

Check point: Mortality assessment in ICU with multivariate physiological time-series

4/3/12

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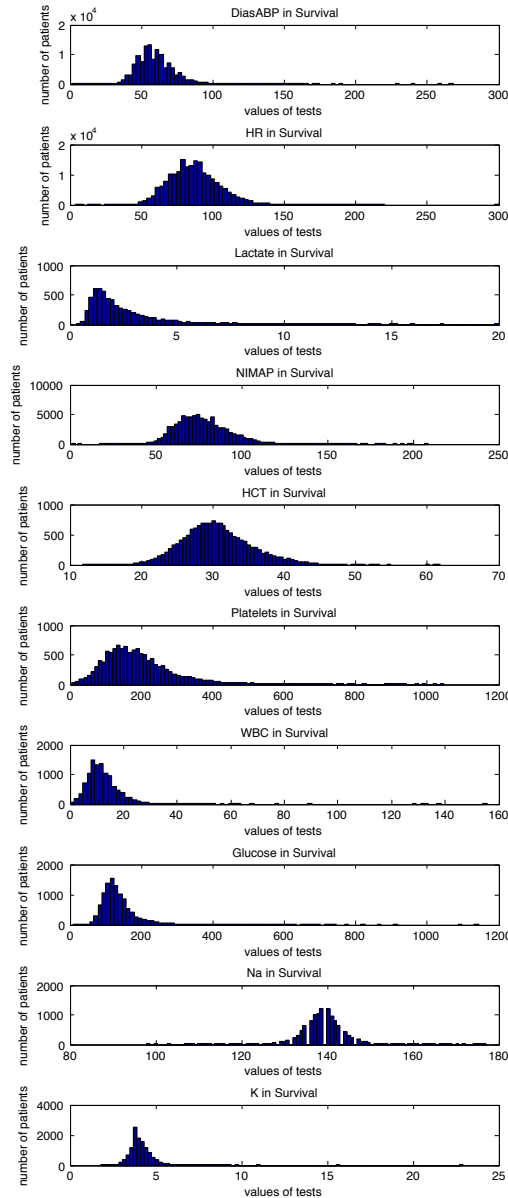
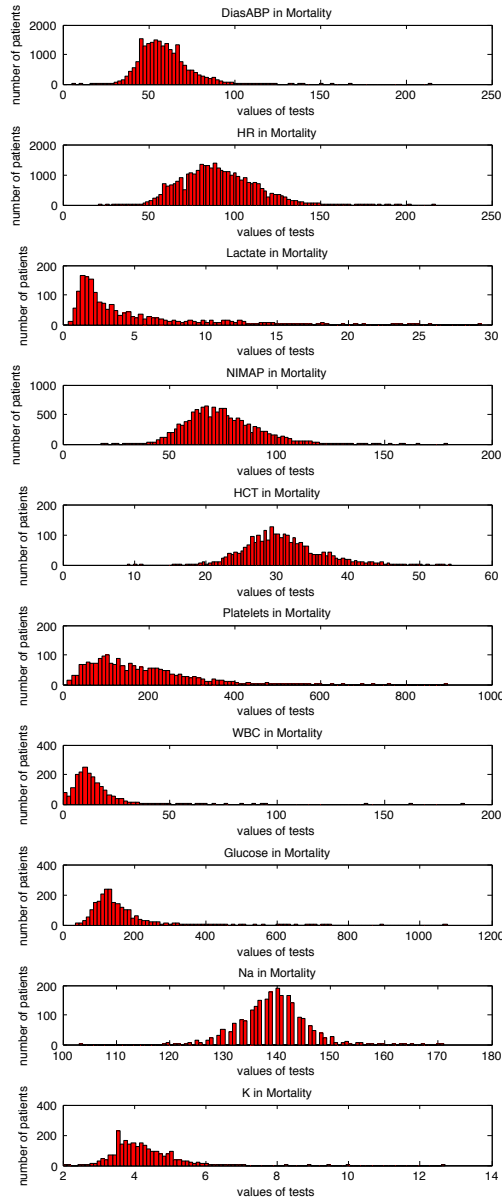
Overview

