International Clinical Analytics Summit

Smarter Hospitals

Safer Patients

Better Outcomes

Improving Safety, Quality, and Costs through Shared Innovative Analytics

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MITRE Baltimore

2275 Rolling Run Drive, Windsor Mill, MD 21244

Using Machine-Learning Principals to Predict the Future in Acute Care Medicine

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Systems Issues in Critical Illness

- Disease phenotype is a mixture of the process and the hosts response to the process
- No two people are alike
- Healthcare systems are inherently complex and inefficient
- Patient safety alerts often artifacts leading to alarm fatigue and failure to rescue
- Goals of therapy are often unknown and commonly change

A Modest Proposal

Make the patient the center

Personalized Medicine

- Unique personal goals and desires
  - Defining start and stopping rules
- Unique expression of disease
  - Defining threshold values for homeostasis
- Unique response to treatment
  - Physiologic and regenerative reserve

How do we identify patterns of health and disease?

Name that tune

Which instruments to listen to
(number of independent sensors)

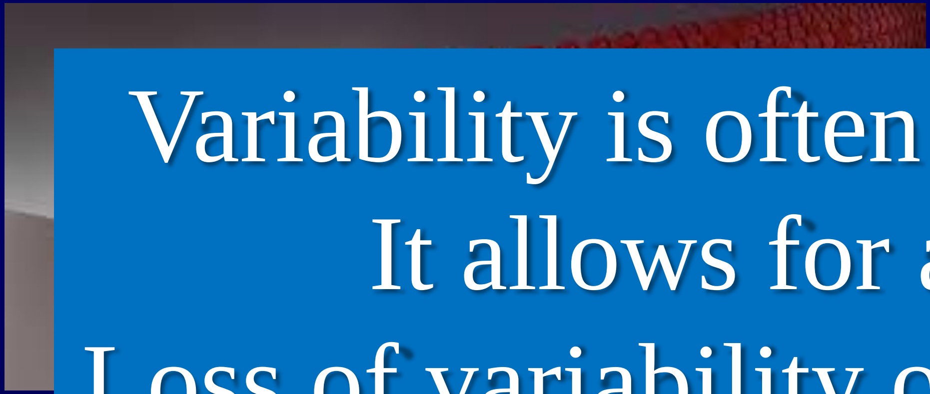
How long to listen
(lead time)

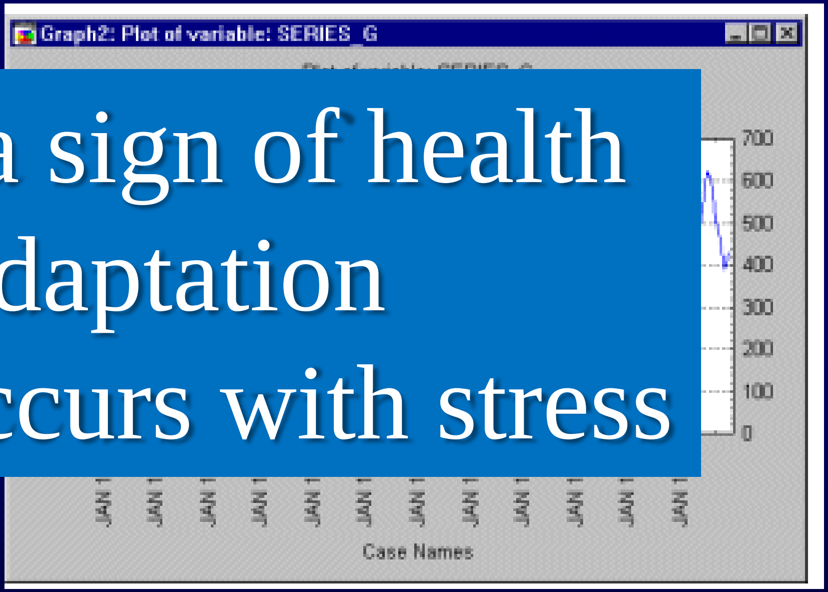
Sampling frequency
(once a second, one a year)

Sometimes it is easy to predict the future

Situational Awareness

Dynamic Changes





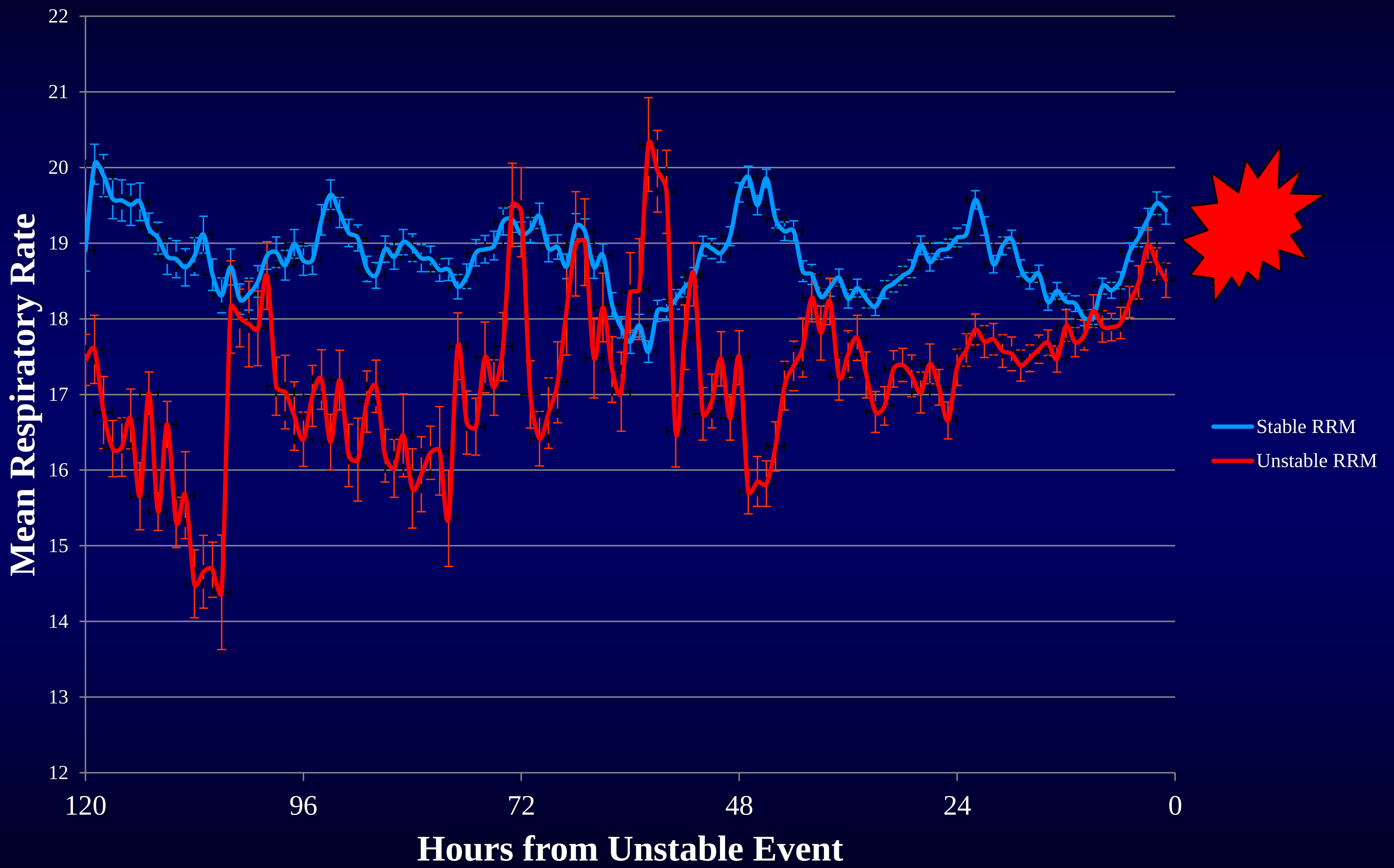
Variability is often a sign of health
It allows for adaptation
Loss of variability occurs with stress

