

# Hospital Admission Prediction

Mid-Term Presentation Course: BA878E1 Dt. 24th Oct 2023

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#### **Mission**

To enhance emergency care by providing real-time, data-driven insights for optimized hospital admission decisions, improving resource allocation and patient outcomes.

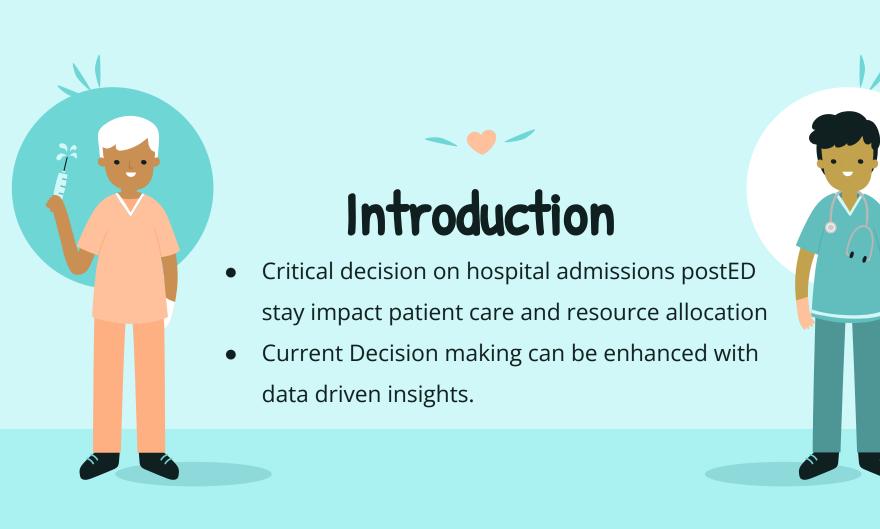
#### **Vision**

To seamlessly integrate machine learning in healthcare, facilitating proactive decision-making, improved patient satisfaction, and operational efficiency in emergency departments, leading towards a more responsive healthcare system.

"Harnessing data is about ensuring the right care, at the right place, at the right time for every patient."

-Chat GPT





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#### **Data Center**

Acquire the MIMIC-IV-ED database & link to BQ



#### First Look

Feature Engineering & EDA





#### Model Development

Regression for its interpretability



# Recommendations & Next Steps

Model Improvements, & documentation of findings

### Data Overview

- The MIMIC-IV-ED dataset is a comprehensive collection of data related to emergency department (ED) admissions at the Beth Israel Deaconess Medical Center from 2011 to 2019.
- Dataset Composition:
  - Total ED Stays: "~425000"
  - Time Frame: "2011-2019"
- Data Categories:
  - Diagnoses: "ICD coded diagnoses for each admission."
  - o ED Stays: "Details of each ED visit including admission and discharge times."
  - Medication Reconciliation: "Medication information at the time of admission."
  - Medication Administration: "Detailed medication administration records during ED stay."
  - Triage: "Vital signs and chief complaints at the time of admission."
  - Vital Signs: "Continuous monitoring of vital signs during ED stay."

Info: All data have been de-identified to comply with HIPAA Safe Harbor provisions.





# First Look

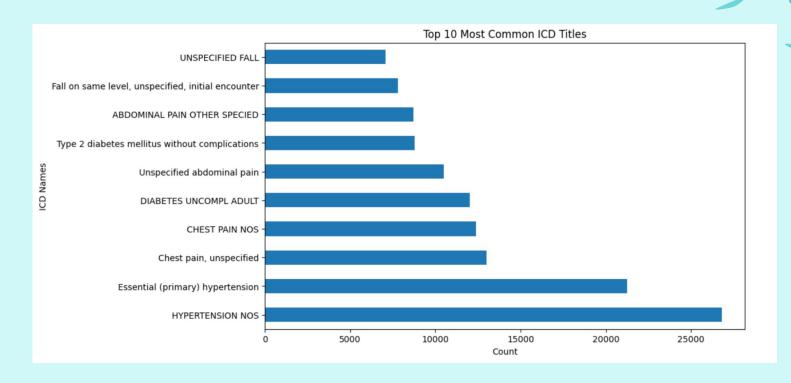
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# Imputing Nulls