- [Albumin](#) (g/dL)
 - [ALP](#) [Alkaline phosphatase (IU/L)]
 - [ALT](#) [Alanine transaminase (IU/L)]
 - [AST](#) [Aspartate transaminase (IU/L)]
 - [Bilirubin](#) (mg/dL)
 - [BUN](#) [Blood urea nitrogen (mg/dL)]
 - [Cholesterol](#) (mg/dL)
 - [Creatinine](#) [Serum creatinine (mg/dL)]
 - [DiasABP](#) [Invasive diastolic arterial blood pressure (mmHg)]
 - [FiO2](#) [Fractional inspired O₂ (0-1)]
 - [GCS](#) [Glasgow Coma Score (3-15)]
 - [Glucose](#) [Serum glucose (mg/dL)]
 - [HCO3](#) [Serum bicarbonate (mmol/L)]
 - [HCT](#) [Hematocrit (%)]
 - [HR](#) [Heart rate (bpm)]
 - [K](#) [Serum potassium (mEq/L)]
 - [Lactate](#) (mmol/L)
 - [Mg](#) [Serum magnesium (mmol/L)]
 - [MAP](#) [Invasive mean arterial blood pressure (mmHg)]
 - [MechVent](#) [Mechanical ventilation respiration (0:false, or 1:true)]
 - [Na](#) [Serum sodium (mEq/L)]
 - [NIDiasABP](#) [Non-invasive diastolic arterial blood pressure (mmHg)]
 - [NIMAP](#) [Non-invasive mean arterial blood pressure (mmHg)]
 - [NISysABP](#) [Non-invasive systolic arterial blood pressure (mmHg)]
 - [PaCO2](#) [partial pressure of arterial CO₂ (mmHg)]
 - [PaO2](#) [Partial pressure of arterial O₂ (mmHg)]
 - [pH](#) [Arterial pH (0-14)]
 - [Platelets](#) (cells/nL)
 - [RespRate](#) [Respiration rate (bpm)]
 - [SaO2](#) [O₂ saturation in hemoglobin (%)]
 - [SysABP](#) [Invasive systolic arterial blood pressure (mmHg)]
 - [Temp](#) [Temperature (°C)]
 - [TropI](#) [Troponin-I (µg/L)]
 - [TropT](#) [Troponin-T (µg/L)]
 - [Urine](#) [Urine output (mL)]
 - [WBC](#) [White blood cell count (cells/nL)]
 - [Weight](#) (kg)
- Measurements may be recorded at regular intervals ranging from hourly to daily, or at irregular intervals. Not all time series are available in all cases.
 - In a few cases, such as blood pressure, different measurements made using two or more methods or sensors may be recorded with the same or only slightly different time-stamps.

