Optimizing bed demand for the post-anesthesia care unit (PACU) at Brigham & Women's Hospital

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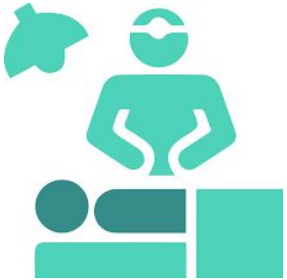
Outline

- Background
  - Problem Context
  - Surgical Workflows
- Exploratory Data Analysis (EDA)
- Modeling Considerations
  - Models
  - Features
  - Metrics
- Pilot Model & Dashboard
- Future Work

Background

Where do Patients go after Surgery?



BWH has **43 Operating Rooms** that are used for adult and infant surgeries

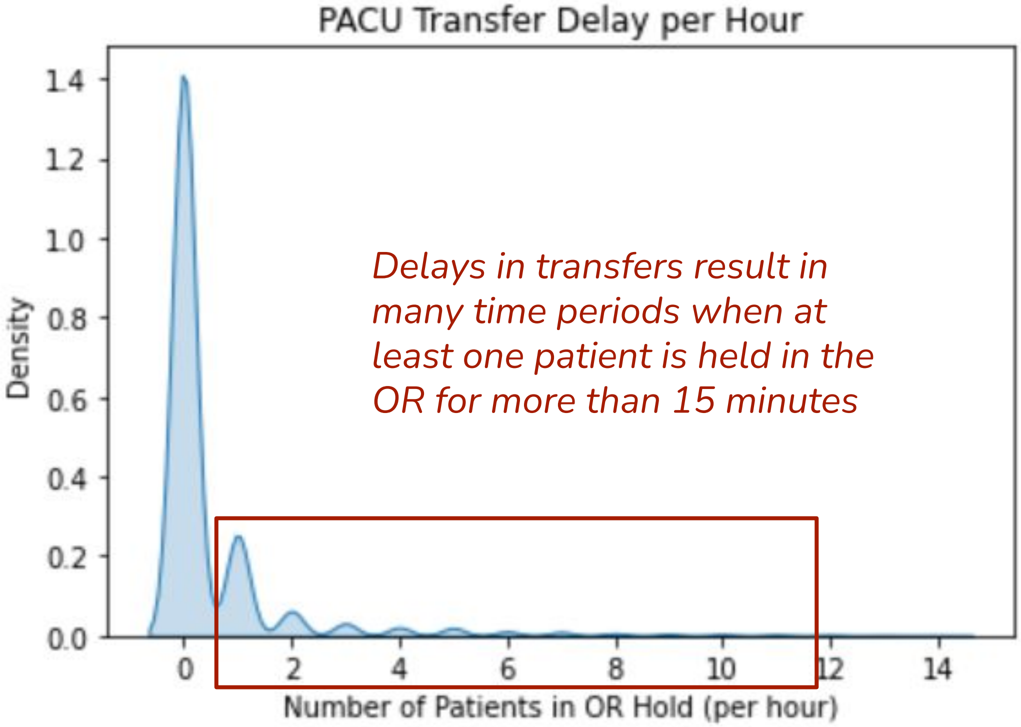
Following surgeries, patients are transferred to one of the **60 PACU beds** for monitoring

After recovery, patients are transferred to in-patient units for additional care or released

What happens if PACU beds are not available?

- PACU staff are specially trained in medication safety, care coordination, infection control, and equipment use
- Inadequate care during recovery can result in complication such as:
    - improper upper airway support
    - irregularities in blood pressure (hypertension & hypotension)
    - tachycardia
    - heart palpitations
    - cardiac arrest
    - brain damage due to lack of oxygen
    - death

Current Delays in PACU Transfers



Delays in transfers result in many time periods when at least one patient is held in the OR for more than 15 minutes

Rethinking the Solution

Predicting Duration for Each Surgery

Predicting Number of Patients Ready to be Transferred to the PACU Per Hour

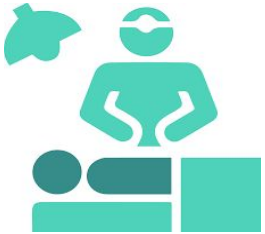
- Aggregated value more robust to error than specific case predictions
    - Case level predictions are a mixture of patient & process level factors, whereas considering the aggregate value is more process focused
- Info can be directly used for planning by PACU staff
- Difficult to identify drivers for delay using this approach

Project Goals

Design and deploy a model that predicts **the number of patients** who will be ready to be **transferred to the PACU each hour** for better operational efficiency.

Visualize the model results in a consumable dashboard to help end users make better scheduling decisions.

Target Users:



ANESTHESIOLOGISTS

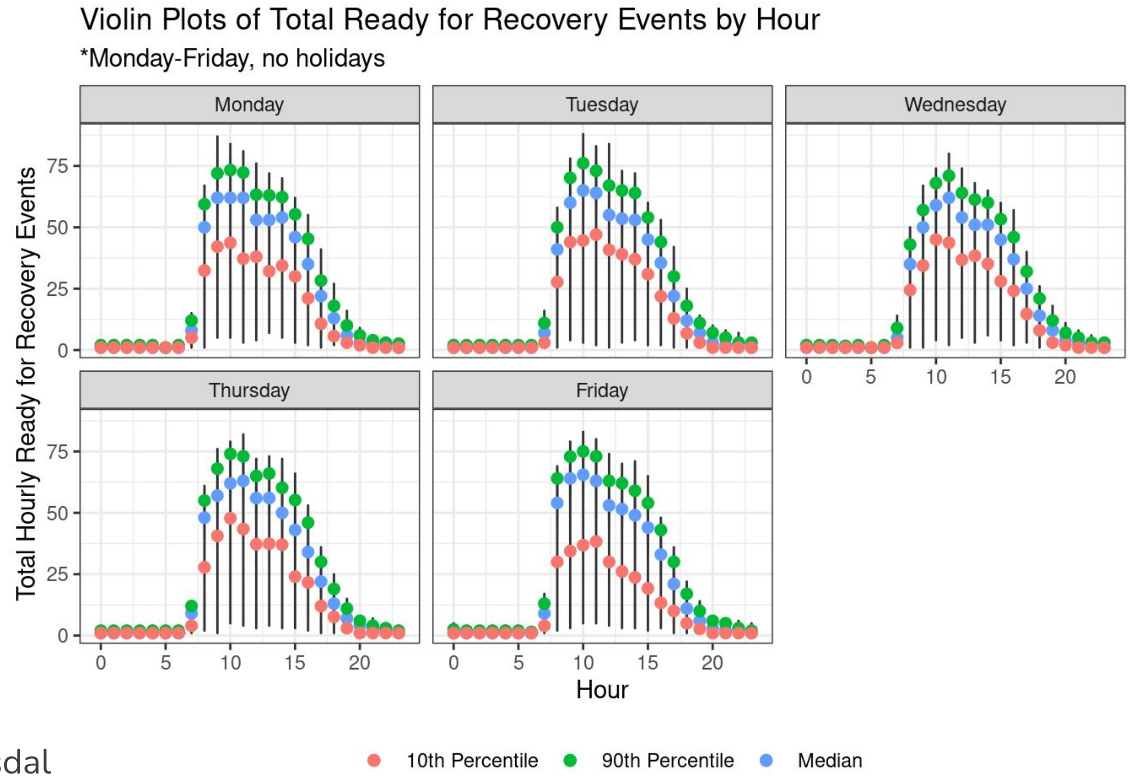
PACU NURSING TEAM

Exploratory Data Analysis

Exploratory Data Analysis

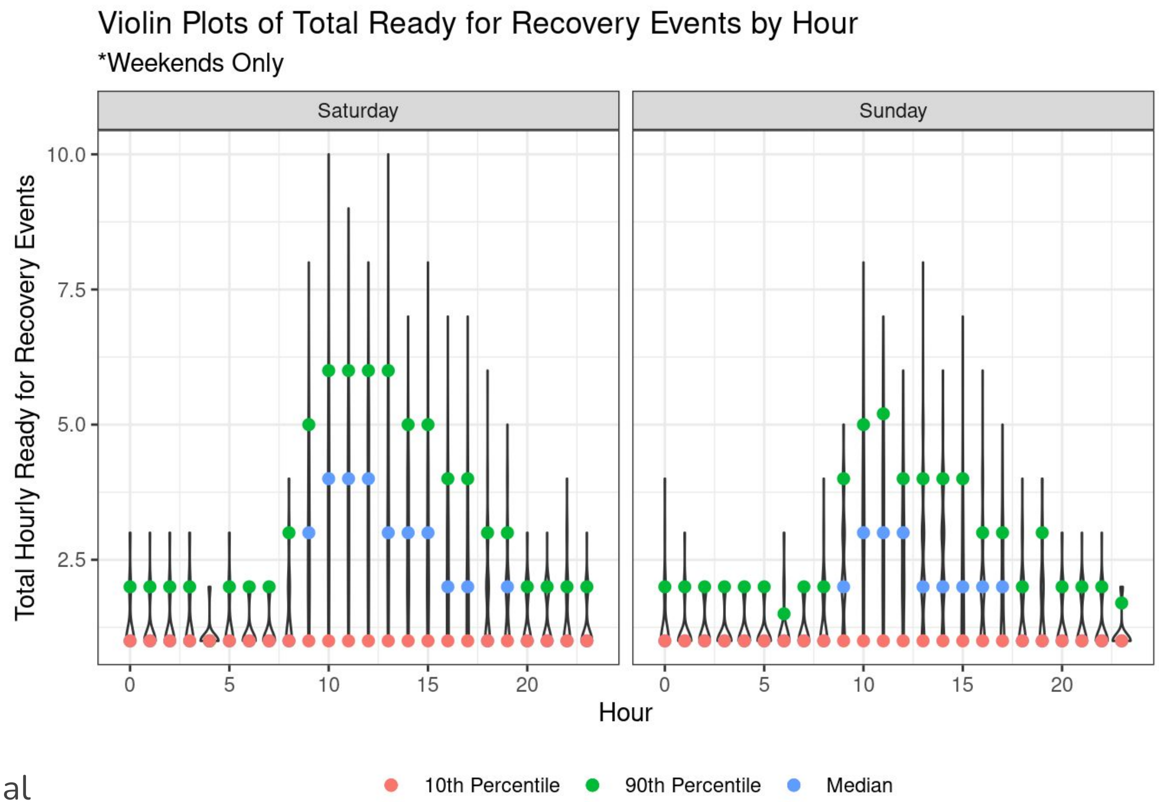
- PACU patient transfer patterns
  - time of day
  - day of week
- Drivers for PACU transfer delays
  - Surgeon related delays