Box & Jenkins, 1976, p. 531

Heart Rate Variability Indicies Predict Instability

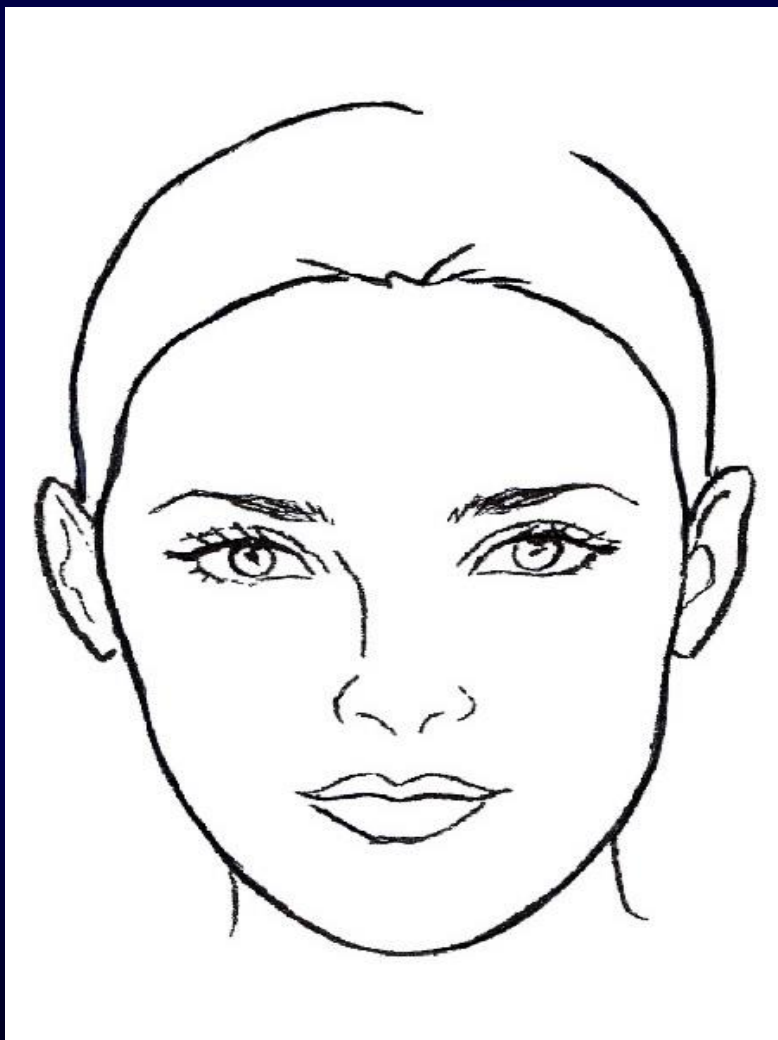
7, 2013

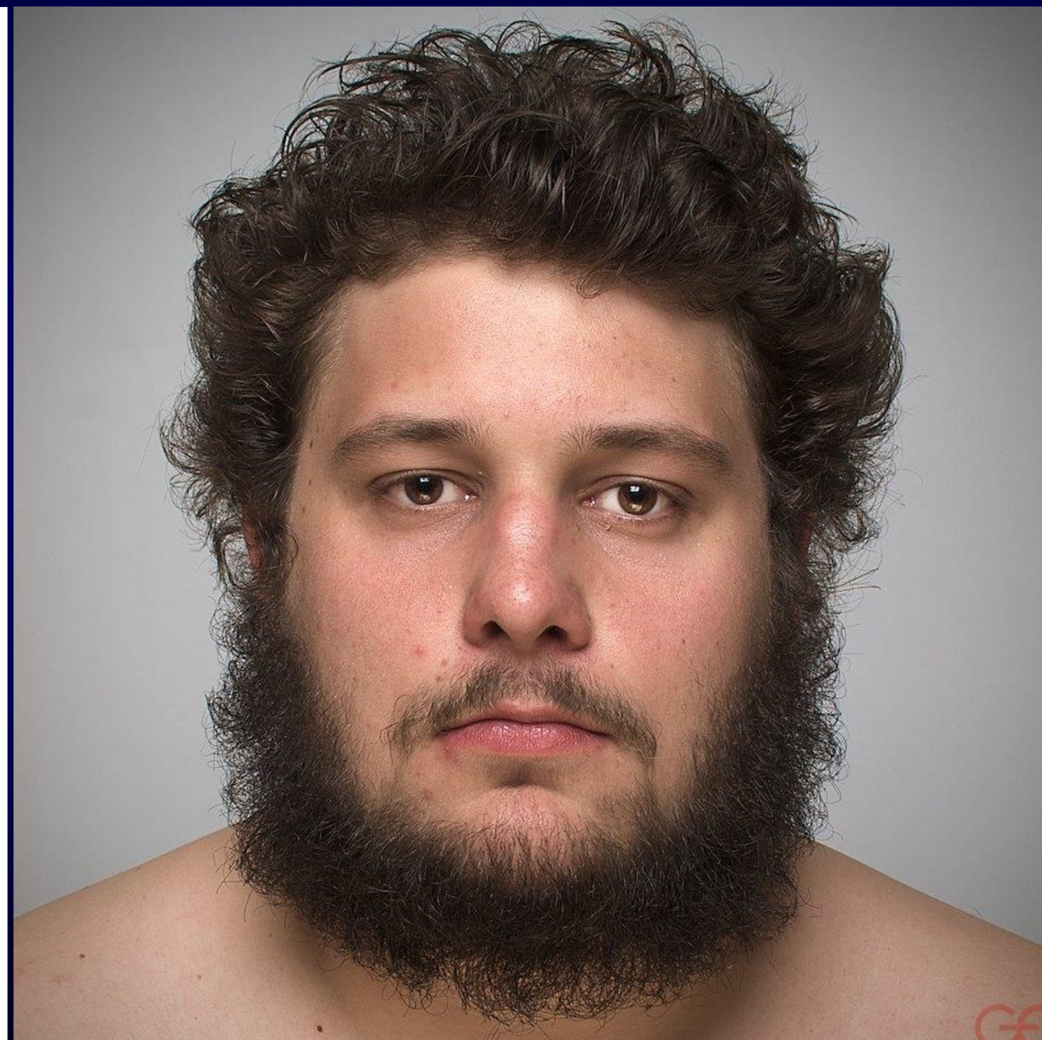
Mean Respiratory Rate Does Not



Ogundele et al. Am J Respir Crit Care Med 187: A5067, 2013

Increasing Dimensionality Improves Recognition





