Session #11:

New Ways to Improve Hospital Flow With Predictive Analytics

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Agenda

- Review learning objectives.
- Meet our organization, data science team, and environment.
- Understand the problem.
- Frame the question to be answered.
- Review our models.
- Discuss how adoption was operationalized.
- Summarize lessons learned.

Learning Objectives

- Discover how we framed the real question that needed to be answered.
- Discuss how we engaged leaders up front – with the goal of operationalizing our analytics.
- Summarize the types of machine-learning (ML) methods we employed.
- Show how we operationalized the results.

Cedars-Sinai

CEDARS-SINAI

Hospitals

Cedars-Sinai Medical Center

- 958 bed hospital in Beverly Hills.
- Nonprofit, tertiary care center.
- Ranked the number 8 hospital in the U.S. by U.S. News and World Report.
- ~50,000 inpatient admissions per year.
- 2,166 physicians on staff.
- 437 medical residents and fellows.

Marina del Rey Hospital

- 154 bed hospital acquired in 2015.
- 458 physicians on staff.

Outpatient Services

Cedars-Sinai Medical Network

- ~350,000 outpatient visits annually.
- Urgent cares in Playa Vista, Culver City, and Beverly Hills.

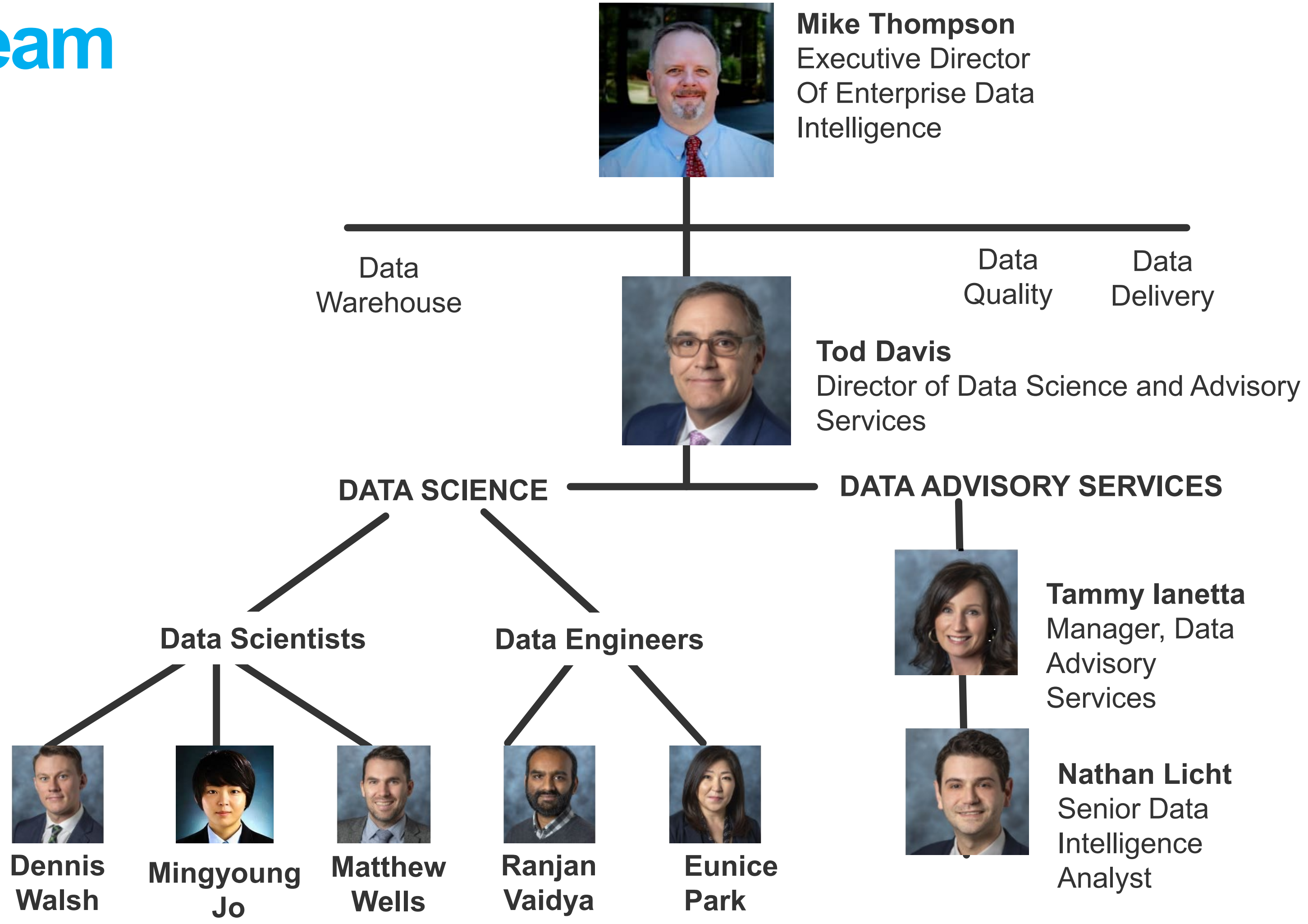
The Cedars-Sinai Enterprise Data Intelligence (EDI) Team

EDI

Prior to Mike Thompson's hiring in 2017, Cedars-Sinai had a relatively decentralized approach to analytics. Under Mike, all analytics and reporting teams have been brought together under the EDI umbrella. There are currently ~70 employees.

Data Science

The data science team is unique in that they focus on projects with a predictive component.



Cedars-Sinai End-to-End ML Pipeline

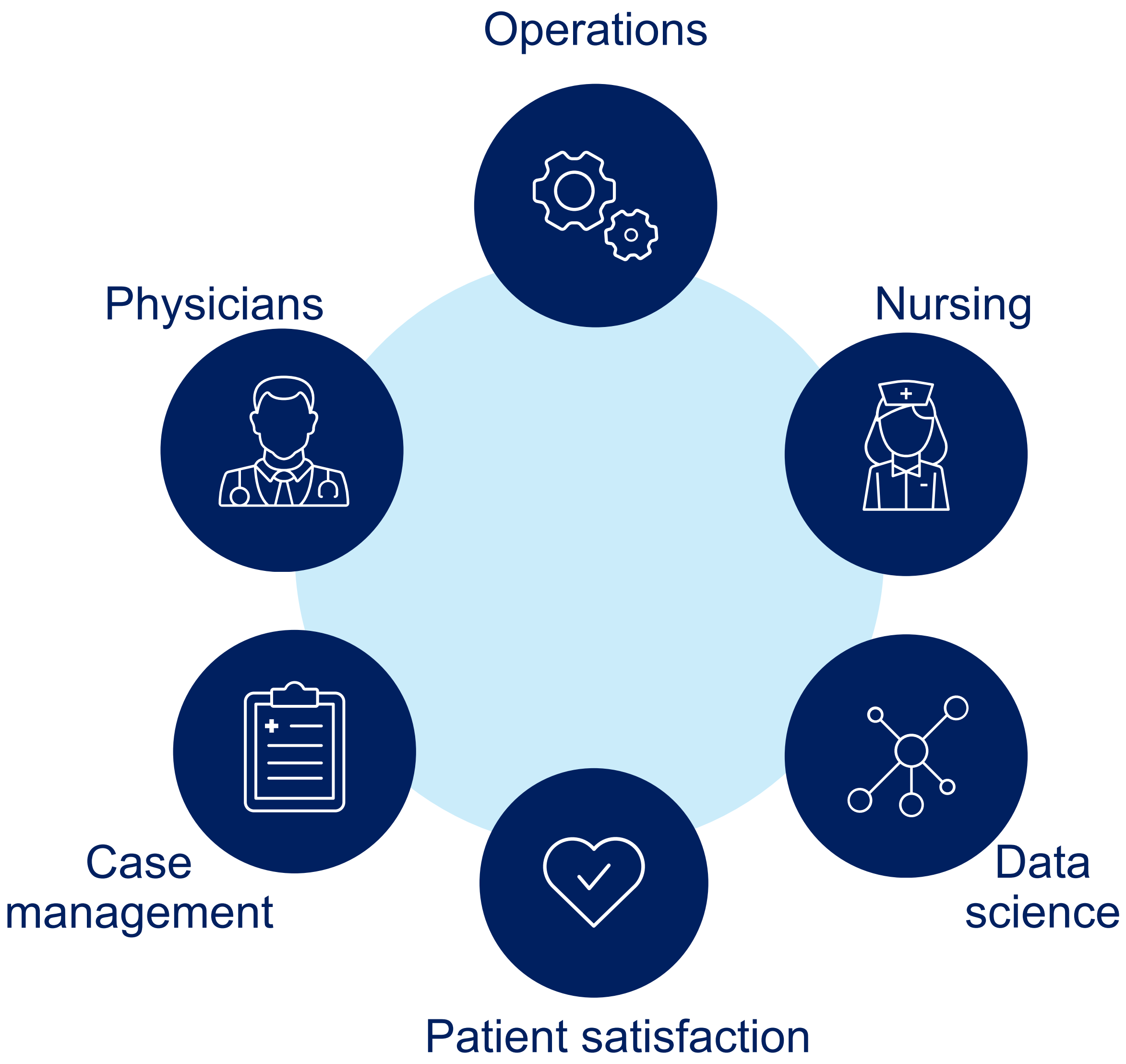
Over the course of the past year, we've developed an end-to-end ML pipeline leveraging a mix of best-of-breed open source and proprietary technologies.

Data Sources	Data Storage	Data Transformation and Modeling	Data Visualization
• EHR. • Medical device monitors. • Consumer devices. • Online surveys.	• Enterprise data warehouse. • Storage of real-time rectangular data. • Storage of other files needed for modeling.	• Open-source programming language for statistical computing and graphics. • Julia, Python, and R. • Digital storage solution.	• Data visualization software. • Interactive visualization software.

The Project Team

Meeting once a week, the team fashioned the problem statements, reviewed the data and validated the results from the ML/predictive models.

Using this information, the team interactively fashioned strategies.

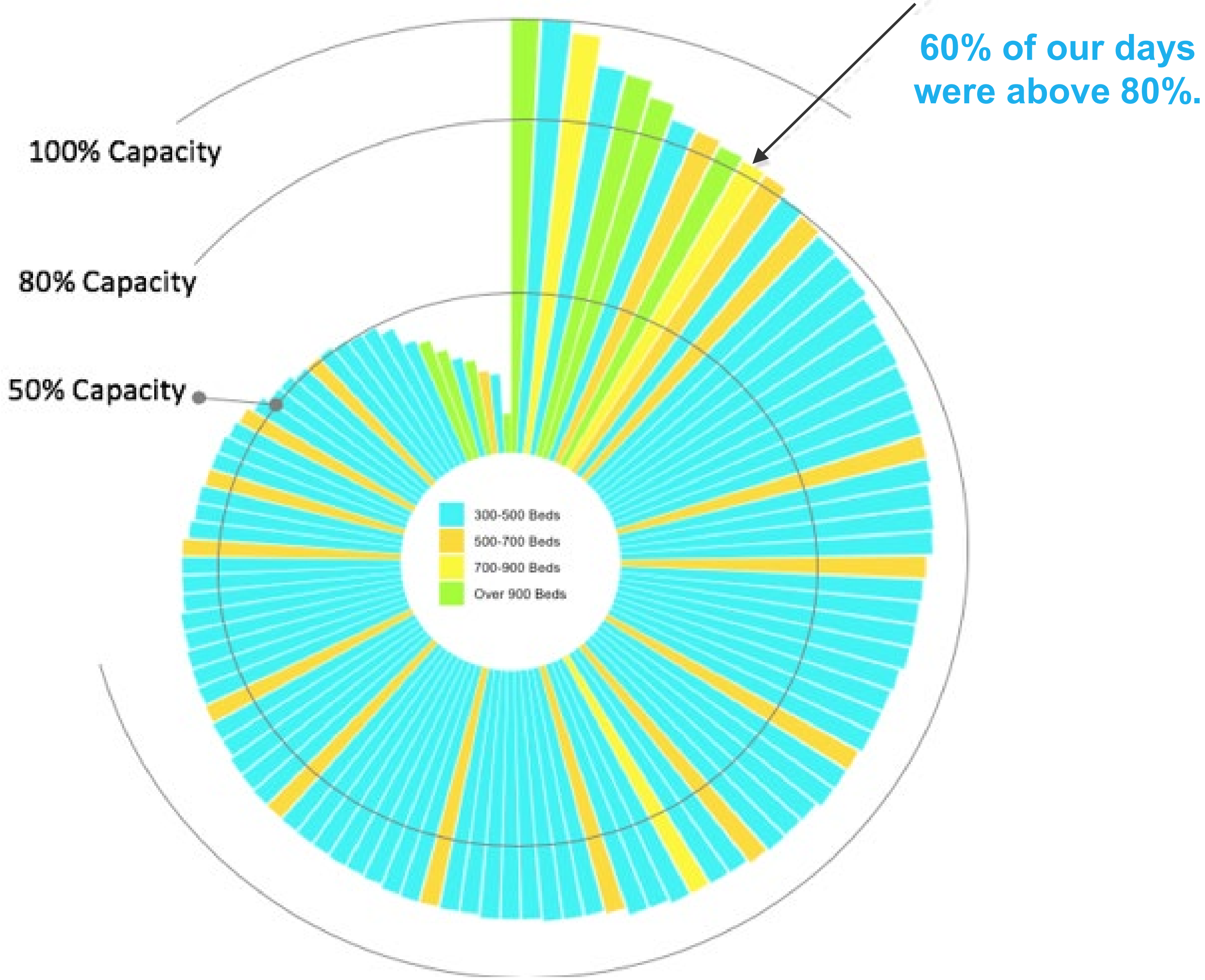


Capacity Strain

“Capacity strain” can be defined as capacity on any day that exceeds 80%, resulting an “excessive demand on the strength, resources, or abilities…”

In 2018, 12 California hospital facilities experienced a constant strain (total patient bed days divided by total registered bed days), while others have strain surges through-out the year.

