Comparing Patient Outcome Predictability for AI-assisted Sepsis Treatment

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Introduction

- Researchers want to improve AI-assisted sepsis treatment strategies in the ICU
  - **Sepsis** is when infection causes the body to attack itself, causing organs to fail

- Significance of AI and ML work in healthcare
  - Potential to aid clinician decisions
  - Potential to improve patient outcomes

- **<u>Problem:</u> Does providing future clinician actions help improve AI model predictions**
  - **Previous studies** analyzing data from a publicly available dataset (525348 entries), MIMIC, showed **no significant difference**
  - **My research** involves analyzing data from **UPMC**, a large private dataset (1331040 entries) with data from various hospitals across Allegheny County

Methodology

- **Training XGBoost ML Models**
  - X features: states (patient vitals) and clinician actions
  - y variables: Change in disease severity (a.k.a. change in SOFA values)

Note:
- Clinicians provide patients with **two treatments:** IV fluid and/or Vasopressor drugs
- Change in disease severity is calculated by the difference between **SOFA scores**, a score created to indicate the severity of the patient's illness, across six time intervals

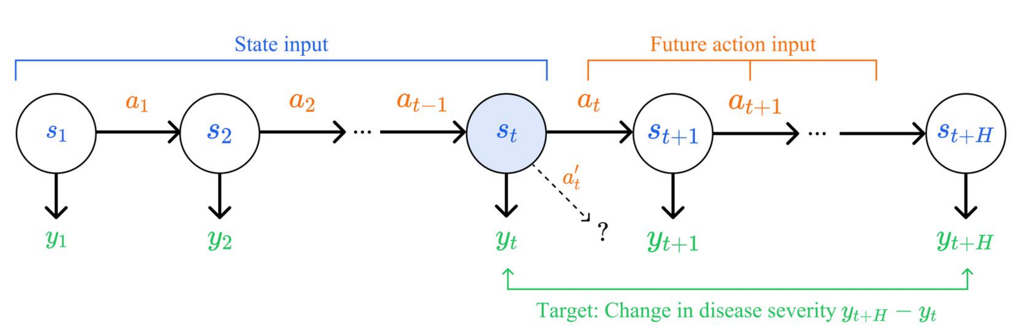
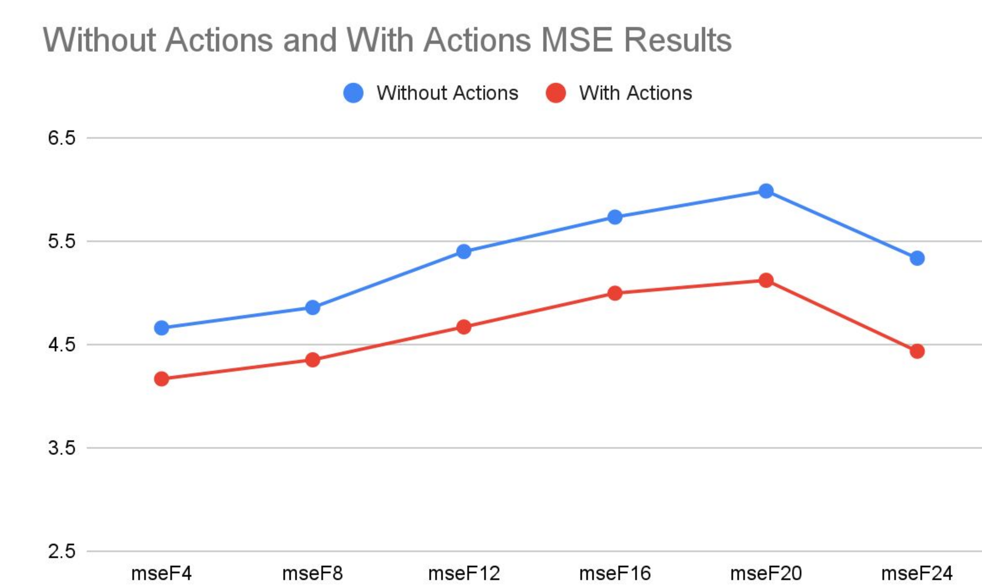


