

UC San Diego
SCHOOL OF MEDICINE

**Department of
BioMedical Informatics**

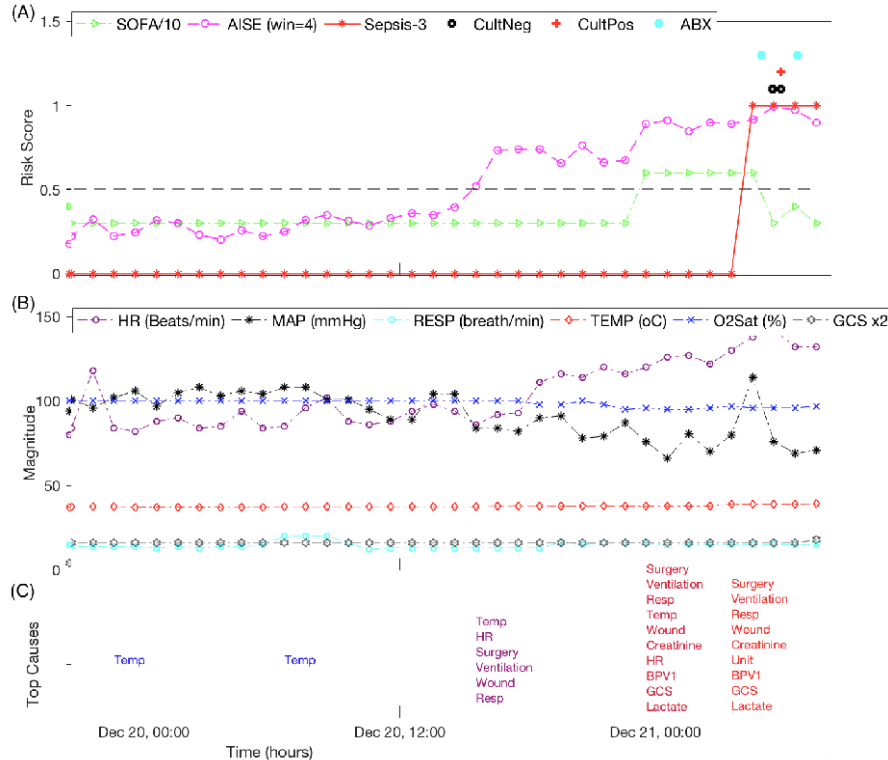
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Building and Evaluating Machine Learning Algorithms

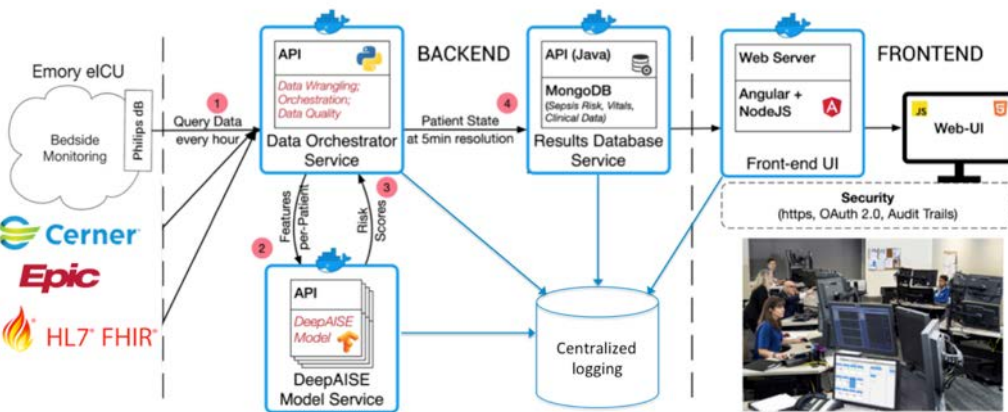


An Interpretable Machine Learning Model for Accurate Prediction of Sepsis in the ICU

