Machine Learning on Structured EHR Data for Prediction in Schizophrenia: Feature engineering and pipeline construction

Kamyar Yazdani, Abhi Jadhav, Aakash Thumaty, Sanya Kochhar, Pranav Warman, Jane P. Gagliardi, MD, MHS[2], Jessica D. Tenenbaum, PhD[1]
[1]Department of Biostatistics & Bioinformatics and [2]Psychiatry, Duke University Medical Center, Durham, NC
✉ jessie.tenenbaum@duke.edu

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Background/Objective

- Schizophrenia is a severe mental disorder that affects ~1.1% of the US population and often requires lifelong treatment.[1]
- Improvement in the ability to predict which patients will need more intensive care in the near future could have a significant clinical value to prevent ED visits.
- This research project aims to apply machine learning to structured clinical data to predict patient ED visits and hospital admission.
- The first semester of this Bass project was dedicated to data acquisition, exploration, and wrangling as well as designing a feature matrix including both direct data and derived features using hierarchical terminologies and clinical prior knowledge.

Data

- A de-identified version of structured EHR data were extracted from Duke's data warehouse using DEDUCE (Duke Enterprise Data Unified Content Explorer) under Duke IRB protocol (Pro00081628)
- Inclusion criteria was at least one inpatient or two outpatient schizophrenia-related diagnosis codes in encounters from 1/1/2014 to 4/10/2017.
- Data types included demographics, diagnosis codes, and medications for encounters during the period in question.
- Overall, our dataset included ~115,000 encounters for 2,800+ patients.

[1]Schizophrenia. (n.d.). Retrieved from https://www.nimh.nih.gov/health/topics/schizophrenia/index.shtml