Updated Deliverables

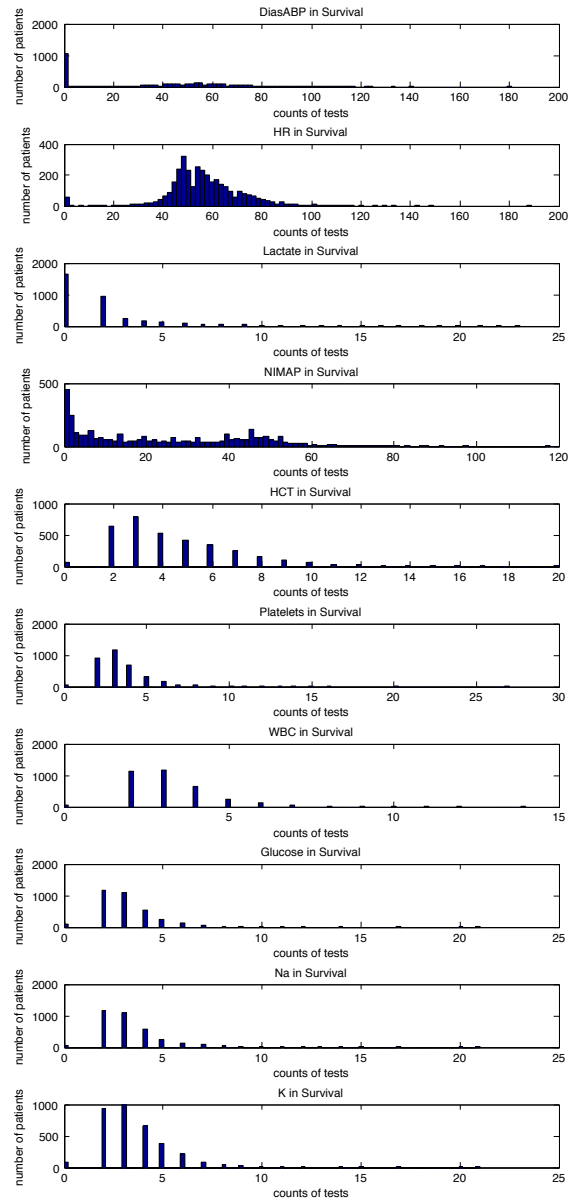
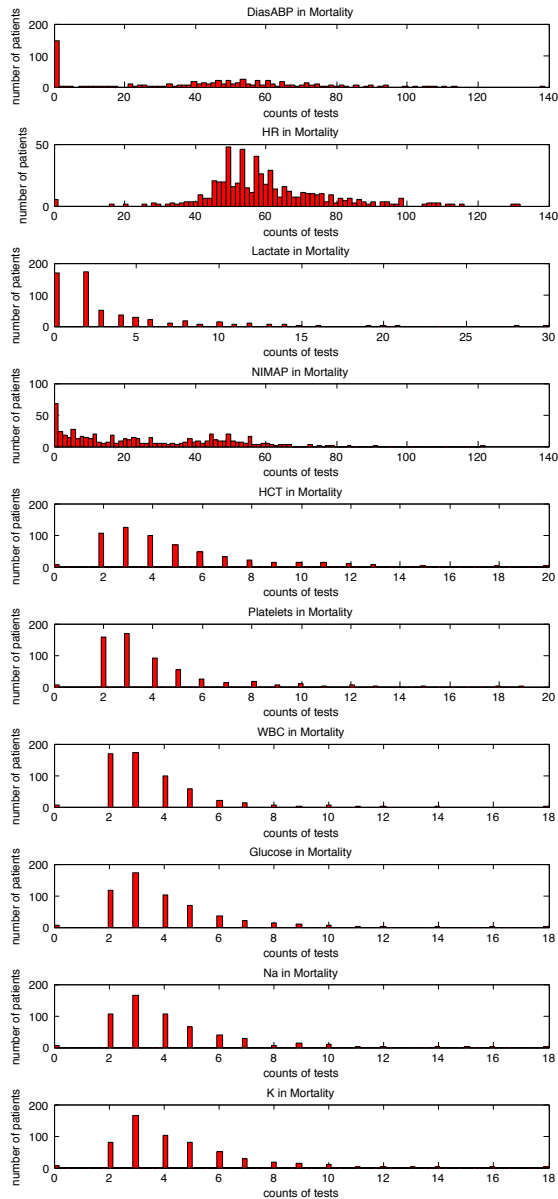
- **Minimum (Done)**
 - Logistic regression with log odds ratios as risk features
 - Performance evaluation: ROC, AUC
- **Expected**
 - **Model analysis (Done)**
 - Incorporating waiting time until the critical events (hold on)
 - Try features constructed from standard HMM, Kalman Filter (code is ready, but how to apply to this study?)
 - Incorporate dependencies between observations (e.g. autoregressive process)
- **Maximum**
 - Optimize features to achieve better classification performance
 - Documentation
 - partial AUC

