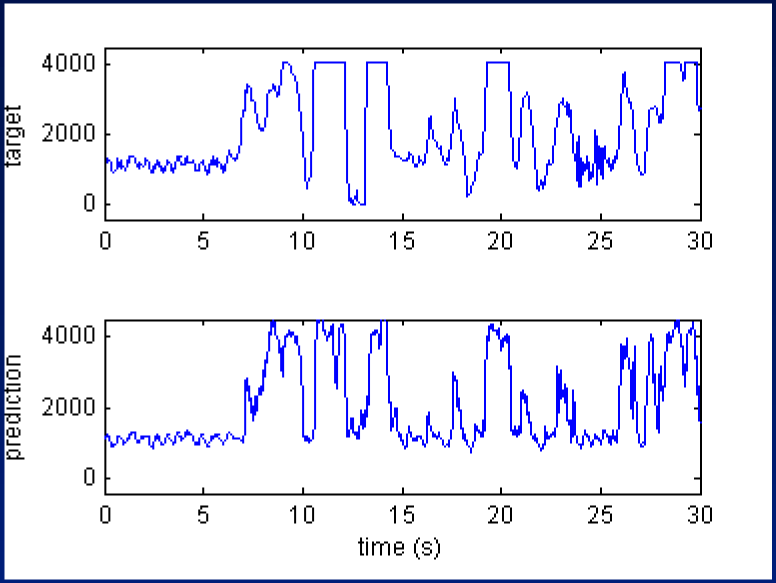
Method and Results



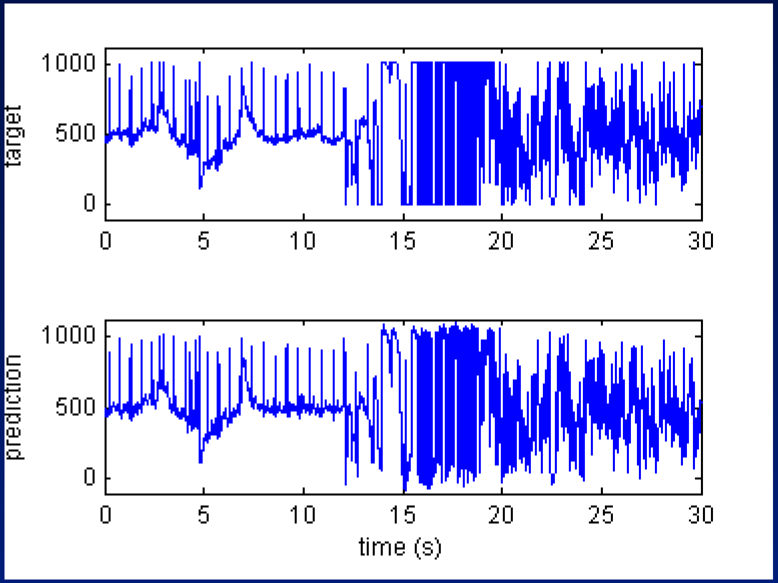
Pink: neural net; Black: mixed memory; Blue: feedback; Red: averaging