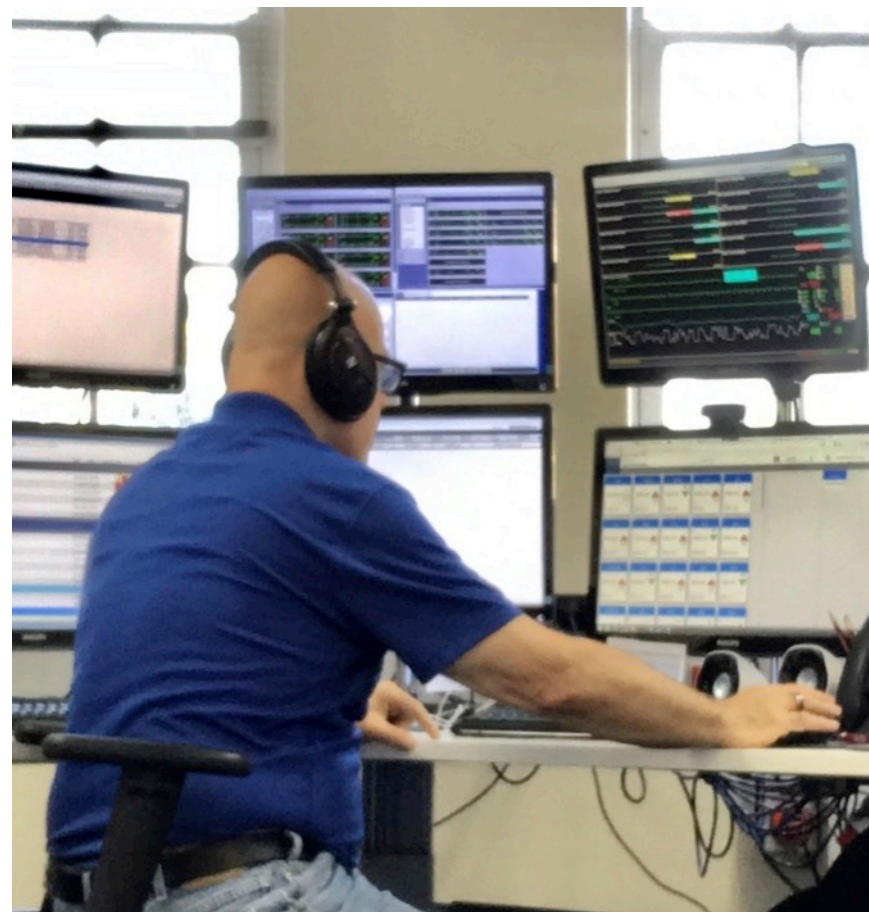
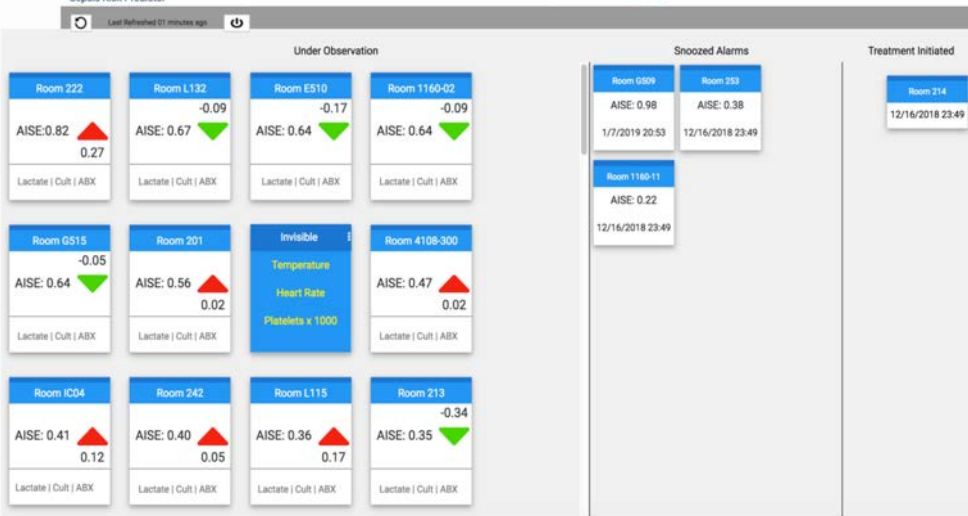