2018 California Bed Occupancy Rates Hospitals with > 300 beds.



Date source: Office of Statewide Health Planning & Development.

Poll Question #1

Over the last year, how many times has your organization experienced capacity strain?

a) Less than 25%
b) 25-50%
c) 51-75%
d) Greater than 75%
e) Unsure or not applicable

The Impact of Capacity Strain: What we are Solving

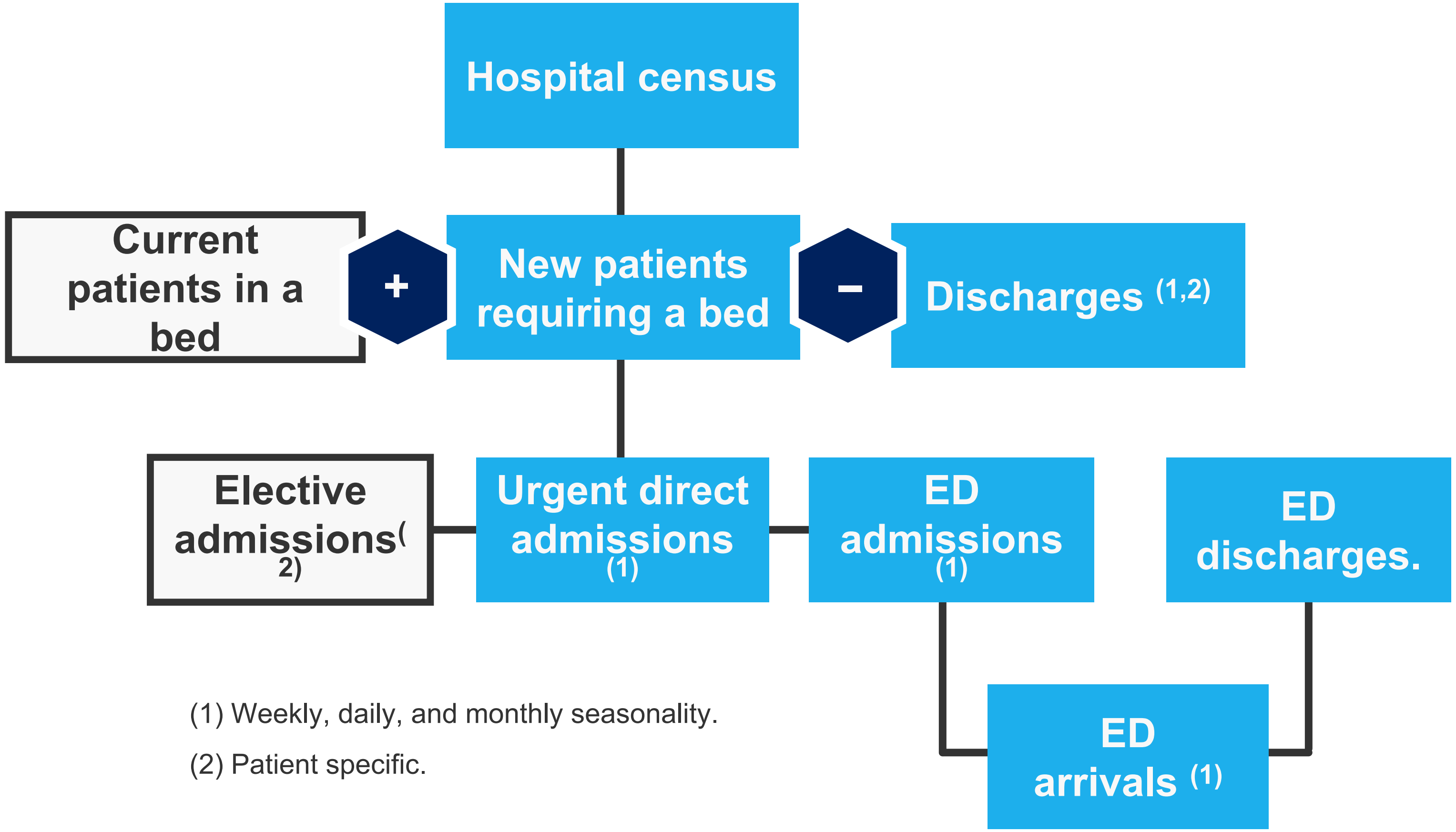
- Patients are “boarded” in the emergency department (ED), waiting to be admitted to a hospital bed.
- ED crowding—leading to left-without-being seen, and increased wait times.
- Patients have overnight stays in the post-op recovery rooms.
- ICU readmits within 24 hours.
- Delays or cancelations of surgeries.
- Physicians, nurses, and staff are overloaded—resulting in burnout of clinicians and staff.
- Throughput is decreased (there are delays in transferring patients to appropriate units based on their clinical conditions and in discharging patients).

Goals with Predictive Analytics and ML

- Reduce the need for regular surge plans.
- Prevent diversions and overcrowding in ED.
- Eliminate waits and delays for surgical procedures, treatments, and admissions to inpatient beds.
- Improve staff schedules to match demand, while reducing excessive overtime.
- Increase the number of patients admitted to the appropriate inpatient unit based on a patient's clinical condition.
- Utilize case management strategies to reduce the length of stay for "outliers."
- Improve discharge and bed capacity management planning.

Predicting Potential Hospital Census Requires Multiple Input Models

Blue boxes represent predicted values; white boxes are input values known at the time of model.

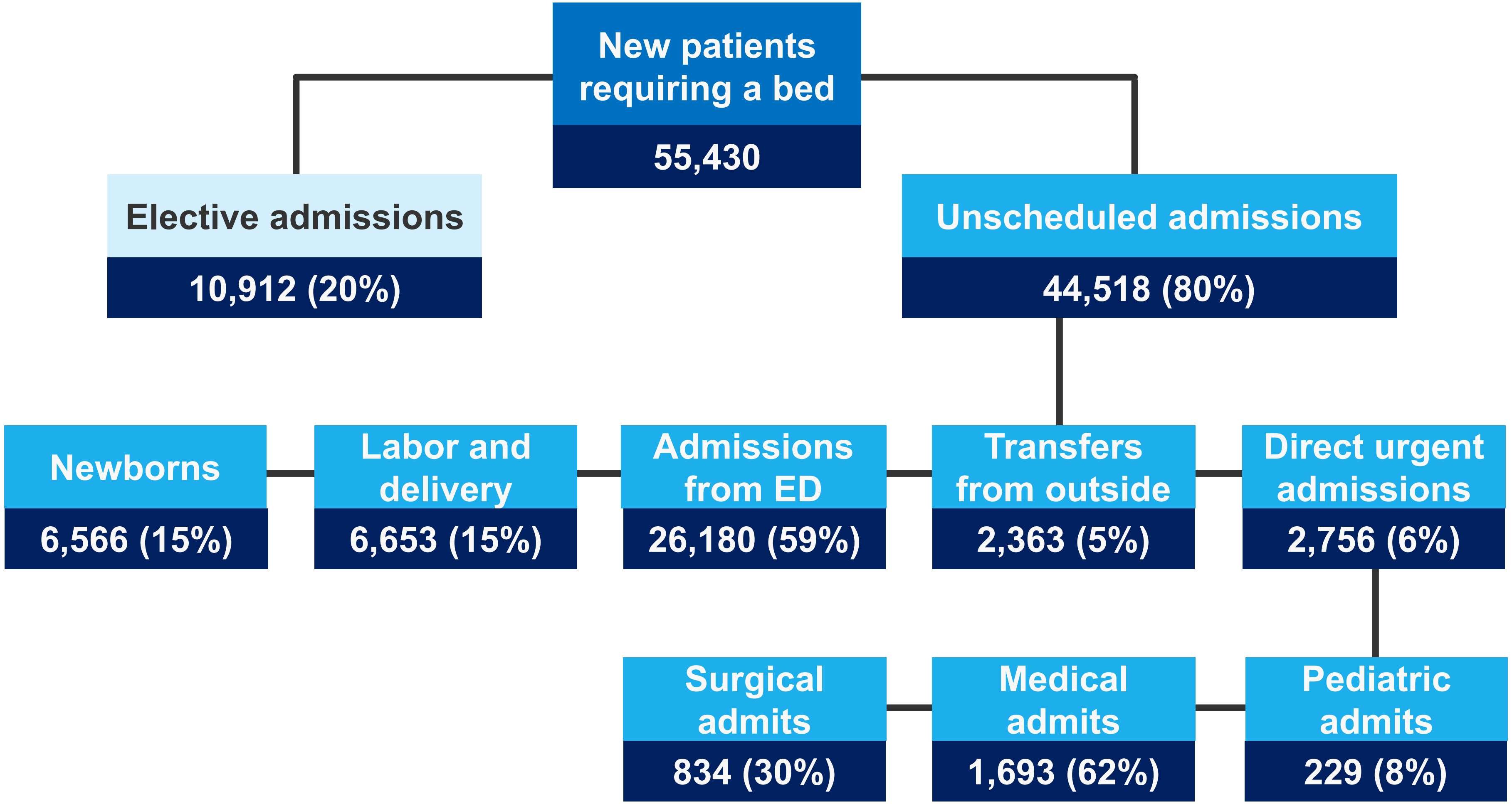


(1) Weekly, daily, and monthly seasonality.

