Prediction in Practice: An Implementation Framework For Clinician Centered Machine Learning Models

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Abstract

The Control Tower project aims to provide a decision support tool for palliative care clinicians in the inpatient setting. Leveraging machine learning techniques, a risk score predicting the need for a palliative care consultation is delivered to clinicians. Control Tower construction is categorized into three processes that required the coordination of multiple stakeholders: creation of training data, model development/deployment, and model evaluation/validation.

With consultation from subject matter experts, we identified extractable information from the Electronic Health Record (EHR) that is relevant to palliative care consultation. Multiple databases from the Unified Data Platform (UDP) were then used to aggregate data, engineer features, and construct a training set for the algorithm. A Gradient Boosted Machine (GBM) model for time to event (i.e., palliative care consult) was then fit to the training dataset and tuned with 10-fold cross validation. We then built a standalone platform via a Docker Container to house the GBM model and constituent code files. The Docker Container initiated real-time delivery and retrieval of data through API's. Data cleaning logic was integrated into the container and workflow. The handling of retrospective versus real-time data differ considerably, and thus it was necessary to anticipate what was to be fed into the model. After the model was fit and validated, clinicians were then provided a graphical user interface (GUI) that displays model risk prediction scores and influential covariates. The Control Tower patient cohort was monitored by clinicians in a real time production environment in the GUI to easily identify candidate patients for palliative care consultation. The creation of a logging system allowed for data collection on model output and performance. Log data was used to assess the model's translation to production. A pragmatic randomized clinical trial (RCT) is being conducted this year to estimate the efficacy of the Control Tower decision support tool. The RCT will implement the decision support tool in several (~13) inpatient care units. This framework has the potential to be applied to various clinical problems requiring the use of evidence based decision making, Machine Learning, and AI.