Ready For Recovery Patterns: Weekdays



Produced by Alex Fiksdal

Ready For Recovery Patterns: Weekends



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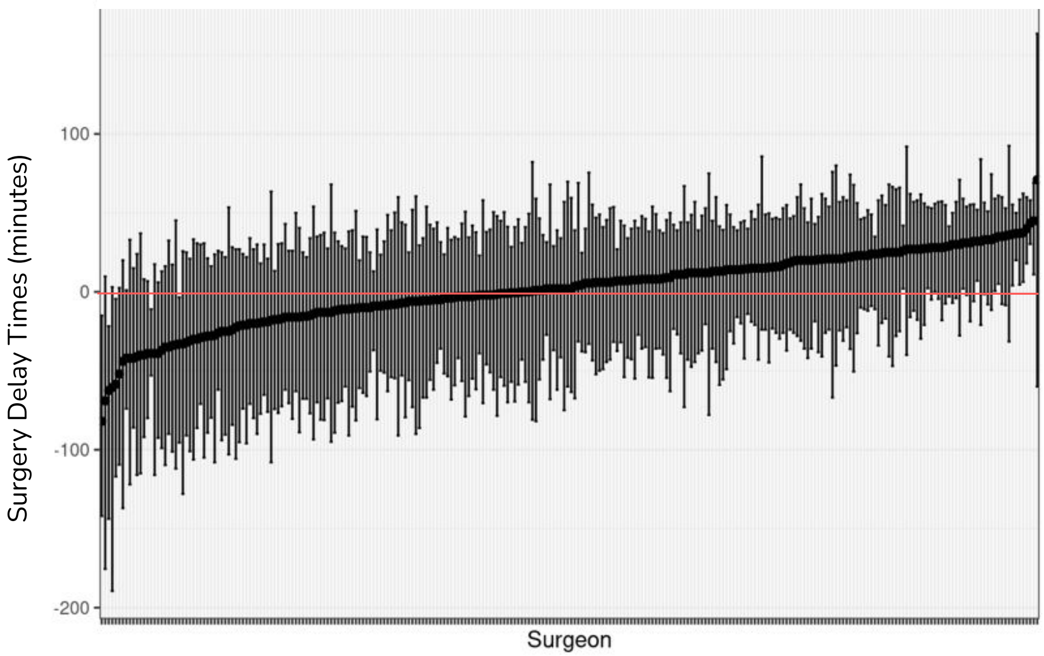
Surgeon-based Residual Analysis

Interquartile Range of Surgery Delay Times by Surgeon (sorted)
* only surgeries w/>= 25 procedures since Jan 2019



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EDA Summary

- PACU patient transfer patterns
  - Time of day and day of week should be included as features in model
- Drivers for PACU transfer delays
  - Surgeon-based features should be included as features in future work

Modeling Considerations

Modeling Methods

Direct Calculation of # Patients/hour ready to be transferred to PACU

1. Baseline model: Linear Regression

2. Alternative:
    a. Poisson Regression
    b. Zero-Inflated Negative Binomial Regression
    c. GAM
    d. Random Forest

Key Features

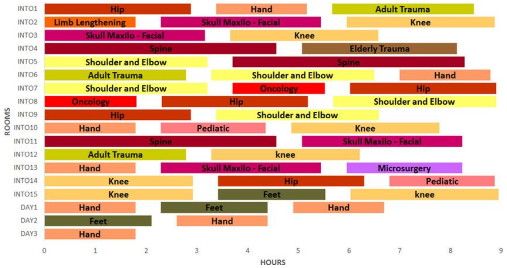
Temporal Features

- Weekday flag
- Hour of the day

Patient Features

- Hypertension status
- Percentage of female
- American Society of Anesthesiologist patient health rating

Case Features



- Median number of procedures in surgeries
- Scheduled number of patients

Comparison of Performance

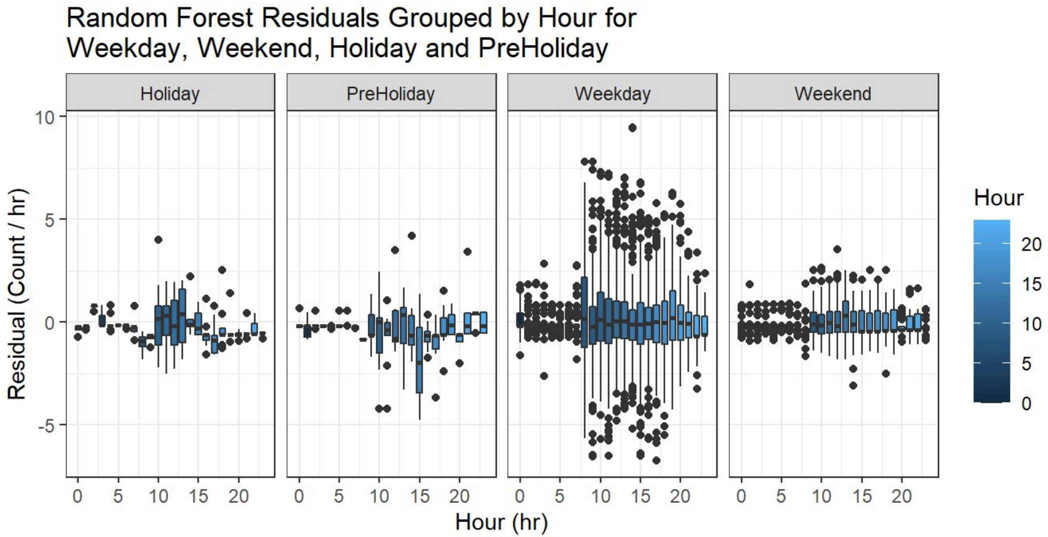
RMSE:
Target Error Value - 6 patients/hr

Poisson Reg	Zero-inflated NB Reg	Linear Reg	GAM	Random Forest
4.916	2.258	2.216	2.028	1.712