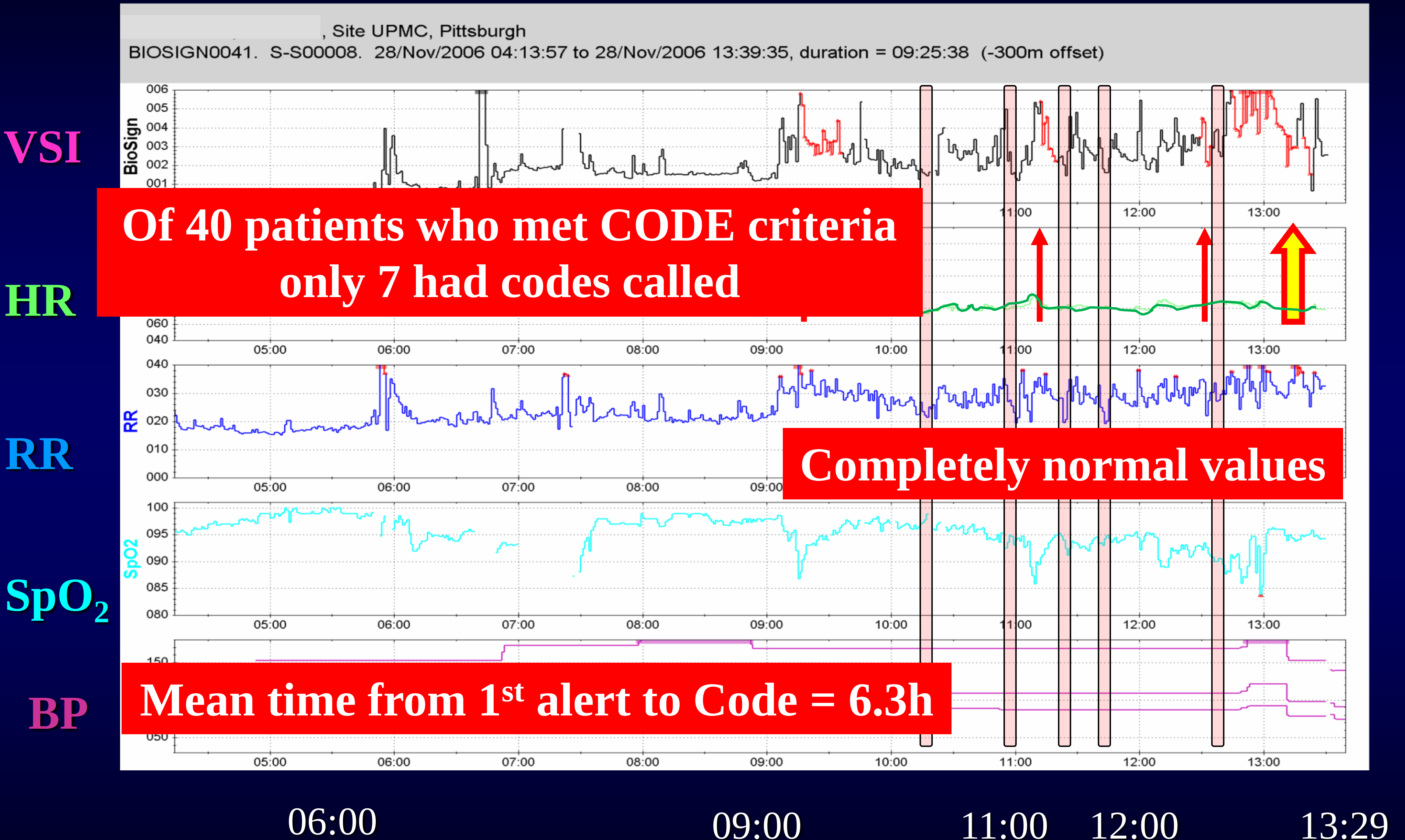
Health and Disease Defined as a Time-Space Continuum

- In a static field of single point-in-time data health and disease can be separated in stochastic fashion using **Artificial Neural Network** approach to create a probabilistic equation:

  Fused parameter VSI

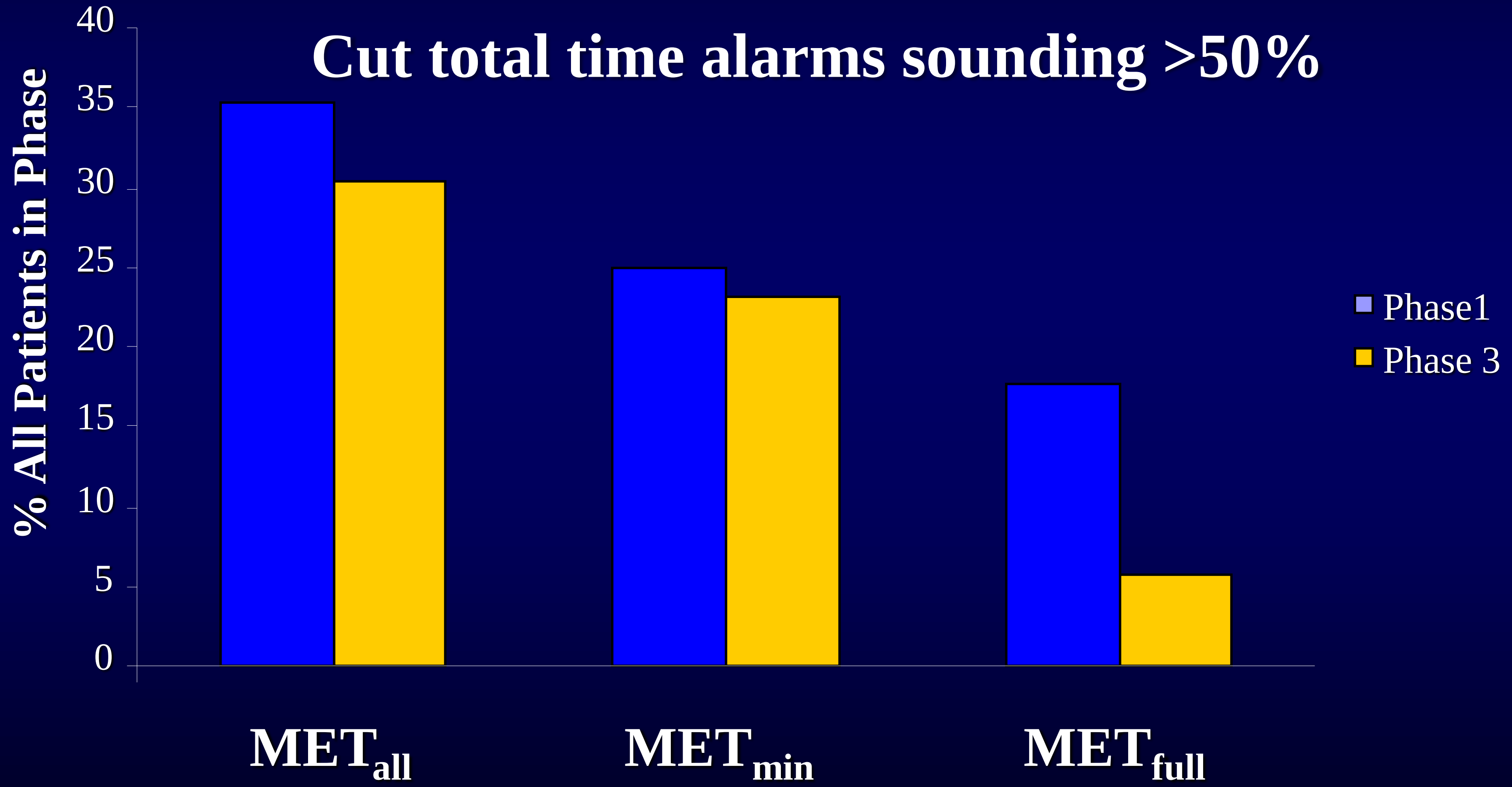
- In a dynamic field of continuously changing but inter-related variables, **Machine Learning** data-driven classification techniques: **Principal Component Analysis, Support Vector Machines, K Nearest Neighbors, Random Forests, Naïve Bayesian Classifier**

Vital Sign Trends Over 8 Hours in a SDU Patient



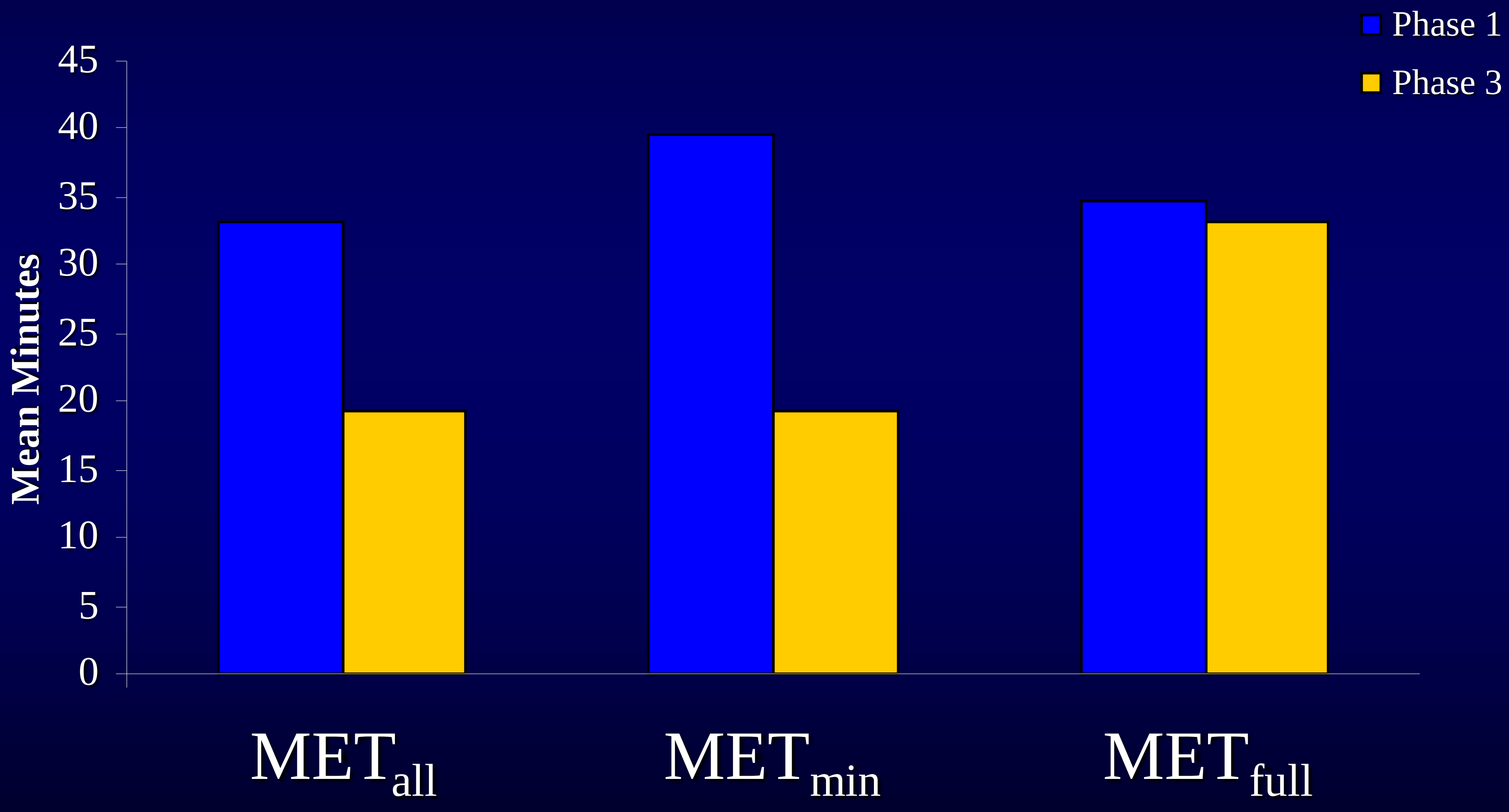
Hravnak et al. Arch Intern Med 168:1300-8, 2008

Percentage of Patients in Each Phase who Experienced a MET State



Hravnak et al. Crit Care Med 39:65-72, 2011

Duration Patients in MET State (for those who experienced it)



