Predicting Readmissions: Cohort Selection

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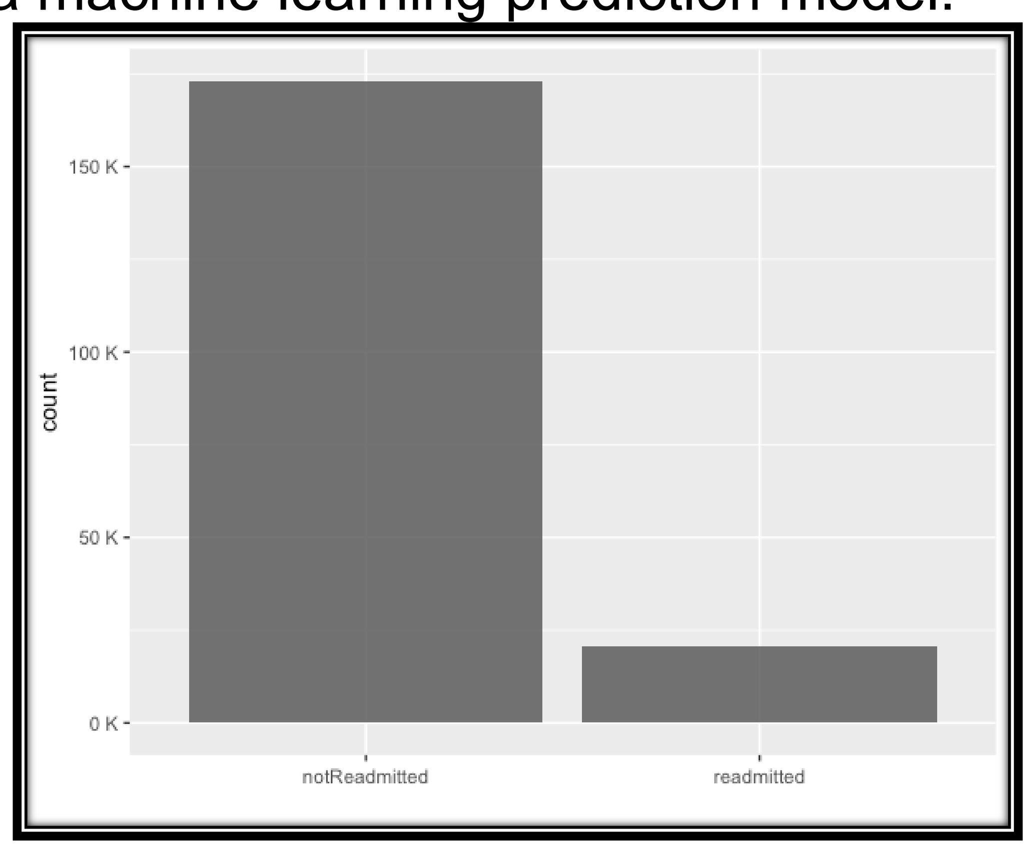
Motivation

- "Hospital Readmission Reduction Program" established by Medicaid since October 1, 2012.
- About half of US registered hospitals receive reduced payments for **excess** readmission rates.
- Historically, **nearly 20%** of Medicare discharges have a readmission **within 30 days**.
- **Heart Failure is the most expensive diagnosis** for hospitalizations in the US accounting for 70% of total costs for heart failure. **CHF is the most frequent diagnosis for 30-day readmissions**.

Accurate prediction model can help to readjust health care, reduce readmission rate and health care costs.