Distributions of values in two classes



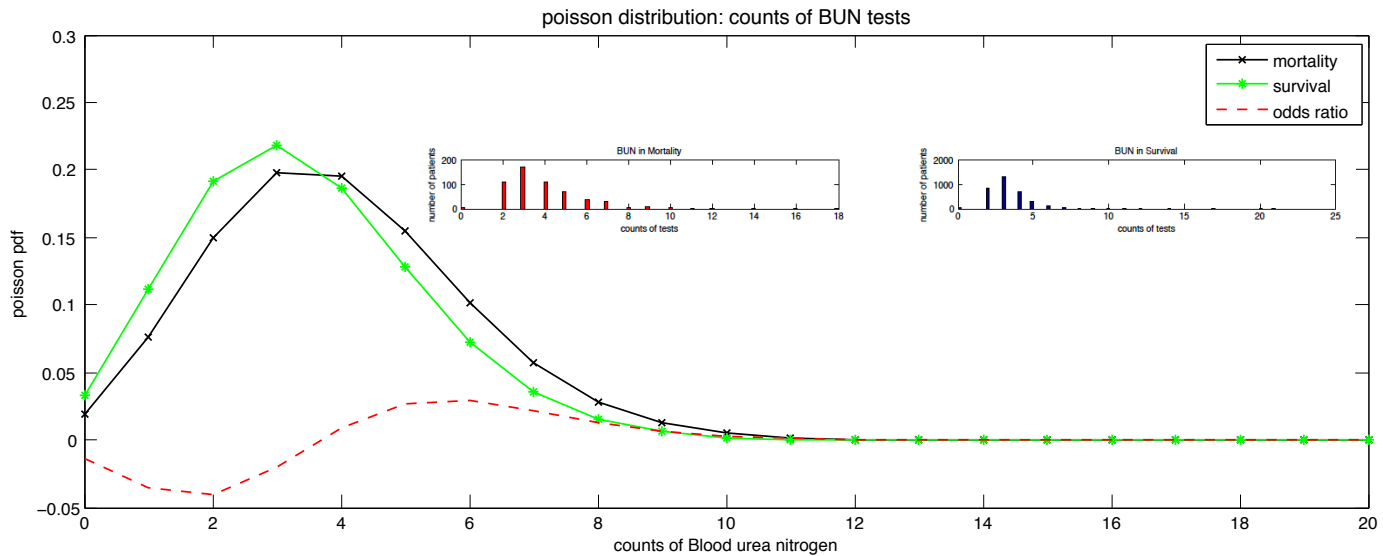
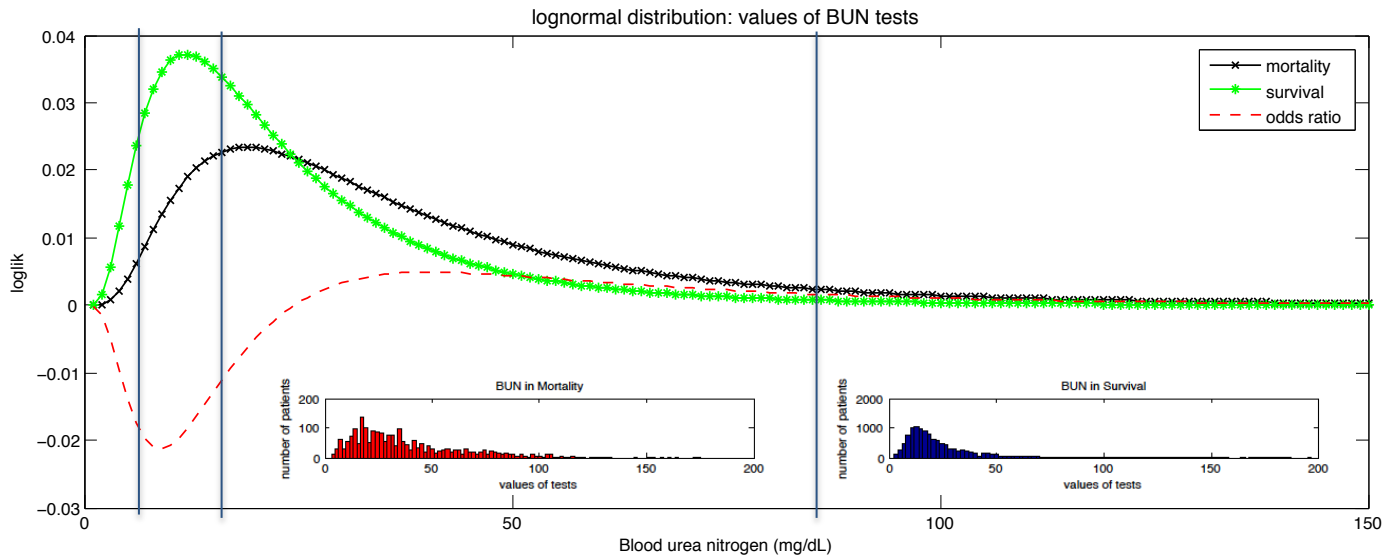
Fit with five candidate long-tailed distributions: Exponential, lognormal, gamma, normal or weibull