Hravnak et al. Crit Care Med 39:65-72, 2011

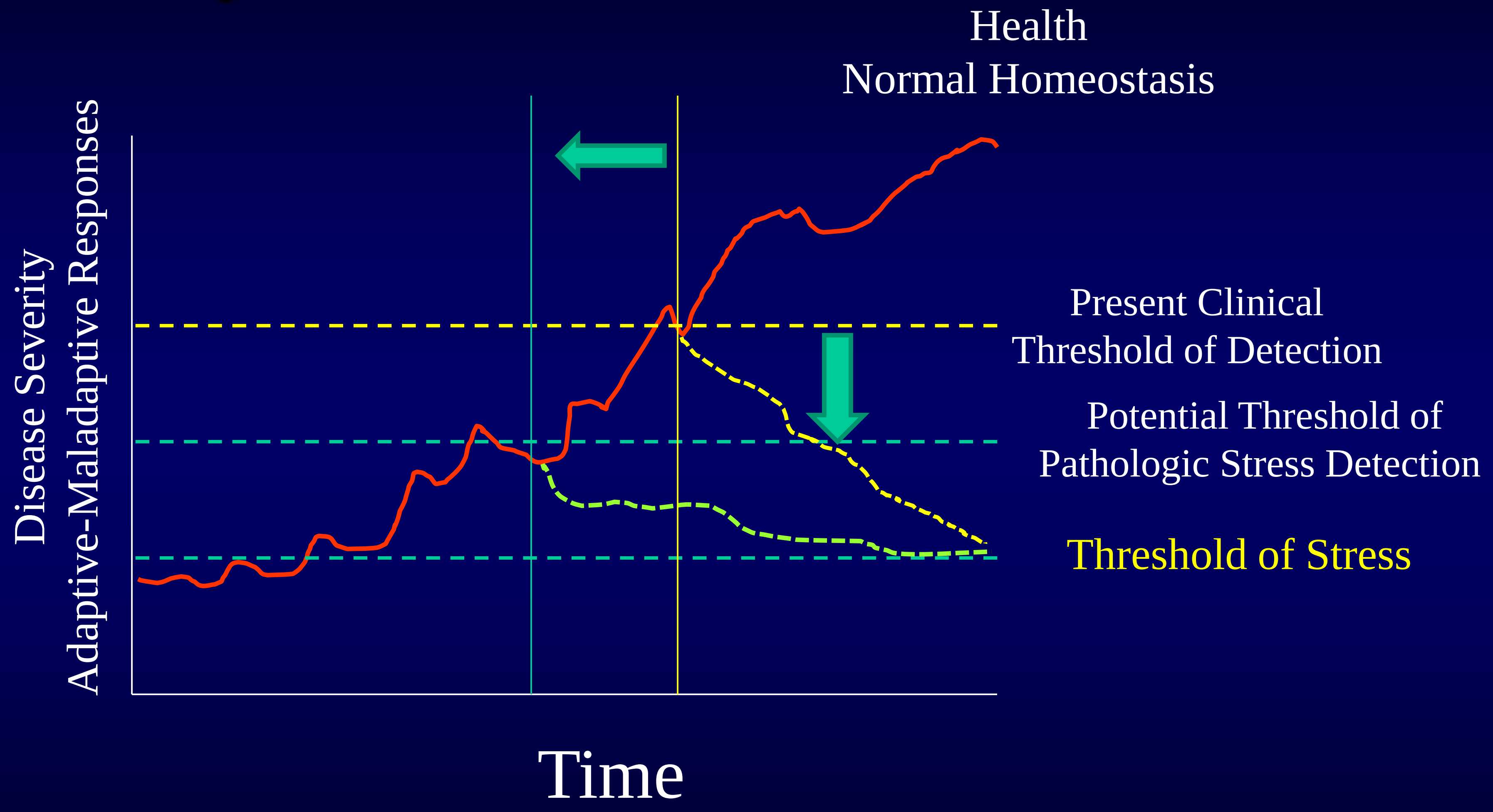
- ECRI Institute's Top Patient Safety Concern: **Health Data Integrity Failures**

Alarm Fatigue: Is the Alert Real, Real Important or Artifacts

Using Machine Learning we could discriminate real from artifact SpO_2, RR & HR alerts >90% of the time

Hravnak et al. Crit Care Med 42:42, 2015

Early Detection of Disease Model



Identifying Hemodynamically Unstable Patients

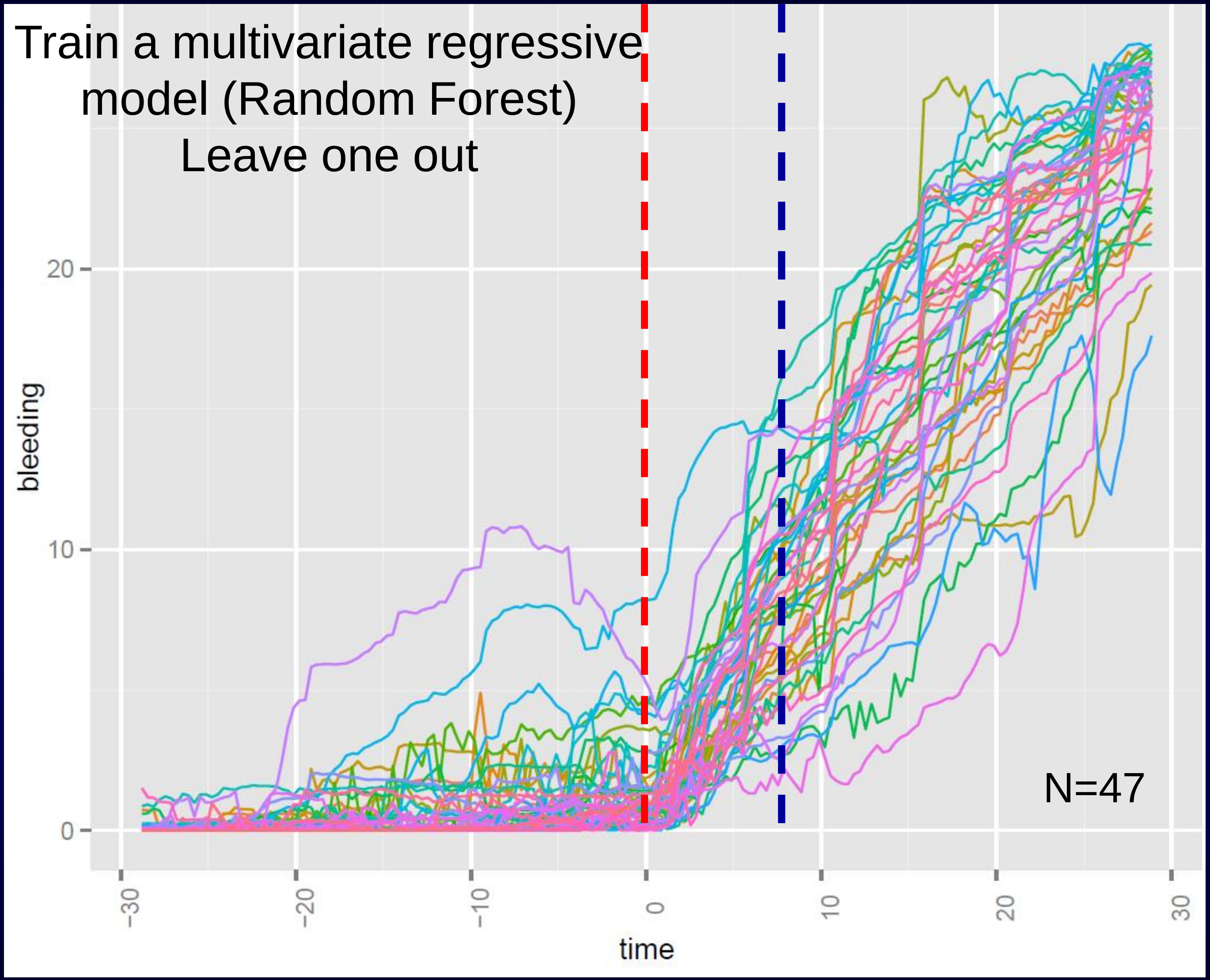
- What is the minimal data set needed to predict instability: **Monitoring parsimony**
  - Number of independent monitoring variables
  - Lead time
  - Sampling frequency
- What additional information will improve specificity
- Monitoring response to therapy and define end-points of resuscitation