Tasks

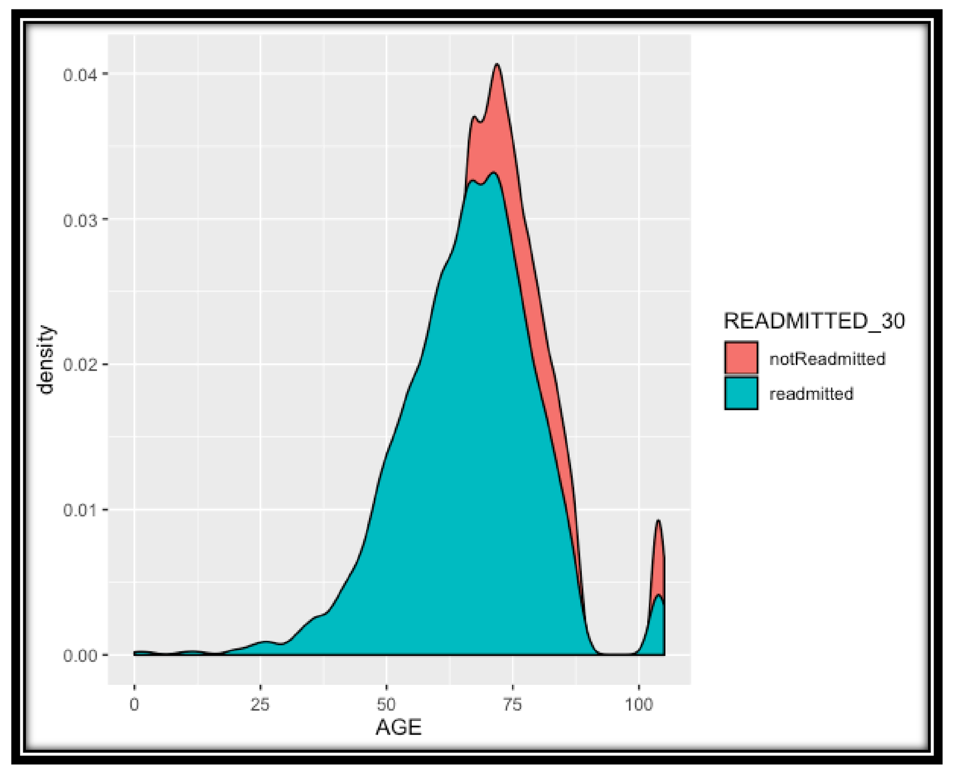
1. Define the cohort of CHF patients. Criteria: length of stay>0, non-deceased patients with discharge status code "to home or self-care", ICD-9 codes, and CHF diagnosis.
2. Data pre-preprocessing: compute new features. Original Humana dataset: medical, lab, patient, and pharmacy records of 12.9 million patients for 2013-2015. Total 20,415 (10.55%) positive readmissions out of 193,419 CHF hospital admissions.
3. Partition to training, testing, and validation datasets.
4. Build a machine learning prediction model.

