

Improving risk prediction in heart failure using multivariate analysis techniques from high energy physics

Eric D. Adler MD¹, Adriaan A. Voors MD², Liviu Klein MD, MS⁸, Fima Macheret MD⁷, Oscar O. Braun MD³, Marcus A. Urey MD¹, Wenhong Zhu PhD⁶, Izhiah Sama PhD², Matevz Tadel PhD⁵, [Claudio Campagnari PhD⁴](#), Barry Greenberg MD¹, Avi Yagil PhD^{1,5}

¹ Department of Medicine, Division of Cardiology, UC San Diego, USA

² University of Groningen, University Medical Center Groningen, Groningen, The Netherlands

³ Departments of Clinical Sciences, Cardiology, Lund University and Skåne University Hospital, Lund, Sweden

⁴ Physics Department, UC Santa Barbara, USA

⁵ Physics Department, UC San Diego, USA

⁶ Altman Clinical and Translational Research Institute (ACTRI), UC San Diego, USA

⁷ Department of Medicine, Divisions of Hospital Medicine and Biomedical Informatics, UC San Diego, USA

⁸ Department of Medicine, Division of Cardiology, UC San Francisco, USA

How did this start

Conversations between exp high energy physicists and clinical cardiologists:

- Attempts to predict heart failure (HF) mortality using clinical variables or risk scores have **not been very successful**
- Fails in one or more of the following ways:
 - limited predictive power (poor AUC, typically < 0.7)
 - loss of accuracy when applied to other cohorts or populations
 - dependence on variables that are subjective or not readily available

**There are many many risk-scores on the market
to the point that “risk-score fatigue” is prevalent**

Today's buzzword...Machine Learning (ML)

- In HEP have been using (simple) ML for > 20 years to categorize “events” or “objects” as “signal” vs. “background”
 - Event = final state of decay or of interaction
 - Object = electrons, photons, bottom quarks, etc
- Can our experience be brought to bear?
 - Signal/Background → Early death/Long term Survival

Primary Objective

Define a risk score aiming to avoid common pitfalls by:

- Using strict data collection and cleanup methodology that ensures maintaining the correlations that define the physical state of the system (patient) within a relatively limited period of time
- Having precise definitions of outcomes.
- Avoiding imputation by requiring all covariates used in the creation of the model to be present.
- Limiting the number of inputs to a small number of widely available covariates that are checked routinely in HF patients.
- Capturing the multi-dimensional correlations between the covariates and the outcomes.