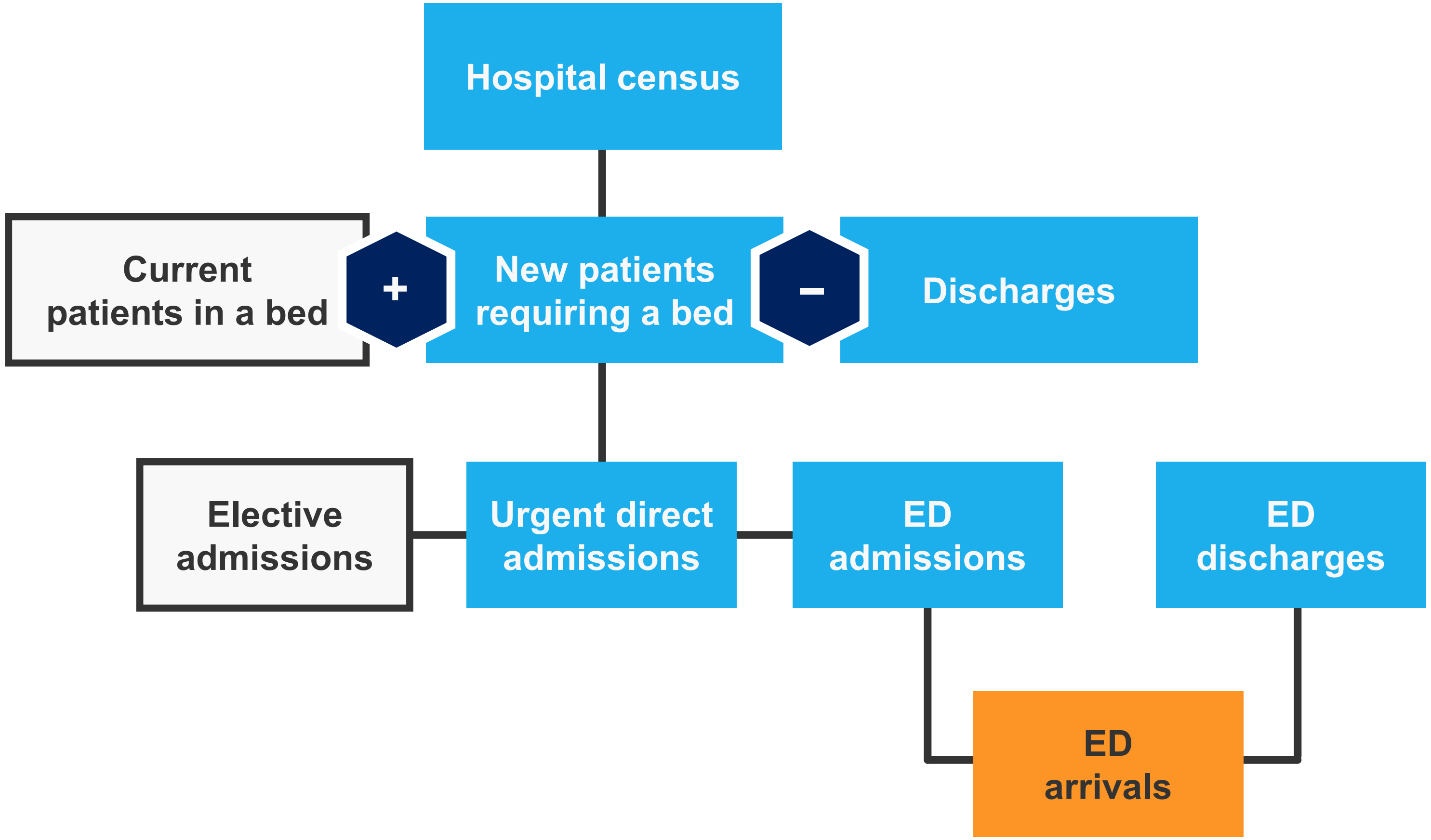
(2) Patient specific.

New Patients Requiring a Bed

"New patients requiring a bed" is all inpatient admits, including admits that are known in advance (elective) and those that must be predicted (unscheduled).

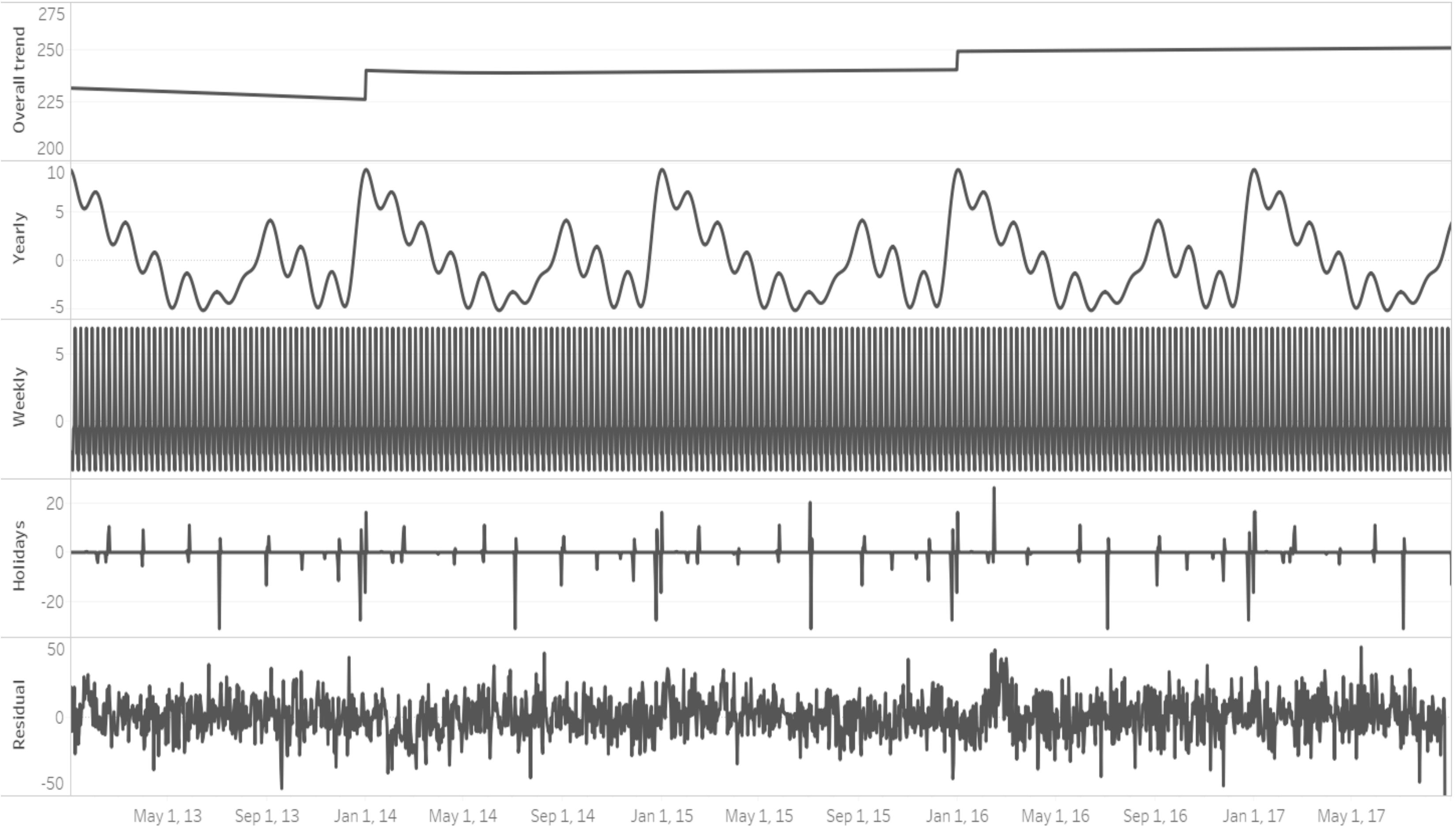


Step One: ED Visit Analysis



Step One: ED Visit Analysis (Continued)

ED Visit Volume Decomposition (2013 – 2017)



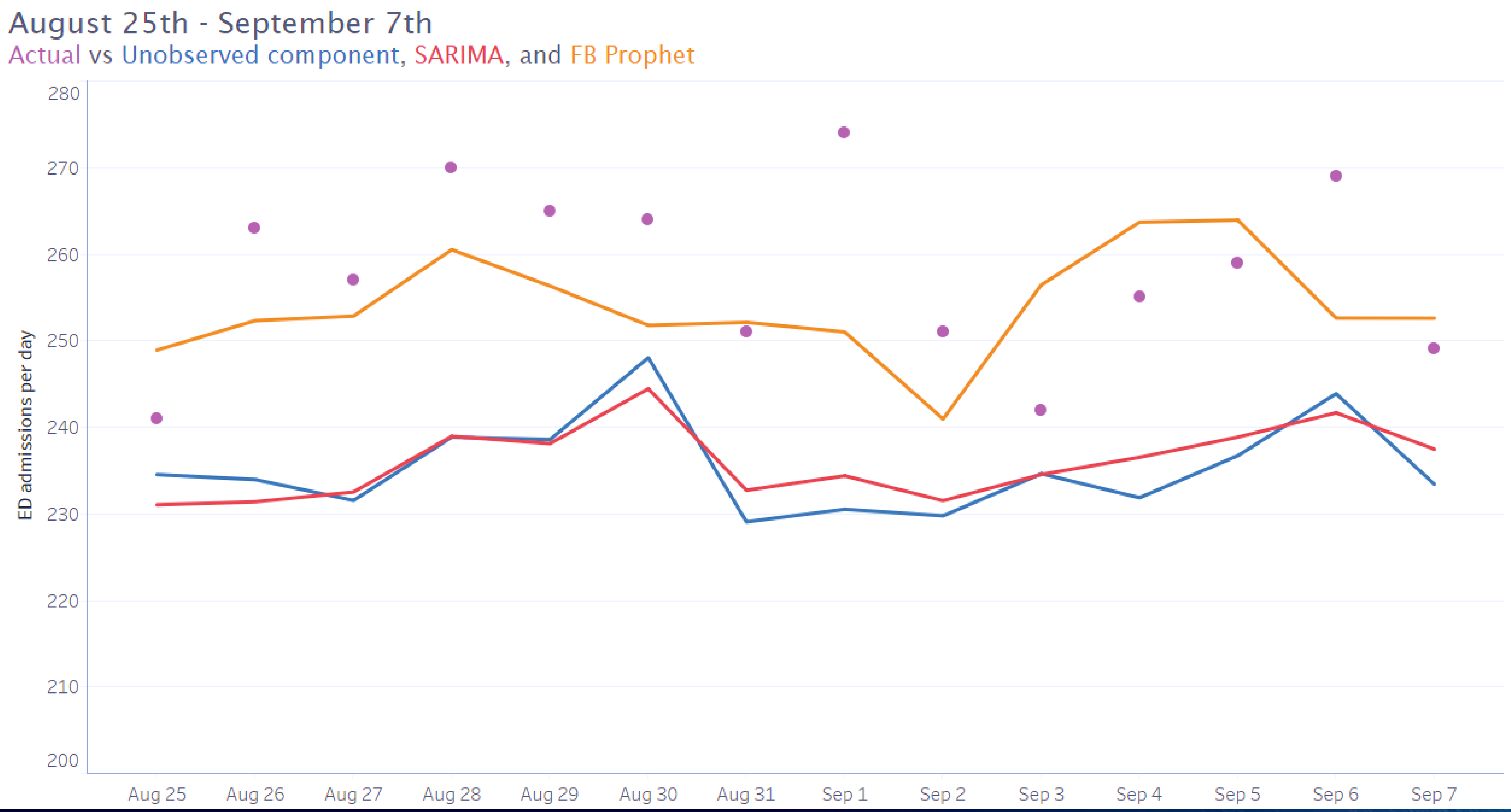
ED Admit Predictive Model Comparison

Model statistical comparison, training data

	Mean absolute error	Mean absolute percentage error	Mean absolute scaled error	Root mean squared error
Unobserved component	10.36	4.33%	0.78	13.19
SARIMA	9.99	4.17%	0.75	12.61
Facebook Prophet (FP)	9.60	4.00%	0.72	12.22
Naïve*	13.29	5.55%	1.00	16.86

*Naïve model treats previous day's value as prediction (e.g. if there were 234 ED admissions on September 12, 2017, then this model predicts 234 admissions for September 13, 2017).

Model Visual Comparison, Predictive Set



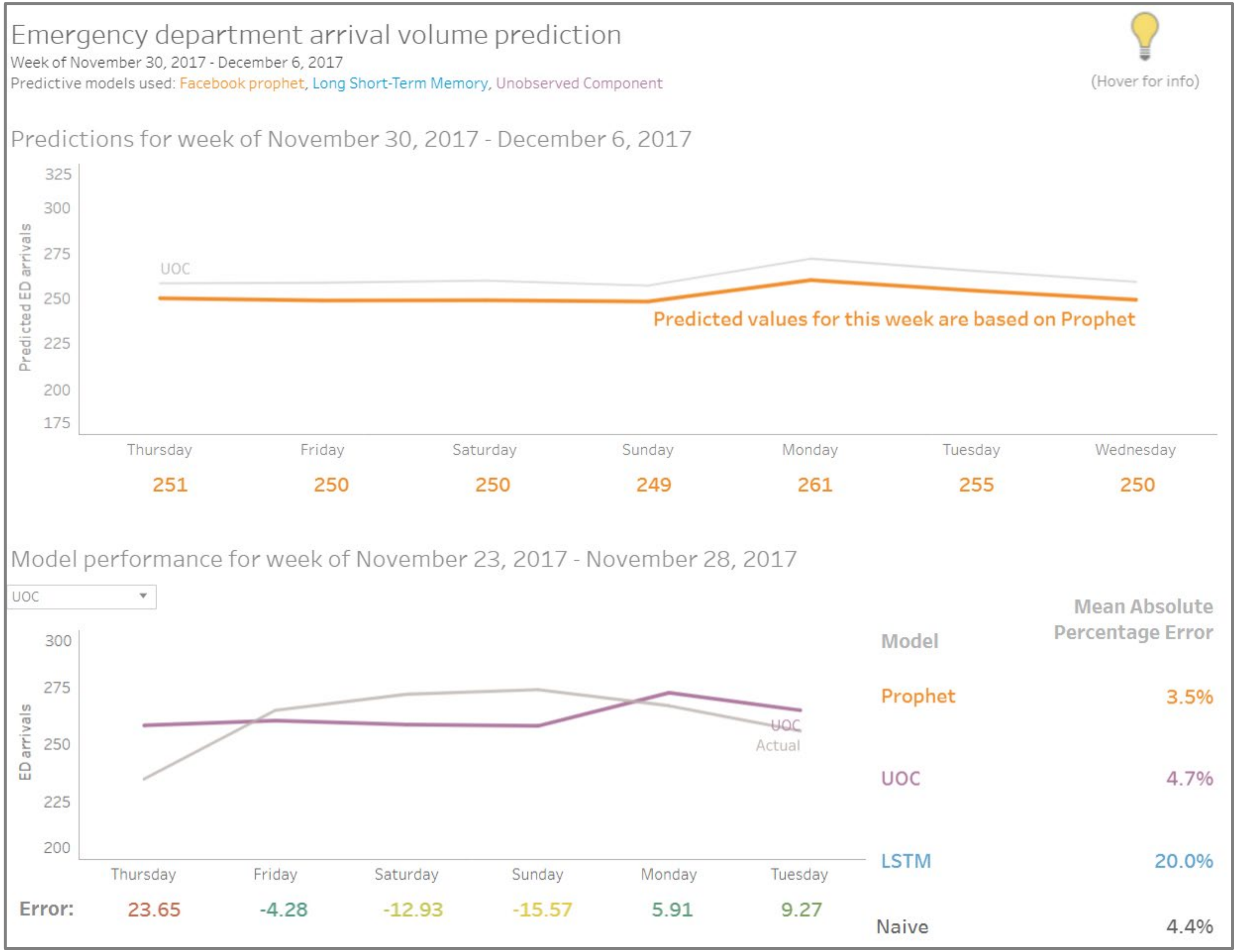
ED Admit Predictive Model Comparison (Continued)