Figure 1: Control Tower Project Overview

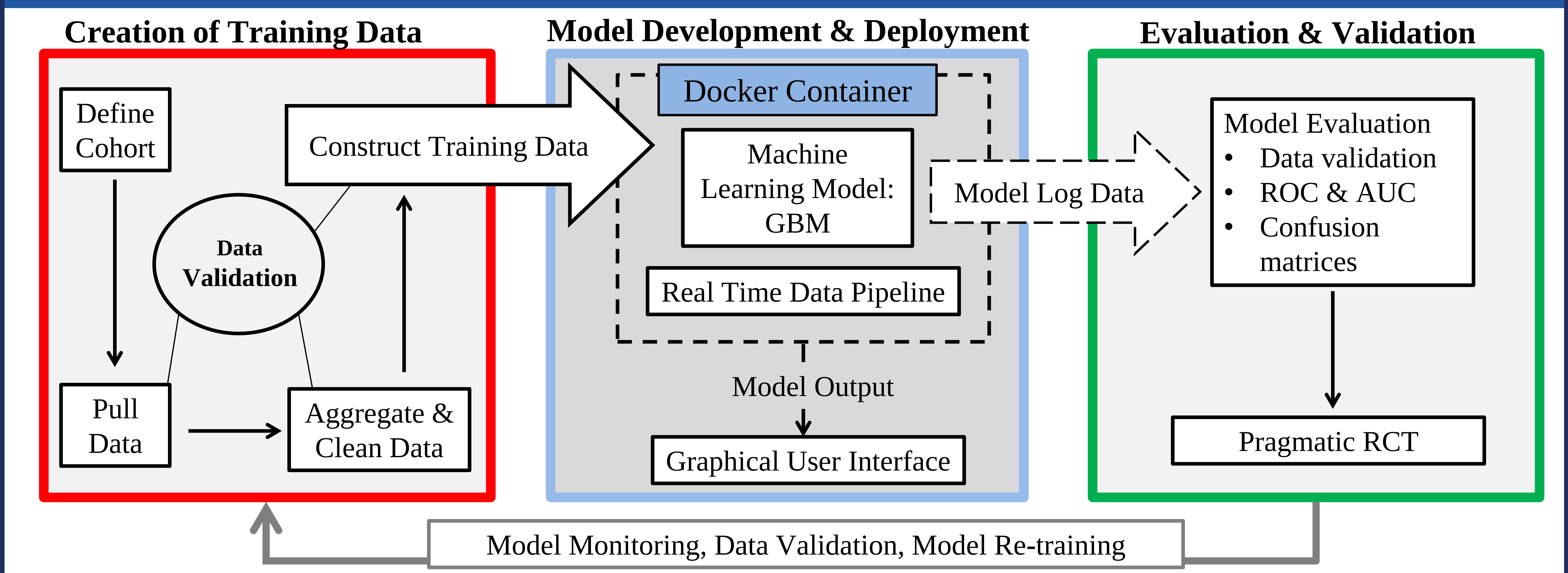


Figure 2

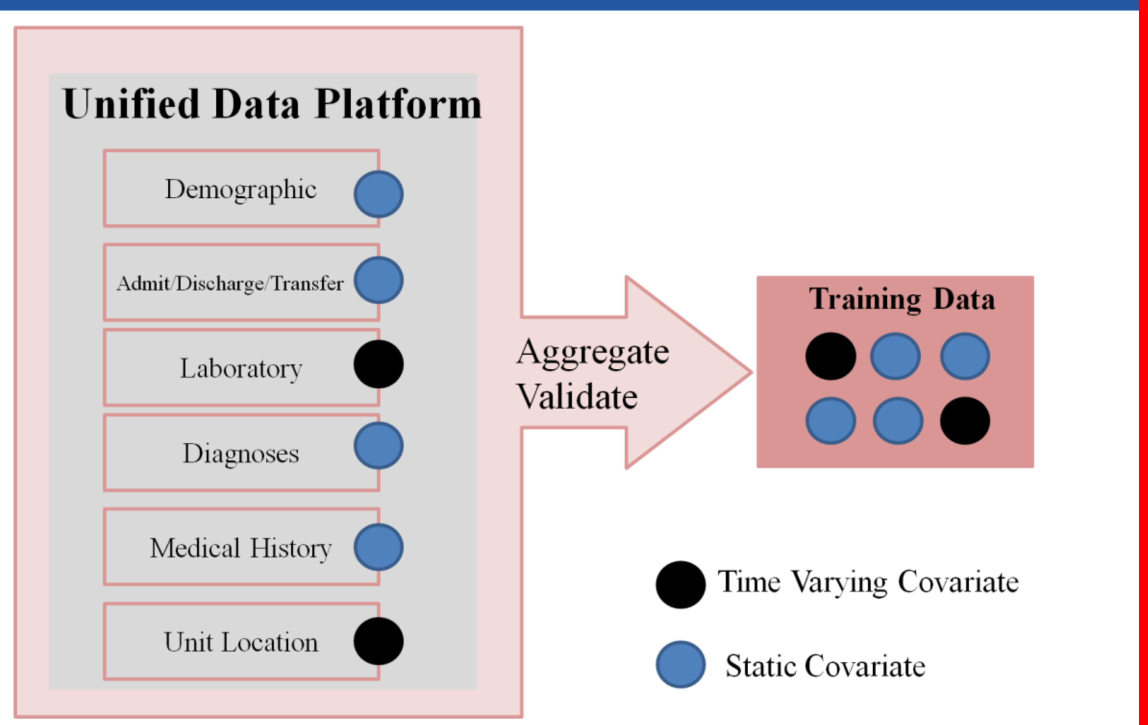
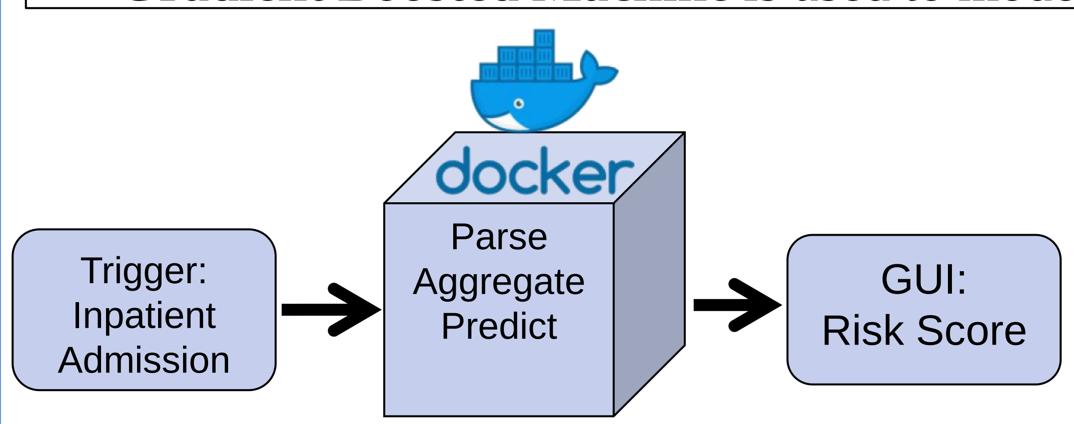


Figure 2: Various databases within The Unified Data Platform (UDP) were used and aggregated to construct the training dataset. Variables are categorized as Time Varying or Static. Time varying covariates were used with a "last observation carried forward" mechanism.