Various methods to detect instability

- **Anomaly detection**
  - Trigger alerts upon significant departure from the envelope of expected variability
- **Classification**
  - Classify current state of a patient as stable or unstable, perhaps identify specific type of instability
- **Regression**
  - Estimate the magnitude of instability as a function of the extent of departure from stable behavior

Pinsky & Dubrawski. AJRCCM 190: 606-10, 2014

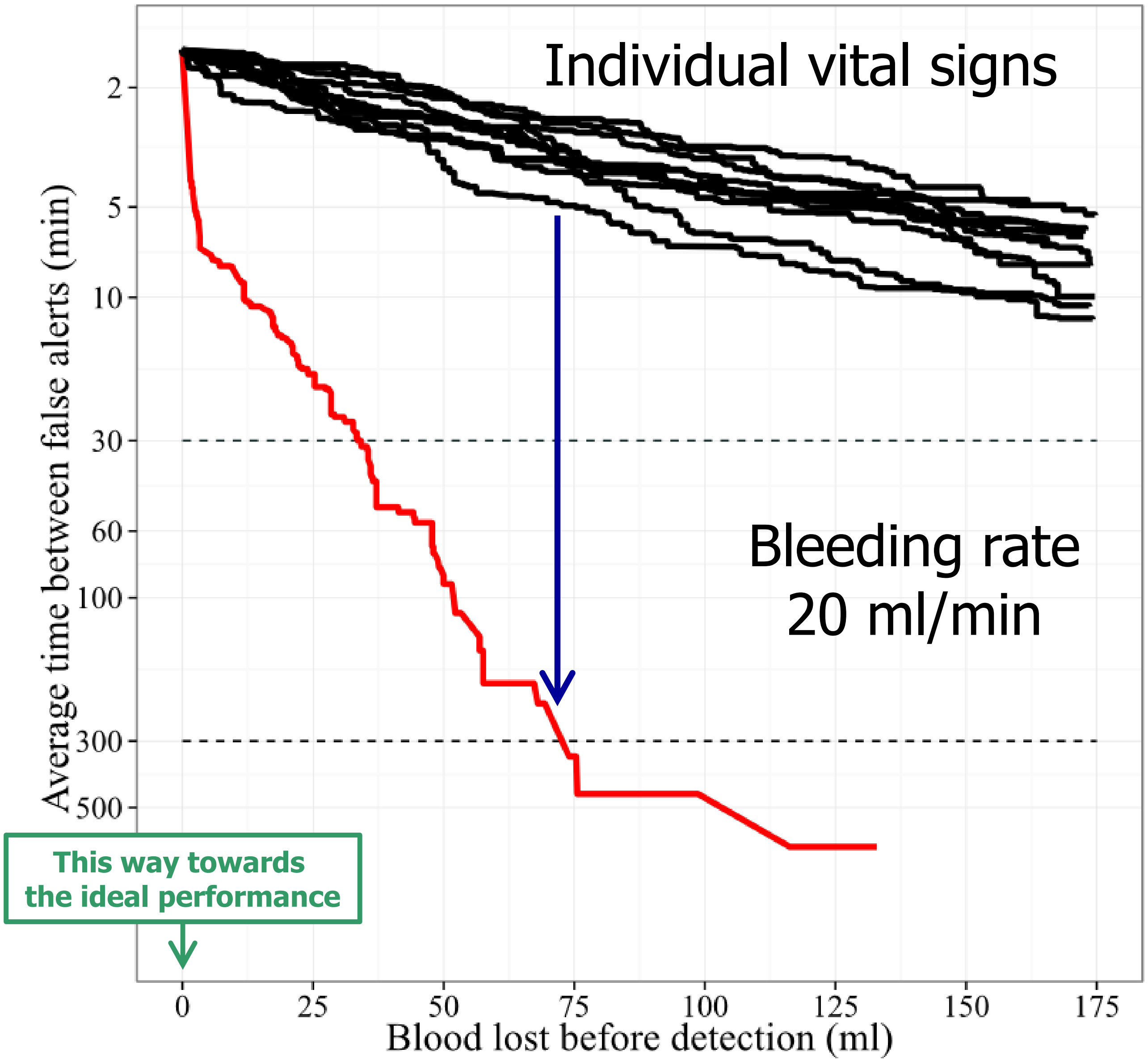
Identify Onset of Bleeding Earlier



Guillame-Bert et al. Intensive Care Med 40: S287, 2014