Training Time: minutes

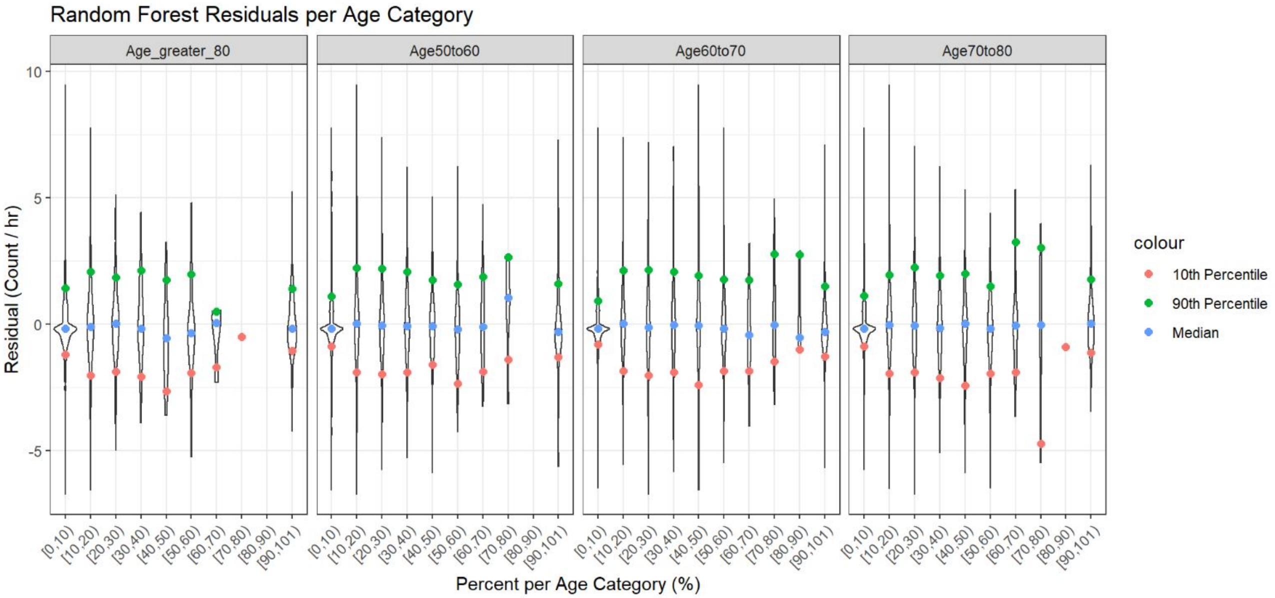
Training Time: 3+ hours

Error Analysis - Time of Day



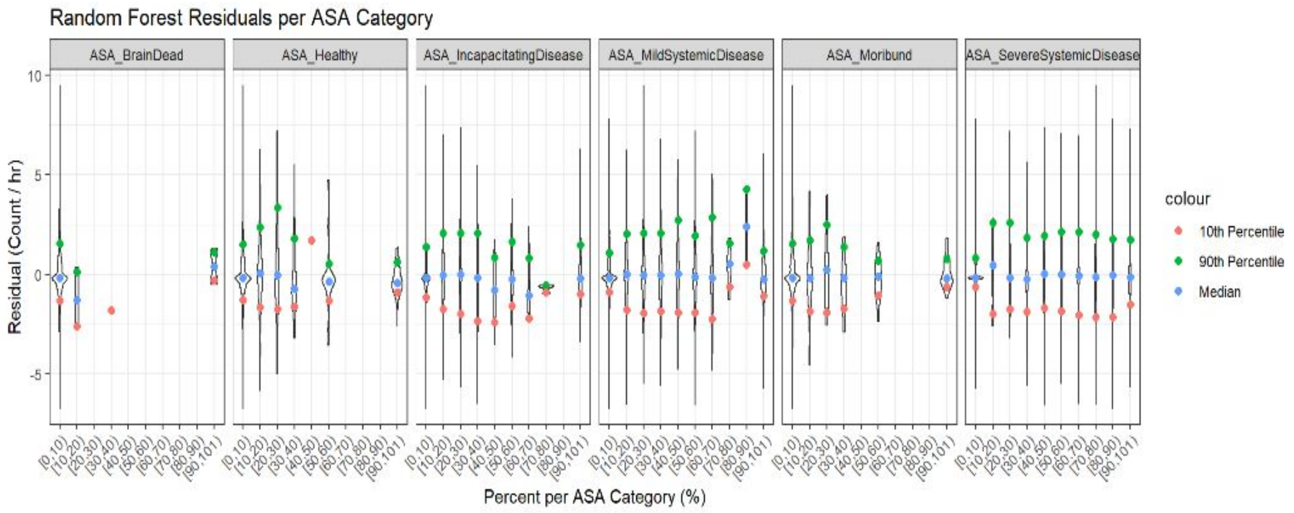
Residuals have more variance during peak hours (8am - 6pm). Hourly predictions during these time intervals may be less reliable compared to other times of day

Error Analysis - Patient Age



Residual patterns are fairly similar across age categories indicating model ***performance does not vary across age groups***

Error Analysis - Case Complexity Rating
(American Society of Anesthesiologist)



*Residual patterns vary based on case complexity, with more extreme residuals observed for surgical cases related to **mild** and **severe systemic diseases**.*

Dataset Feature Availability

DATA CONTEXT:
Scheduled surgery times are uncertain ahead of time. Total number of patients scheduled to finish surgery each hour is often updated the night before the surgery date, and retrospective values are NOT stored in Epic