Model Specifics:

- Palliative Care Consultation treated as a time to event outcome
- Time to Palliative Care is *heterogeneous* Poisson process with rate equal to
$$\lambda(t) = f(X, Z(t))$$
- "Time from admission" variable is recorded in days since admission and included in $Z(t)$. $Z(t)$ is assumed constant between measurements.
- Estimate $f(X, Z(t))$ with any estimation approach that allows for a Poisson likelihood
- **Gradient Boosted Machine** is used to model time to event with 10-fold cross validation.



A docker based runtime environment was deployed to house the GBM and code parsing files. The docker container initiates real-time delivery and retrieval of data through API's. Every inpatient admission triggers a request to obtain each patient's data necessary to construct a prediction. R code then parses and aggregates data to feed a single prediction vector to the GBM. The GBM then outputs a risk based prediction score that is displayed in a GUI (figure 3).

Figure 3

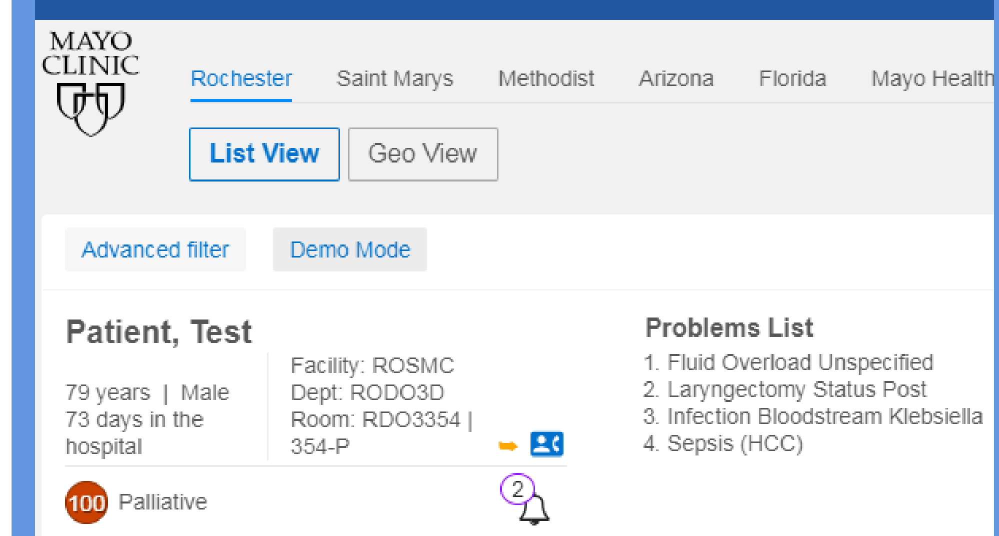


Figure 3: Graphical User Interface (GUI) that shows patients with a high need for Palliative Care Consultation.

Data logging infrastructure captures all model calls, predictions, corresponding covariates, and clinician decisions. Model metrics are extracted from the log data and used to evaluate model performance.