Distributions of counts of tests in two classes



Fit with Poisson distribution

Built up intuition



Nonlinear models of risk factors

- Mainly based on Suchi's paper.

$$f(\mathbf{v}_i) = \begin{cases} \log \frac{P(\mathbf{v}_i | HM)}{P(\mathbf{v}_i | LM)} + \log \frac{P(T | HM)}{P(T | LM)} \\ \log \frac{P(T = 0 | HM)}{P(T = 0 | LM)} \end{cases}$$

where $\log \frac{P(\mathbf{v}_i | HM)}{P(\mathbf{v}_i | LM)} = \sum_{t=1}^T \log \frac{P(v_{it} | HM)}{P(v_{it} | LM)}$

- Method in original paper:

$$f(v_i) = \begin{cases} \log \frac{P(v_i | HM, m_i = 0) \cdot P(m_i = 0 | HM)}{P(v_i | LM, m_i = 0) \cdot P(m_i = 0 | LM)} \\ \log \frac{P(m_i = 1 | HM)}{P(m_i = 1 | LM)} \end{cases}$$

Nonlinear models of risk factors

- Mainly based on Suchi's paper.

$$f(\mathbf{v}_i) = \left\{ \begin{array}{l} \log \frac{P(\mathbf{v}_i | HM)}{P(\mathbf{v}_i | LM)} + \log \frac{P(T | HM)}{P(T | LM)} \\ \log \frac{P(T = 0 | HM)}{P(T = 0 | LM)} \end{array} \right.$$

Poisson distribution

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Five candidate long-tailed distributions:
Exponential, lognormal, gamma, normal or weibull