Model statistical comparison, training data

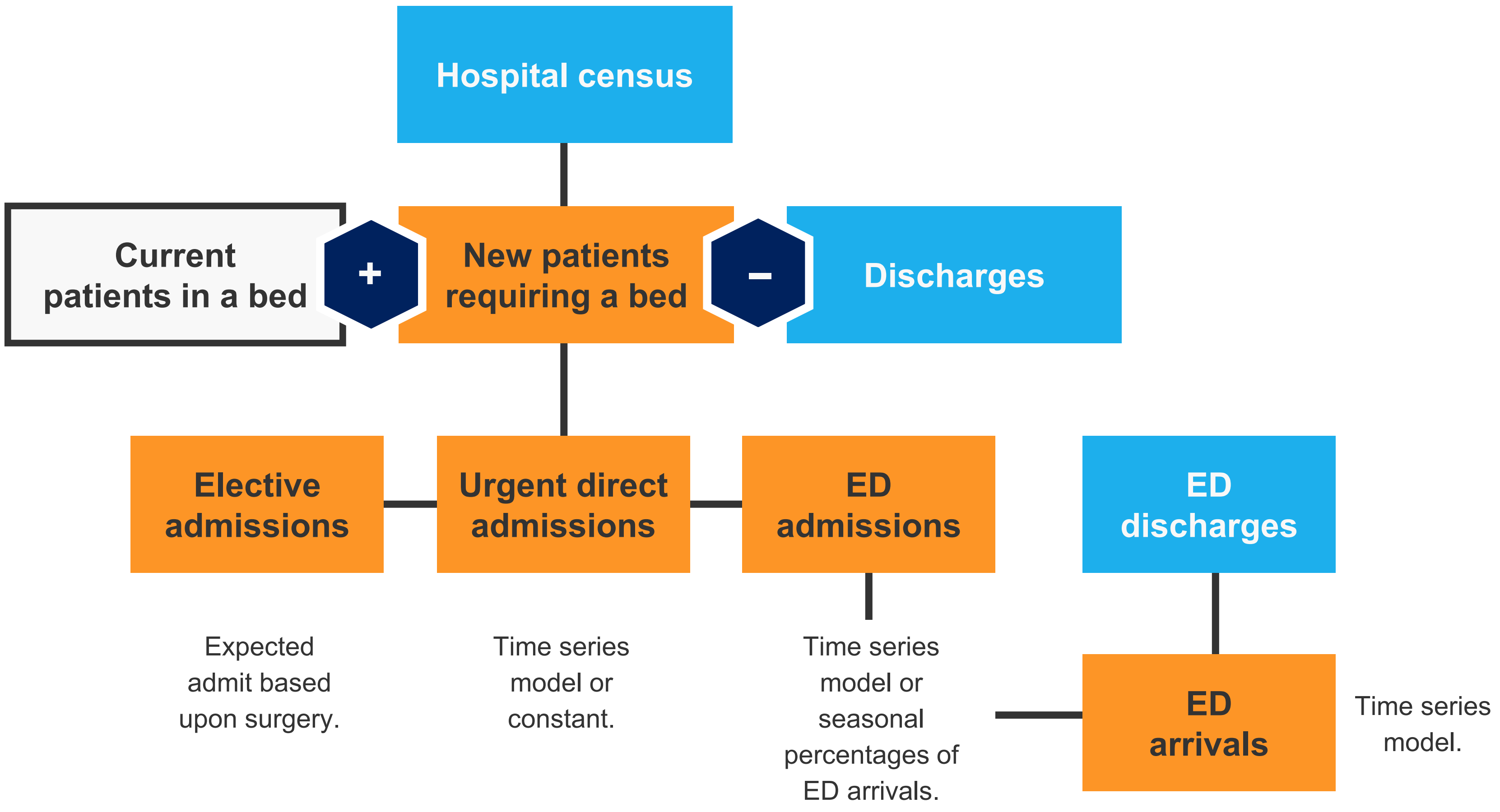
	Mean absolute error	Mean absolute percentage error	Mean absolute scaled error	Root mean squared error
Unobserved component	22.47	8.61%	1.85	24.25
SARIMA	21.84	8.36%	1.80	23.50
FP	9.67	3.72%	0.80	11.11
Naïve*	12.14	4.71%	1.00	14.07

*Naïve model treats previous day's value as prediction (e.g. if there were 234 ED admissions on September 12, 2017, then this model predicts 234 admissions for September 13, 2017).

ED Arrivals Dashboard Snapshot



New Admission Model Summary



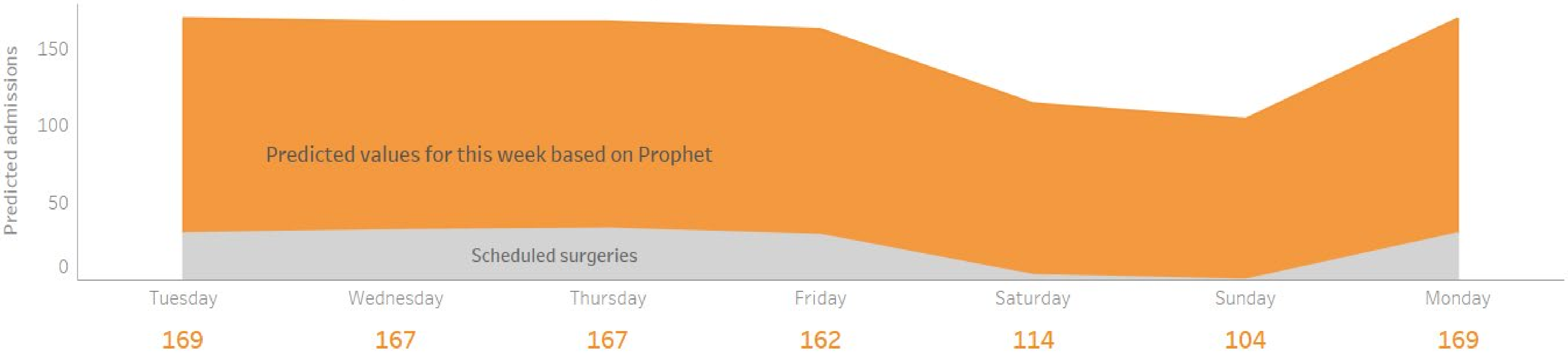
New patient arrival volume prediction

Week of February 20, 2018 - February 26, 2018

Predictive models used: Facebook prophet, Long Short-Term Memory, Unobserved Component

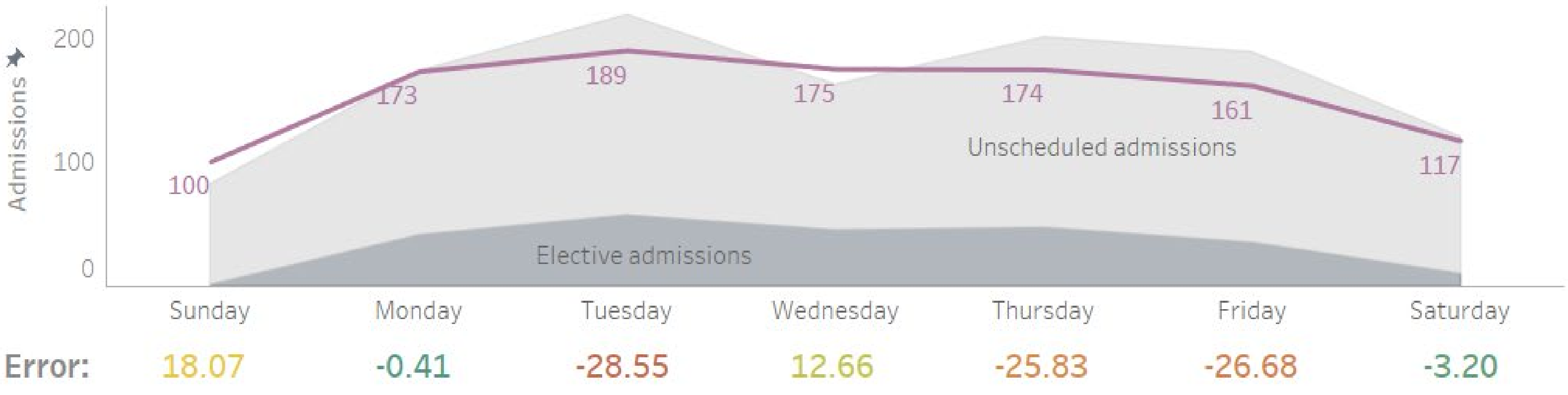
(Hover for info)

Predictions for week of February 20, 2018 - February 26, 2018



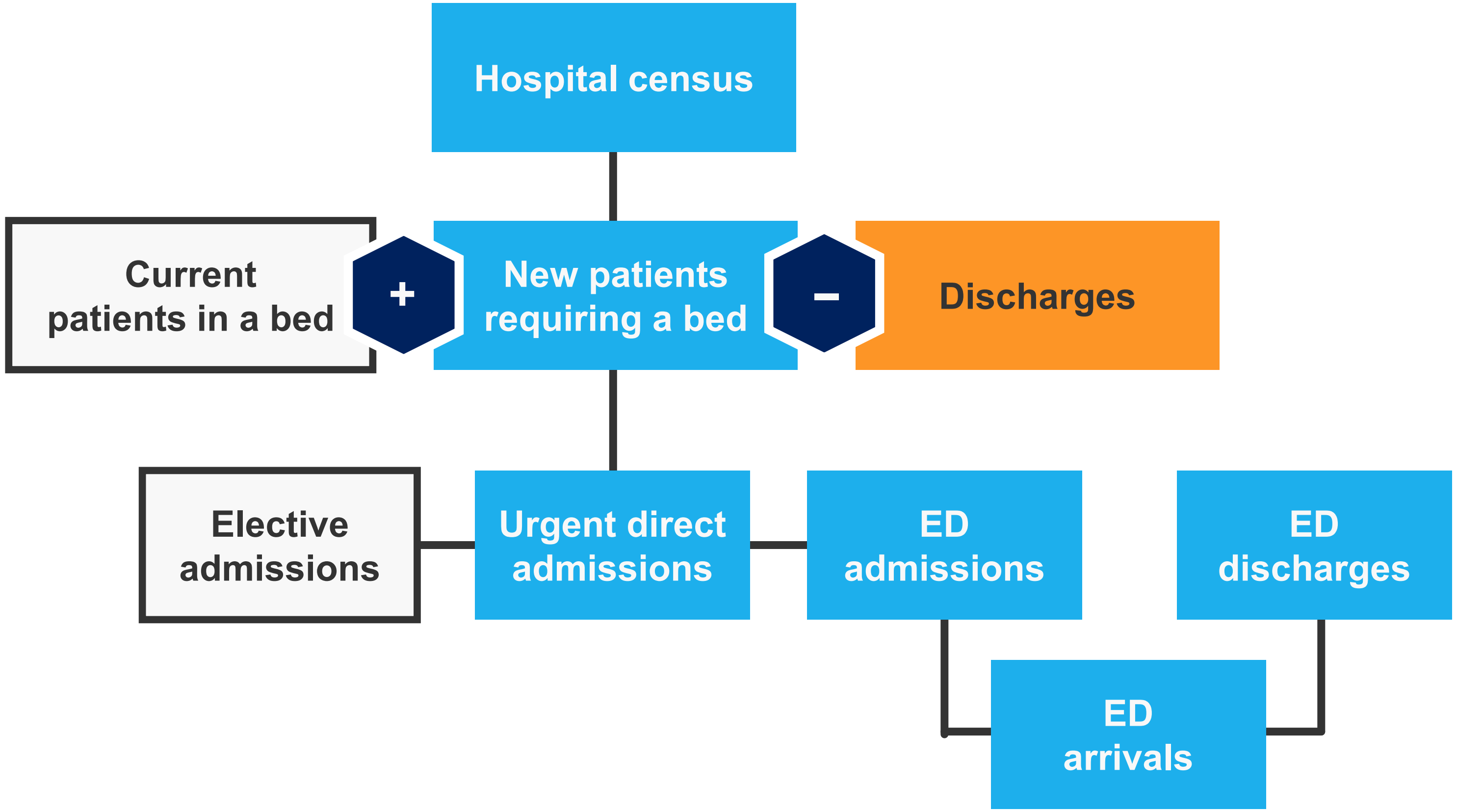
Model performance for week of February 11, 2018 - February 17, 2018