Balancing False Alert Rates with early Bleeding detection

Complete multivariate model vs. univariate detectors



Detect 3′ 40″
False alerts 5 min

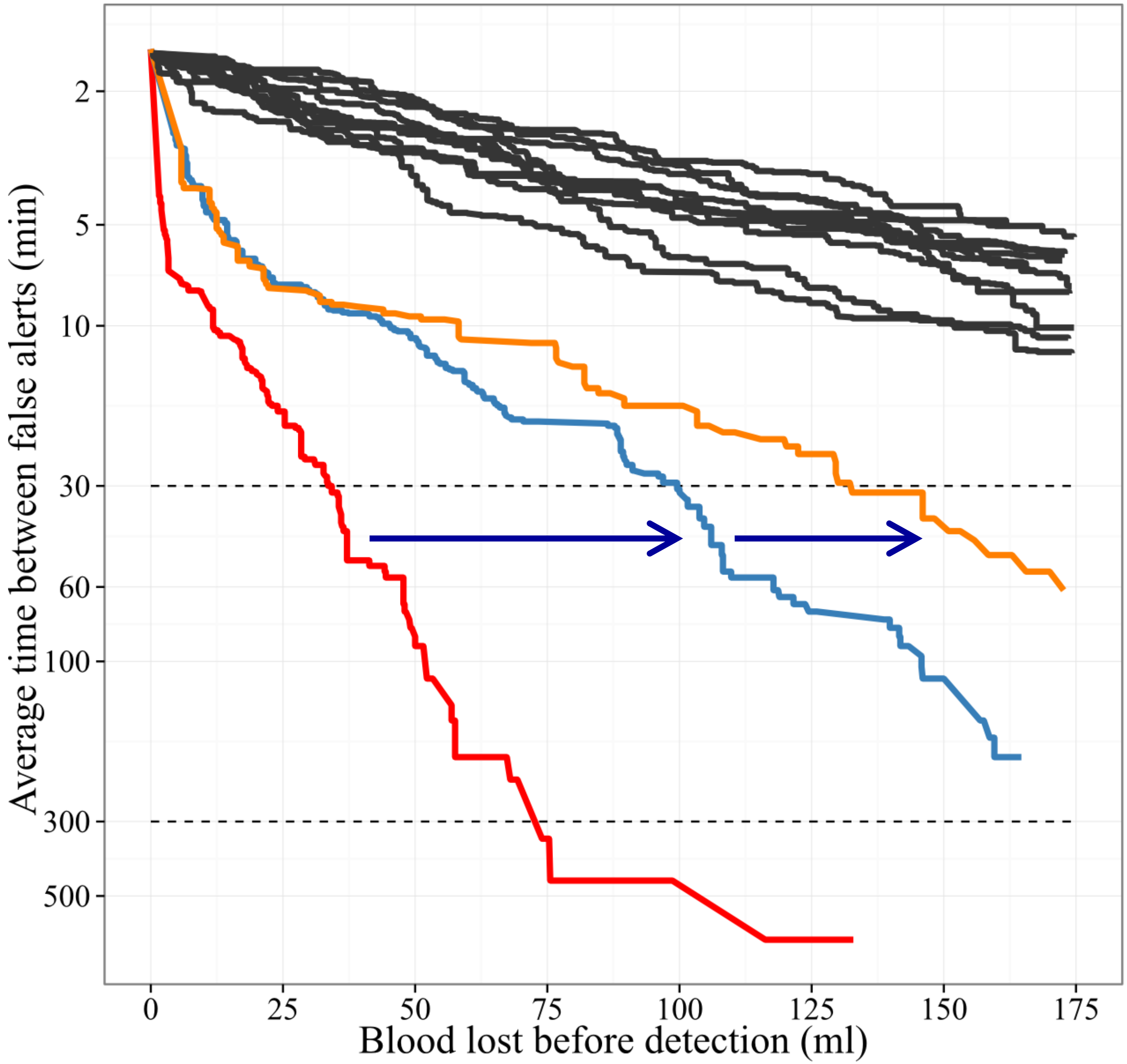
Detect 3′ 40″
False alerts 6 hr

Holder et al. J Crit Care doi.org/10.1016/j.jcrc2013.07.028, 2013

Auton Lab

Density of Data Affects Bleeding Detection

Multivariate models for various groups of measurements



Univariate models

Intermittent

[Sampled every 5 minutes]

Beat−to−beat

[Sampled every 20 seconds]

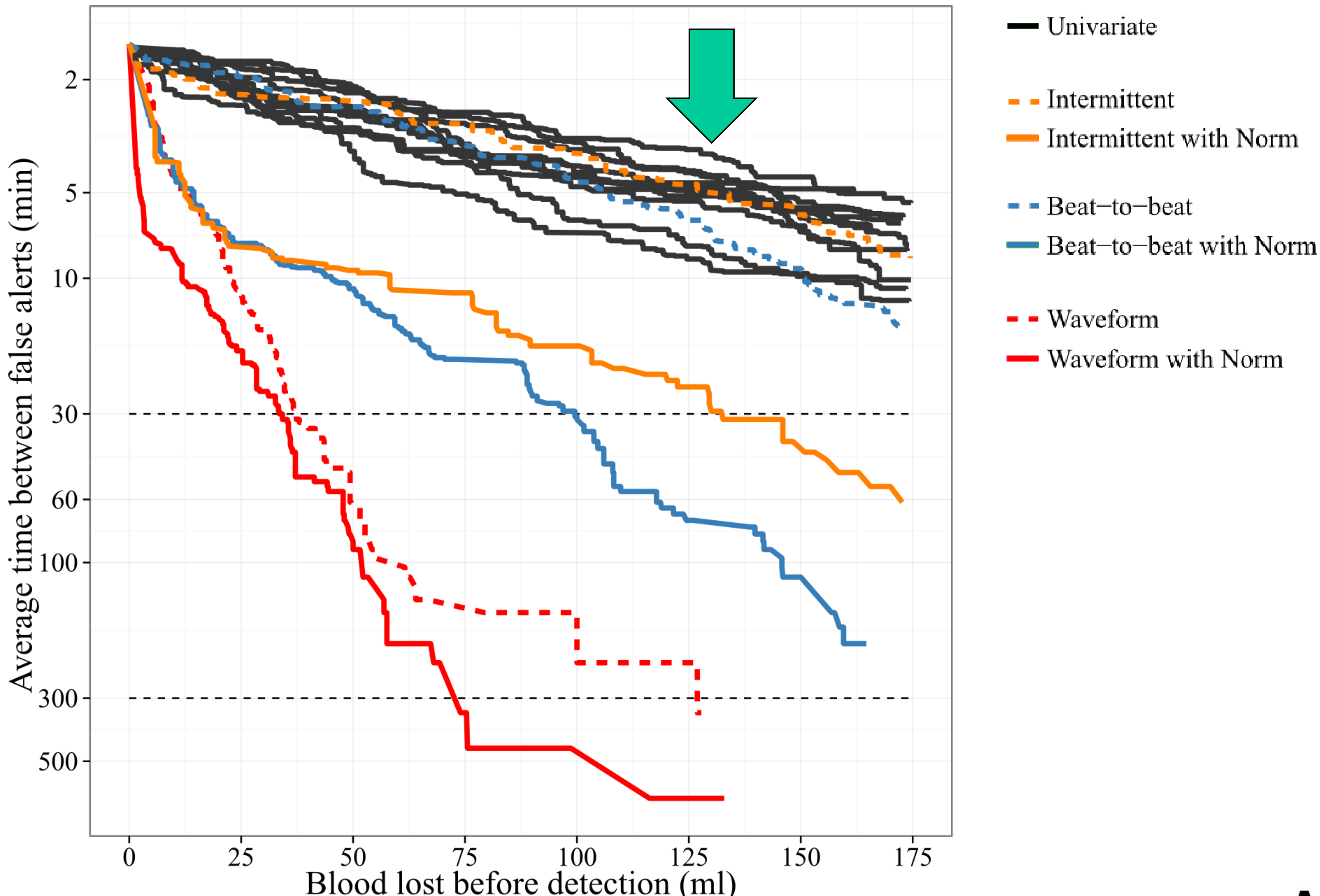
Waveform

[CVP + Arterial Pressure, FFT features, CVP, normalized using personalized baselines]