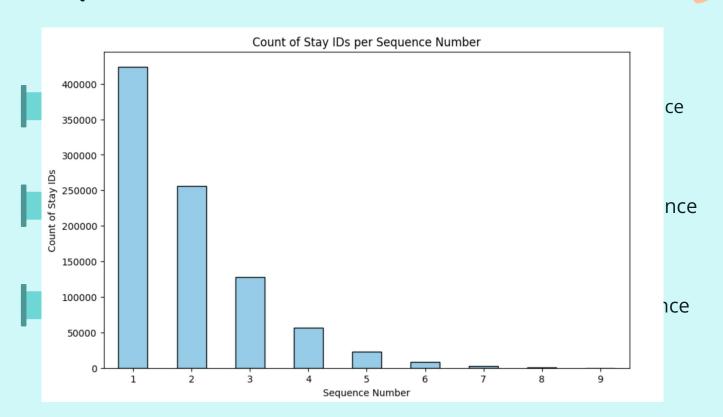
- 1. vitalsign\_df: Imputed missing values in numerical columns with the median of the respective column.
- **2.** triage\_df: Imputed temperature, heart rate, resprate, o2sat, sbp, and dbp columns with their respective median values.

Dataset	Missing Before Imputation	Missing After Imputation
Diagnosis	0	0
ED Stays	222,071	0
Med Recon	23,456	0
Pyxis	35,452	0
Triage	121,758	0
Vital Sign	3,194,329	0
Total	3,597,066	0

