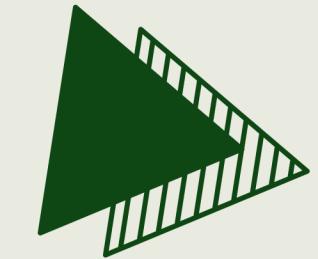


# FAIRCARE ANALYTICS

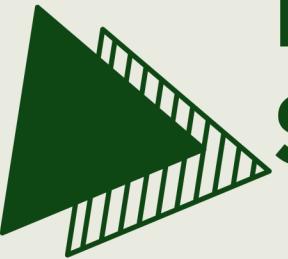


Souradeep Thakur, Kehinde Soetan  
Ricky Lee, Tam Cheetham-West



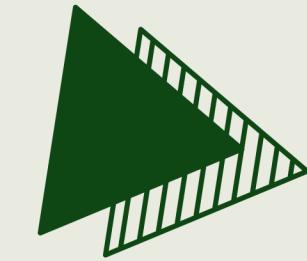
## Problem Statement/Motivation

- Hospital readmissions within 30 days are costly and often preventable. How can we use predictive models to identify high-risk patients?
- If predictive models perform unevenly across racial groups, they risk deepening health disparities.



# Desired outcomes/ Stakeholders

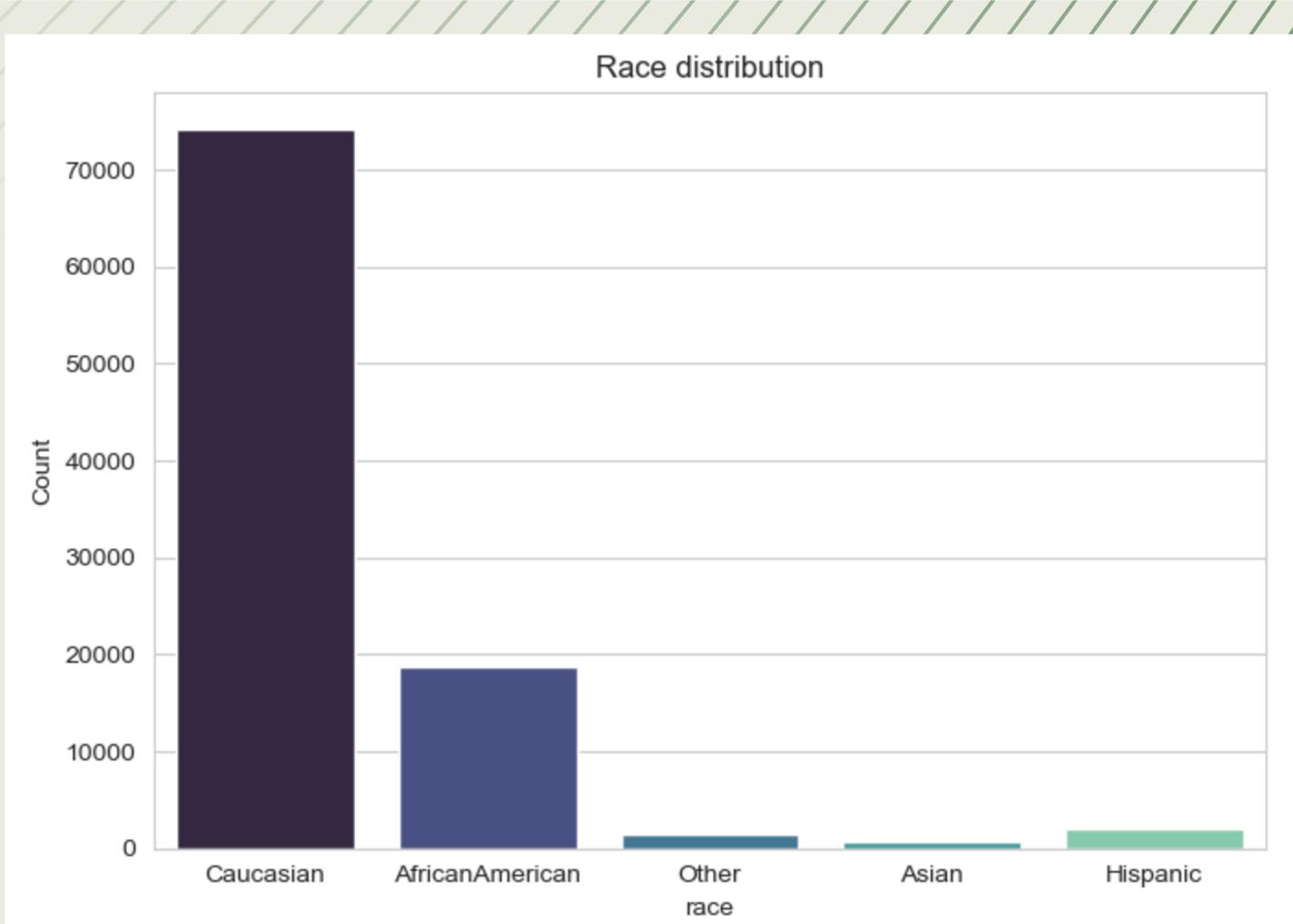
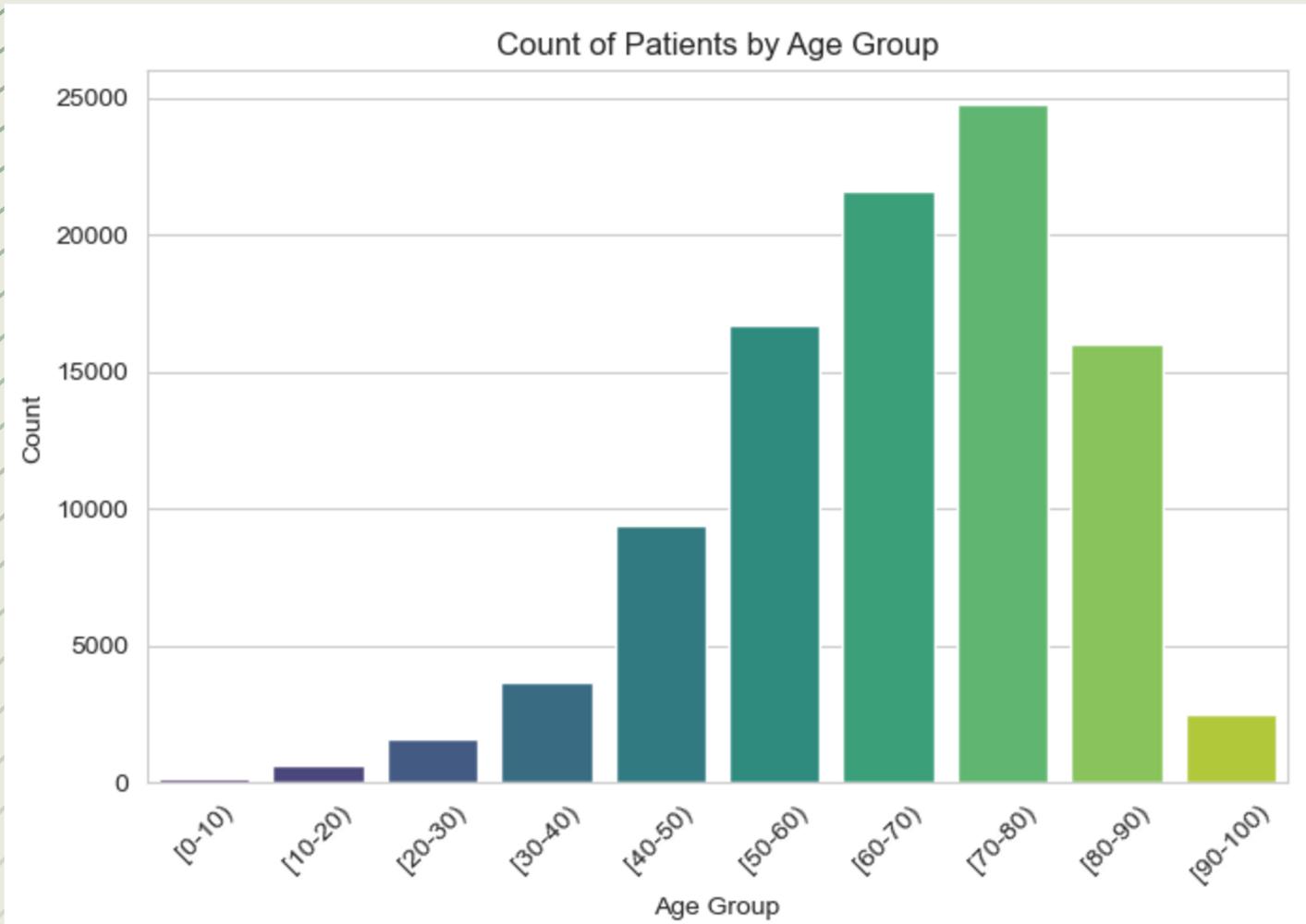
- Use predictive modeling to enable early, patient-centered interventions and optimize resource allocation.
  - Supports **clinicians, hospital networks, and patients.**
    - Ensure models are fair and equitable, avoiding harm to underserved groups.
  - Matters to **policymakers, advocates, and communities.**
    - Improve health system accountability and transparency through interpretable predictions.
  - Engages **health data scientists and public health researchers.**

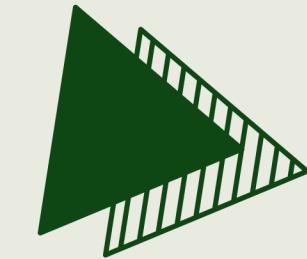


# The dataset

## UCI Diabetes 130-US Hospitals Dataset (1999-2008)

- Over 25,000 patient encounters
- Features include:
  - **Demographics:** race, age, gender
  - **Clinical data:** diagnoses, medications, lab procedures
  - **Hospitalization data:** admission type/source, discharge disposition, time in hospital
- High ratio of records to features.