Holder et al. J Crit Care doi.org/10.1016/j.jcrc2013.07.028, 2013

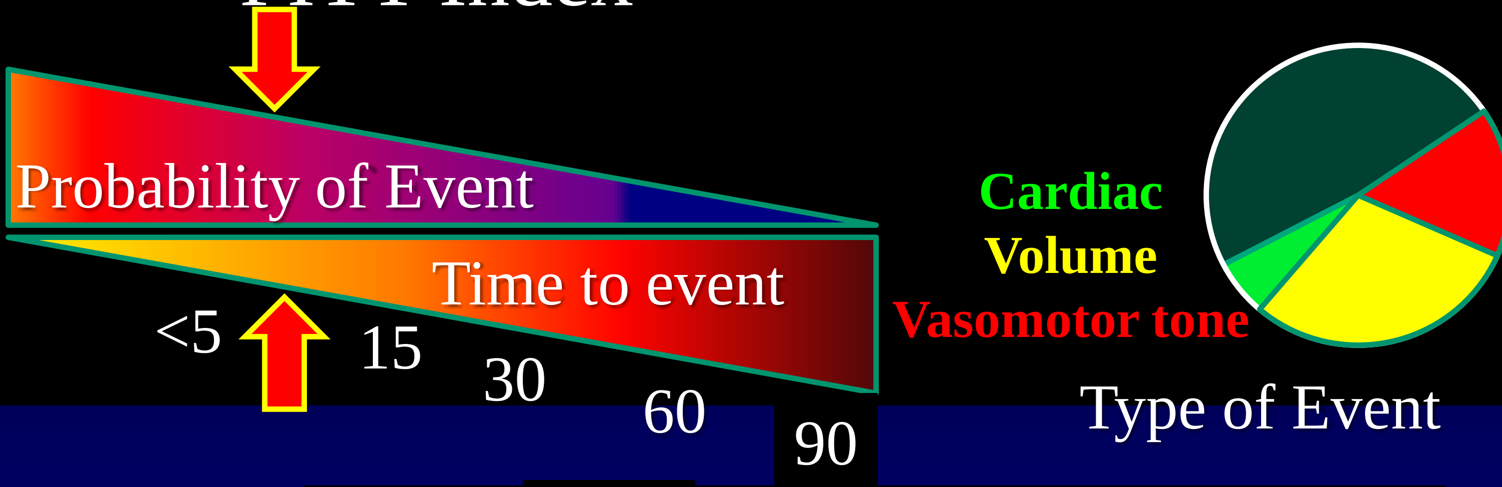
Knowing Baseline Important if Data Sparse

Personalized baselines

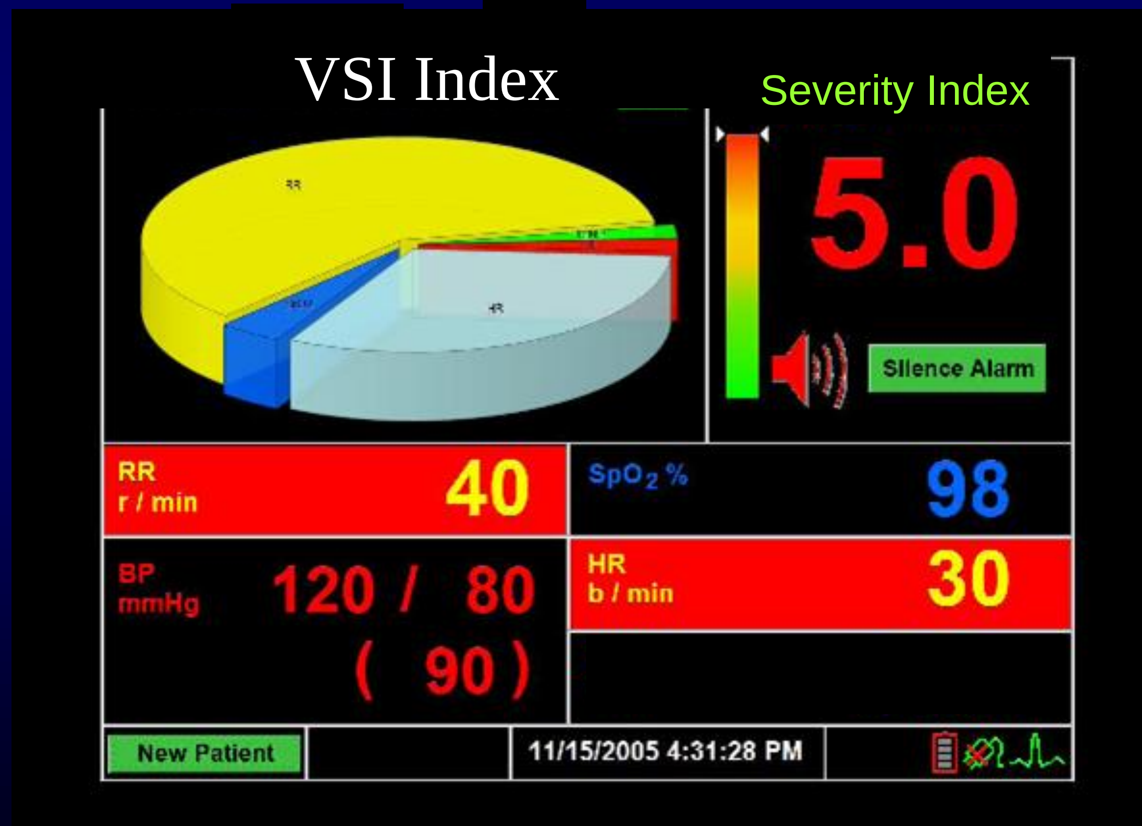


Holder et al. J Crit Care doi.org/10.1016/j.jcrc2013.07.028, 2013

PITT Index



Predicting
Instability
Time and
Treatment



Future of Monitoring

- **Monitor the monitors**
- **Treat the patients**
- Robust artifact detection increases value of alerts and reduces alarm fatigue
- Using fused parameters to define stability
- Scaling of monitoring devices and sampling frequency will vary as patient conditions change

Thank You

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