#### Top 10 most common ICD (International Classification of Diseases)

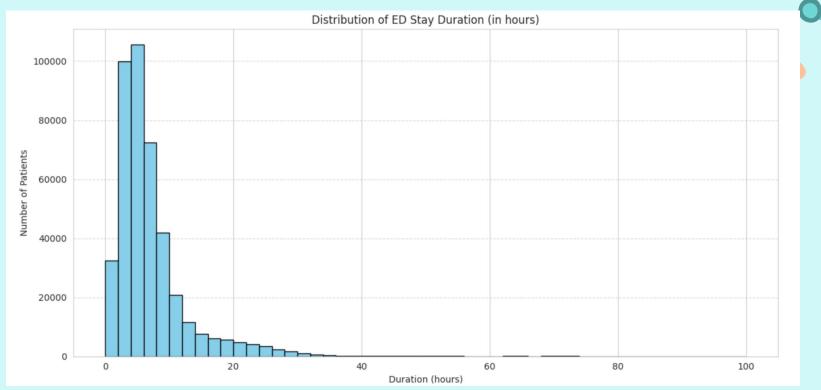


# Stay vs Treatment Order

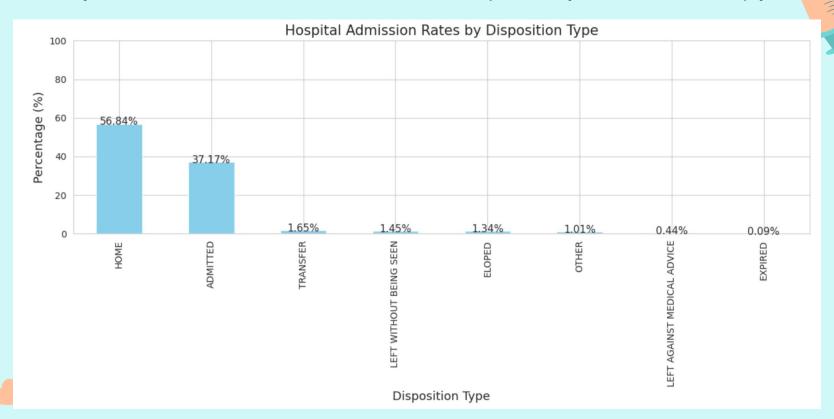


# ED Stay Duration (in hours)

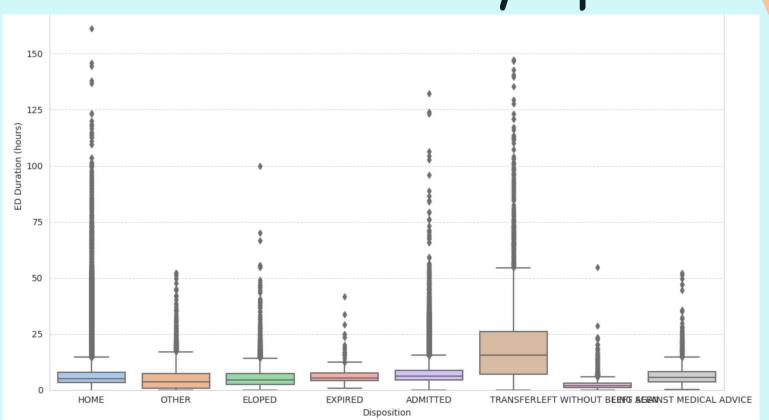




## Hospital Admission Rates by Disposition Type



# **ED Duration Distribution by Disposition**



### Analysis Of Variance



#### Interpretations:

- Diagnosis Dataset: The difference in `stay\_id` across genders is not statistically significant.
- 2. Triage Dataset: There is a highly significant difference in `stay\_id` across genders.
- 3. Vital Sign Dataset: The difference in `stay\_id` across genders is highly significant.

## 03 Model Development:





**Accuracy: 79.59%** 



**ROC-AUC: 0.76** 

Accuracy: 0.7958667576277965 ROC-AUC: 0.7606371138375659

Classification Report:

c tussii i cu cion	precision	recall	f1-score	support
0 1	0.80 0.78	0.90 0.62	0.85 0.69	53514 31504
accuracy macro avg weighted avg	0.79 0.79	0.76 0.80	0.80 0.77 0.79	85018 85018 85018

Confusion Matrix: [[47987 5527] [11828 19676]]

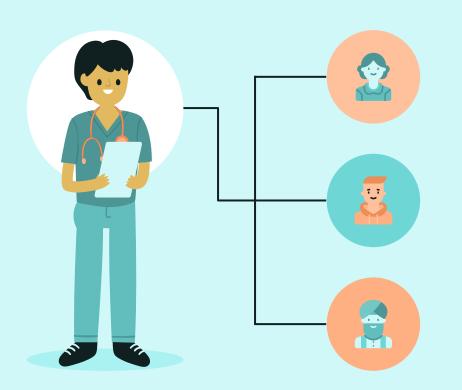




#### Model Coefficients:

	Coefficient
icd_title_Unspecified jaundice	4.879360
icd_title_Acute cholecystitis	4.684009
icd_title_CHOLANGITIS	4.649790
<pre>icd_title_Hepatic failure, unspecified without</pre>	4.632882
icd_title_Cholangitis	4.632338
icd_title_Oth adverse food reactions, not elsew	-4.335766
icd_title_PERSONAL HISTORY OF CONTACT WITH AND	-4.348800
icd_title_SPRAIN OF ANKLE NOS	-4.485867
icd_title_SPRAIN OF NECK	-4.736000
icd_title_OPEN WOUND OF FINGER	-6.020055

#### Current Recommendations, Next Steps & Potential Improvements:



Advanced Algorithms: Random Forest might potentially enhance prediction accuracy.

Class Imbalance: if there's a significant imbalance in the target classes.

Hyperparameter Tuning: Optimize model parameters to achieve better results.

Feature Engineering: Explore additional features or transformations to improve model insights.



### Our Team



**Nurse** Prateek