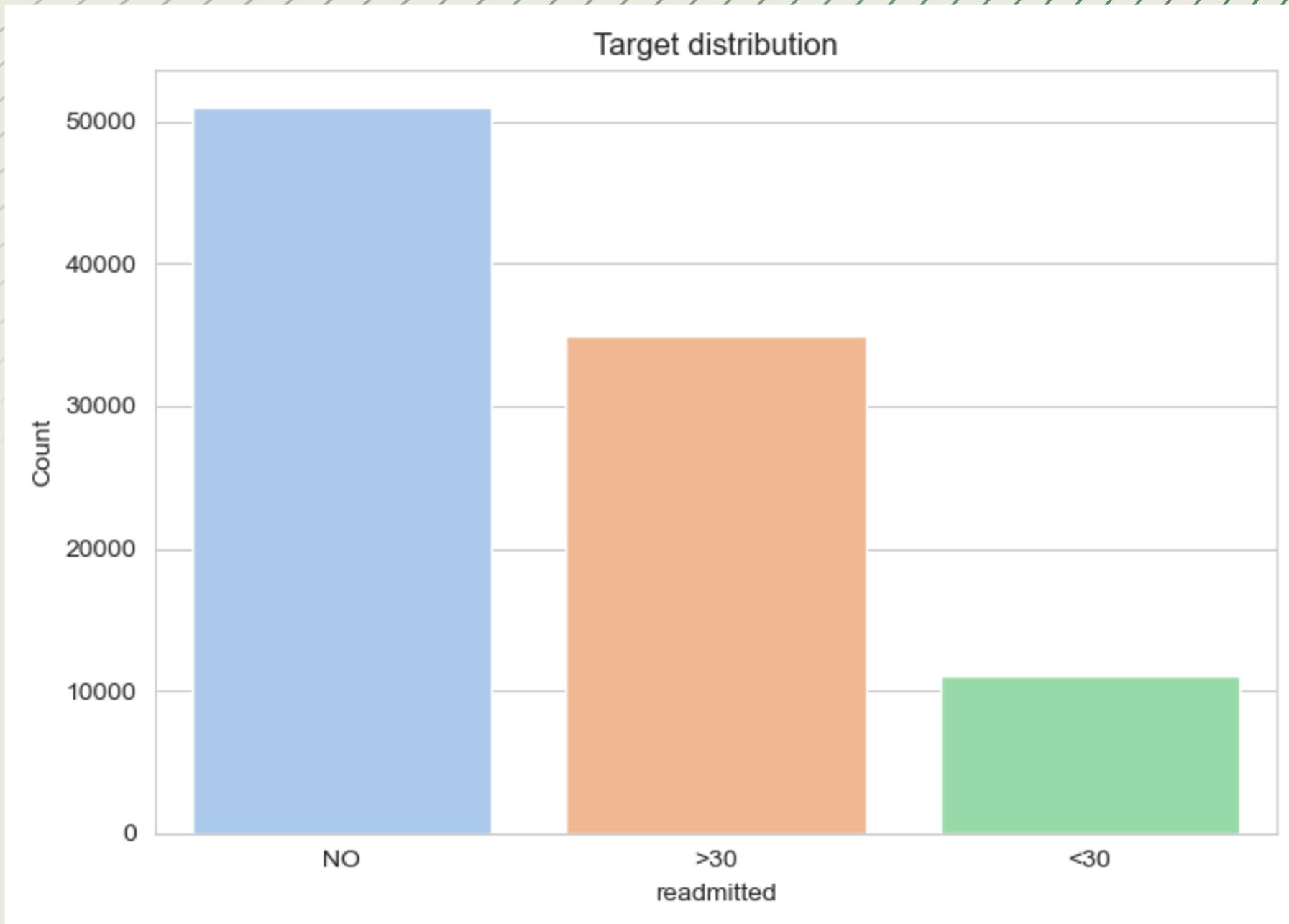


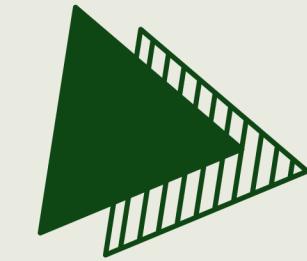


## The dataset

### UCI Diabetes 130-US Hospitals Dataset (1999–2008)

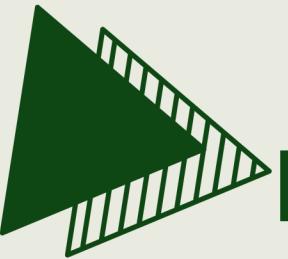
- Many categorical variables.
- **Target variable:**  
**readmitted\_binary** is 1 when a patient has a <30 day readmission in the record and 0 otherwise.