UOC



Model	Mean Absolute Percentage Error
Prophet	9.9%
UOC	10.4%
LSTM	18.8%
Naive	32.3%

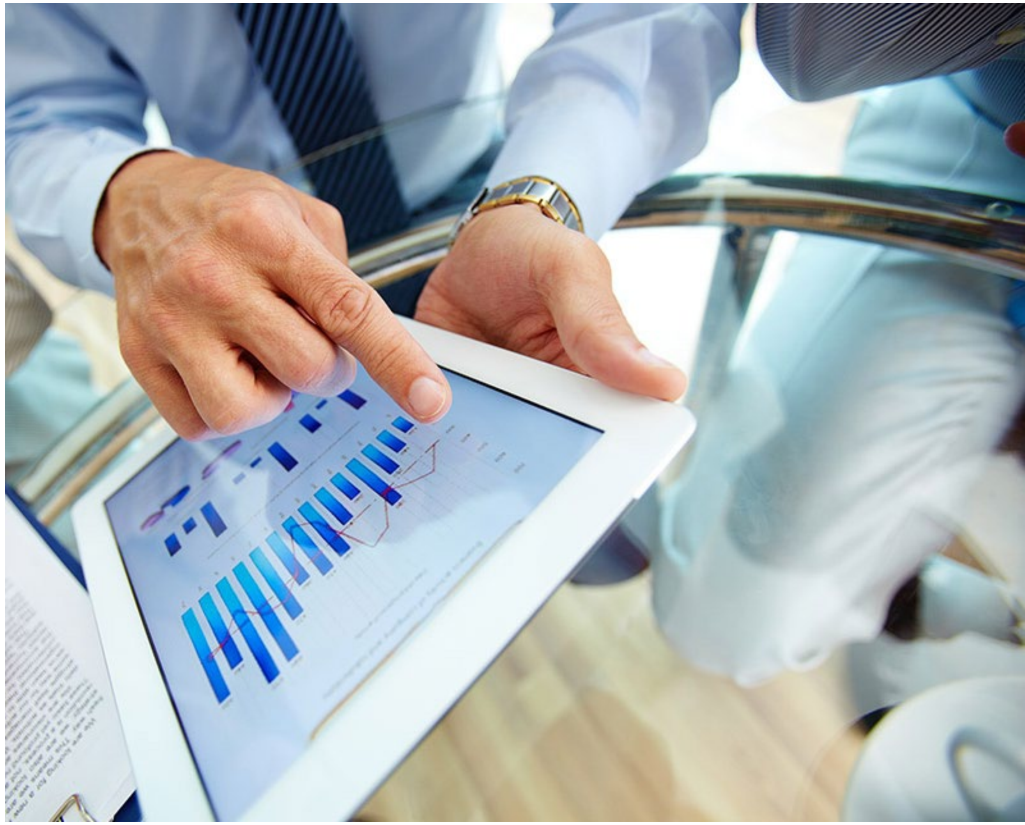
Admits Is Only a Part of the Story: Discharges Were the Next Target



Discharge Prediction Model Options

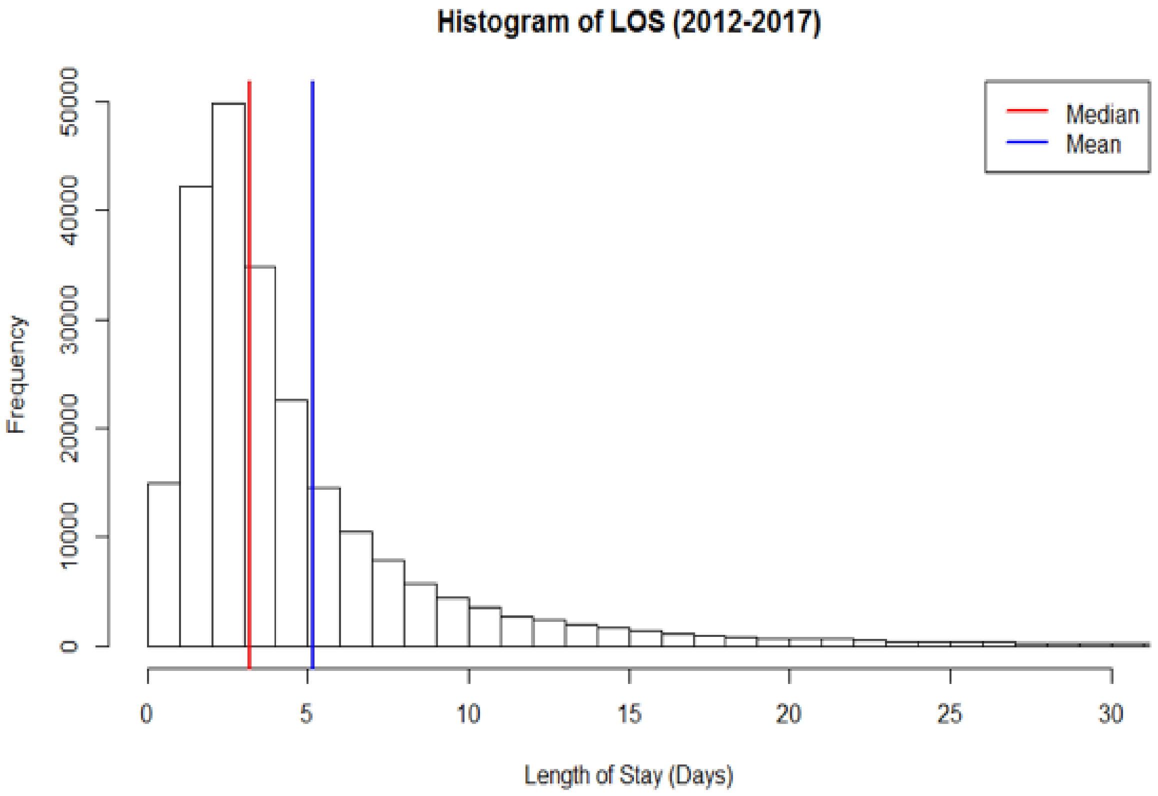
Each with its own pros and cons.

1. Time series model.
2. Expected run-off model.
3. Average length of stay (LOS).
4. Expected discharge inputs.
5. Patient specific LOS.

