

Patient Flow in UCLA Obstetrics

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Background: OB-GYN



Obstetrics and Gynaecology (OB-GYN): Patient Flow and Capacity central to success of operations

- US Complexity: perinatal care <u>complex</u>, <u>shifts between different levels of care</u>
- Sets precedent: Perinatal care <u>vital to long-term sustained health</u> and reduction of chronic diseases
- Innovation: Exciting new technologies and innovations in delivery room tech only useful if actual use and flow of delivery optimized

UCLA Health System

- Delivers close to 4000 babies annually
- OB unit ranked in US Top 10 for Women's Healthcare

Area of Inquiry



Obstetrics

- The obstetric unit is a good sub-system of health care to test simulation models (Cochran and Bharti 2006)
- Ronald Reagan Obstetrics Unit Patient Experience
- How does patient flow impact patient experience in obstetrics?

Patient Flow

- Improving patient throughput by ensuring even capacity utilization, minimizing wait times for resources and care
- Topics of interest: patient classification, path-based modeling, blocking, accounting for swing rooms, time dependent arrival and departure patterns
- Why is improving patient flow in obstetrics units important?

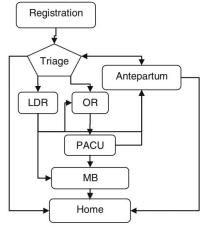


Figure 1: Illustration of Patient Flow Model in OB (Griffin et al. 2011)

Motivation



Proven areas for useful change or optimization

- Unit Capacity especially important in larger health system with multiple locations
- Managing workload with decreasing staff <u>fewer OB-GYNs means heavier workload</u> <u>for remaining</u>, optimization essential to success and stopping burnout
- Healthy Births <u>Improve rates of successful healthy birth for mother and child</u>, <u>particularly in high-risk or lower income areas</u> (some of which UCLA serves)

"Maternity Desert" - wave of maternity ward closings in Los Angeles

- 29 hospitals stopped delivering babies since 2021
- 17 obstetrics departments closed in LA in last decade

Current & Future Gaps



Lack of efficient utilization across locations at UCLA Health - (from UCLA ops)

- Capacity modeling in the UCLA OB would be novel and a definite value-add
- Potential collaborators in OHIA or CTSI

ED and critical care predominant sites for capacity prediction research

• OB ward patient flow work needed, especially given prior context

Insufficient Model Performance

• Rf models predicting capacity have had lower accuracy than ideal for a decision support system within the OB context

OB Complexity

Future modeling efforts could include <u>dynamic</u>, <u>real-time simulation with time-series</u>
 <u>analysis</u>

Problem Framework



Cohort definition

• Labor & Delivery Patients admitted to unit 5OB in Ronald Reagan Medical Center between 01/01/2022 - 09/01/2024

Determining Scope

- Patient-level framework (long-term)
 - On-demand bed assignments based on patient characteristics
- Time-level framework (short-term)
 - Map hospital usage by week over the next year

Analytics & Forecasting Methods



Analytics

- Data Visualizations on:
 - Birthing trends
 - Bed Utilization
 - Weekly Usage

Forecasting

- Defining historical usage
 - Median patients/day in a week
- Long short-term memory (LSTM) model to predict future usage
 - Optimize hyperparameters and use mean absolute error as a loss function

EDA — OB Delivery Dataset



Fig. OB Delivery Dataframe and Dimensions

	PatientEncounterC SNID	EpisodelD	Hospital Admission Time	Hospital Discharge Time	LengthOfStay	IsInpatient	IsObservatio
0	2.103032e+09	5.542547e+18	2022-06-07 16:44:00	2022-06-11 13:48:00	3.836806	1.0	0
1	2.103032e+09	5.542547e+18	2022-06-07 16:44:00	2022-06-11 13:48:00	3.836806	1.0	0
2	2.103032e+09	5.542547e+18	2022-06-07 16:44:00	2022-06-11 13:48:00	3.836806	1.0	0
3	2.103032e+09	5.542547e+18	2022-06-07 16:44:00	2022-06-11 13:48:00	3.836806	1.0	0
4	2.103032e+09	5.542547e+18	2022-06-07 16:44:00	2022-06-11 13:48:00	3.836806	1.0	0