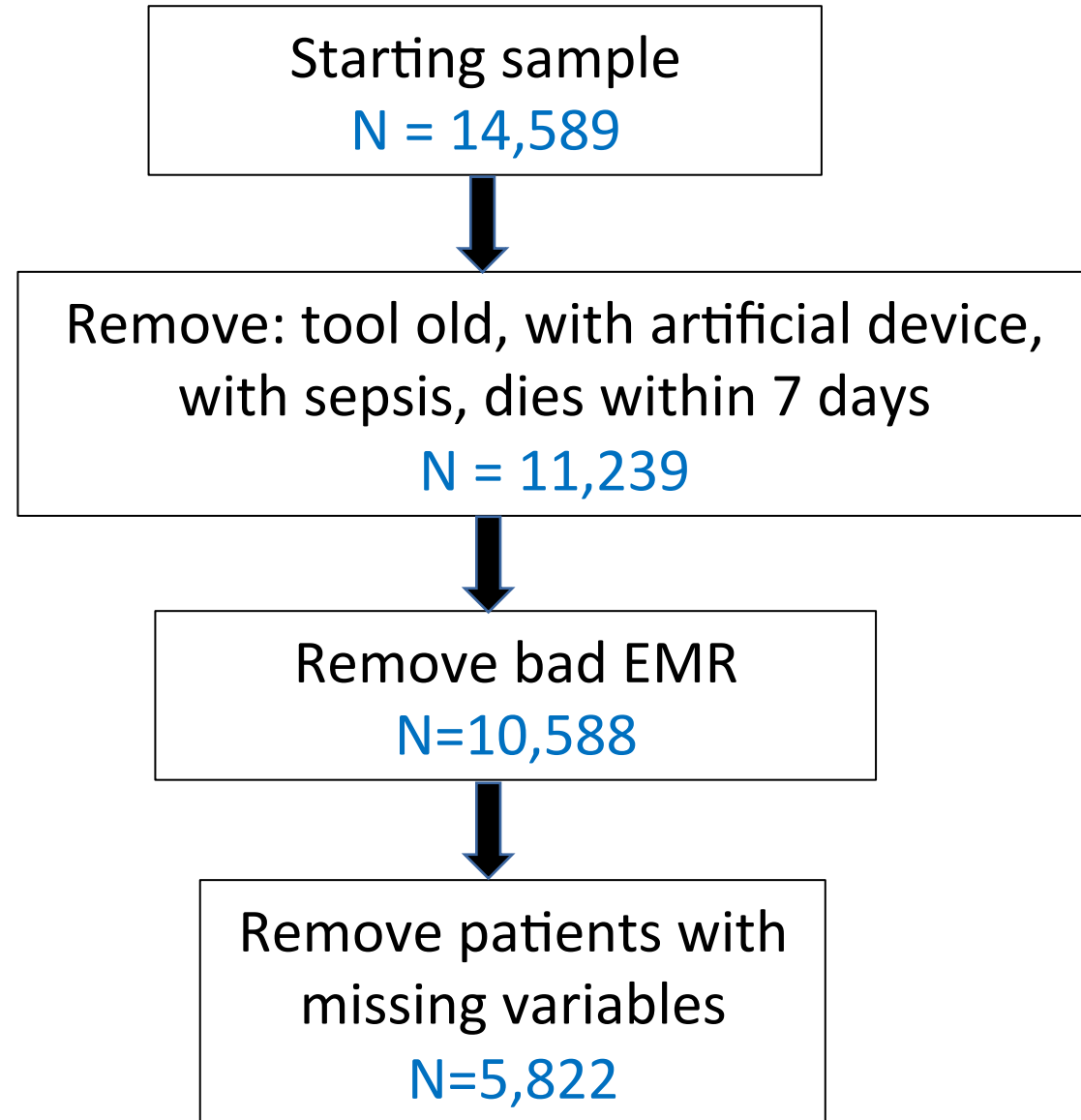
Methods and Study definition

- Retrospectively extracted de-identified EMR of patients in the UCSD health system with 1st recorded diagnosis of Heart Failure.
- Used an iterative process to select a minimal, most common, and discriminating set of variables (only 8)
 - HEP software, TMVA in CERN Root package
- For patient to be included in the analysis **all** variables needed to be present using data collected over a narrow time window (<7 days)
- Excluded patients: over 80, with an ICD, with indication of Sepsis
 - Minimize dilution of outcomes

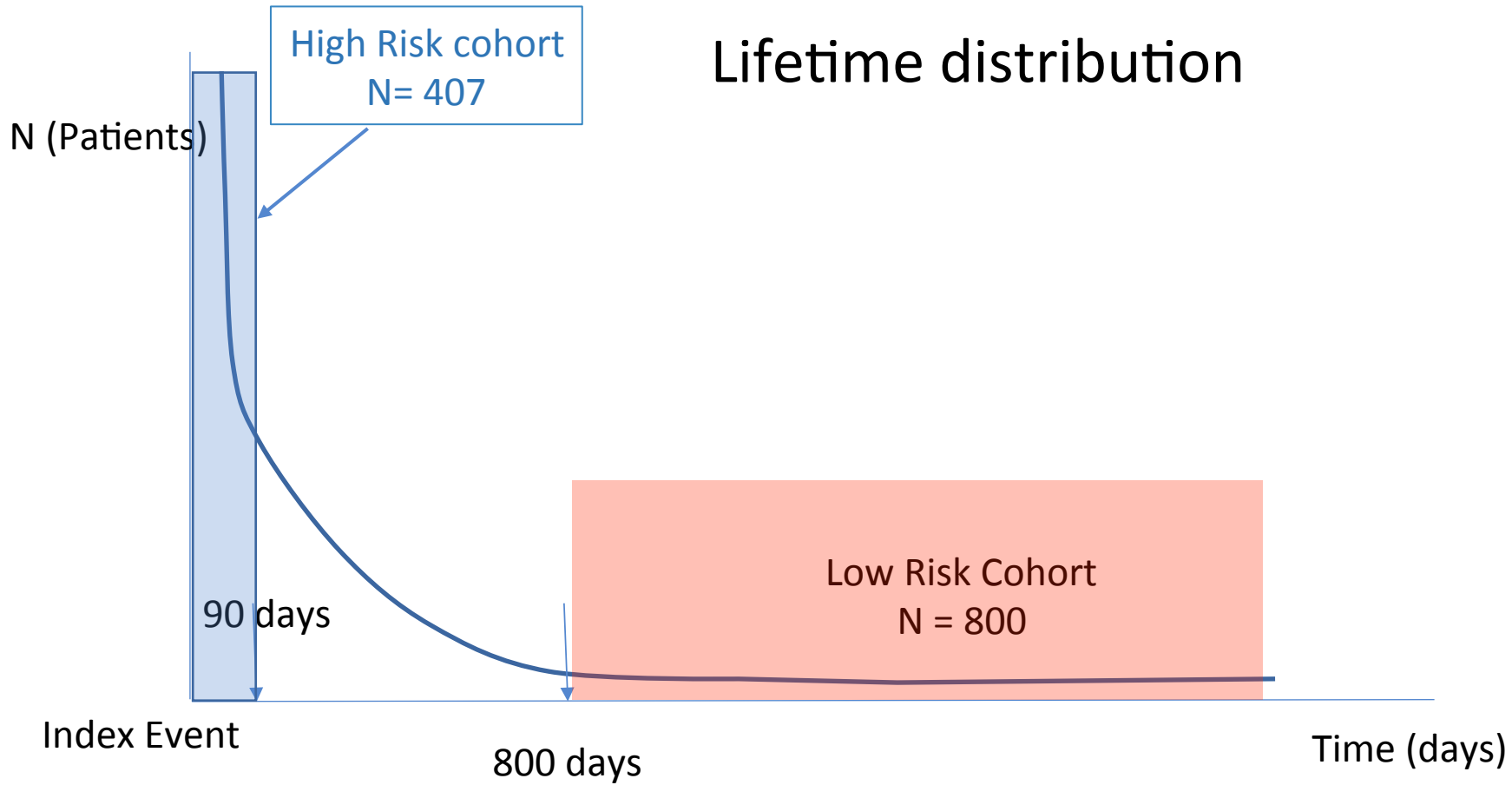
Statistics

Comments:

- Low statistics compared to typical HEP problem
- Dirty data, big loss from missing variables
 - Systematics?
- Extracting data from the EMR was a bit of an “adventure”



Cartoon of samples definition



Variables Used:

Diastolic blood pressure
Creatinine
Blood Urea Nitrogen
Hemoglobin
White blood cell count
Platelets
Albumin
Red Blood Cell Distribution Width

Input Variables

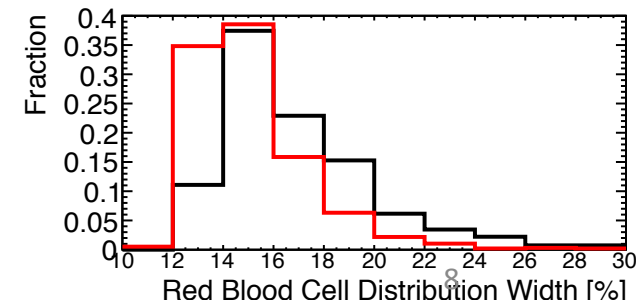
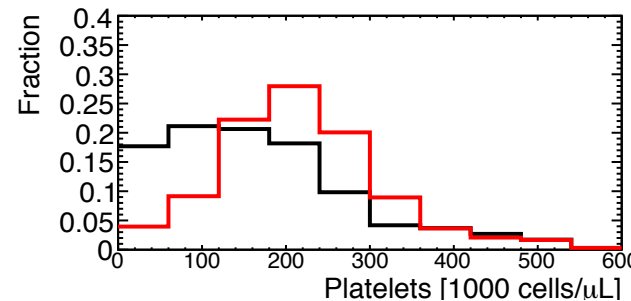
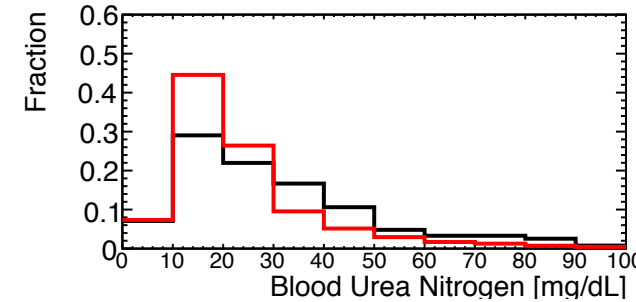
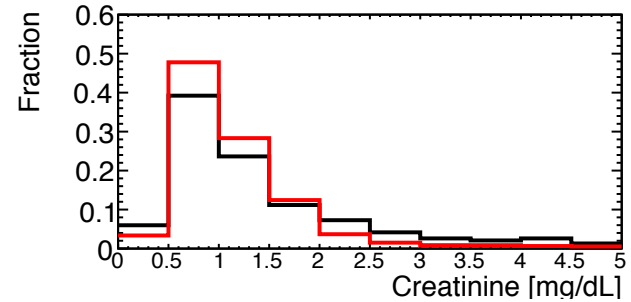
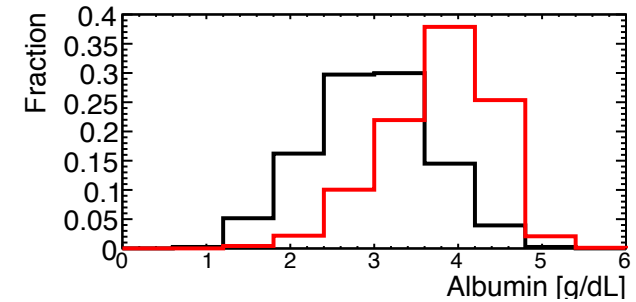
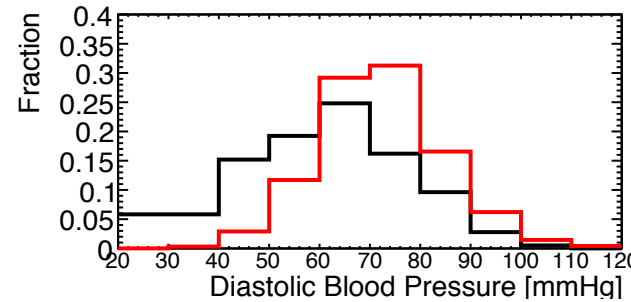
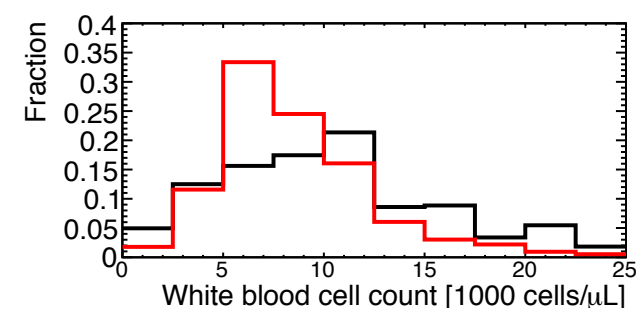
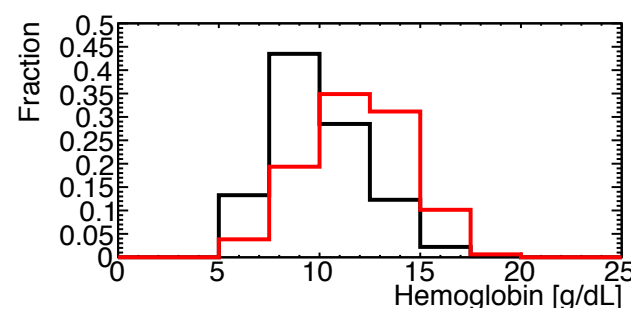
Red - Low risk cohort