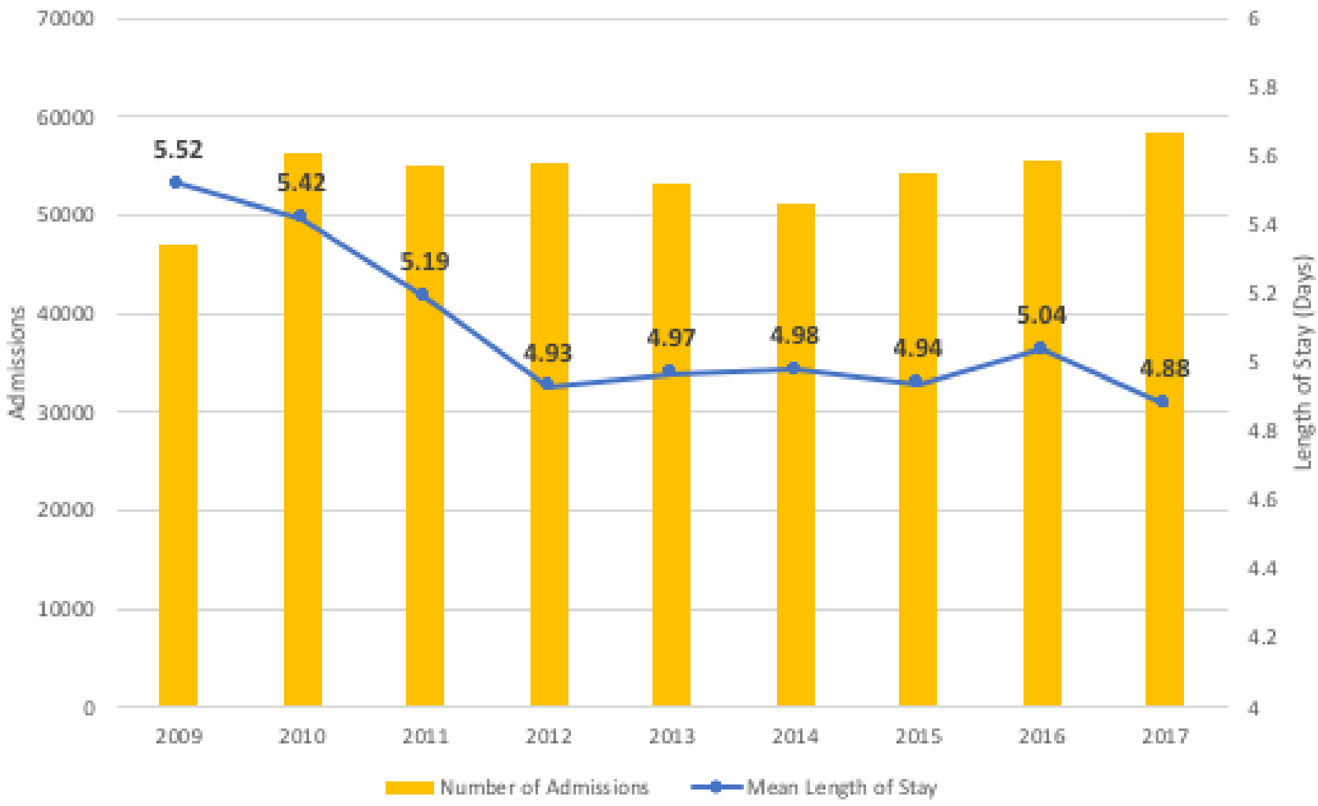


LOS Overview

LOS Distribution



Number of Admissions and Average LOS by Year



Predictive Model Power Research

Validation of prediction model performance by the original authors

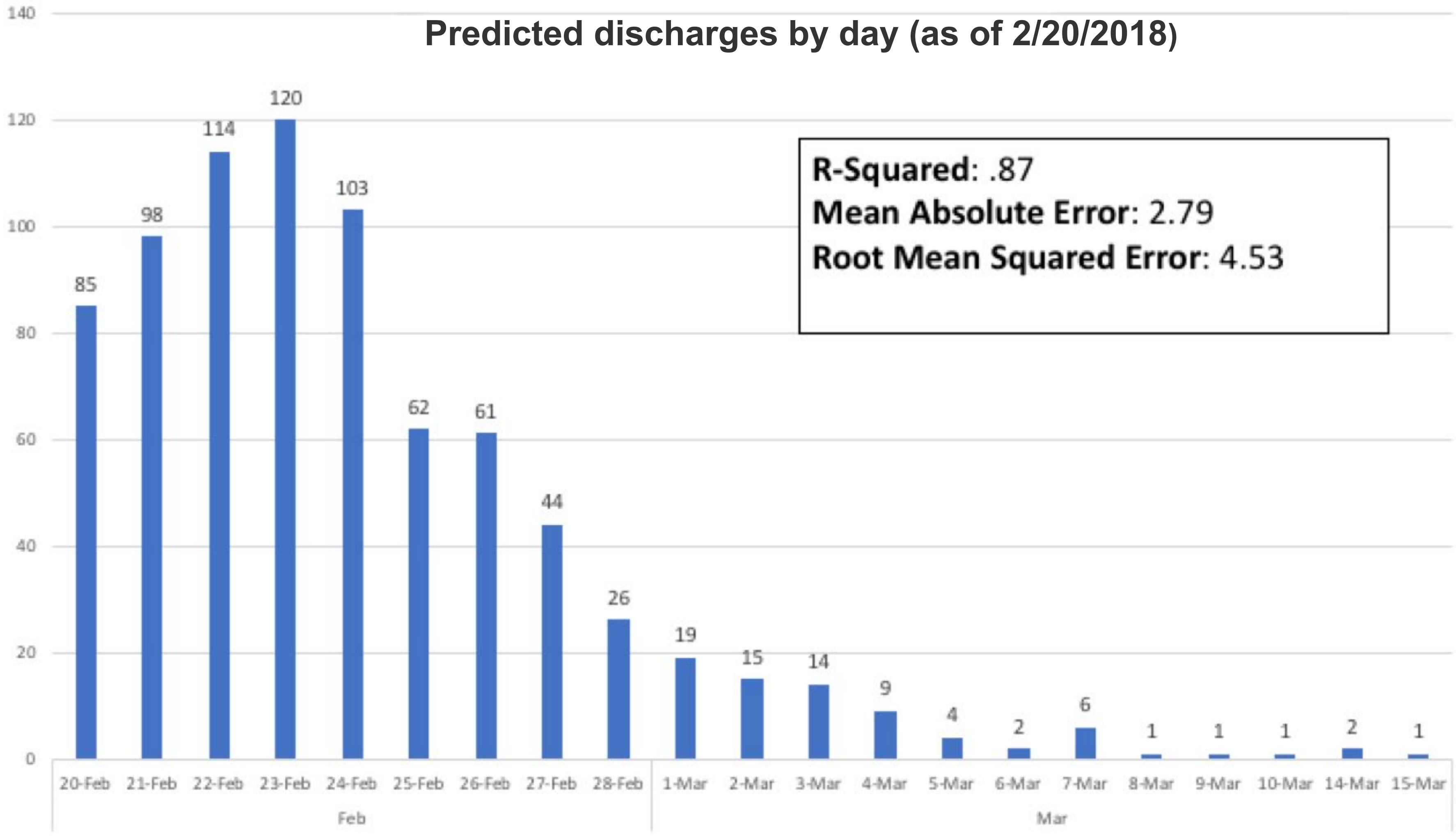
Reference	Model Validation		Model Performance			
	Validation Method	No. of Patients Included in Validation Set	R^2 Across ICU (Validation Set)	R^2 Across Patients (Validation Set)	Difference Mean Observed and Mean Predicted Length of Stay (Validation Set) in Days (Bias)	Recalibration Plot Presented
Clermont et al (25)	12 other ICUs	460	–	–	0.50[a]	No
Perez et al (22)	Random sample (pps) of 50% stratified by Intensive Care National Audit and Research Centre coding method code	1,531	–	–	0.01–6.69[b,a]	No
Zimmerman et al (8)	Simple random sample of 40%	46,517	0.62	0.22	0.08[a]	Yes[c]
Rothen et al (19)	–	–	–	–	0.40[d]	No
Moran et al (23)	Random sample (pps) of 20% stratified by year of admission	44,625	–	0.18	–[e]	No
Moran and Solomon (7), model 1–12	Random sample (pps) of 20% stratified by year of admission	22,333	–	0.18–0.20	0.2–4.7	Yes
Niskanen et al (6), model 1[f]	Simple random sample of 40%	25,586	0.57	0.27	0.01[a]	Yes[c]
Niskanen et al (6), model 2	Simple random sample of 40%	25,586	0.64	0.28	0.76	Yes
Vasilevskis et al (10), model 2[g]	Simple random sample of 40%	4,611	0.28	0.10	0.01[a]	Yes[c]
Vasilevskis et al (10), model 3	Simple random sample of 40%	4,611	0.01	0.05	0.02[a]	Yes
Kramer and Zimmerman (24)	Simple random sample of 50% and different time period	12,904	0.43[d]	0.18[d]	0.02[a] and 0.61[h]	Yes
Al Tehewy et al (26)	Two ICUs and different time period	–	–	0.05	–	No
Verburg et al (11), model 1–8	Bootstrap (100×)	32,667	–	0.09–0.15	–	Yes

Source: Verburg, et. al., (2017). Which models can I use to predict adult ICU length of stay? A systematic review. *Critical Care Medicine, 45*(2), e222-e231.

Our Sample Model Performance

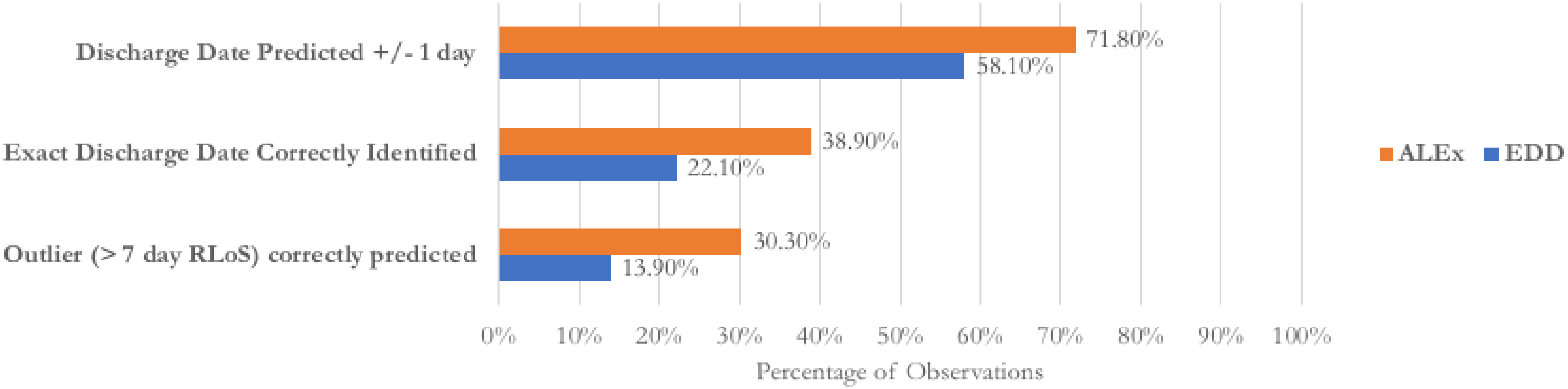
Model	R^2	RMSE	MAE
Advanced GLM Blender	0.403	4.86	2.73
eXtreme Gradient Boosted Trees Regressor with Early Stopping and Unsupervised Learning	0.398	4.88	2.76
RandomForest Regressor	0.383	4.94	2.78
Generalized Additive Model	0.363	5.02	2.86
Ridge Regression	0.325	5.16	2.97
Linear Regression (OLS)	0.319	5.18	3.01

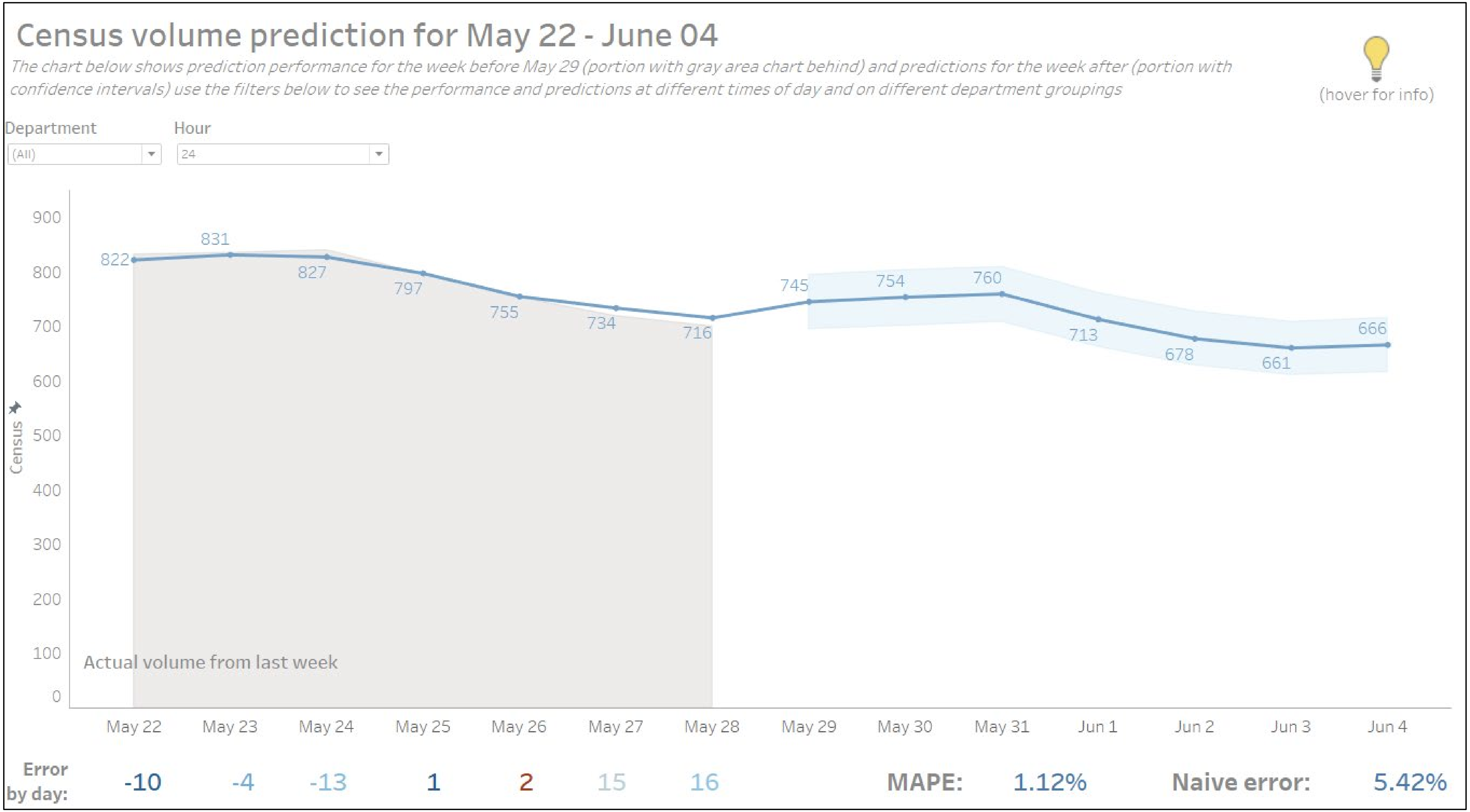
Final Model Predictive Performance



Final Model Predictive Performance (Continued)

Compared to the manually entered Expected Discharge Date in CS-Link, our Automated Learning By Example (ALEx) is more accurate in predicting the patient's date of discharge, and **correctly identifies outlier LOS Patients twice as often.**




Census volume prediction for May 22 - June 04
The chart below shows prediction performance for the week before May 29 (portion with gray area chart behind) and predictions for the week after (portion with confidence intervals) use the filters below to see the performance and predictions at different times of day and on different department groupings
(hover for info)
Department
(All)
Hour
24
Census
900
800
700
600
500
400
300
200
100
0
822
831
827
797
755
734
716
745
754
760
713
678
661
666
Actual volume from last week
May 22
May 23
May 24
May 25
May 26
May 27
May 28
May 29
May 30
May 31
Jun 1
Jun 2
Jun 3
Jun 4
Error by day:
-10
-4
-13
1
2
15
16
MAPE:
1.12%
Naive error:
5.42%

Cedars-Sinai ALEx volume predictions

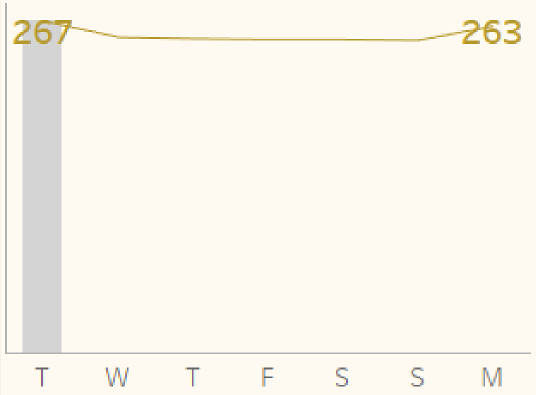
Welcome to the Cedars-Sinai ALEx volume prediction application. Below is high level summary and preview of all of the information available. Click on one of the links below to be directed to the dashboard with detailed information on a more specific type of volume prediction