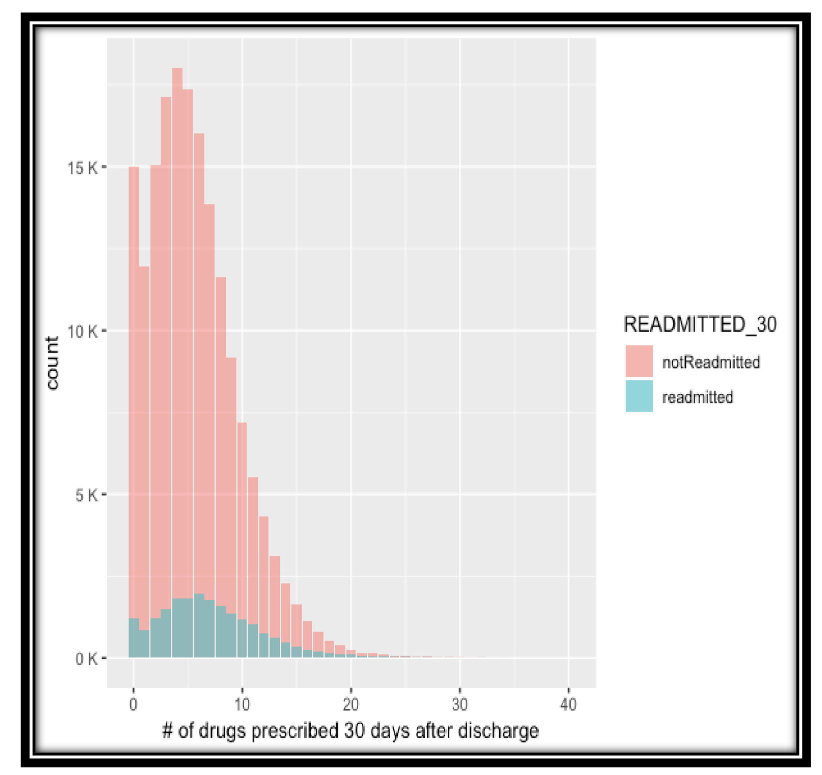


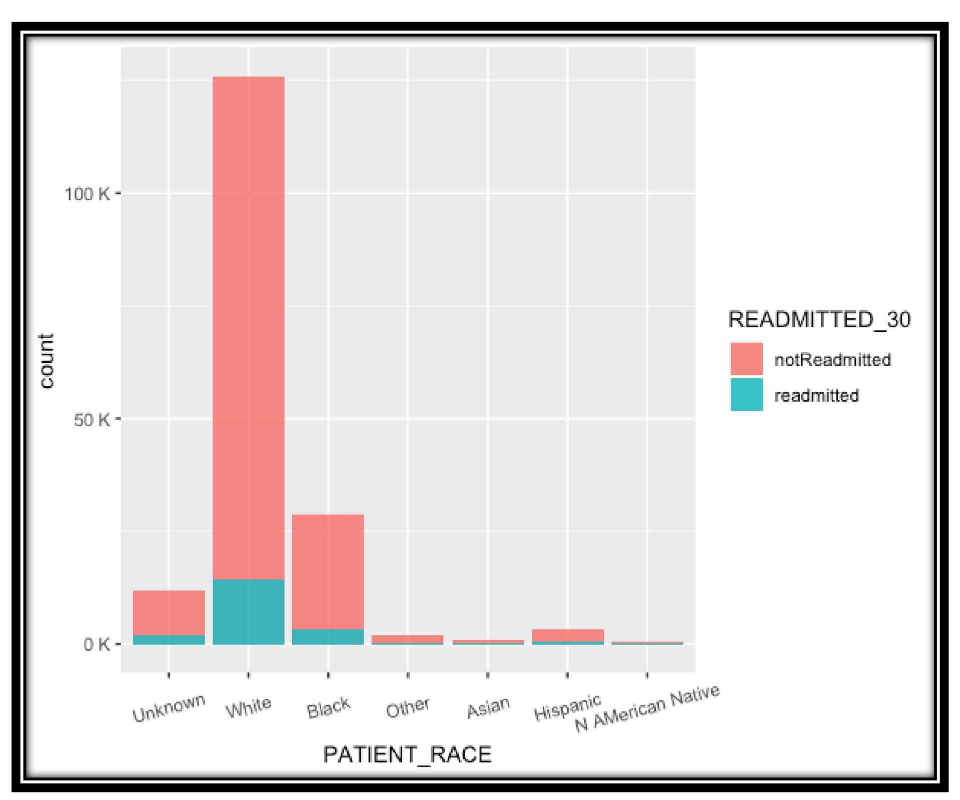
Data Pre-Processing

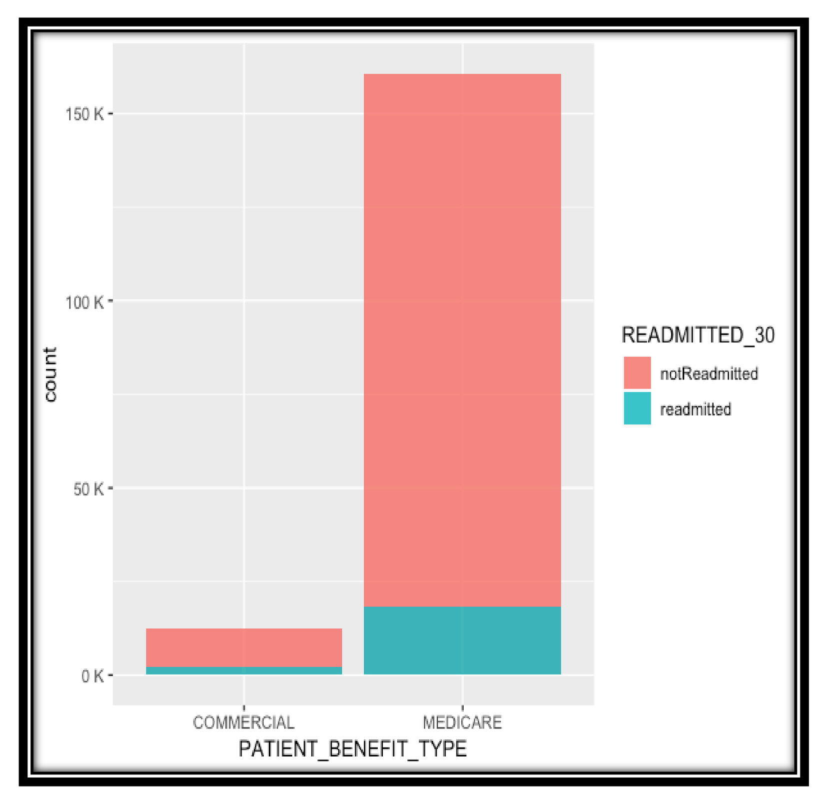
1. Compute readmission interval
2. Compute a target column READMITTED_30
3. Compute the number of unique diagnosis, and the number of chronic conditions for the period 2013-2015. Mean(chronic)= 41.45.
4. Compute the number of unique generic drug names prescribed 30 days before admission, during hospital stay, and 30 days after discharge. Mean(rxAfter)=5.8, Max(rxAfter)=40.
5. Compute the number of unique lab orders 30 days before admission, during hospital stay, and 30 days after discharge. Mean(labDuring)=6.7, Max(labDuring)=240

Visualization









Challenges

- Presence of both ICD-9 and ICD-10 coding classification systems. Overlap during the period 2014-2015. Necessary to build an equivalence table to avoid counting diagnoses twice.
- Negative readmission intervals caused by multiple records related to the same admission event. Need to clarify with experts and, probably, concatenate them into one.
- Lab file is limited (records of 4M patients instead of 12.9M), has parsing problems. Eighty-five percent of CHF admissions have zero lab orders during hospital stay. Probably, the data is incomplete.

Discussion

- Needs further clarifications from the creator of dataset.
- Would benefit from incorporating physician's intuition on the differences of positive and negative readmissions.
- Upon completion of data pre-processing, Random Forest and Support Vector Machines can be applied to the whole dataset first, then on subsets based on gender, different race, and age groups.

Acknowledgements

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