Sepsis Predictive Analytics

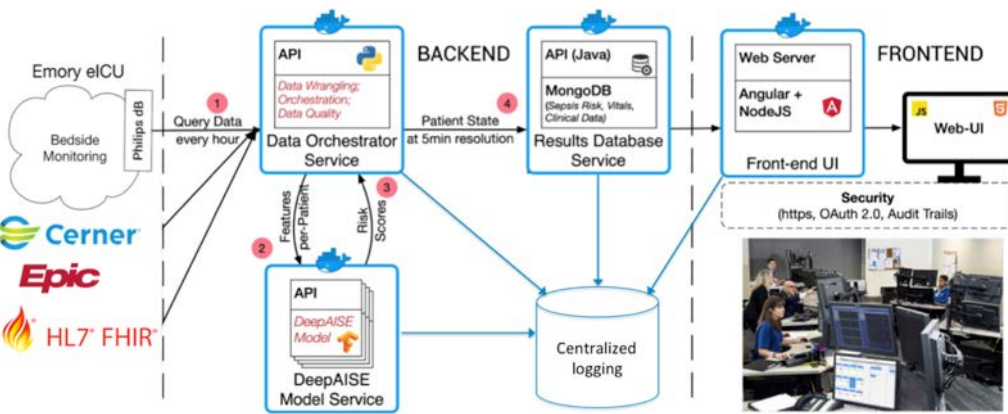
- Artificial Intelligence Sepsis Expert (**AISE**) (CCM, 2017-2018)
- Trained on 30,000 ICU patients from Emory Hospital and externally evaluated on 50,000 ICU patient from the MIMIC-III database
 - Input: commonly measured EHR data (labs, vitals, contextual info)
 - Output: 4-8 hours in advance risk of sepsis with an AUC of 0.85.
- Reveals top causes per each prediction (*interpretable/explainable*)



DeepAISE
Sepsis Risk Predictor

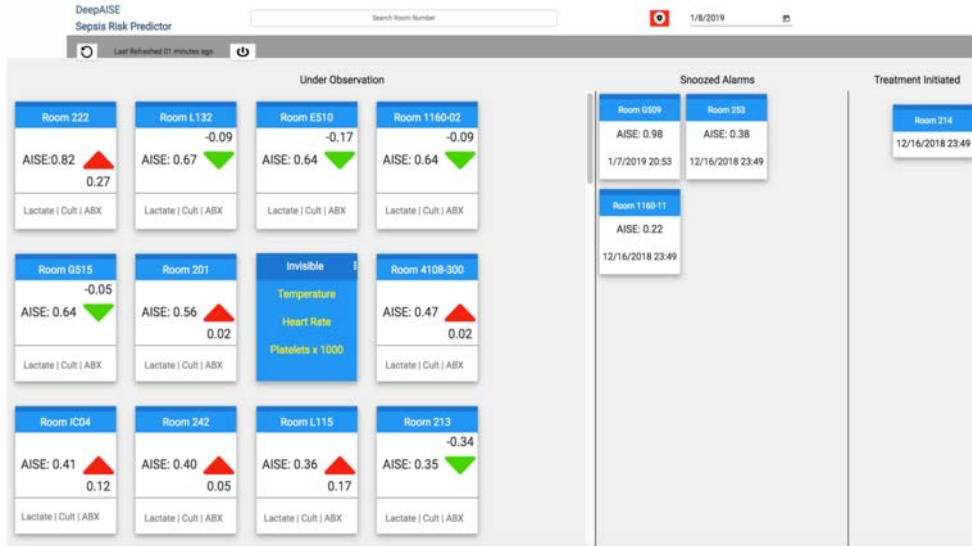


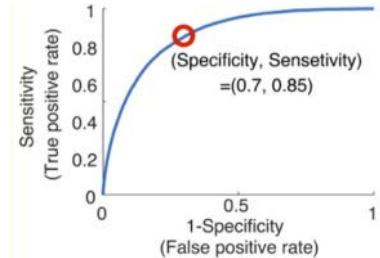
Real-time analytics, workflow integration