ED arrivals volume prediction

ED arrival volume was 4.06% lower than expected over the last 3 days

267

ED arrivals prediction for today

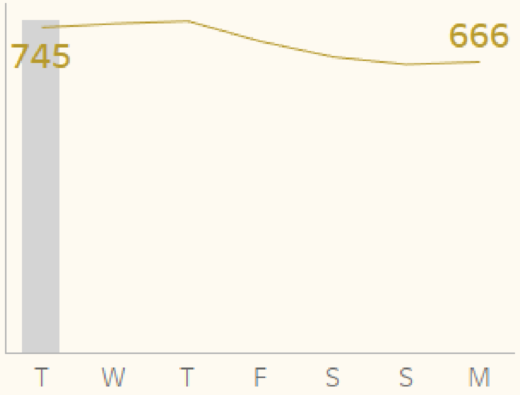


Census volume prediction

There is a greater than 60% chance the census will exceed 775 on May 31 at 7 am

745

Census prediction for today

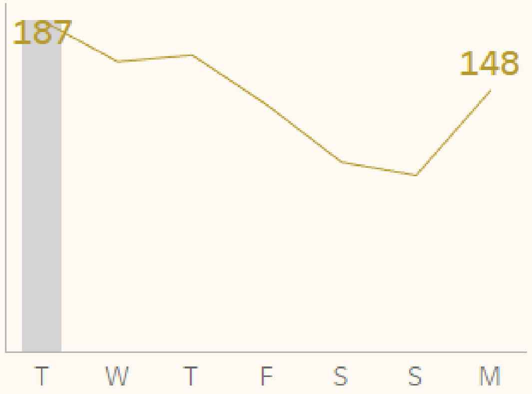


Admissions volume prediction

Occupancy is predicted to be at 94% and 92% on May 31 at 7 am for SURG and MED departments respectively. These occupancy rates are driven by admissions of 63 and 64 on that day

187

Admissions prediction for today

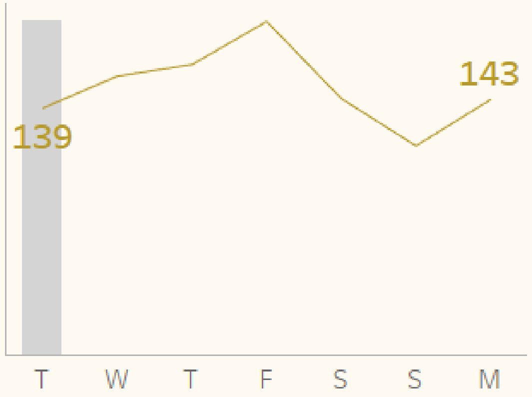


Discharges volume prediction

Advanced discharge planning of an additional 4 discharges per day before May 31 would likely result in reduction in census from 782 to 775 on that day

139

Discharges prediction for today



Prediction Accuracy

The Cedars-Sinai Data Science team has been using a time series algorithm to predict admissions week by week since the beginning of 2018. The chart below shows performance during that time.

Admission prediction accuracy, 2018.

93.1%

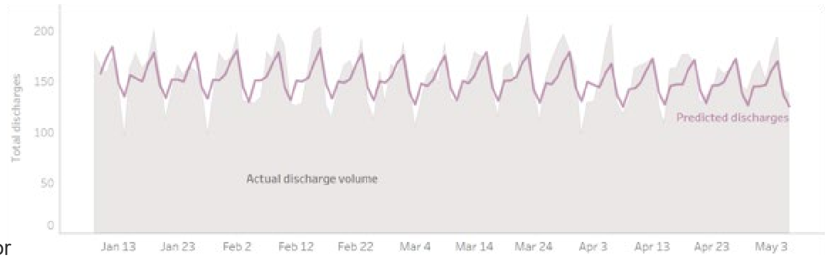
Mean absolute percent accuracy for admissions predictions, 2018 YTD.

Discharge predications are also made, based on the LOS distribution of current patients and expected admissions. Below is a chart showing performance in 2018.

Discharge prediction accuracy, 2018.

91%

Mean absolute percent accuracy for admissions predictions, 2018 YTD.

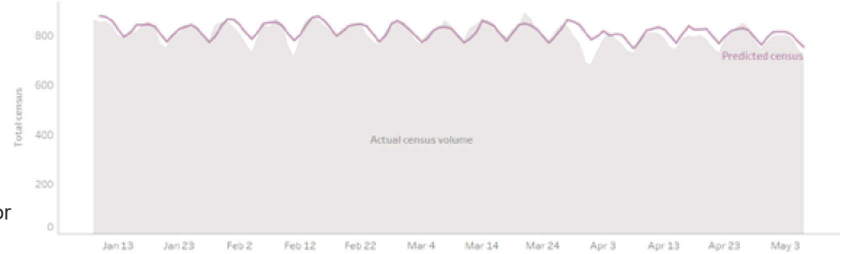


Admission and discharge predications are combined to create an estimated census predication. Below is a chart showing performance in 2018.

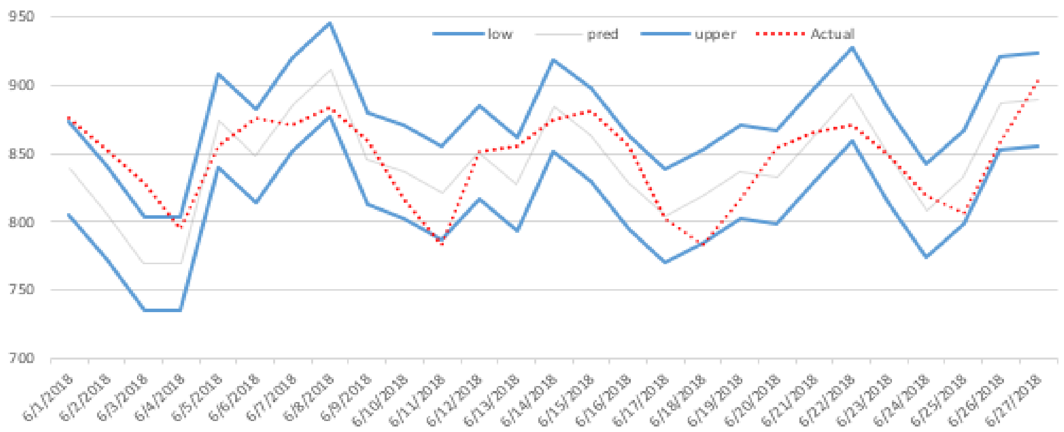
Census prediction accuracy, 2018.

97.1%

Mean absolute percent accuracy for admissions predictions, 2018 YTD.



Accuracy

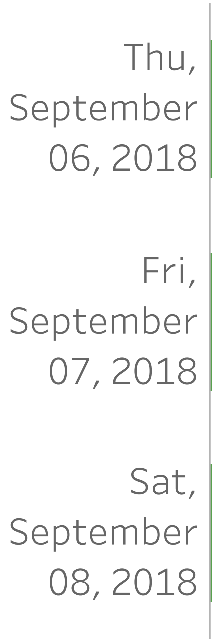


What We Are Doing with the Information

The results of the prediction are currently being sent out as alerts to the executive leadership team. The alerts are triggered whenever the alert level for one of the next three days is either high or very high. The table below shows the conditions for each alert level.

Alert level	Alert trigger	Descriptive text
Very high	Lower band above 850.	Very high risk of census exceeding 850 on Tuesday.
High	Projection line above 850.	Census is likely to exceed 850 on Tuesday.
Medium	Upper band above 850.	Current conditions suggest there is a chance census could exceed 850 on Tuesday.
Low	No bands above 850.	Census is unlikely to exceed 850 on Tuesday.

The chart below is sent out as part of the executive alert for a predicted elevated census. The black dot indicates the alert level for each day.



Actions Taken by Leaders Based on the Information

The table shows the intersection of each alert level and the different types of actions that can take place. For each square, the leadership team is helping to define what the appropriate intervention actions are.

Action	Low	Medium	High	Very High
Discharges	No change in normal behavior.	No change in normal behavior.	Push for discharge orders before 11am.	Discharge patients to holding.
Clinical staffing	Consider flexing staff.	Follow current staffing plan.	Call in additional staff.	Redistribute staff, utilize break relief.
Support services staffing	Consider flexing staff.	Follow current staffing plan.	Call in more staff for next day.	Call in more staff for next two days.
Transfer center	No change in normal behavior.	No change in normal behavior.	All lateral transfers on hold.	Only accept Emergency Medical Treatment & Labor Act (EMTALA) transfers.
Overflow units	Varies by specialty.	Varies by specialty.	Follow volume OF policy.	Open all + command center.
Monitoring	No change in normal behavior.	Check census levels At 7am, 7pm.	Check all volumes every 4 hrs.	Check hr. by hr. volume progress.

Poll Question #2

On a scale of 1 to 5, how would you rate your organization's effectiveness in using predictive model information to make decisions?

1) Not at all effective
2) Somewhat effective
3) Neutral
4) Moderately effective
5) Extremely effective
6) Unsure or not applicable

Current Focus: Ease of Use and More Rapid Data Refresh

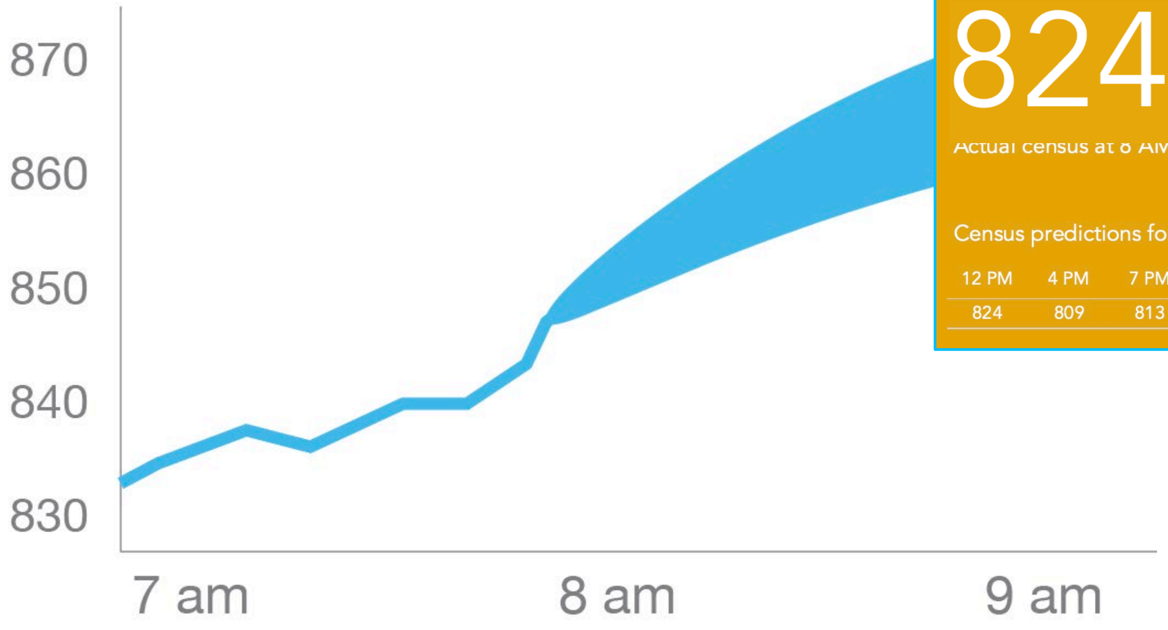
Predictions are now taking into account real-time data.

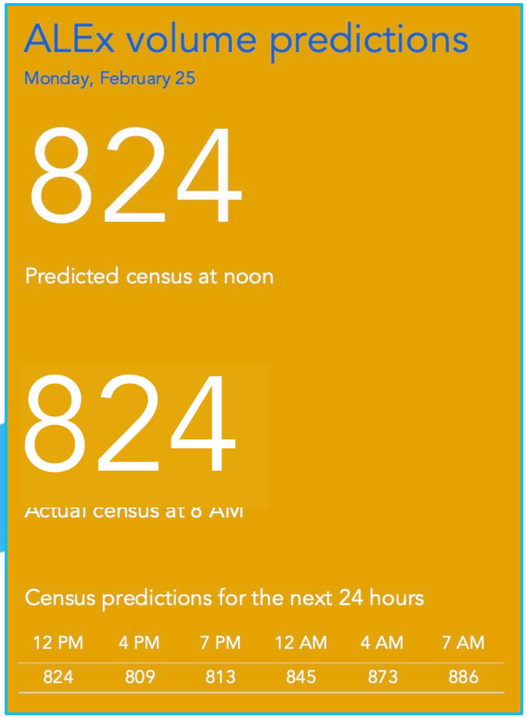
We have recently introduced a mobile version of the census that provides simplified forecasting numbers.