Image source: Grace Park

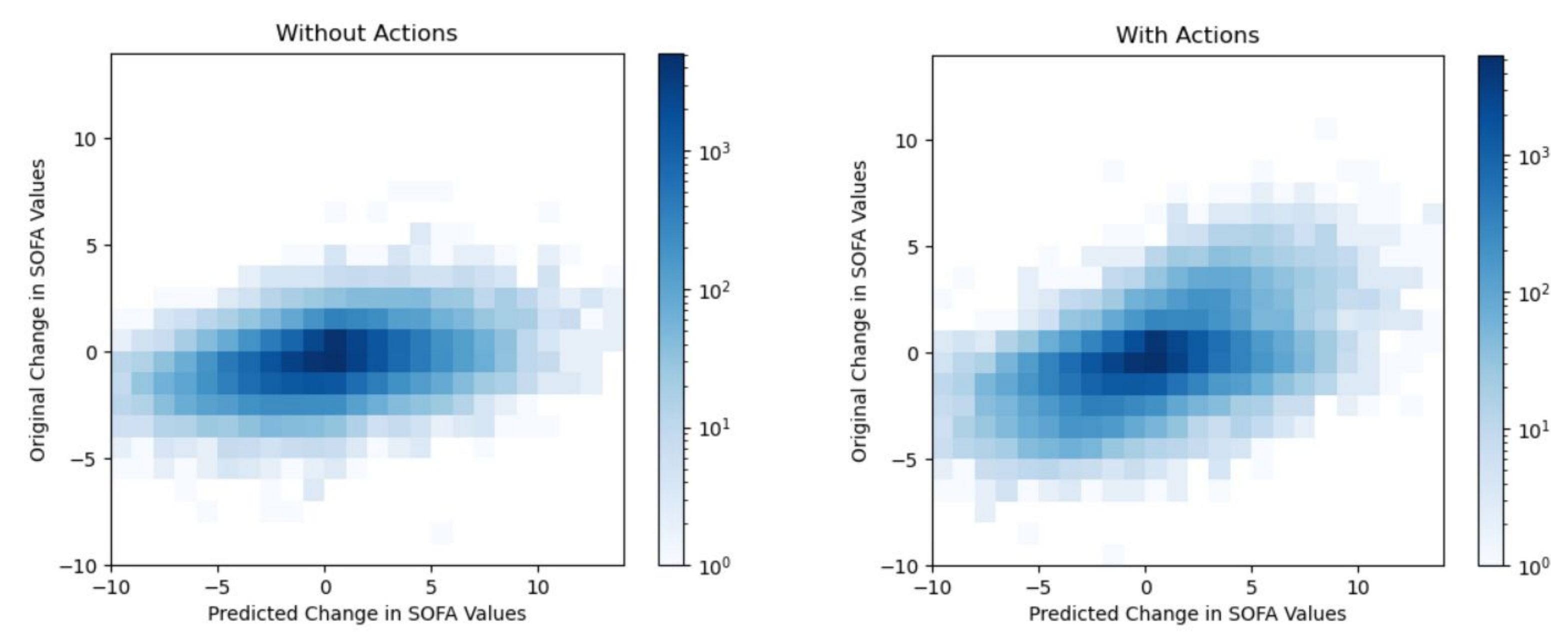
Analysis and Results

1. Calculating Mean Squared Error (MSE)

We report the MSE between the change in the original SOFA y values and the model predicted change in SOFA y values, conducting this analysis for each of the six time intervals provided by the dataset. Overall, with clinician actions has **lower MSE** than without clinician actions

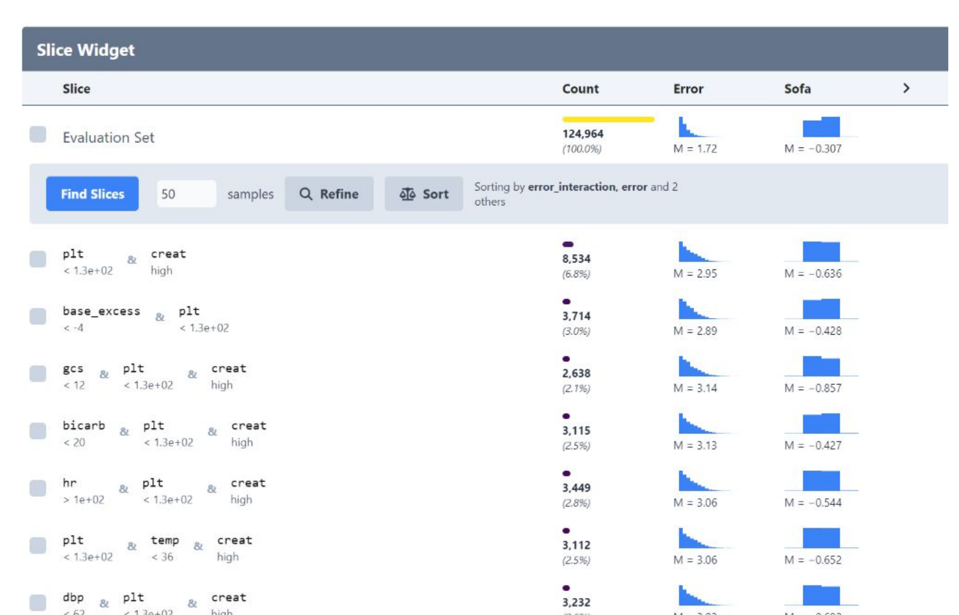


Using the Divisi tool, we see in the graphical representation that there is **a more defined correlation** with clinician actions than without.



2. Slice-Finding Analysis Tool
- Finds data subgroups with significant differences within the dataset
- Conducted by discretizing each column into different bin sizes and specifying which slice type should be ranked higher.
- Allows us to analyze a large dataset quickly.

We can use the slice-finder tool to analyze patient states/vitals that have high frequencies in errors. For example, since we see that plt (platelets) comes up in multiple slices, we can hypothesize that low plt may be associated with more variation in predicting patient outcomes.



Discussion

- The **original study** conducted on the **MIMIC** dataset showed **no significant difference** in providing future clinician actions.
- **Our study** with the **UPMC** dataset showed **significant difference** in providing future clinician actions
- Treatment plans and clinician decisions within the same hospital may stay consistent while vary tremendously across hospitals.
- We **hypothesize** this discrepancy is due to the difference that **MIMIC** data was collected from **one hospital** while **UPMC** data is larger and was collected from **various hospitals**.

Future Work

- Since patient vitals may vary tremendously, being able to predict the effects of clinician actions can help optimize the treatment strategy and provide additional sources of information to clinicians.
- Our next steps would be to utilize the slice-finding discovery tool to better understand slices with areas where treatment could be most helpful.

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