Figure 4

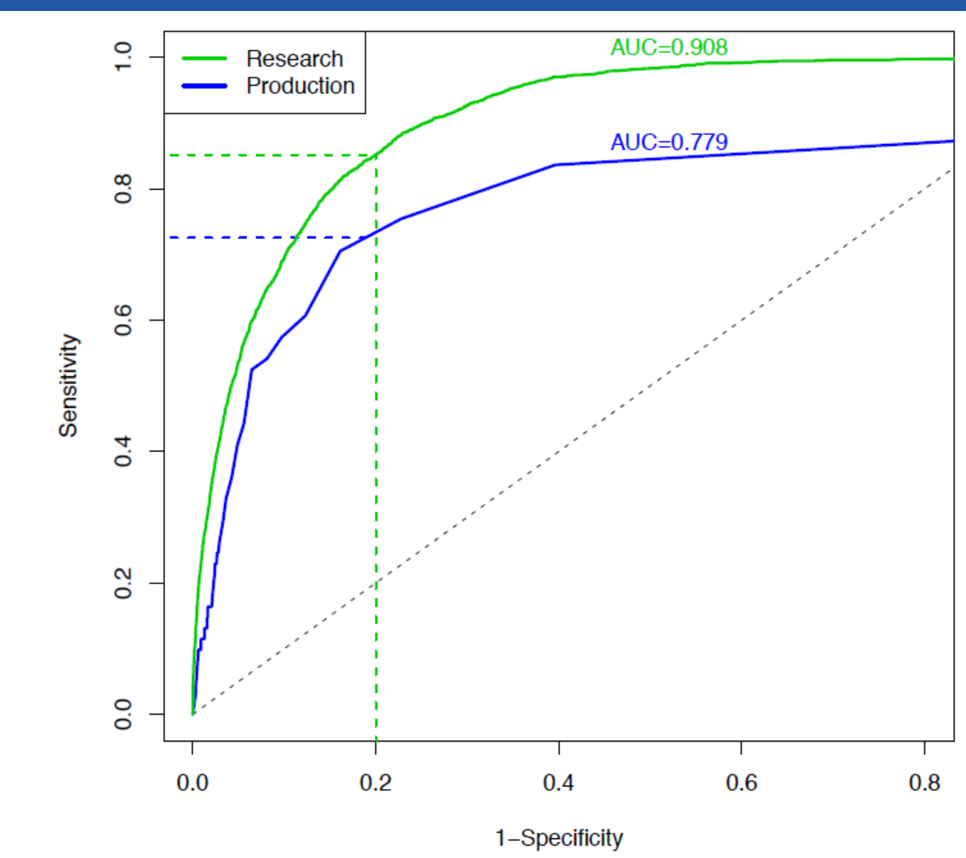


Figure 4: Log data is used to compare AUC metrics in the research setting with training data versus real-time production data.

A pragmatic Randomized Clinical Trial is being conducted this year to test if the Control Tower tool will accurately identify patients who may benefit from a comprehensive review by a palliative care specialist, and decrease time to receiving a palliative care consult in an inpatient setting.

Figure 5

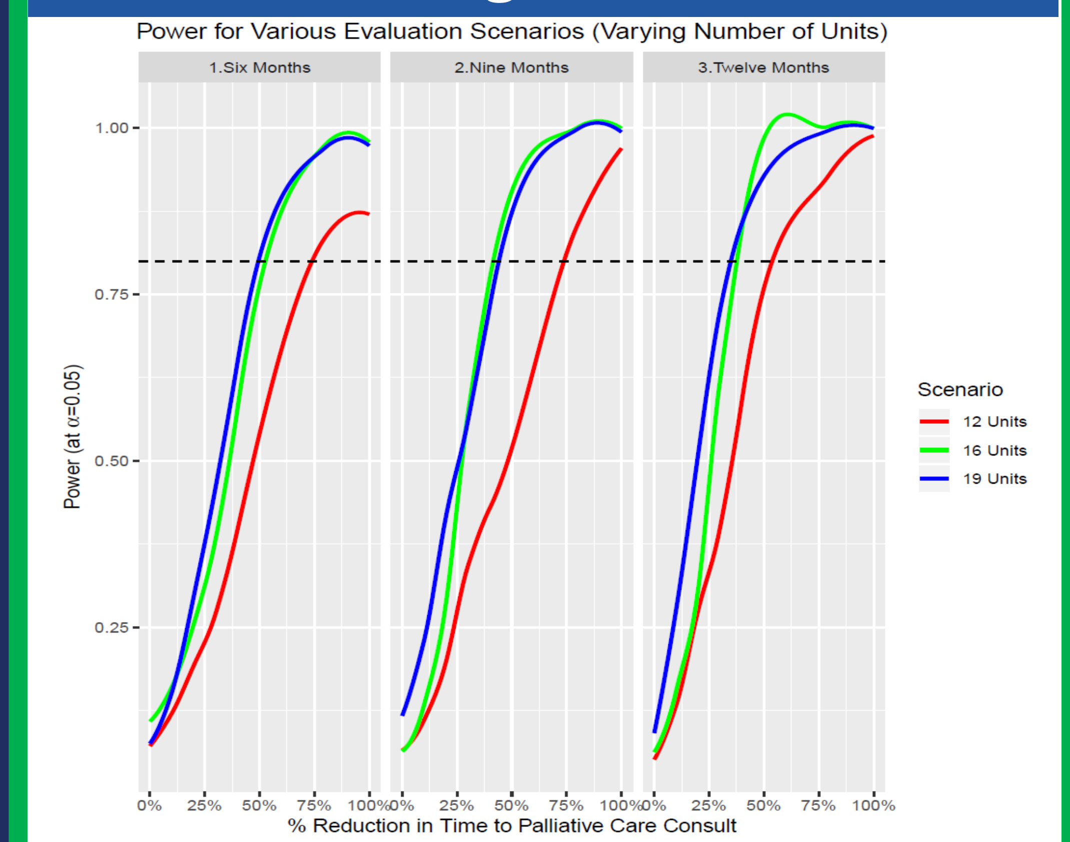


Figure 5 – A stepped-wedge cluster randomization trial is used on pilot data. Power curves for several hypothetical scenarios are shown. All curves were estimated using pilot data and Monte Carlo simulation.

Discussion & Conclusions

- Continual data validation and model upkeep proved to be a universal challenge faced throughout the entirety of the project. This challenge was exacerbated with the EHR source change to EPIC.
- Subject level experts from various domains contributed to the success of the Control Tower project. Early and frequent collaboration between teams was vital in the project's success.
- The framework implemented in the Control Tower project has the potential to be applied to various clinical problems requiring the use of evidence based decision making, Machine Learning, and AI.

References

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