We are testing more granular predictions with higher frequency.

We have also made some efforts to integrate patient level modeling of estimated discharge date based.

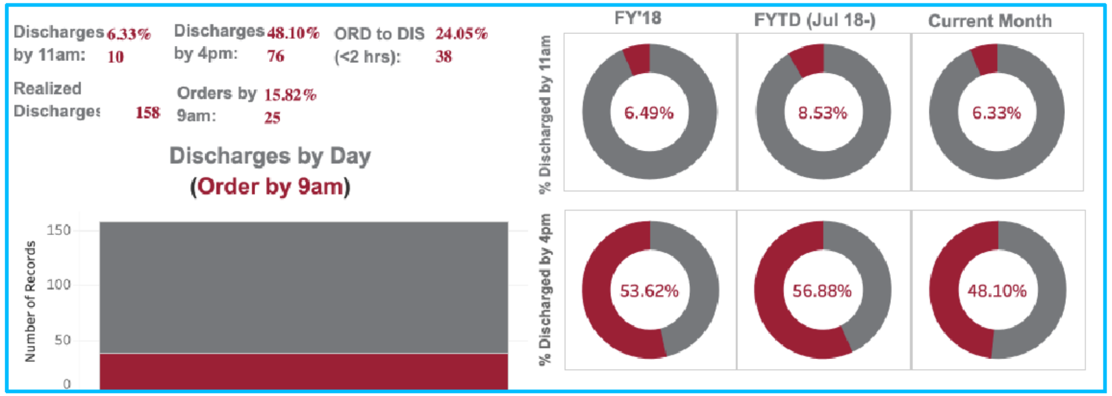
Census prediction with real-time updating



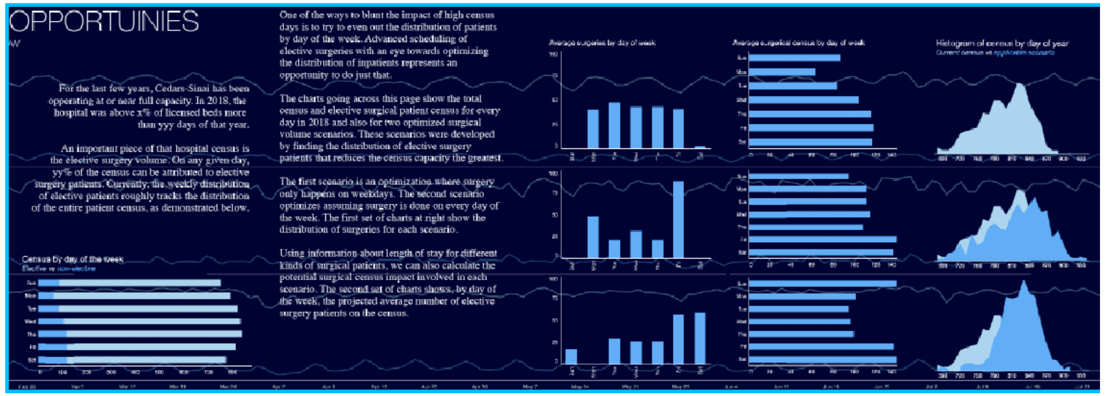


Initiatives Using Prediction Results (last 6 months)

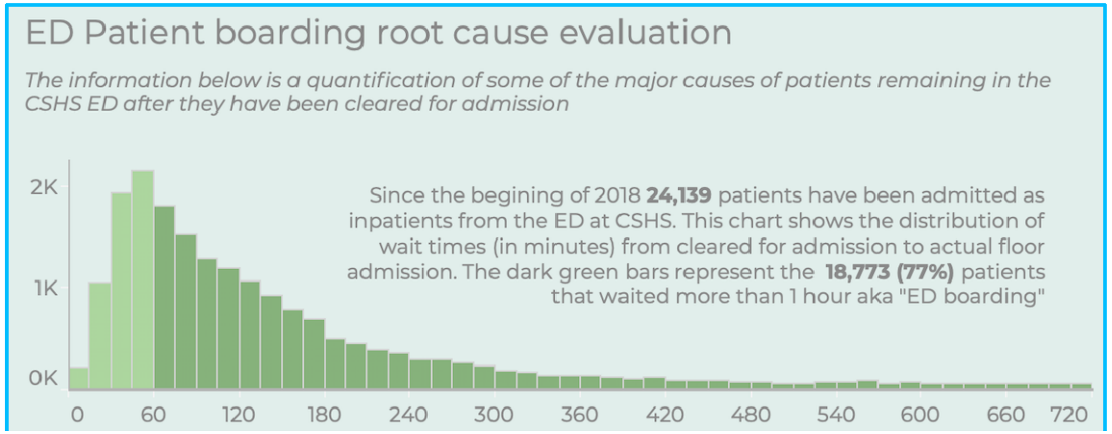
Hospital flow app



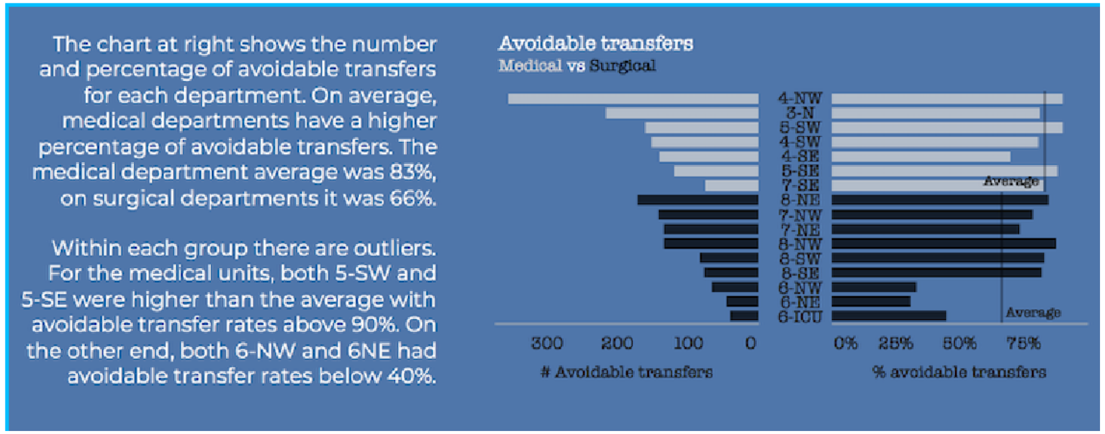
Transfer turn rate



ED boarding prediction



OR optimization



Results

1. The predictive models for predicting high census days has been over 97% accurate, and they are prominent within the bed huddle meetings.
2. The discharge lounge usage has increased by 200%, freeing up rooms by more than 4 hours earlier.
3. Daily bed huddles have created a method for communicating potential flow issues.
   - For example, over 100 barriers were reported at bed huddles that could be addressed.
4. 50 percentage point increase in discharges before 11 a.m.
5. 25 percentage point decrease in average minutes in ED boarding.
6. No impact to readmission rates and patient experience scores are noted at this time.
7. Model inputs are used in staff planning scenarios, operating room optimization, and case management.
8. New models for predicting patient specific variation in length of stay have become more prominent.

Lessons Learned

Hospital flow issues are **not a single department problem.**

For changes to occur, we must **involve operational and clinical leaders.**

Everyone wants data, and **interpretation of the data vary**.

Data architecture was a critical piece to the success of the project; it will require an **agile process** to allow leaders to **'experience' the data.**

For an operational initiative to succeed, you need a **passionate/credible champion.**

Getting people to look at dashboards is tough. The information needs to occur in the format the user will act upon it (e.g., mobile, email, PDF, or interactive).

Lessons Learned (Continued)

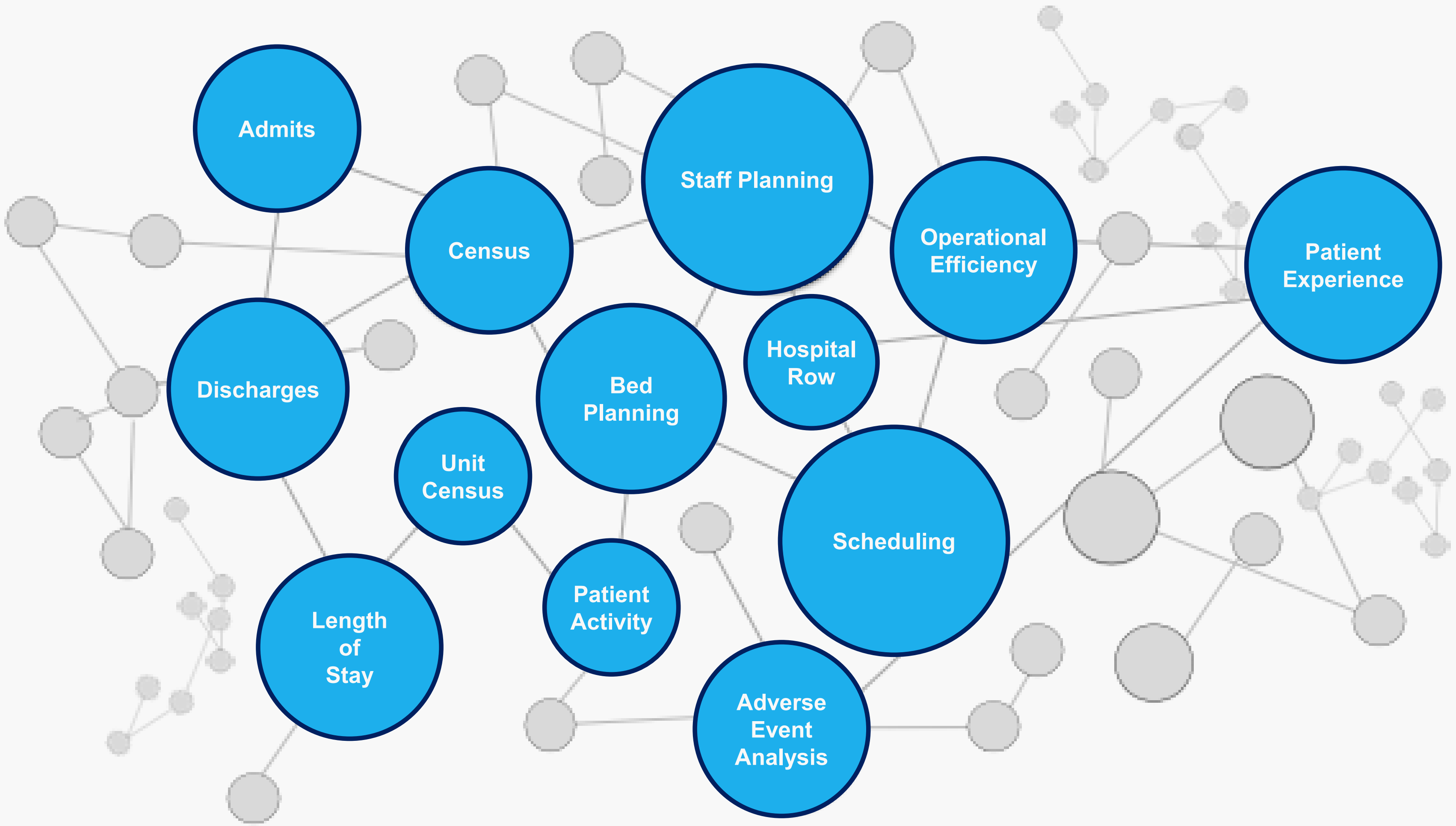
Do not overestimate the level of knowledge your audience has on **statistics and ML**.
It is a learning experience for all; you need to approach with care and cooperation.

Frequent meetings are required to keep the initiative at the forefront. The data science team must **bring a new insight to the meeting** and must leave with a new question to resolve. This keeps people interested and feeling like progress is being made.

Our belief was that **data/analytics can assist humans** by providing insights, suggestions, and potentially relevant information to guide human decisions. Therefore, when working with leaders we asked key questions on targets for metrics. But more importantly, we **documented what actions should be undertaken if the metrics are off-target.** By capturing this 'collective wisdom,' we were able to begin the creation prescriptive analytics to add in decisions and what-if analytics.

Data science is **not a singular event.**

Another Key Lesson: Predictive Models Are Connected



Questions and Answers

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