PROBLEM: Model performance on retrospective data won't reflect real-time prediction performance

SOLUTION: Deploy a POC model and record out-of-sample predictions in parallel to understand the impact of this data integrity issue

POC Model & Dashboard

Proof of Concept Model

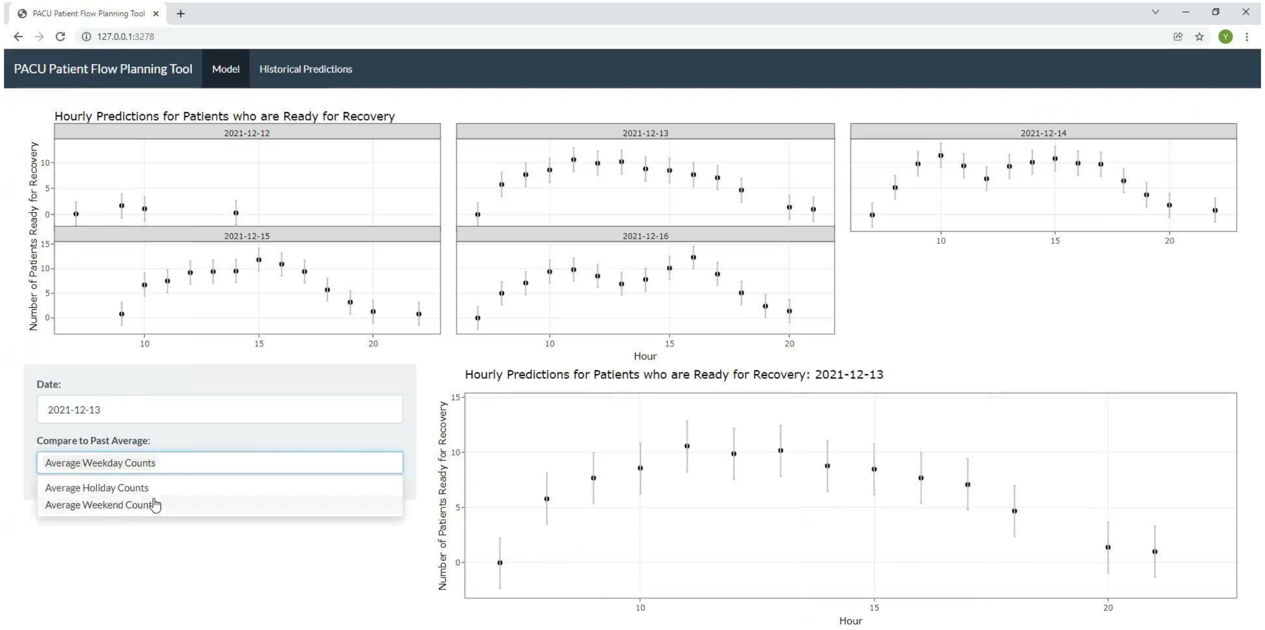
Linear Regression Model w/ 145 Features

- Temporal Features
- Patient Features
- Case Features

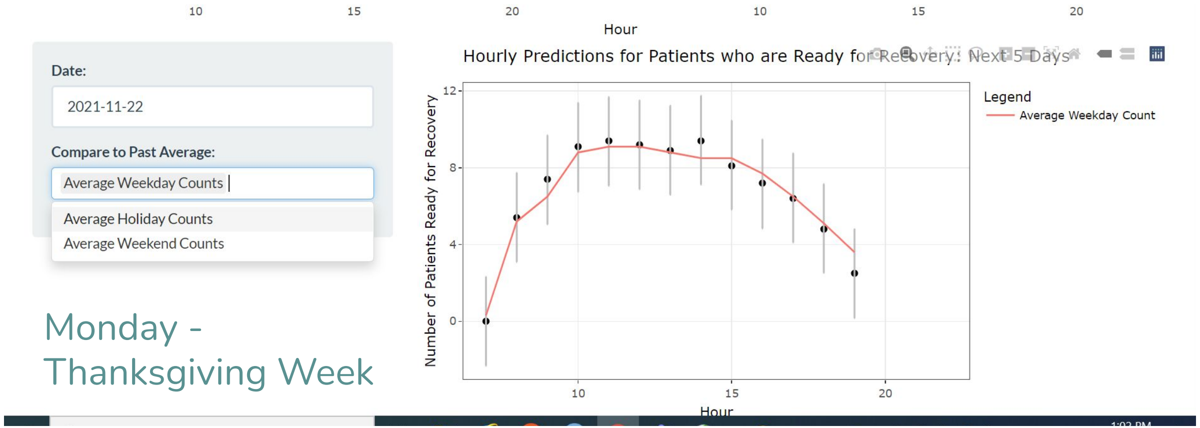
Model is deployed in end-to-end process, and is currently being **retrained each day** on new data.