Black - High risk cohort

Important: No "silver bullet":

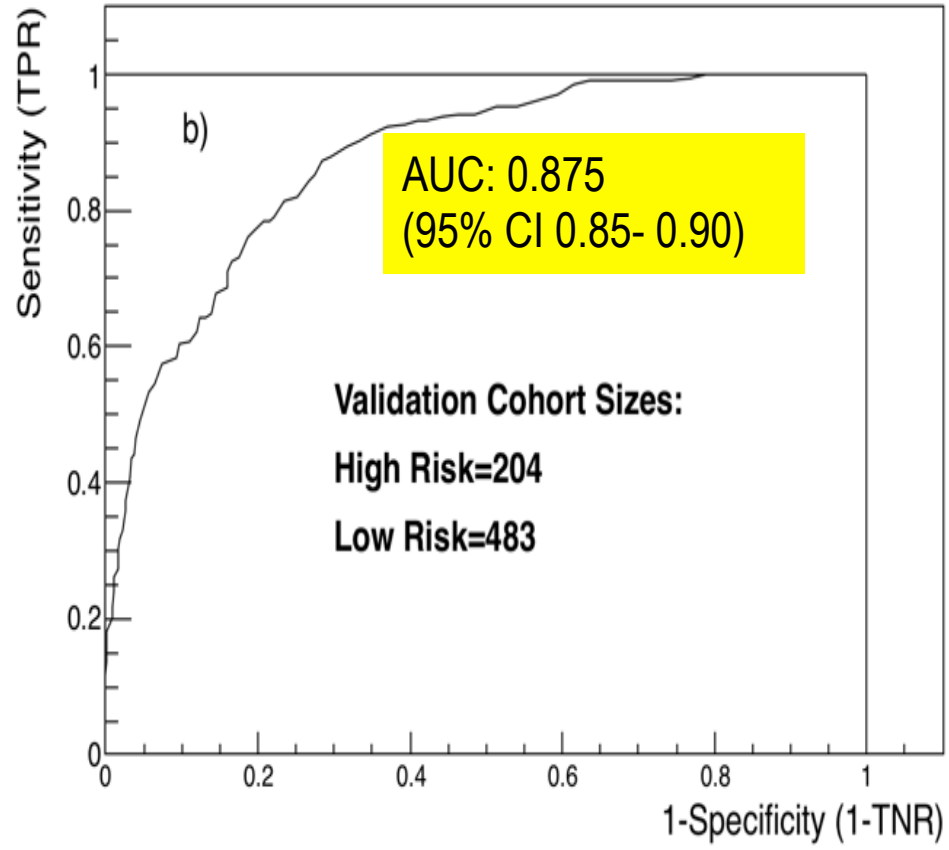
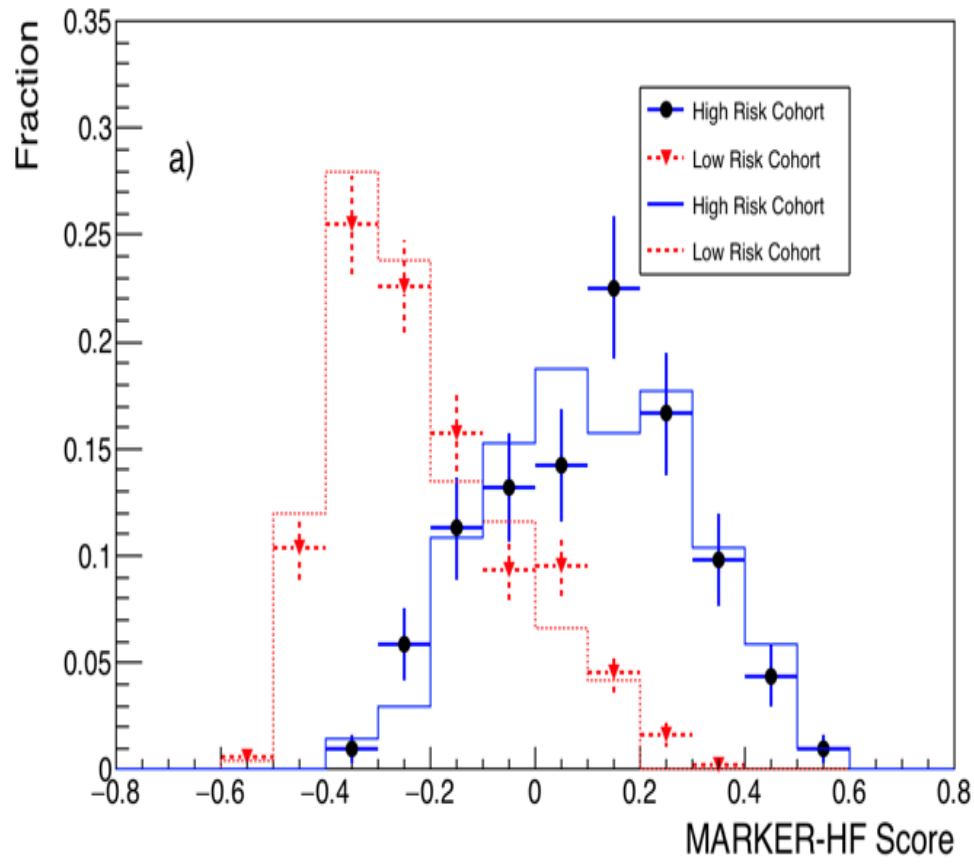
- No single discriminating variable.
- Each shows some separation.
- But poor AUC, individually.