Results: 2nd place in Physionet Challenge 2010

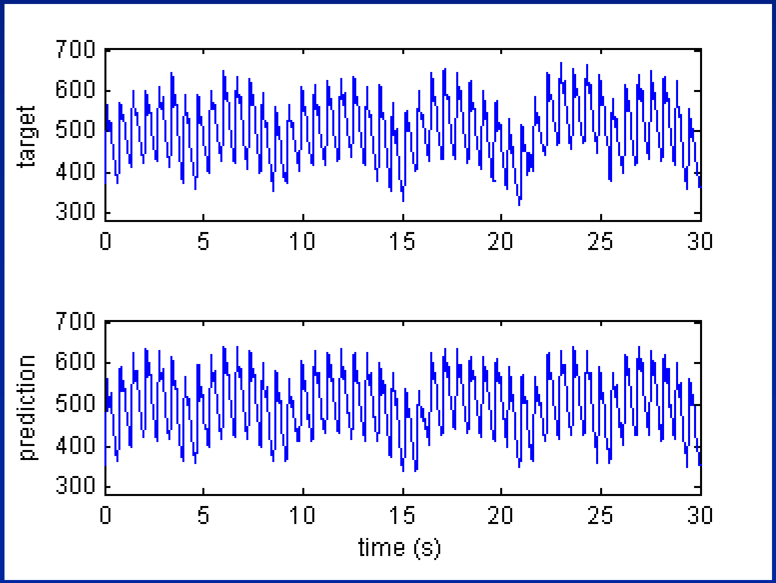
Blood Pressure



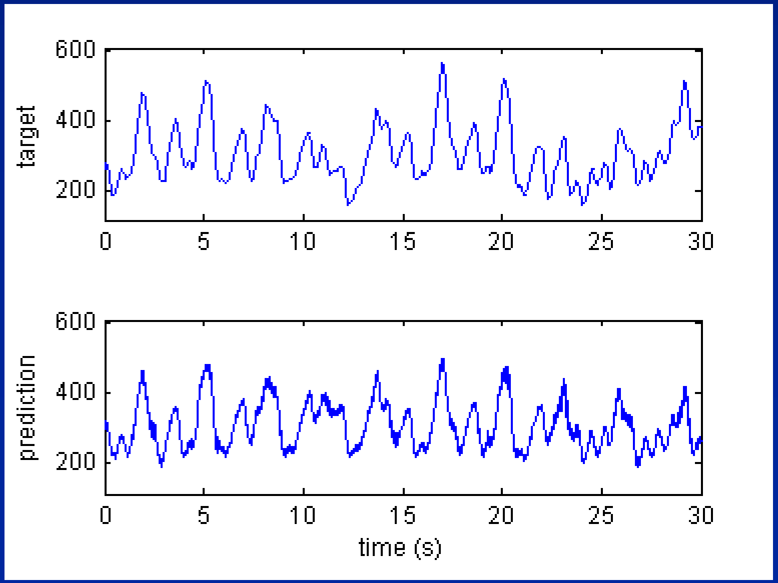
ECG



Photoplethysmography



Respiration



Problem Statement: Improving the Quality of ECGs Collected Using Cell Phones