# Data processing

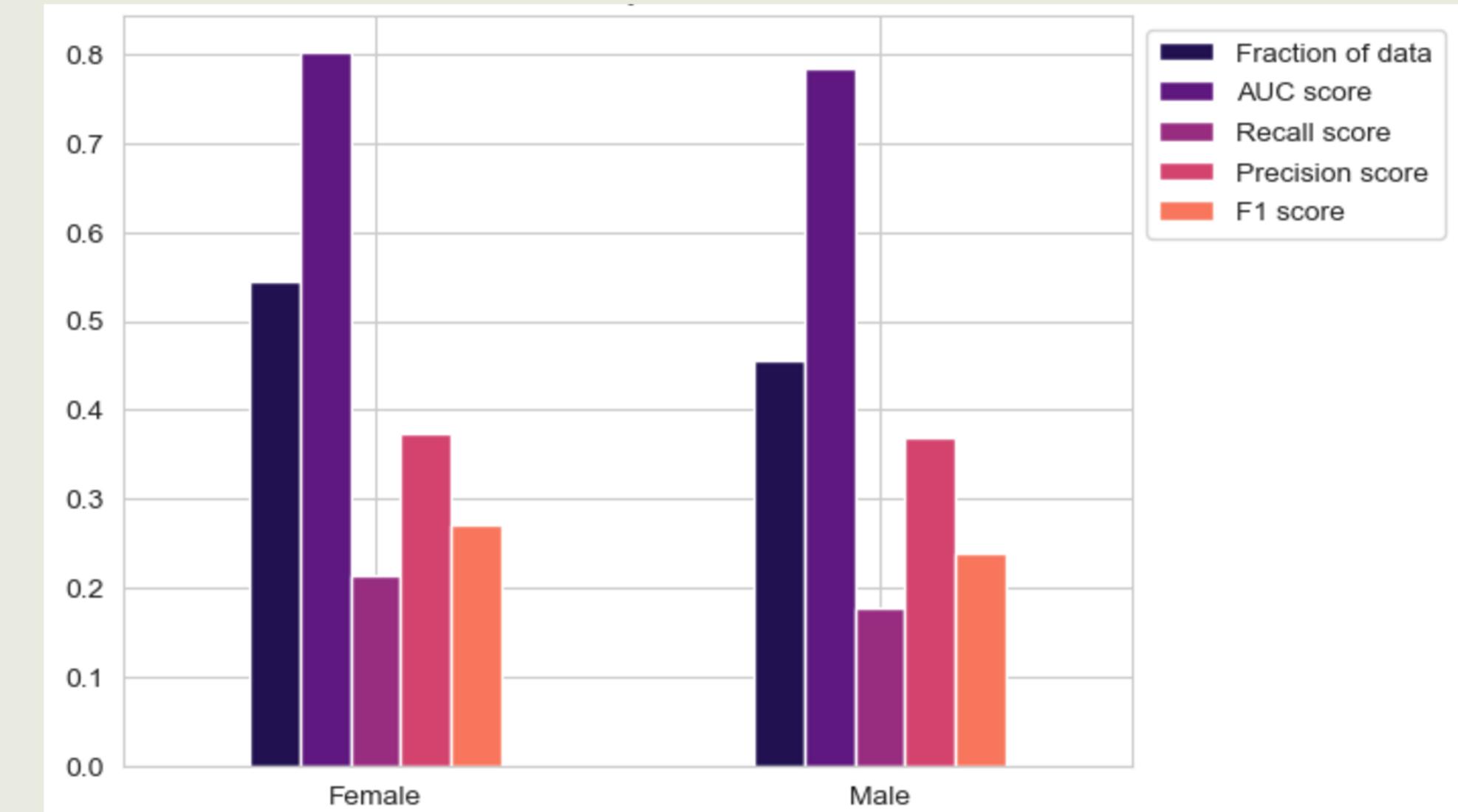
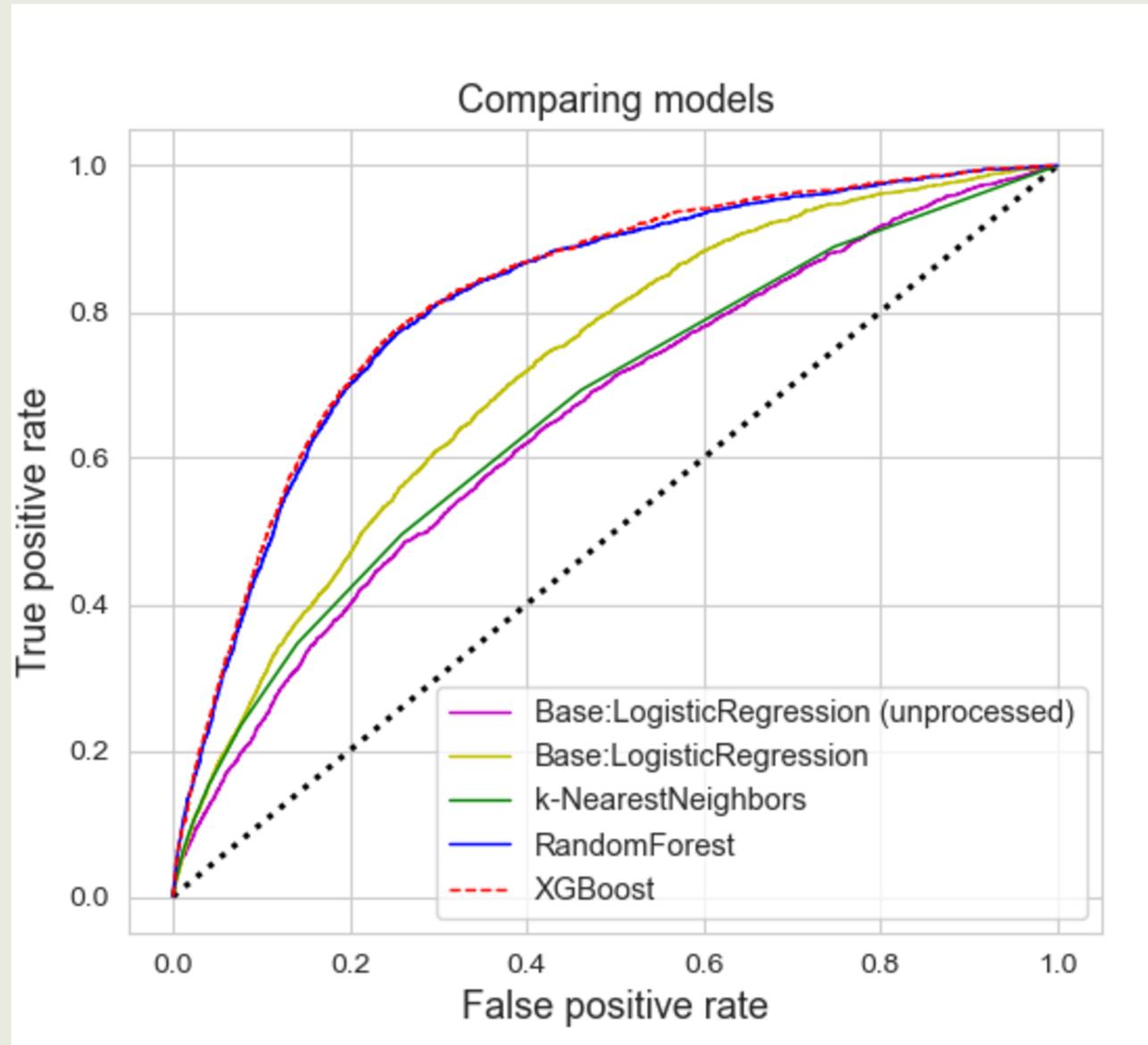
- **Integer encodings**
  - drug features (metformin, glimepiride, insulin, etc.)
  - test results (A1Cresult, max\_glu\_serum)
- **Grouping codes**
  - admission\_type\_id, discharge\_disposition\_id, admission\_source\_id.
  - diag\_1, diag\_2, diag\_3 into groups such as circulatory, digestive, etc.
- **Additional features:** patient histories, high-risk diagnoses.