Key is the combination and correlations between the whole set



MARKER-HF Training and Performance

A Boosted Decision Tree algorithm was used (200 trees, maximum depth of 2) to derive a model and relate variables to the known outcome using the training subset of the sample only. *Similar results obtained with ANN)



TPR = True Positive Rate
TNR = True Negative Rate

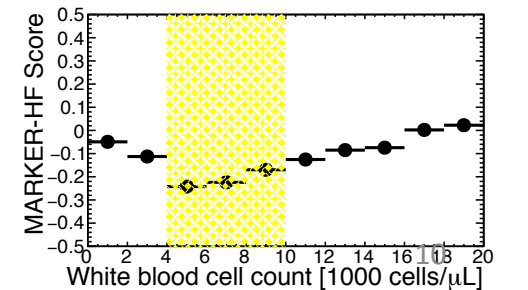
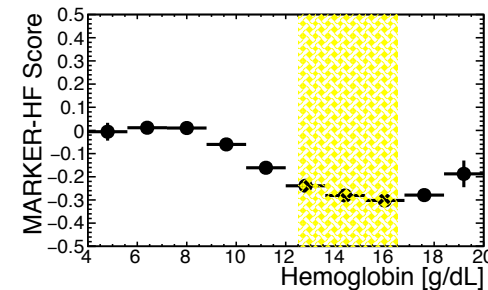
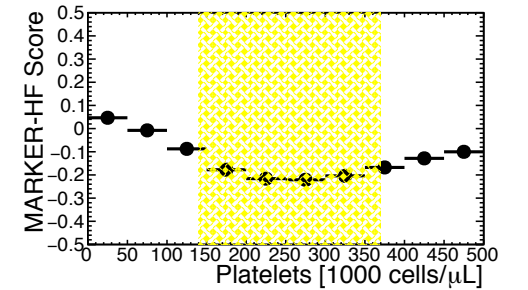
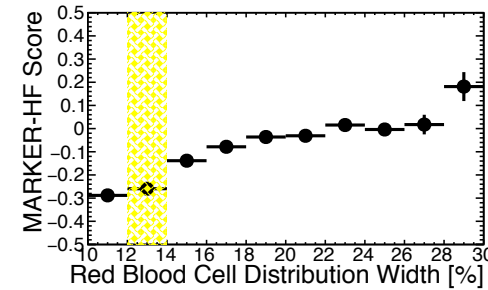
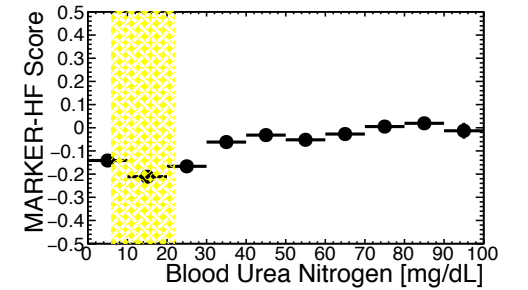
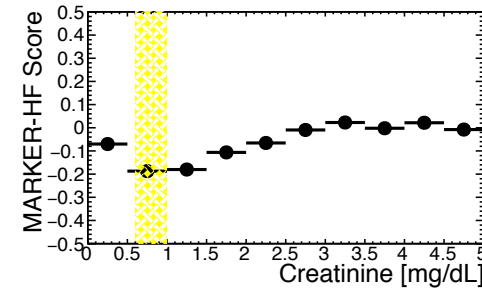
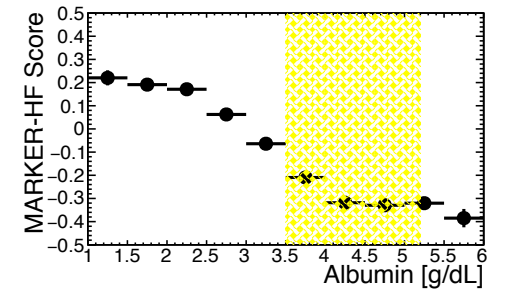
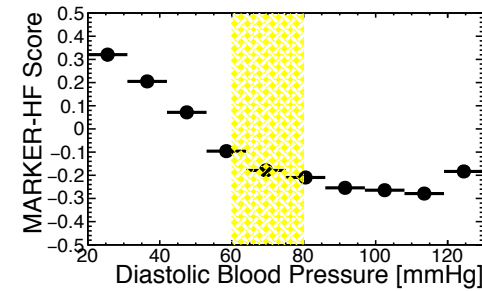
Does it make sense clinically?