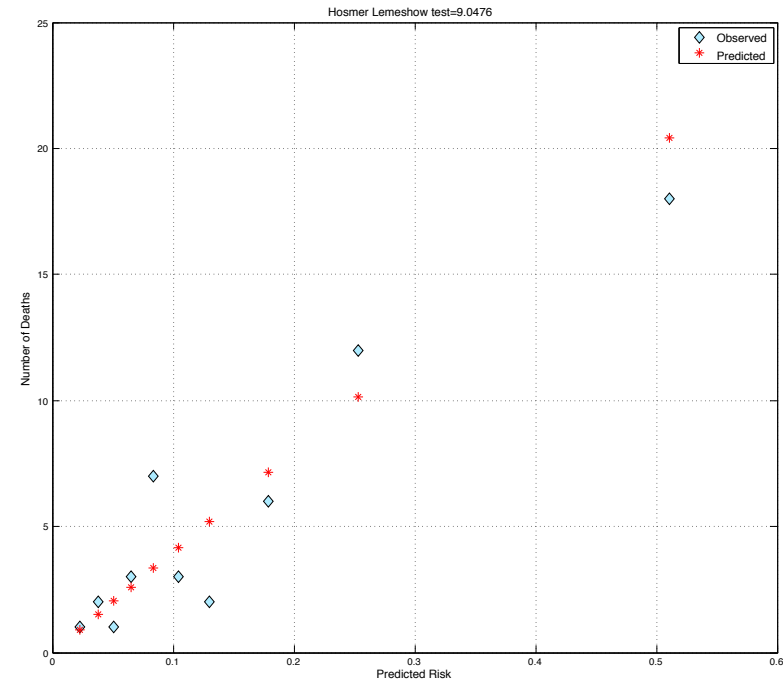
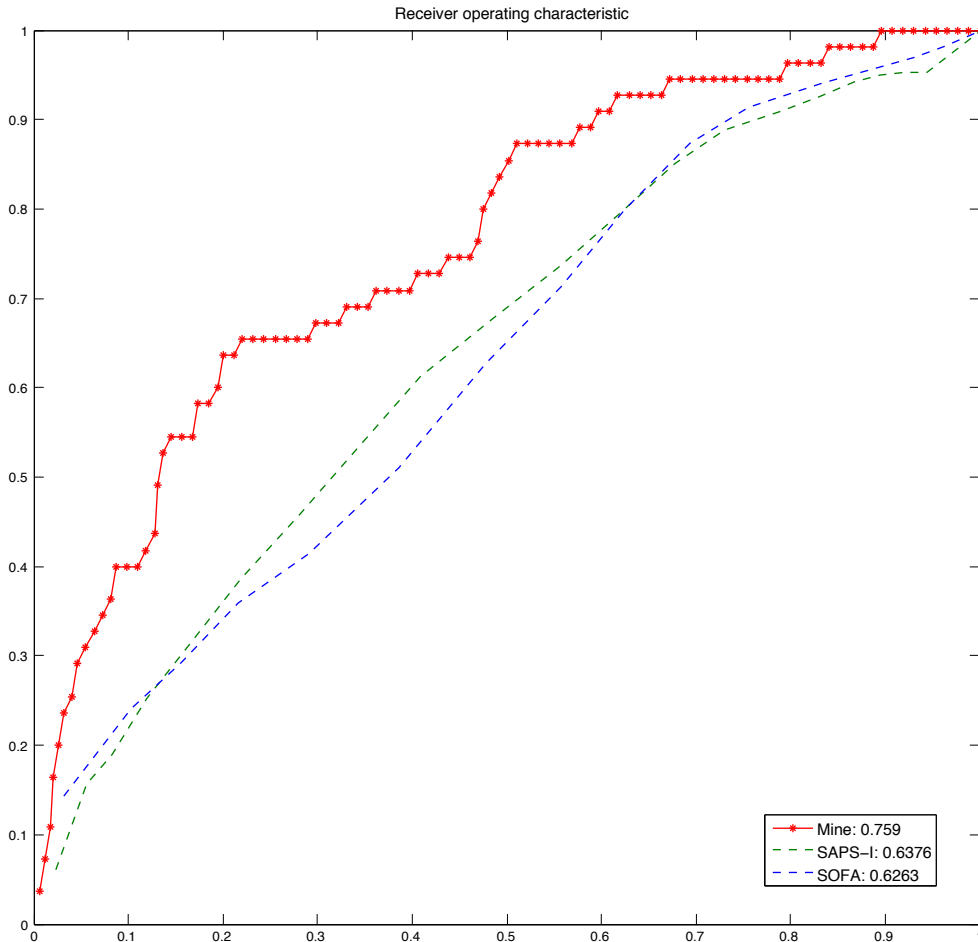
- Assuming the values of tests and the counts of tests are independent