The Five Rights of CDS:

1. The **right information** (reliable predictions, top causes / context)
2. To the **right person** (tele-ICU nurses)
3. In the **right CDS intervention** format (e.g., alert)
4. Through the **right channel** (e.g., EMR)
5. At the **right time**
 - Actionable window (4-12 hours in advance)
 - Prior to clinical recognition
 - Prior to initiation of treatments



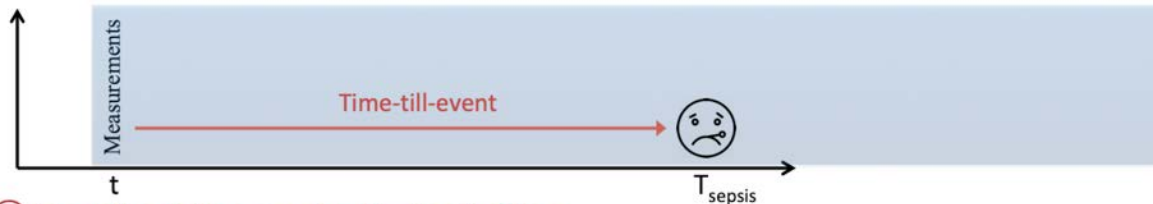


How many evaluation protocols are there?

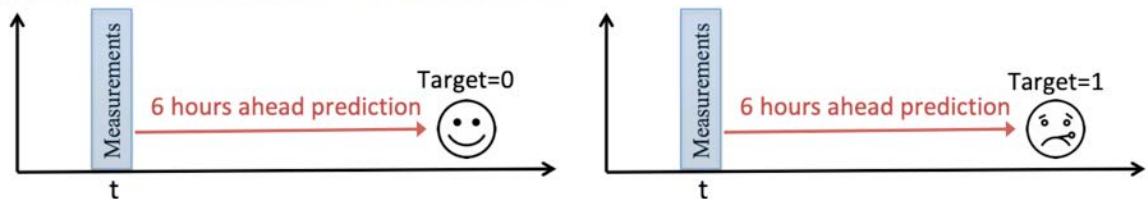
- ① Infinite horizon
- ② Look-back
- ③ Sequential
- ④ Case-control
- ⑤ Max value
- ⑥ One-shot (at time of admission or time of clinical suspicion)
- ⑦ ...

Can we compare AUCs, PPVs, across all these protocols? **No!**

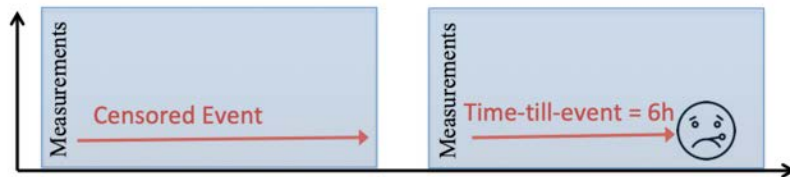
① Sepsis Prediction as a Survival Analysis Problem