Does a high score corresponds to abnormal values of the measured inputs??

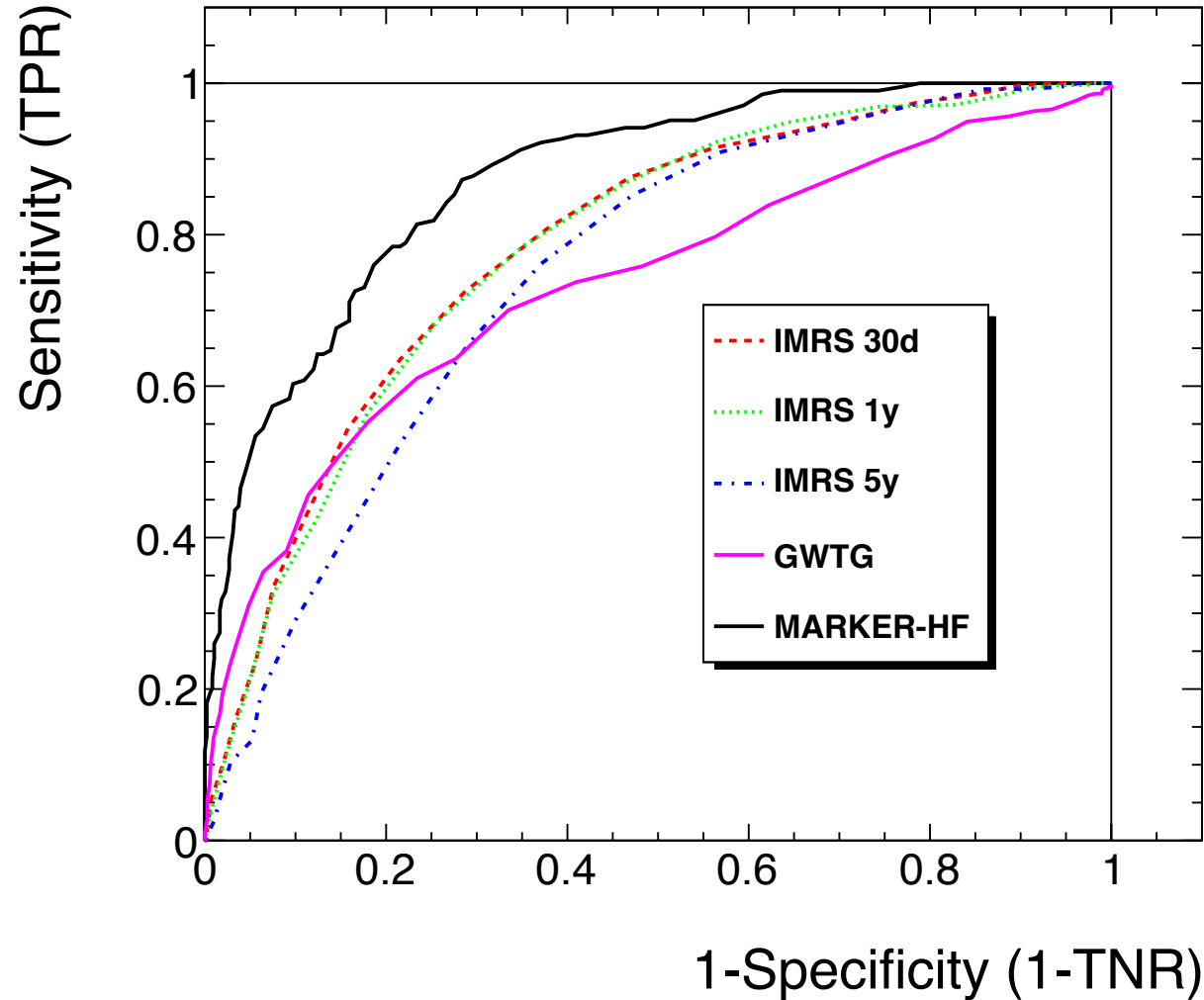
- Input variables plotted against the mean score

- The yellow bands represent the normal ranges.