# Models

Model	AUC Score	Precision	Recall
Baseline - Linear Regression	0.7193	0 : 0.89 1: 0.39	0 : 0.99 1: 0.04
k-Nearest Neighbors	0.6640	0 : 0.89 1: 0.48	0 : 1.00 1: 0.02
RandomForest	0.8034	0 : 0.89 1: 0.50	0 : 0.99 1: 0.10
Final - XGBoost	0.7937	0 : 0.90 1: 0.37	0 : 0.96 1: 0.20

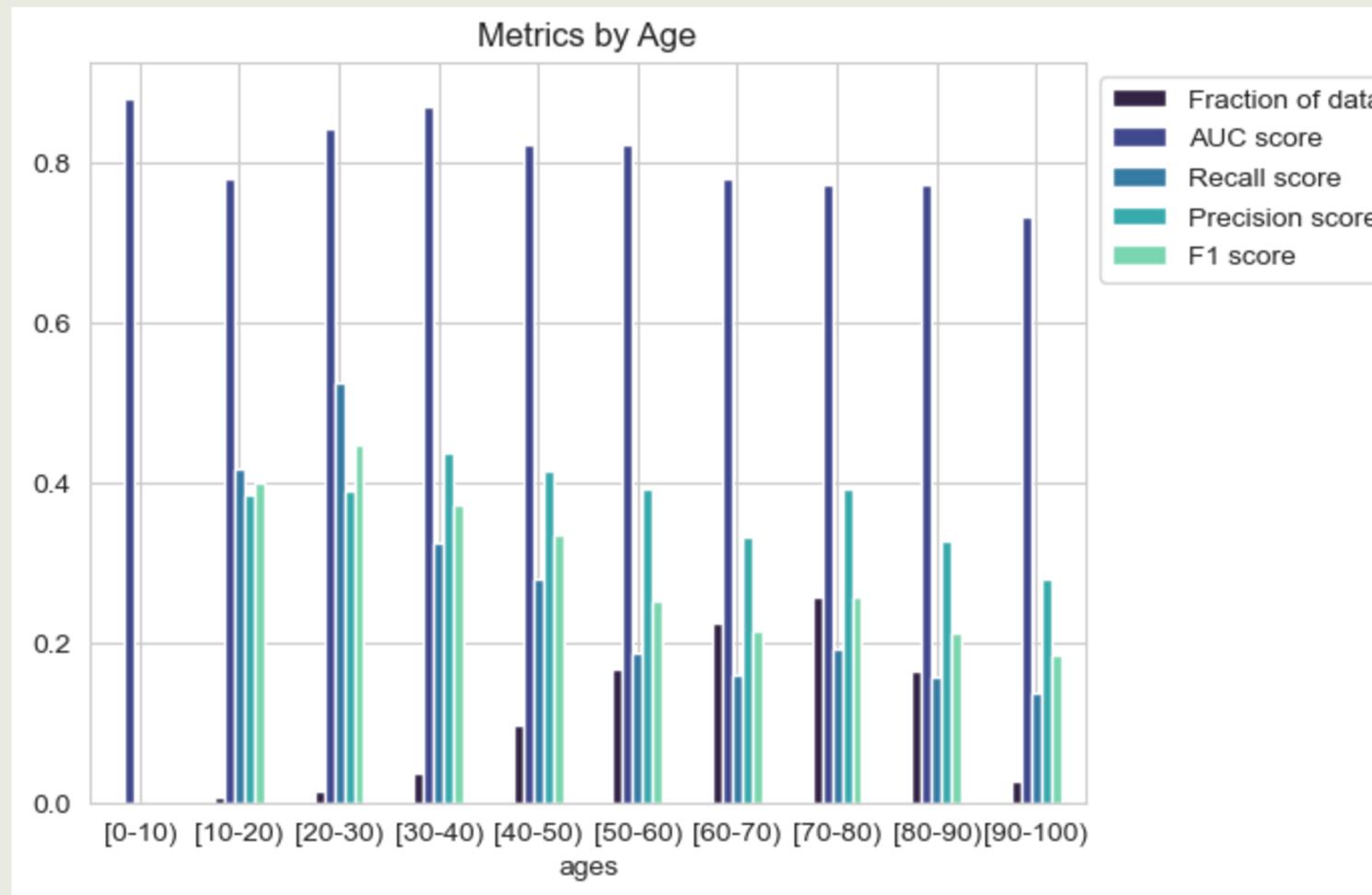
# OUR METRICS/OUTCOMES



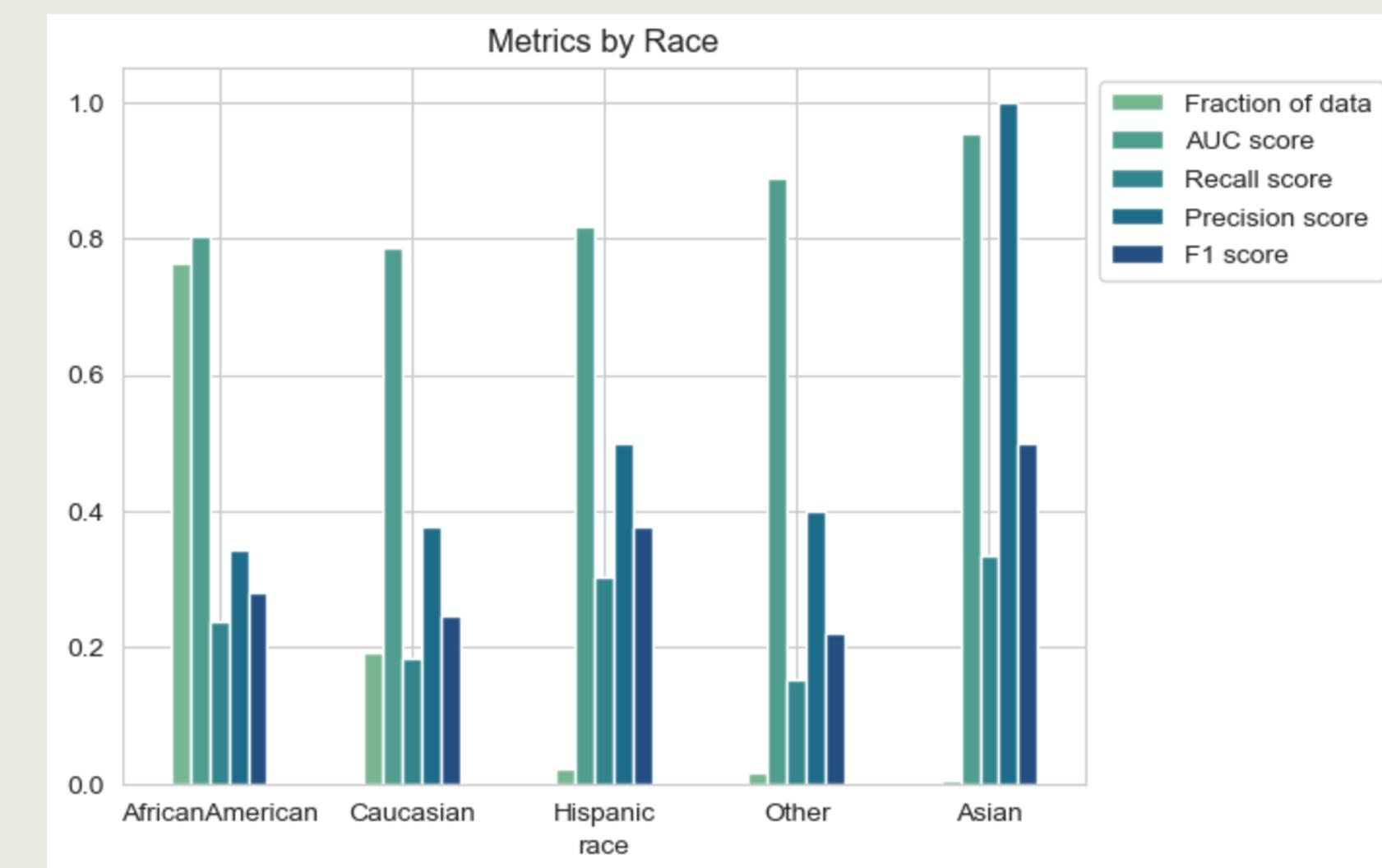