② Sepsis Prediction as a classification Problem



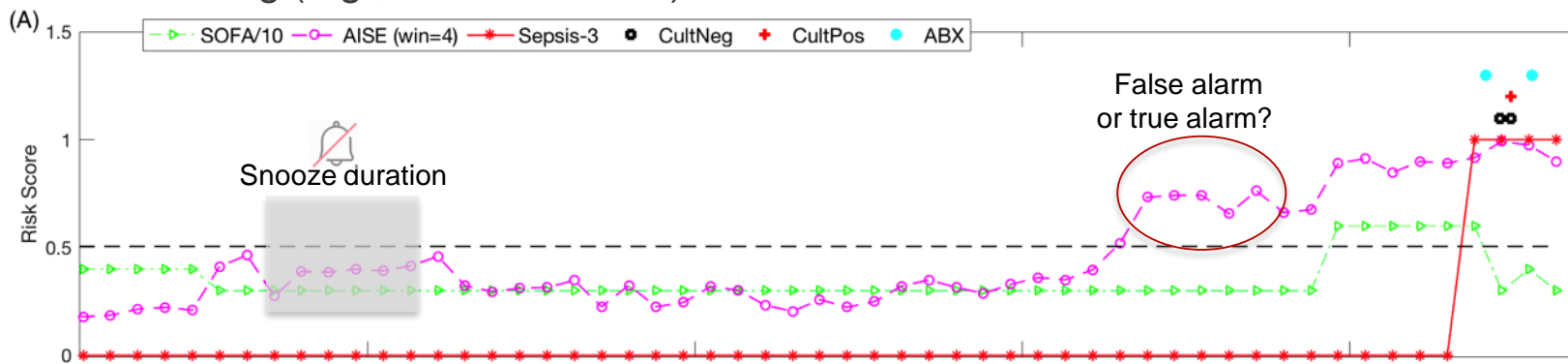
③ Sepsis Prediction as a short-term Survival Analysis Problem



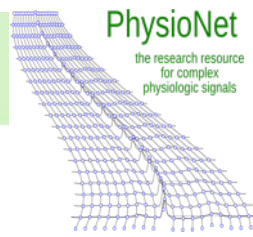


Designing Clinically Meaningful Evaluation Metrics

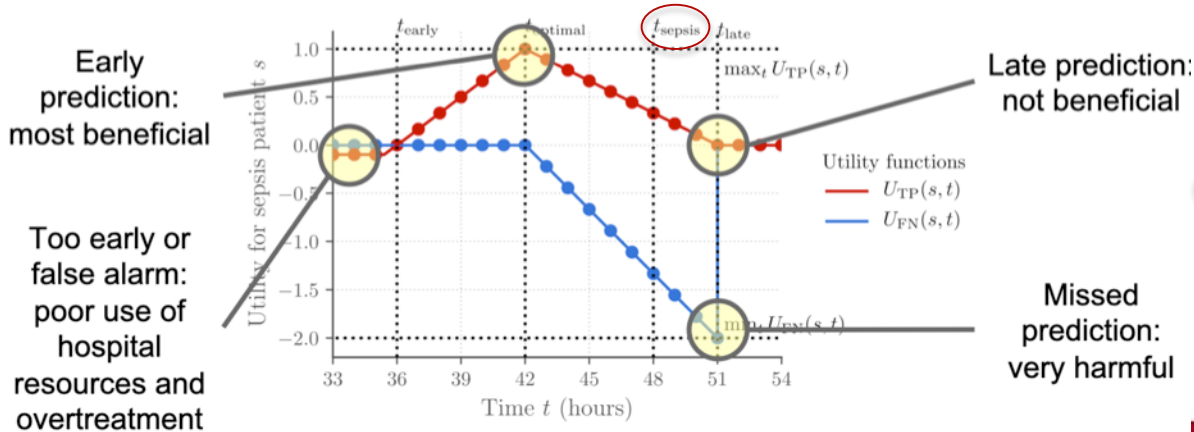
- **Utility** of a model is intimately connected to the clinical protocols under which the model is evaluated
 - Snooze
 - Prediction horizon and actionable window (e.g., 6hr)
 - Setting (e.g., ED versus ICU)