Each day, the model makes predictions for the **next 5 days**, and stores results that are then used for a POC RShiny dashboard

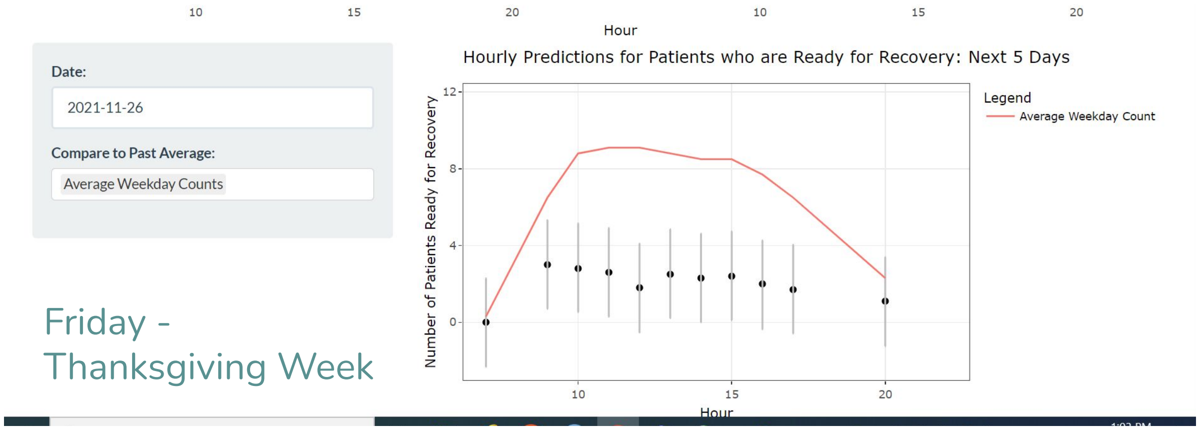
RShiny Dashboard



RShiny Dashboard: *Predictive Performance*

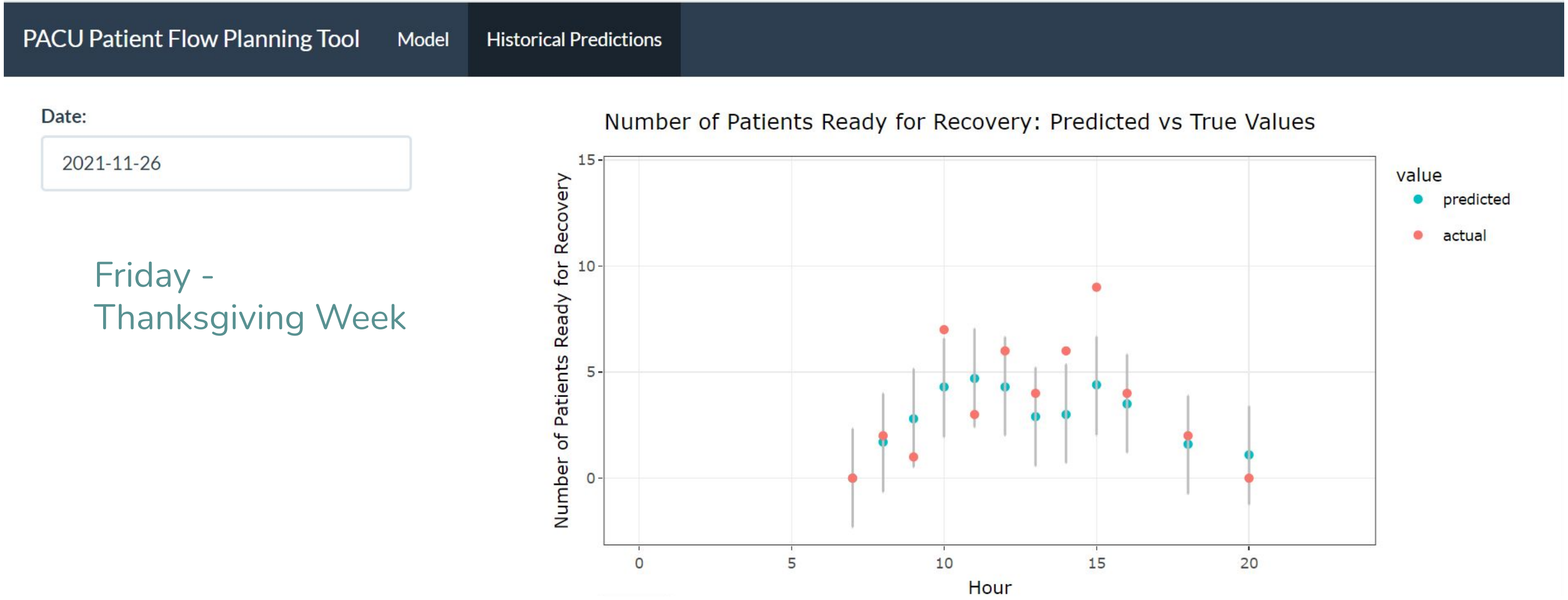


Monday - Thanksgiving Week

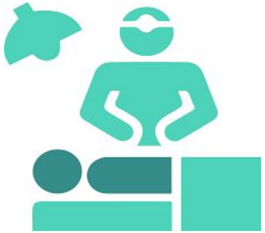


Friday - Thanksgiving Week

RShiny Dashboard: *Predictive Performance*



Actionable Insight for Target Users



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- Reschedule non-urgent surgeries

PACU NURSING TEAM

- Leadership can staff PACU based on anticipated patient volumes
- Plan patient transfers to downstream units (hoteling stations, inpatient care units)