**ROC curves for all models**

**Final XG Boost Metrics by gender**

# OUR METRICS/OUTCOMES

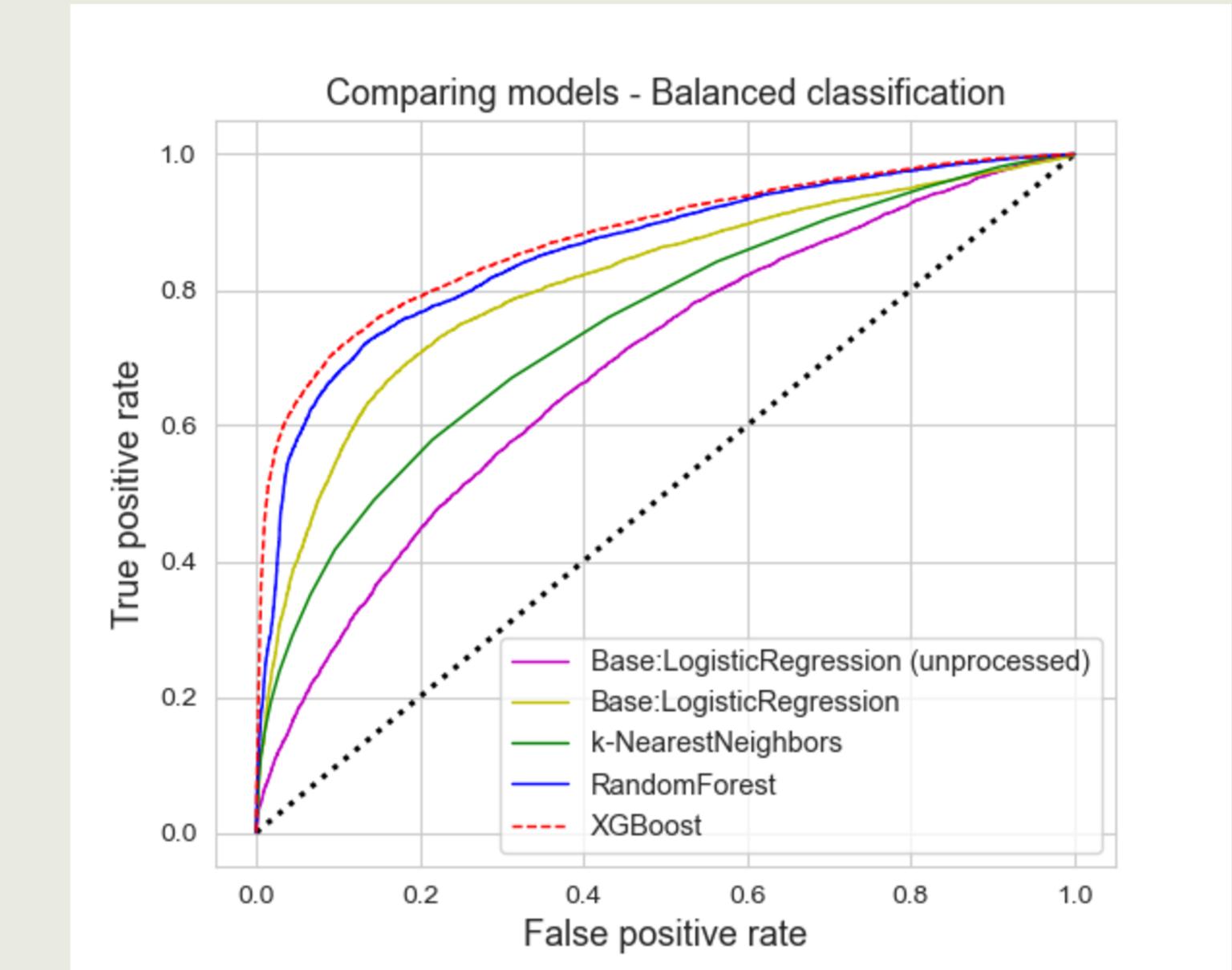
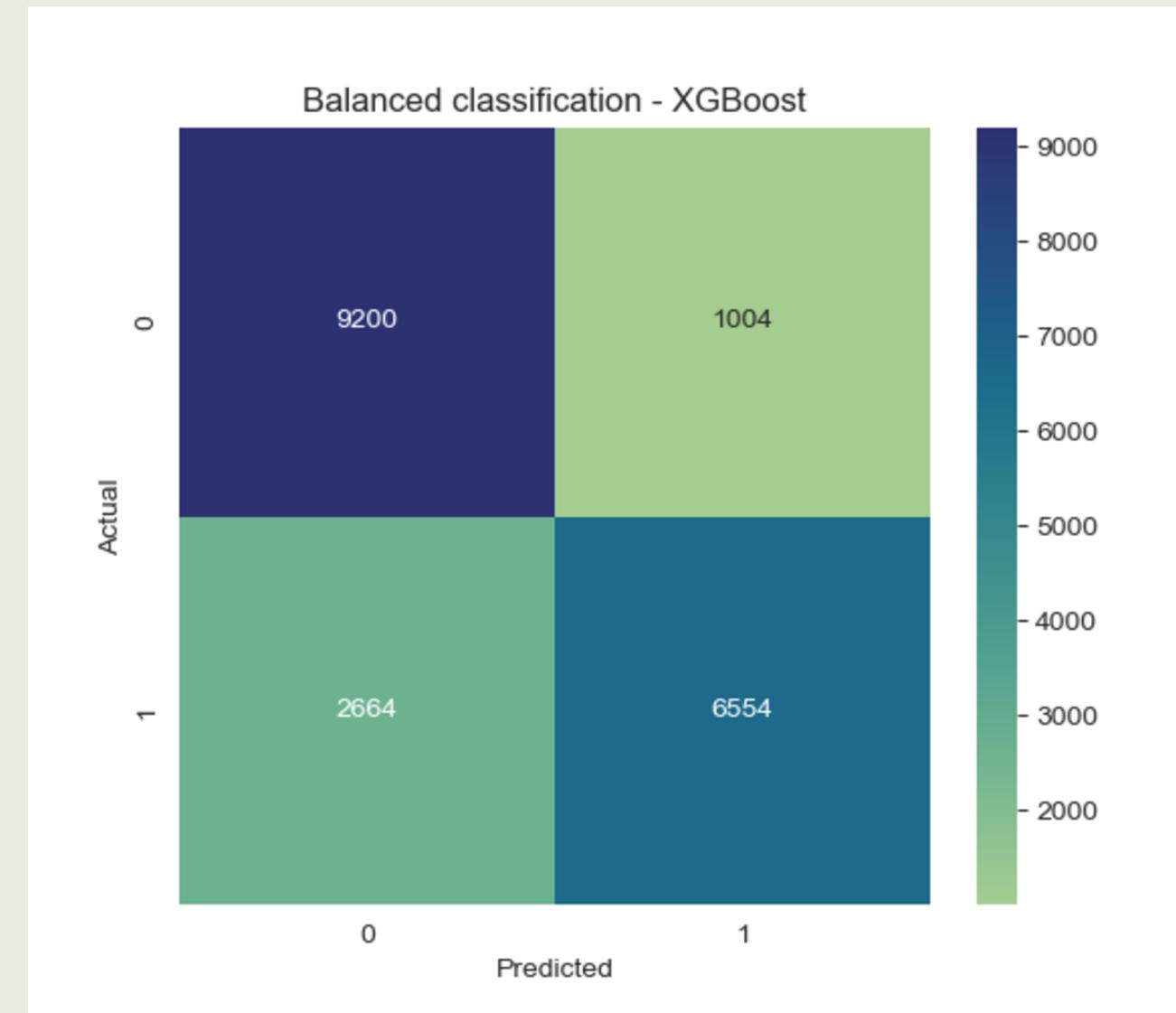