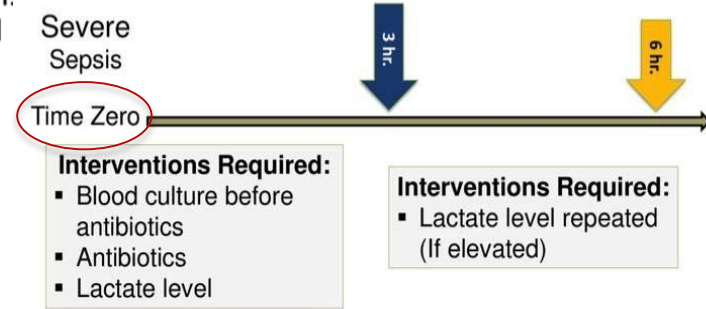
EARLY PREDICTION OF SEPSIS FROM CLINICAL DATA: THE PHYSIONET/COMPUTING IN CARDIOLOGY CHALLENGE 2019



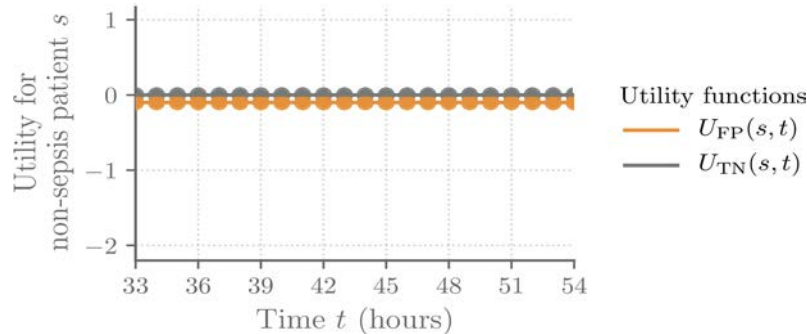
Utility function: rewards early predictions and penalizes late predictions as well as false alarms.



SEP-1: EARLY MANAGEMENT BUNDLE



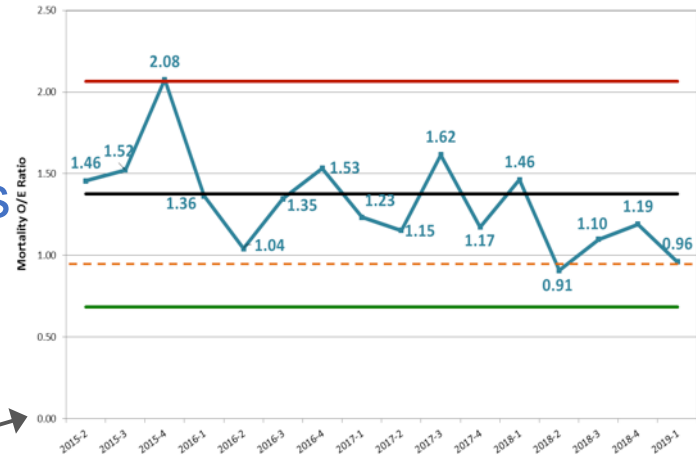
Set Measure ID # SEP-1-8; Early Management Bundle, Severe Sepsis/Septic Shock





Designing Prospective Evaluation Methods

- Multiple Reader Multiple Case (MRMC)
- Quality Improvement (QI) study
 - Improving SEP-1 compliance rate
 - Lowering Mortality **O/E** ratio
 - Hospital ranking
- Single Center (pilot) and Multicenter clinical trials
 - Mortality, LOS, days on MV, Pressors, etc.



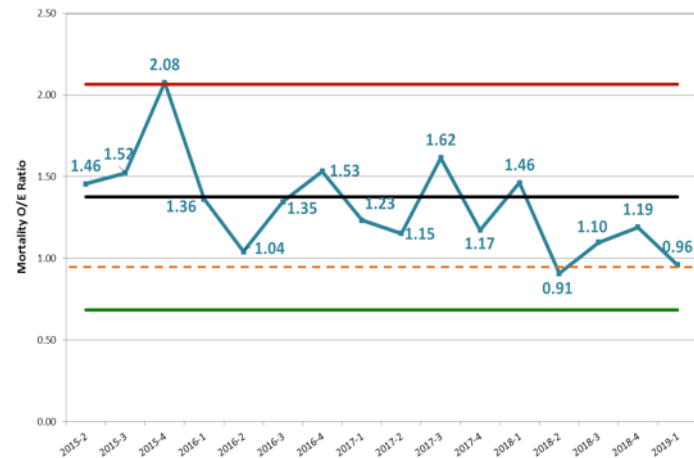


Designing Clinically Meaningful Evaluation Protocols for National Ranking

- Task: Prediction of shock
- End-point: O/E (Observed over Expected Mortality)