80956 rows × 36 columns

Key Data Elements

- Encounter Records
- Delivery Episodes
- Department + Bed Utilization Records
 - RR 5DR, RR PERIOPERATIVE AREA, RR 5FDU IOF, RR 5EOB, RR 7ICU
- Patient Obstetric Histories
- Temporal Attributes (i.e. dates, times, seasons)

Fig. Columns

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 80956 entries, 0 to 80955
Data columns (total 36 columns):

	columns (cocal so column	-).						
#	Column	Non-Null Count	Dtype					
0	PatientEncounterCSNID	80956 non-null	int64					
1	EpisodeID	80954 non-null	float64					
2	CheckinTime	0 non-null	float64					
3	CheckoutTime	0 non-null	float64					
4	HospitalAdmissionTime	80955 non-null	datetime64[ns]					
5	HospitalDischargeTime	80683 non-null	datetime64[ns]					
6	LengthOfStay	80645 non-null	float64					
7	IsInpatient	80955 non-null	float64					
8	IsObservation	80955 non-null	float64					
9	BedID	43325 non-null	float64					
10	BedName	43325 non-null	object					
11	BedInCensus	43325 non-null	float64					
12	RoomID	66724 non-null	float64					
13	RoomName	71675 non-null	object					
14	RoomGroupName	6946 non-null	object					
15	DeliveryDate	80955 non-null	datetime64[ns]					
16	BirthDateTime	77606 non-null	datetime64[ns]					
17	LaborOnsetDateTime	47422 non-null	datetime64[ns]					
18	DeliveryMethodCode	77346 non-null	float64					
19	FirstStageLengthHours	38297 non-null	float64					
20	SecondStageLengthHours	50767 non-null	float64					
21	ThirdStageLengthHours	78475 non-null	float64					
22	NumberOfBabies	3347 non-null	float64					
23	EstimatedDateOfDelivery	3341 non-null	object					
24	DeliveryDepartmentID	77599 non-null	float64					
25	DepartmentName	80955 non-null	object					
26	IsPrimaryDeliveryUnit	80955 non-null	float64					
27	TotalLaborMinutes	46196 non-null	float64					
28	GravidaCount	3347 non-null	float64					
29	ParaCount	3347 non-null	float64					
30	PretermCount	3347 non-null	float64					
31	IsWeekend	80955 non-null	float64					
32	IsHoliday	80955 non-null	float64					
33	MonthName	80955 non-null	object					
34	QuarterNumber	80955 non-null	float64					
35	Year	80955 non-null	float64					
<pre>dtypes: datetime64[ns](5), float64(24), int64(1), object(6)</pre>								
memory usage: 22.2+ MB								

EDA — Visualizations



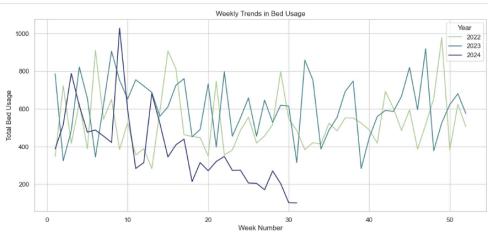
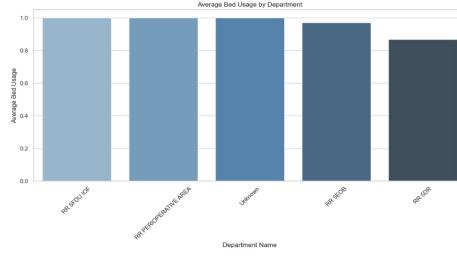