Final XG Boost Metrics by age



Final XG Boost Metrics by race

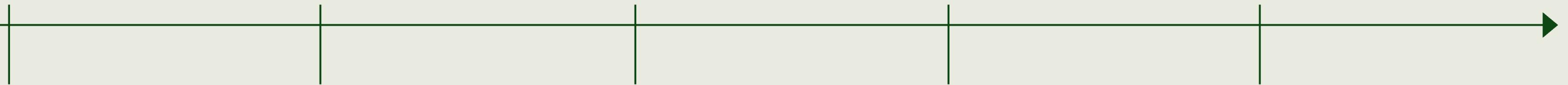
# OUR METRICS/OUTCOMES



**Confusion matrix for balanced classification (readmitted vs not)**

**Comparing models**

# CONCLUSIONS



## *Evaluate*

While we can classify readmissions vs non-readmissions, distinguishing <30 day readmissions among the other data remains a difficult open problem.

## *Adapt*

In future, we hope to incorporate a bias audit framework to review the methods, metrics and outcomes in order to ensure fairness.

Use deep reinforcement learning models to improve precision and recall scores.

## *Launch*

Procedures and processes can be applied to much larger electronic health record datasets like MIMIC-III or MIMIC-IV.

Collaborate with industry experts, incorporate domain knowledge into models, obtain practical action items.

## *Monitor*

Track metrics and performance across larger/different datasets.

## *Iterate*

The processes outlined can be modified for standalone inpatient provider using their historical clinical data, or a provider network.

# Thank you.