Future Work

Model Improvements

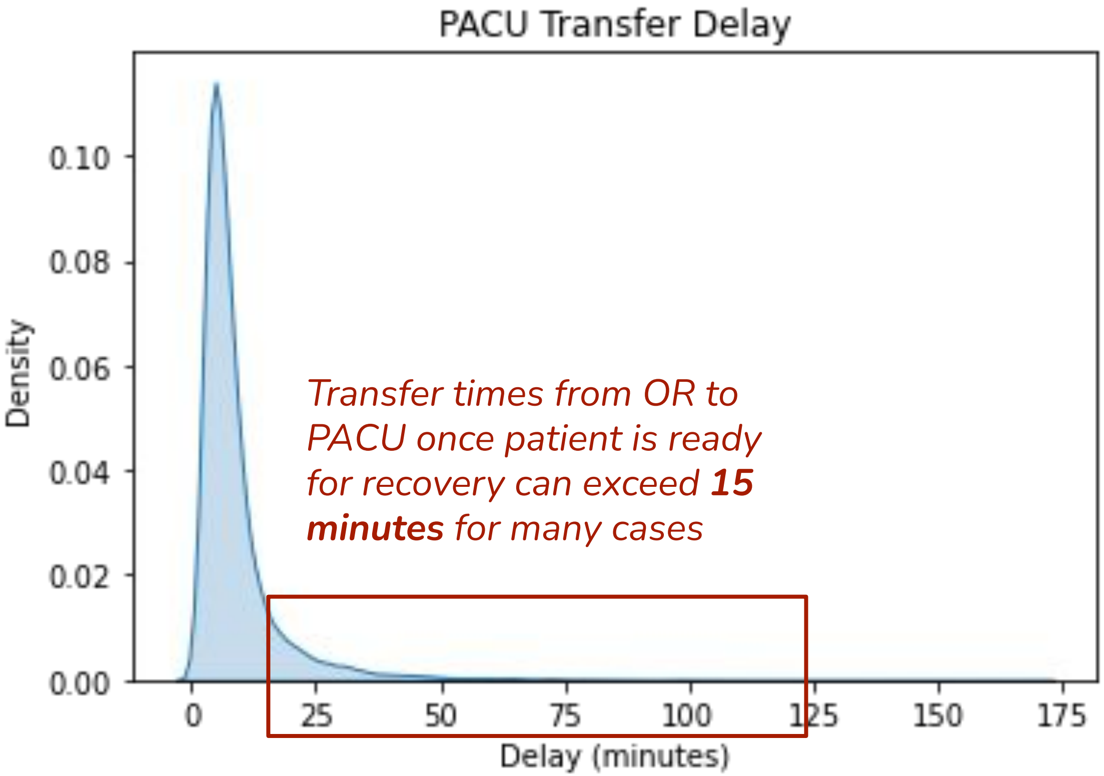
- Deploy a tree-based model (tuned Random Forest or XGBoost) for better prediction accuracy
- Consider additional surgeon related features
  - Years of experience, number of recent procedures, adverse outcomes
- Perform feature selection based on learnings from exploratory modeling process
- Consider model and app design changes to target surgery schedulers as future users
- Provide close to realtime, hourly predictions for more dynamic reporting to adapt to unexpected changes

Thank you!

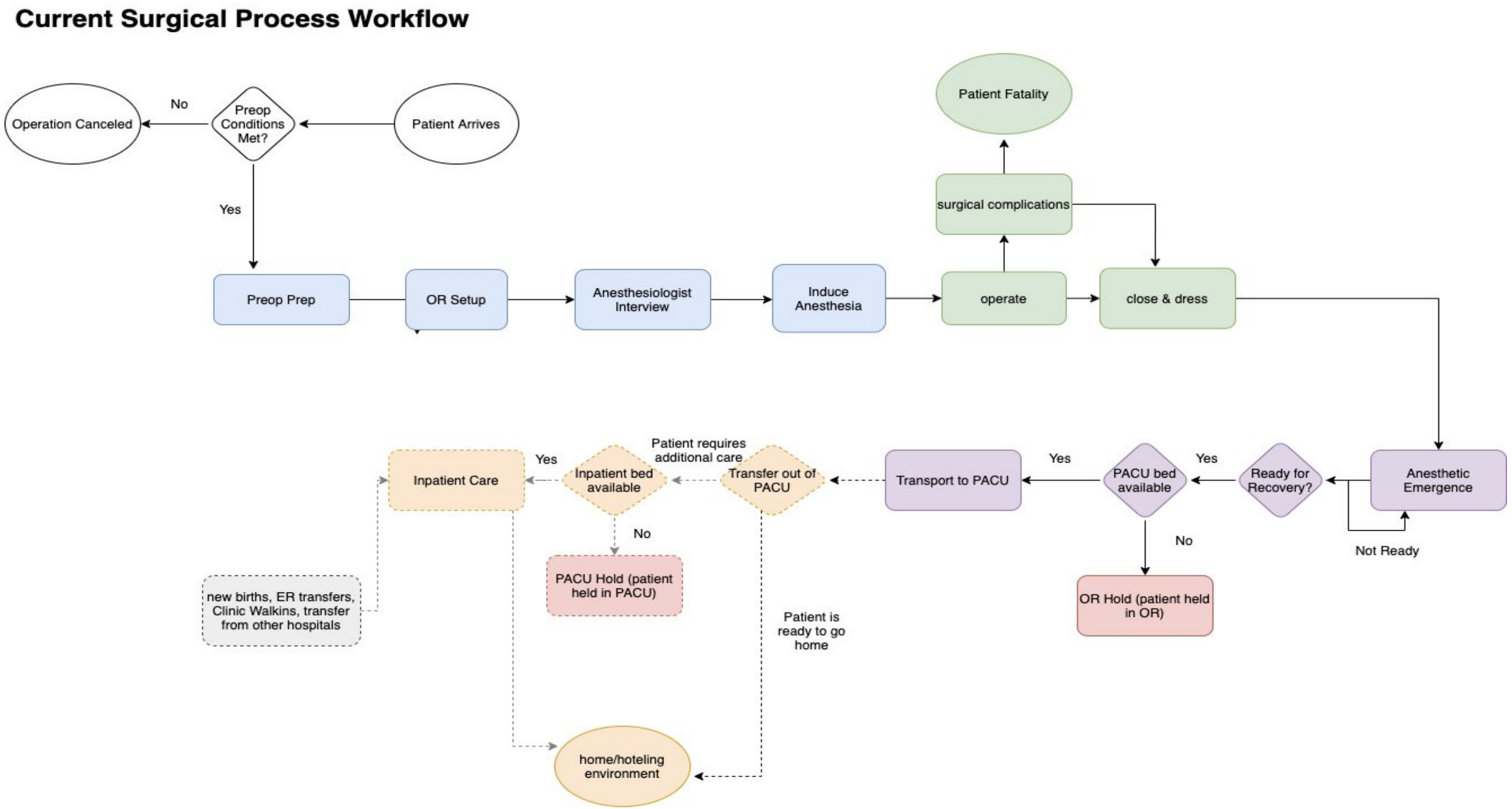
Questions?