Artifacts in ECG

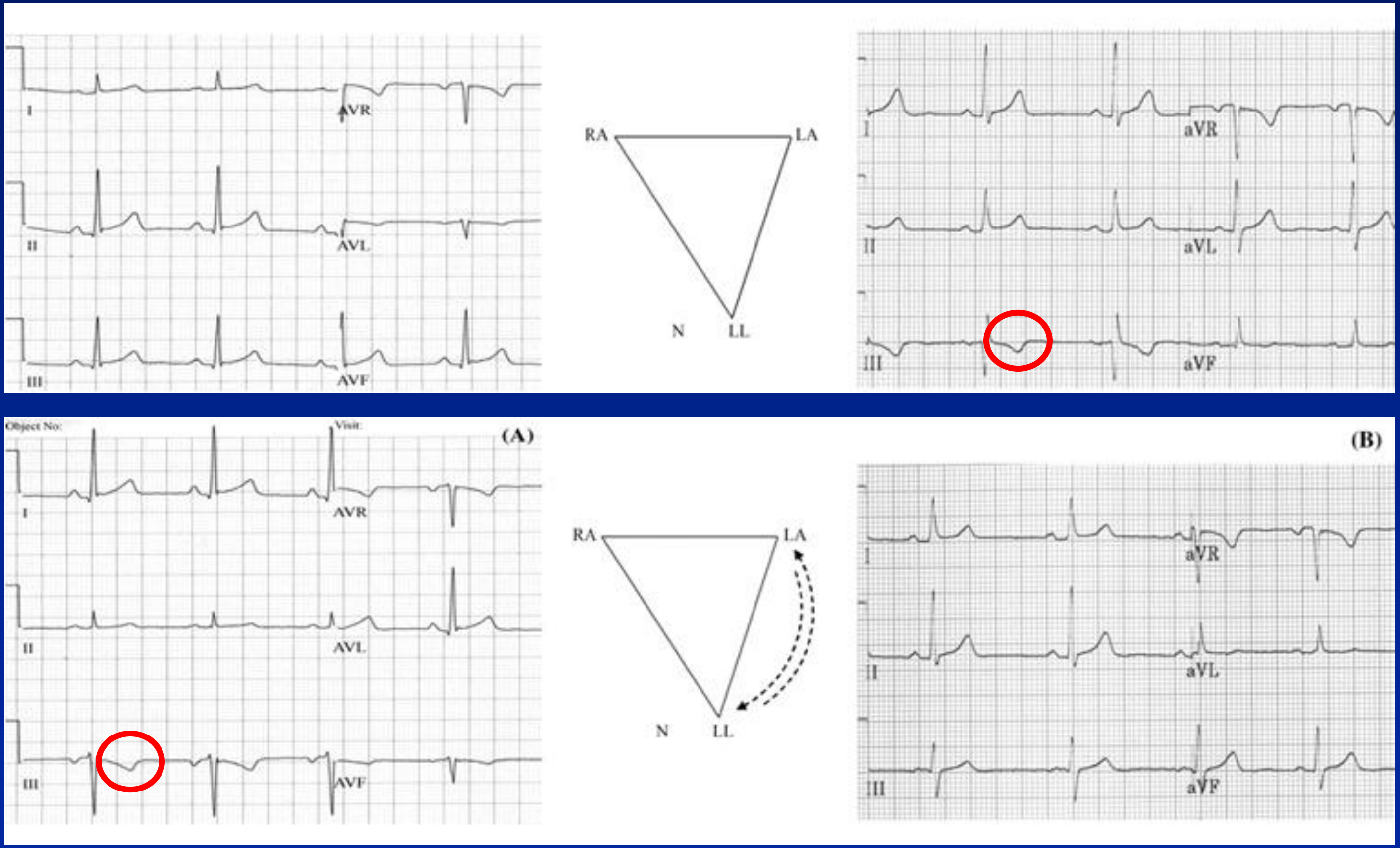
- Degrade diagnostic information
- Increase number of false alerts
- Delay proper treatment or cause a wrongful, detrimental treatment
- Increase workload of health providers