Fig. — Weekly Trends in Bed Usage by Year

Fig. — Average Bed Usage by Department



EDA — Visualizations



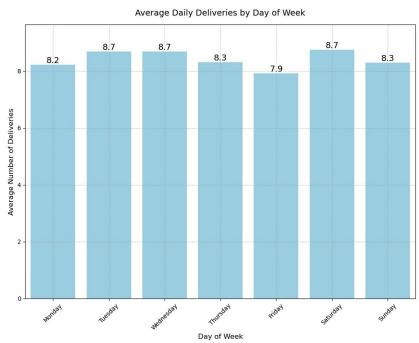
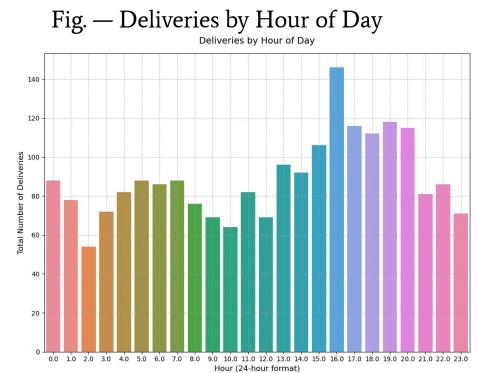


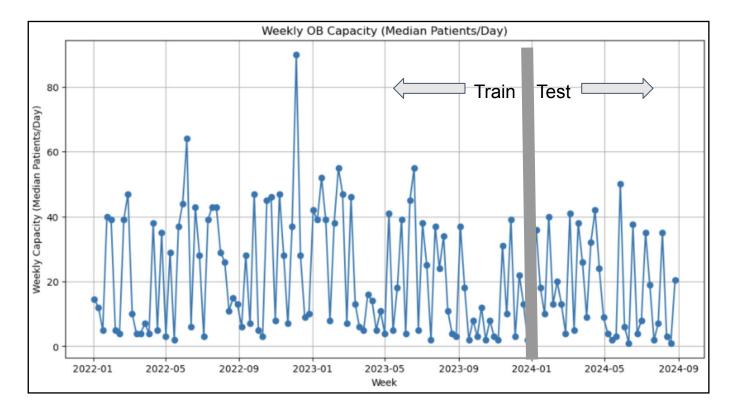
Fig. — Average Daily Deliveries by Day of Week



Usage Trend - Median Patients/Day



- No seasonality
- No YOY trend
- Regular fluctuations



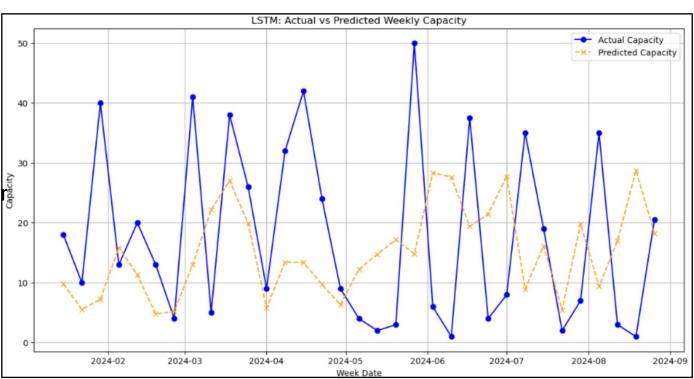
Usage Forecasting Results



Long short-term memory (LSTM)

Test Root Mean Squared Error (RMSE): 17.69

Test Mean Absolute Error (MAE) = 14.71



Discussion



Actionable insights

- Number of staff necessary per week
- Scheduling C-sections according to predicted capacity
- Planning to send appropriate patients to other facilities (ex: Santa Monica) during high-capacity weeks

Next Steps



Include currently unavailable data to model capacity

- Predicted due-dates for UCLA patients
- Scheduled C-sections
- Scheduled staffing

Model Optimization

- Additional hyperparameter range exploration using GridSearchCV
- Model stacking or ensemble learning with regression-based models after additional features included (above)

Broader Implications

- Using and adapting model for other, potentially more complex departments
- Continued training for longer term prediction, increasing accuracy

Q&A