Appendix

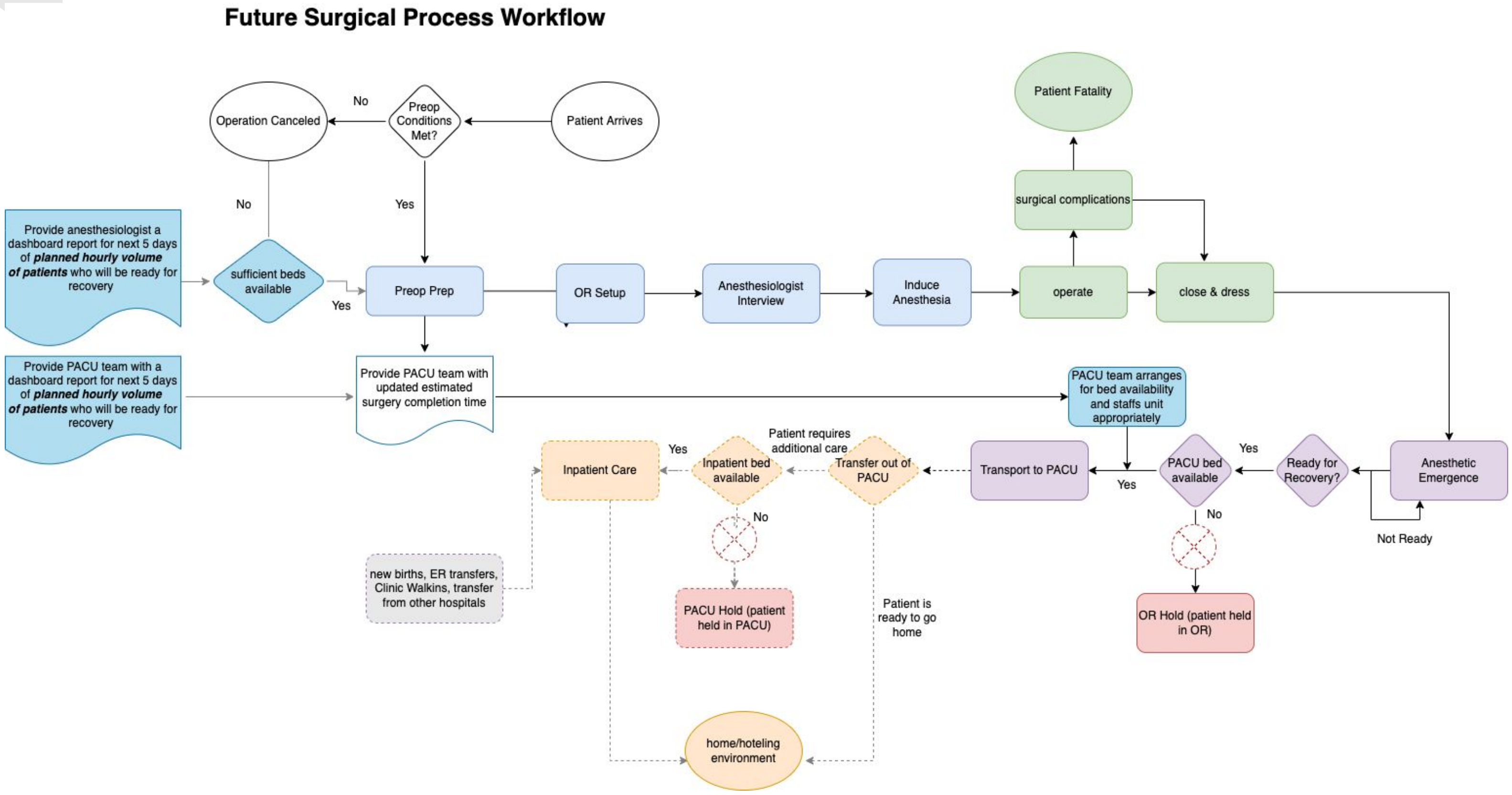
Current Delays in PACU Transfers



Problem Context: Current Surgery Workflow



Initial Planned Solution



Limitations & Additional Features

Data limitation: loading more than 5 days of historical predictions results in slow launch times for the app. Additional cloud resources or updated data pipeline needed to include 30+ days of historical predictions in future iterations of app

Hour

Show 10 entries

Search:

	Hour	Weekday Hourly Error (MAE)	Weekend Hourly Error (MAE)	Holiday Hourly Error (MAE)
1	7	0.5	0.5	
2	8	1.4		
3	9	1.9		
4	10	2.4		
5	11	2.2		
6	12	2	1	
7	13	2		
8	14	2		
9	15	3.7		
10	16	1.3		

Additional columns distinguishing errors based on type of day

Flagging high error hours