Errors in ECG

Normal ECGs may look "Abnormal"	Abnormal ECGs may look "Normal"

Electrodes Correctly Placed

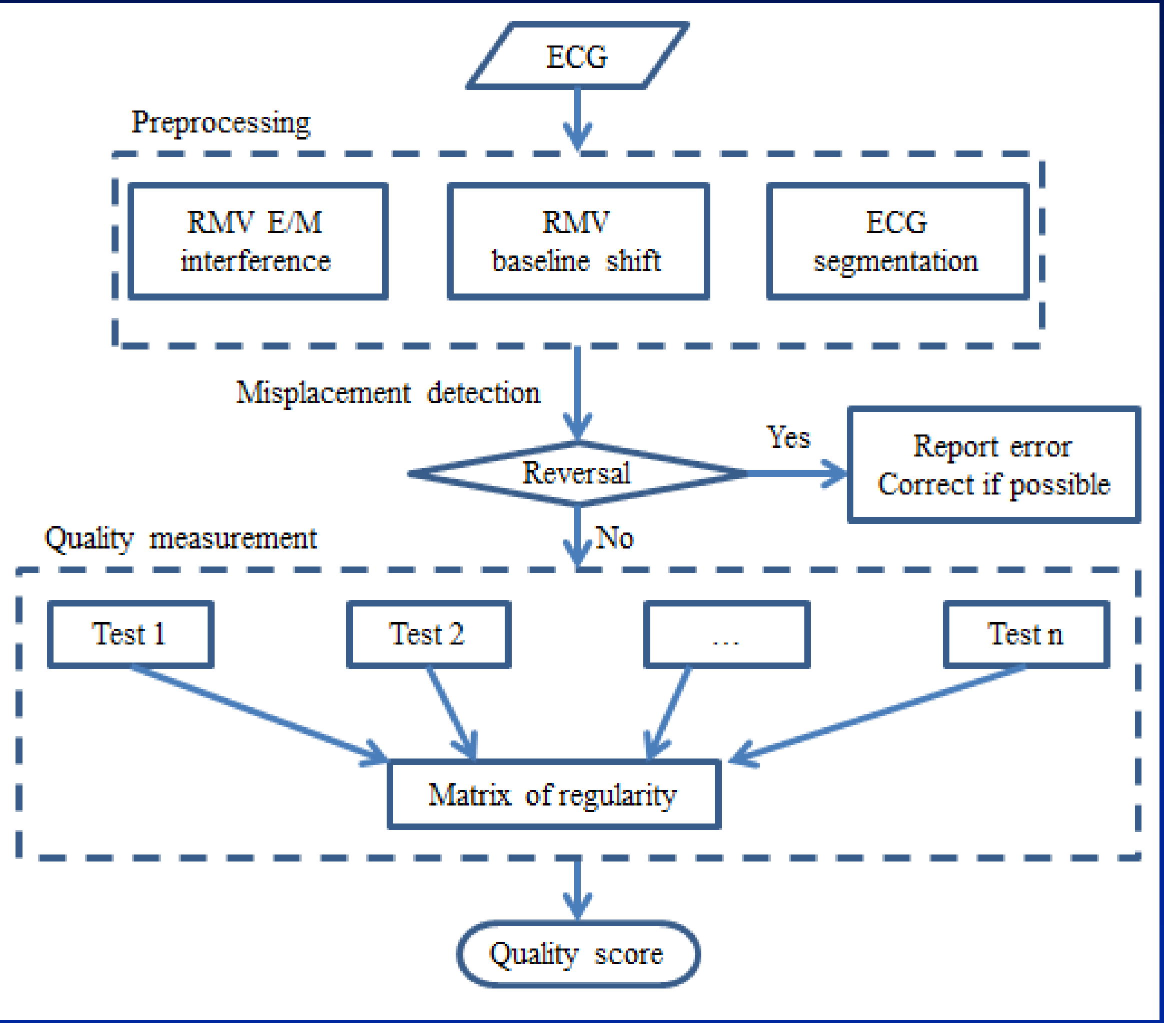
Electrodes Misplaced



Batchvarov V N et al. Europace 2007;9:1081-1090

Method and Results

Matrix of Regularity



Outcome

Accuracy = 95.1%
Sensitivity = 88.4%
Specificity = 97.0%

Receiver Operating Characteristics
AUC =0.97

Performance is comparable to human experts

Results: 1st, 1st, 3rd in Physionet Challenge 2011

Problem Statement: ICU Mortality Prediction

- Patient specific mortality prediction using physiological measurements
- Application: examine the efficacy of medications, care guidelines, surgery, and other interventions

Importance of severity evaluation

- ICU improves outcome for seriously ill patients significantly
  - However, it is expensive: in 2005, mean ICU cost is $31,574 for patients requiring mechanical ventilation and $12,931 for those not requiring mechanical ventilation

- Severity evaluation
  - allows to restrict ICUs to patients most at need
  - provides doctors a way to judge the treatment method

Data

- Physionet data: 4000 ICU records
- 5 static variables at admission:

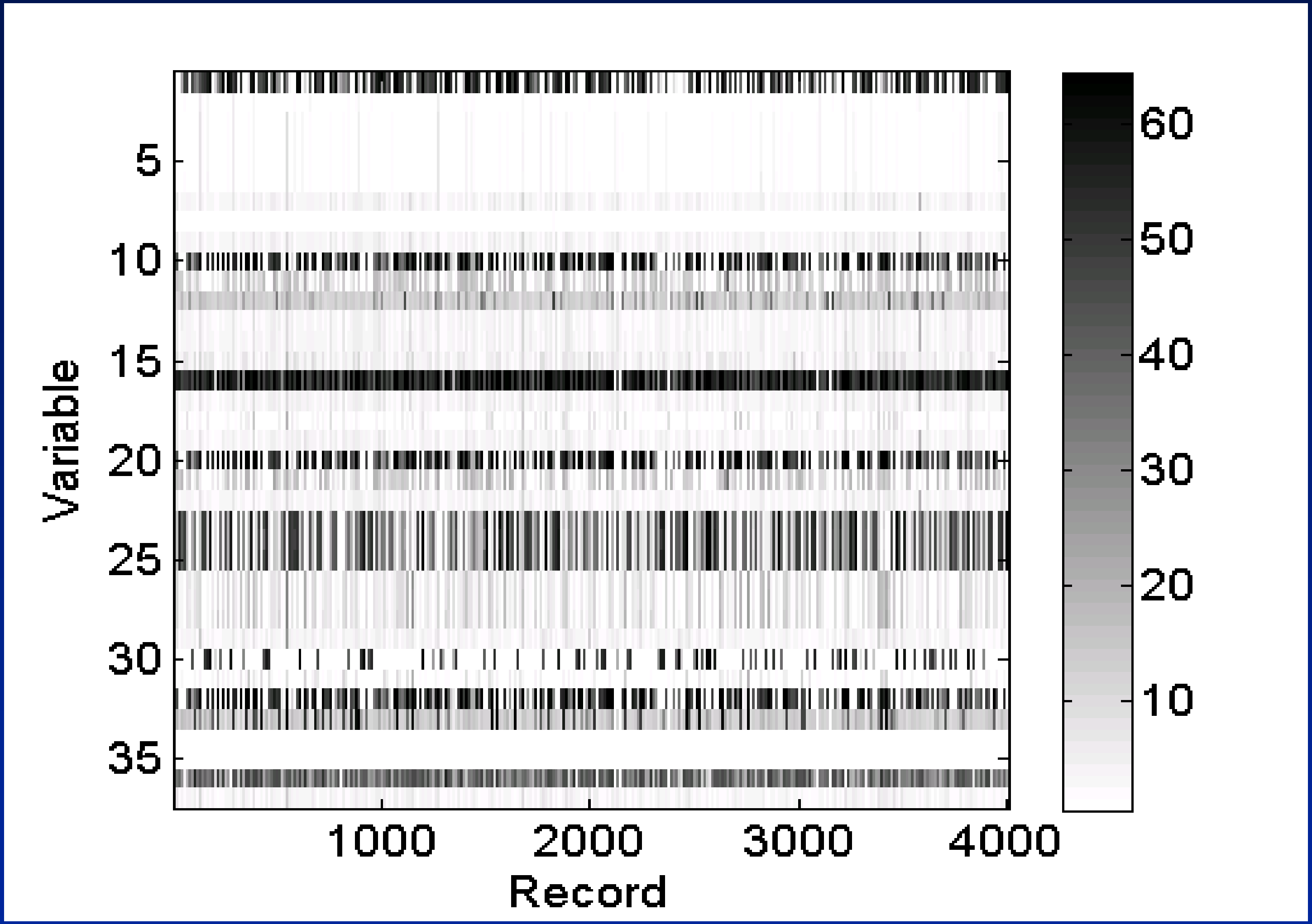
    Age, Sex, Height, Weight,

    ICU Type (Coronary Care, Cardiac Surgery Recovery, Medical, or Surgical)
- 37 dynamic variables recorded multiple times in 48 hours

Dynamic Variables

• *Albumin*	• *HCT*	• *pH*
• *ALP*	• *HR*	• *Platelets*
• *ALT*	• *K*	• *RespRate*
• *AST*	• *Lactate*	• *SaO2*
• *Bilirubin*	• *Mg*	• *SysABP*
• *BUN*	• *MAP*	• *Temp*
• *Cholesterol*	• *MechVent*	• *TropI*
• *Creatinine*	• *Na*	• *TropT*
• *DiasABP*	• *NIDiasABP*	• *Urine*
• *FiO2*	• *NIMAP*	• *WBC*
• *GCS*	• *NISysABP*	• *Weight*
• *Glucose*	• *PaCO2*	
• *HCO3*	• *PaO2*	