➔ **NOT** an explicit input to the model.
“Learned” by the training



Comparisons with similar risk scores

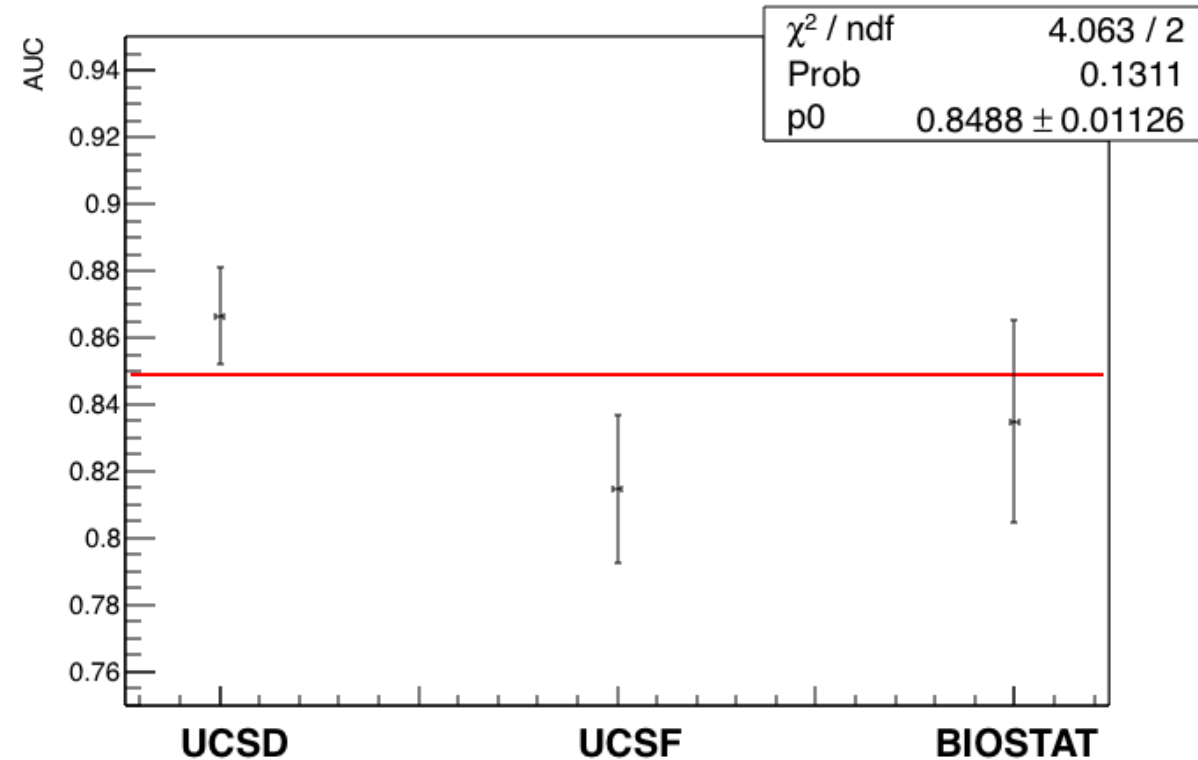


IMRS: *American Journal of Medicine*,
122(6):L550-558, 2009

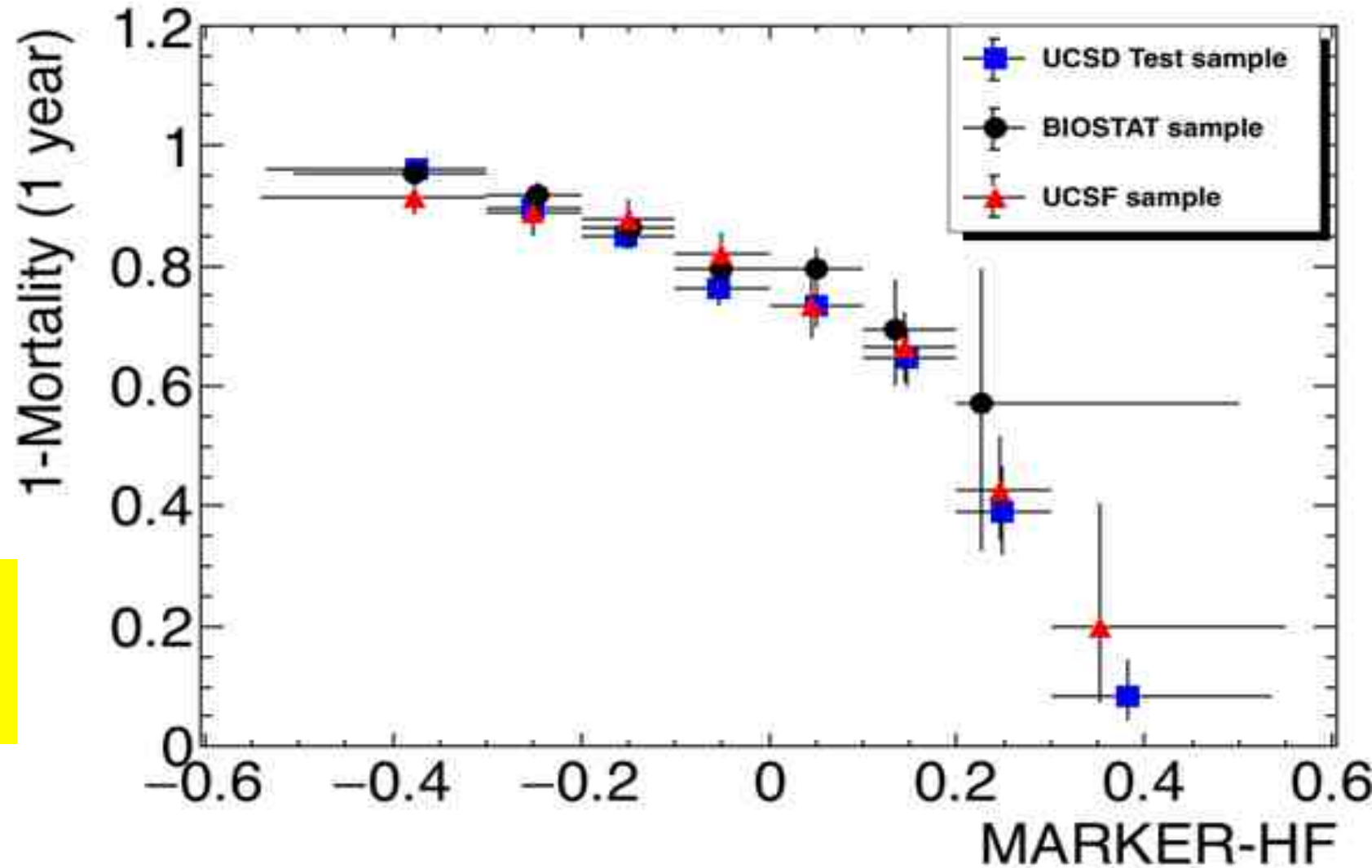
GWTG: *Circulation: Cardiovascular
Quality and Outcomes*, 3(1):25-32, 2010