Model Results (Significant Predictors)

Explanatory Variable	Beta	OR
Intercept	-4.644	
Vent on Admission Day	1.445	4.242
Female, Age >= 85	1.437	4.208
ECMO on Admission Day	1.434	4.195
DIC	1.380	3.975
Necrotizing Fasciitis	1.318	3.737
Tumor Lysis Syndrome	1.316	3.730
Shock	1.269	3.557
⋮		
⋮		



Snooze for
3 hours

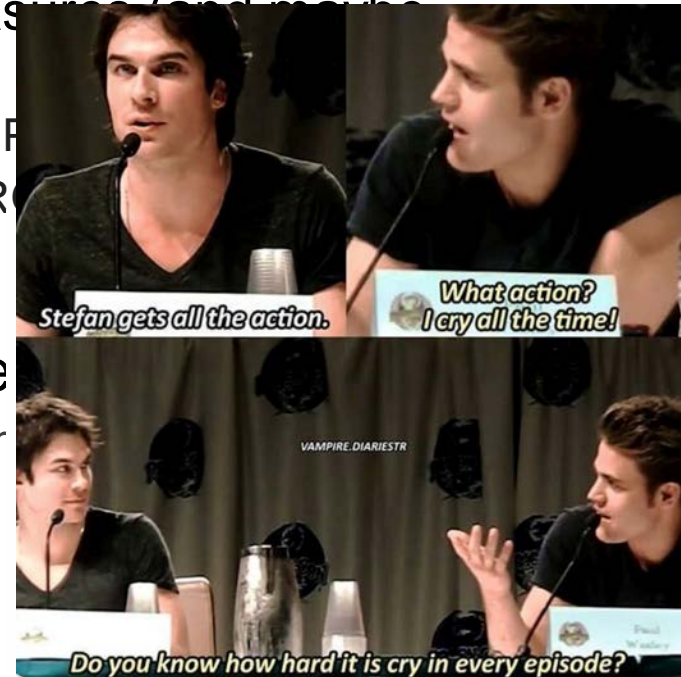


Snooze for
10 hours



Conclusion

- Performance metrics that take into account care protocols, case mix complexity (CPT modifiers), cost, quality measures (and maybe hospital rankings)
 - Can this AI tool make me more compliant with SEP
 - Can this AI tool reduce cost within a given MS-DRG
- All the buzz is about AI, but QI gets all the credit
 - To encourage adoption of AI/ML we need to rethink metrics and encourage QI-AI team building



Do you know how hard it is to change a menu item in Epic?



Thank You!

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- Gordon and Betty Moore Foundation, “SEP1+: A Composite Measure to Accurately Assess Early Sepsis Management” (2020-2021)
- National Institutes of Health (NIH), “Deep Learning and Streaming Analytics for Prediction of Adverse Events in the ICU” (2015-2021)
- Biomedical Advanced Research and Development Authority (BARDA), “Multicenter Deployment and Evaluation of DeepAISE-on-FHIR for Early Prediction of Sepsis” (2019-2020)
- National Science Foundation (NSF), “Leveraging Heterogeneous Data Across International Borders in a Privacy Preserving Manner for Clinical Deep Learning” (2018-2021)
- National Institutes of Health (NIH), “DeepFHIR: A Fast Healthcare Interoperability Resources (FHIR)-enabled Deep Learning Platform for Prediction of Decompensation in Critically Ill Patients” (2017-2019)