Occurrence frequency of each variable



Example record

- Time, Parameter, Value
- 00:00,RecordID,12539
- 00:00,Age,54
- 00:00,Gender,0
- 00:00,Height,-1
- 00:00,ICUType,4
- 00:00,Weight,-1
- <u>00:07,GCS,15</u>
- 00:07,HR,73
- 00:07,NISysABP,147
- 00:07,RespRate,19
- 00:07,Temp,35.1
- 00:07,Urine,900
- 00:37,HR,77
- 00:37,NIDiasABP,58
- 00:37,NIMAP,91
- 00:37,NISysABP,157
- 00:37,RespRate,19
- 00:37,Temp,35.6
- 01:37,NIDiasABP,62
- 01:37,NIMAP,87
- 01:37,NISysABP,137
- 01:37,RespRate,18
- 01:37,Urine,30
- 02:37,HR,62
- 02:37,NIDiasABP,52
- 02:37,NISysABP,123
- 02:37,RespRate,19
- 02:37,Urine,170
- 03:08,HCT,33.7
- <u>03:37,GCS,15</u>
- 03:37,HR,80
- 03:37,NISysABP,114
- 03:37,RespRate,20
- 03:37,Temp,37.8
- 03:37,Urine,60
- 04:37,HR,74
- 04:37,RespRate,20
- 05:37,NISysABP,110
- 05:37,RespRate,17
- 05:37,Urine,170
- <u>07:37,GCS,15</u>
- 07:37,HR,64
- 07:37,NIDiasABP,49
- 07:37,NIMAP,68.33
- 07:37,NISysABP,107
- 07:37,RespRate,15
- 07:37,Temp,38.1
- 07:37,Urine,120
- 08:37,HR,64
- 08:37,NIDiasABP,56
- 08:37,NIMAP,71.33
- 08:37,NISysABP,102
- 08:37,RespRate,14
- 08:37,Urine,80
- ………… For 48 hours

Data Preprocessing

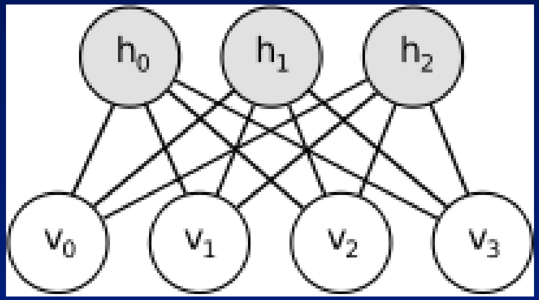
- Data like a time-series; but, not really….
  Need to extract features from raw data:
  - Mean
  - Median
  - First
  - Last
  - Min
  - Max
  - Number of values
  - Trend
  - Standard Deviation
  - Sum (urine)
  - …
- Have to deal with missing data values
- Have to transform data

A Deep Learning Approach

- Use unsupervised learning to learn a model of the data that uses multiple layers of features (features of features)

- Use these multiple feature layers to initialize a deep neural network and then discriminatively fine-tune with labeled data

The Restricted Boltzmann Machine (Binary Visible and Hidden Units)



Model parameters: $\theta = \{W, b, c\}$

The probability of joint configuration (*v*, *h*): $p(v, h; \theta) = \frac{e^{-E(v,h;\theta)}}{Z(\theta)}$

The energy function: $E(v, h; \theta) = -h^T W v - b^T v - c^T h$

The partition function: $Z(\theta) = \sum_{v^*} \sum_{h^*} e^{-E(v^*, h^*; \theta)}$

Preliminary Results: skewed data

		Observation	
		Died in-hospital (Positive)	Survivor (Negative)
Prediction	Died in-hospital (Positive)	True Positive (TP)	False Positive (FP)
	Survivor (Negative)	False Negative (FN)	True Negative (TN)

$$\text{accuracy} = \frac{TP+TN}{TP+FP+TN+FN}, \quad \text{sensitivity} = \frac{TP}{TP+FN}, \quad \text{specificity} = \frac{TN}{TN+FP},$$

$$PPV = \frac{TP}{TP+FP}, \quad NPV = \frac{TN}{TN+FN}.$$

Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	Score (%)
86.23±0.14	50.29±0.22	92.01±0.21	50.29±0.50	92.01±0.00	50.29±0.22

Score=Min (PPV, Sensitivity)

Random guessing: score = 13.86%

Other ongoing work

- ECG Analysis

  Fetal ECG, T-wave alternans, Sport ECG, Cloud software
- Scalp EEG analysis for cognitive deficits
- Intraoperative monitoring
- Critical care data analysis
- Spatiotemporal dynamics in the heart

Summary

- Physiological monitoring faces various challenges
- Integration between signal processing and machine learning may improve performance on automated decision making