Logistic regression

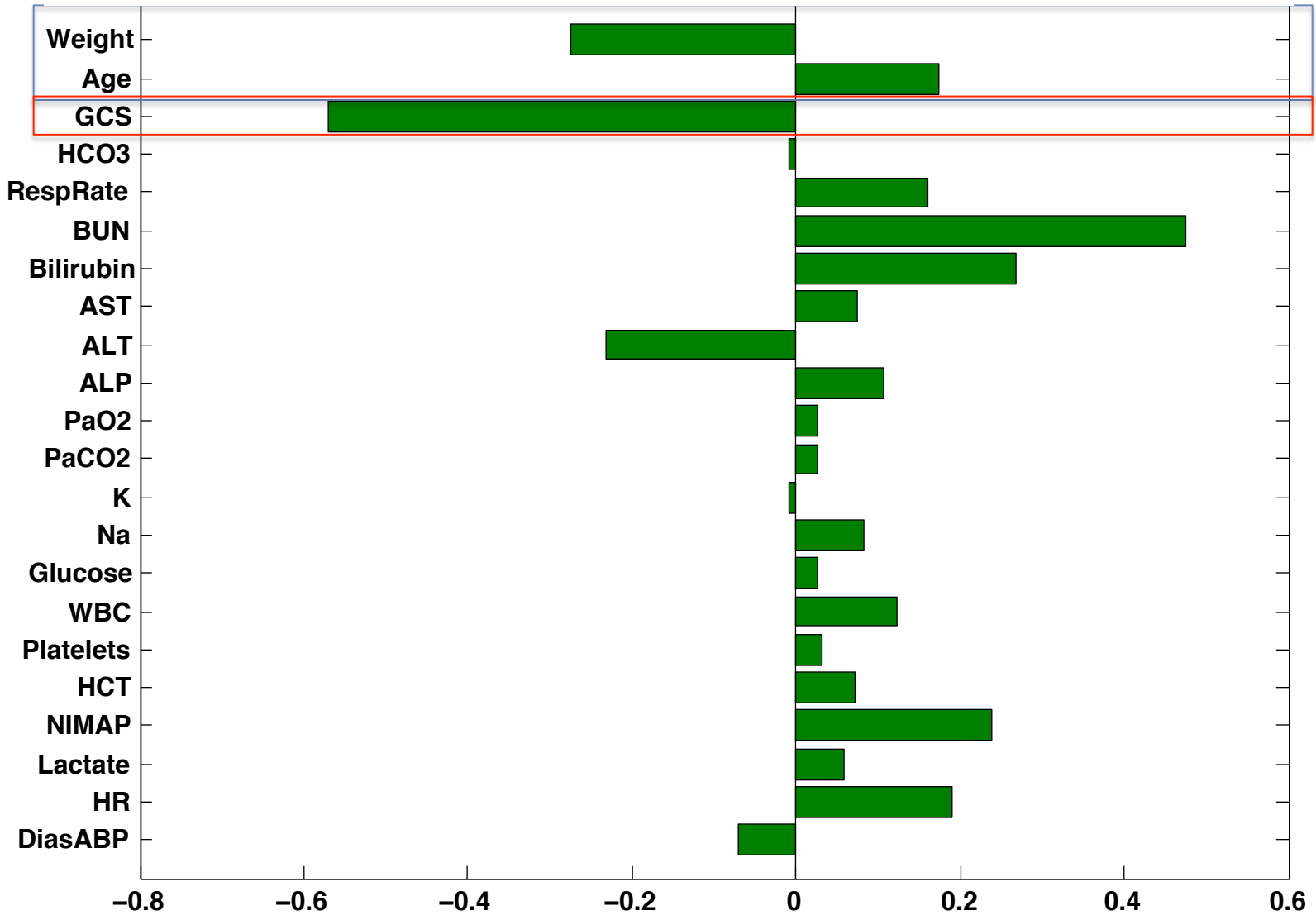
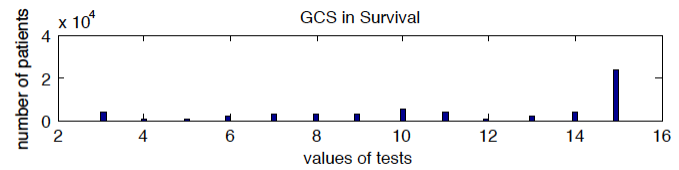
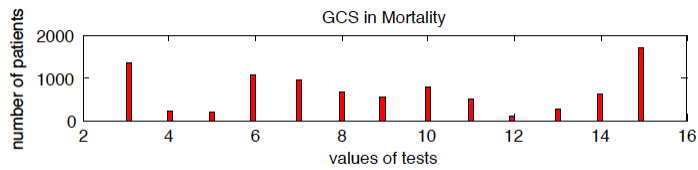
$$P(HM \mid \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_{20}) = \frac{1}{1 + \exp\left(b + \sum_{i=1}^n w_i \cdot f(\mathbf{v}_i)\right)}$$

$$\arg \max_{w, b} \sum_{j=1}^n \log P(HM \mid v_1^j, v_2^j \dots v_{20}^j) - \lambda \sum_i w_i^2$$

Classification evaluation and goodness-of-fit (10-fold CV)



Not very satisfying currently,
AUC=0.76 on held-out samples.



● Scale and center the variables, so that the weights are comparable. ●

What's next?

- **Expected**

- Try features constructed from standard HMM, Kalman Filter (Implementation is fast, but how to apply to this study?)

- Incorporate time dependencies between observations (e.g. autoregressive, but cannot be applied directly)

- **Maximum**

- Optimize features to achieve better classification performance

- Documentation

- partial AUC



Thank you !
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