Reproducibility with patients not from UCSD

- “Local” bias of studies major concern in medical field
- Applied model derived on UC San Diego patients on patients from
 - UC San Francisco EMR
 - BIOSTAT—CHF
 - A study from 69 centers in 11 EU countries
- **AUC is statistically consistent in the 3 cohorts of patients**



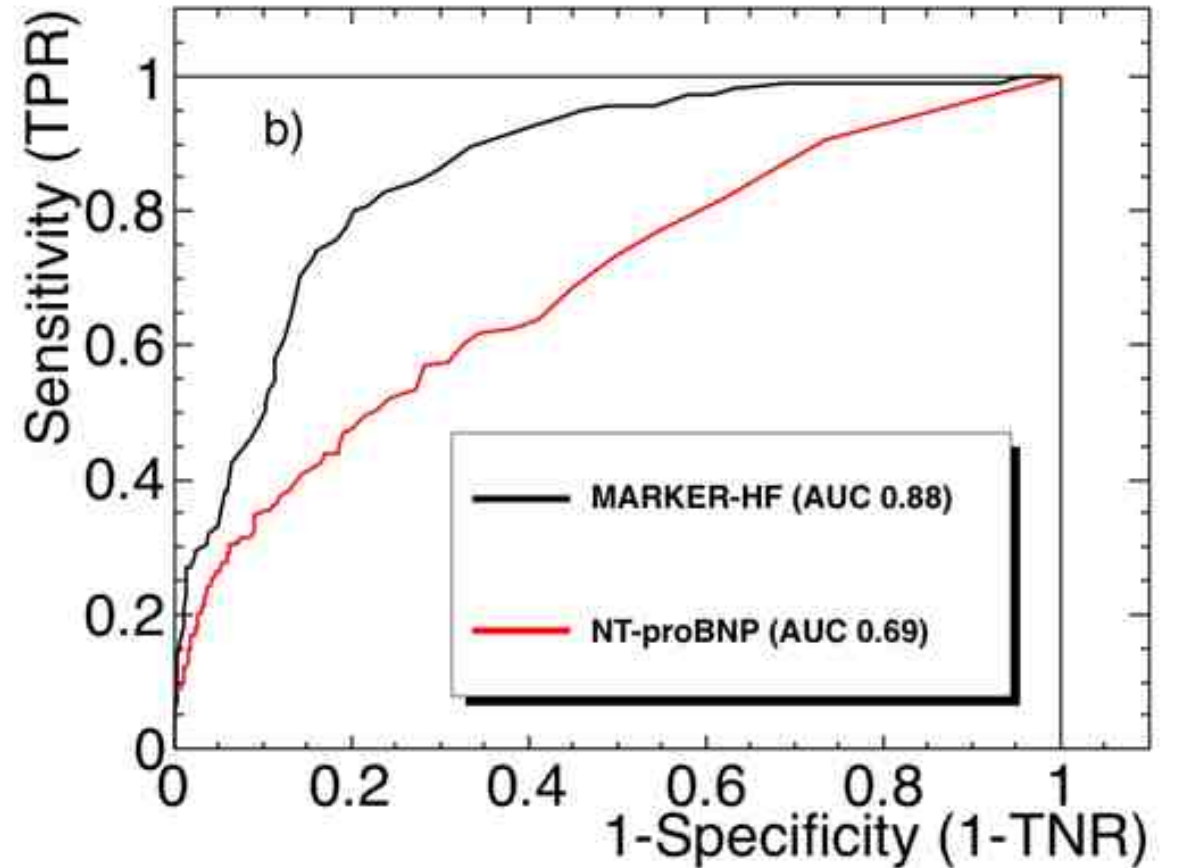
Applicability to all patients, ie, not just the “high risk” and “low risk”



Consistency between the 3 cohorts

Comparing NT-proBNP and Marker-HF

Amino-terminal pro-B-type natriuretic peptide, (NT-proBNP) is a well validated biomarker associated with HF



Other features that did not have time to cover

Consistent performance in

- Men vs. Women
- As a function of ethnicity
- As a function of age
- For in- vs. out-patients (proxy for health status)
- Patients with pulmonary edema vs. other HF diagnoses
- No detectable bias due to excluding patients with missing variables

Conclusion

- Succeeded in designing predictive risk score algorithm for HF using ML
- Key features, some based on HEP experience
 - Tight data collection requirements → Clean training/testing samples
 - Clear definition of outcomes using the extrema
 - Automatic inclusion of correlations (potentially non-linear)
- Paper submitted to medical journal
- Starting to think about further studies, still in cardiology, e.g., can we predict which patients will suffer major bleeding with anticoagulants?