Patient Population

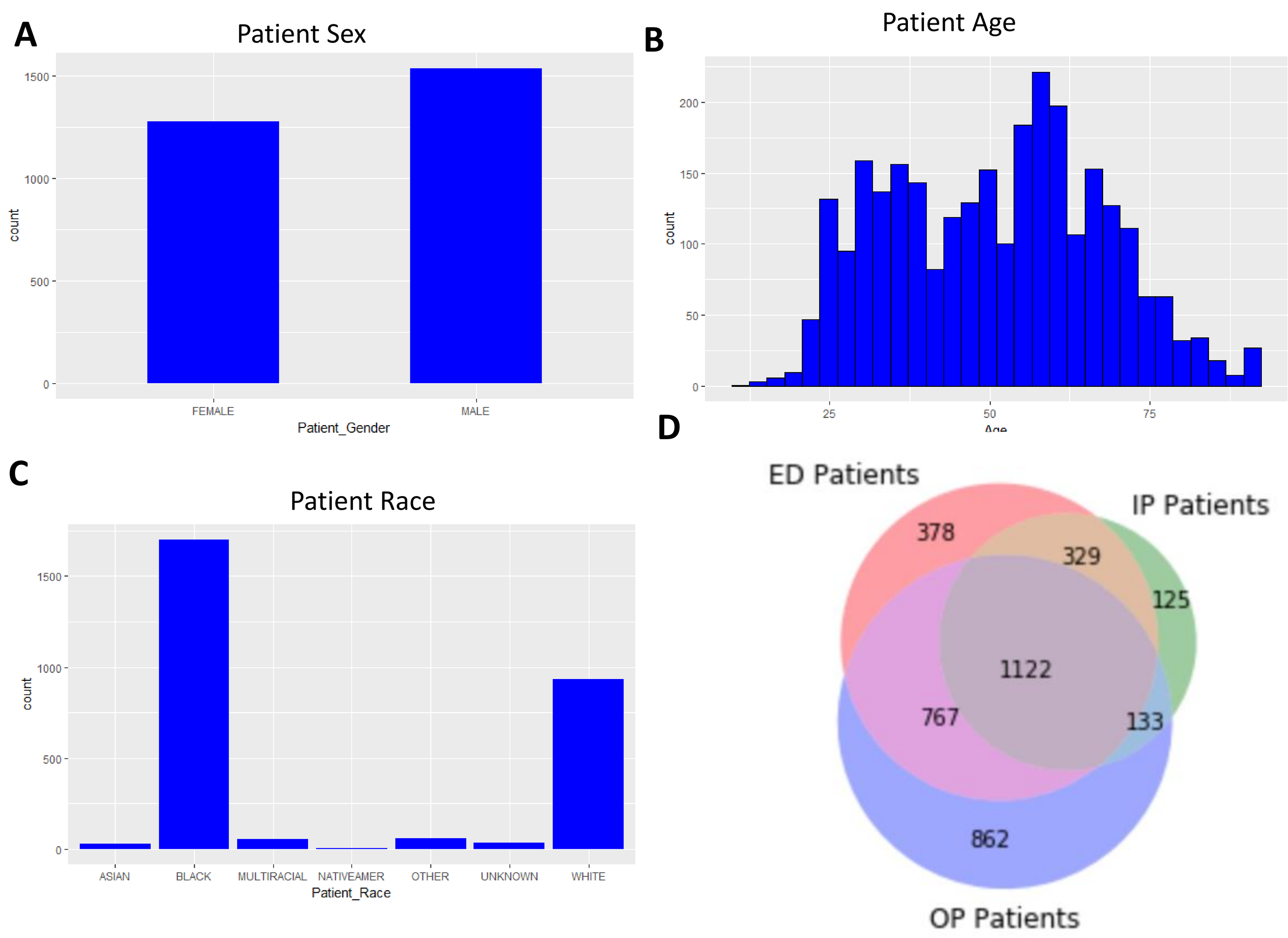


Figure 1: A-C. cohort demographics. D. Counts and overlap of inpatient, outpatient, and ED encounters.

Feature Matrix Construction

- Each row of the feature matrix represents a patient encounter
- Direct features include demographics, insurance information, visit type- IP (inpatient) vs OP (outpatient), total hospital stay, and psychiatric medication data.
- Computed features include the trend of patients' encounters over time, drug classes, and disease classes, which were derived by mapping ICD codes to hierarchical SNOMED codes.
- Medication and diagnosis data are represented as binary values based on whether that diagnosis or drug was recorded at a given encounter.
- Structured data will ultimately be combined with NLP-based symptom data.

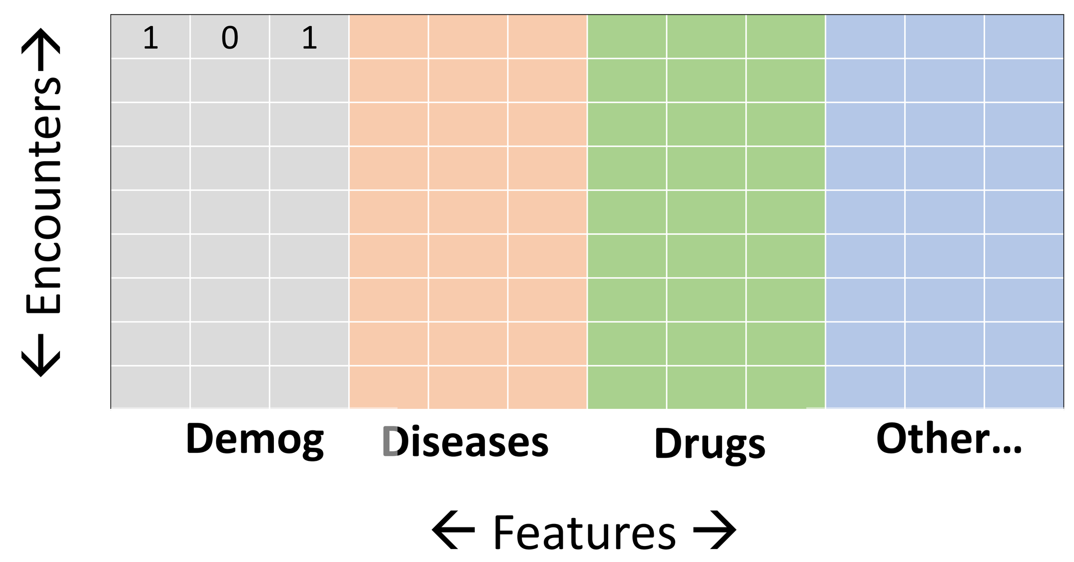


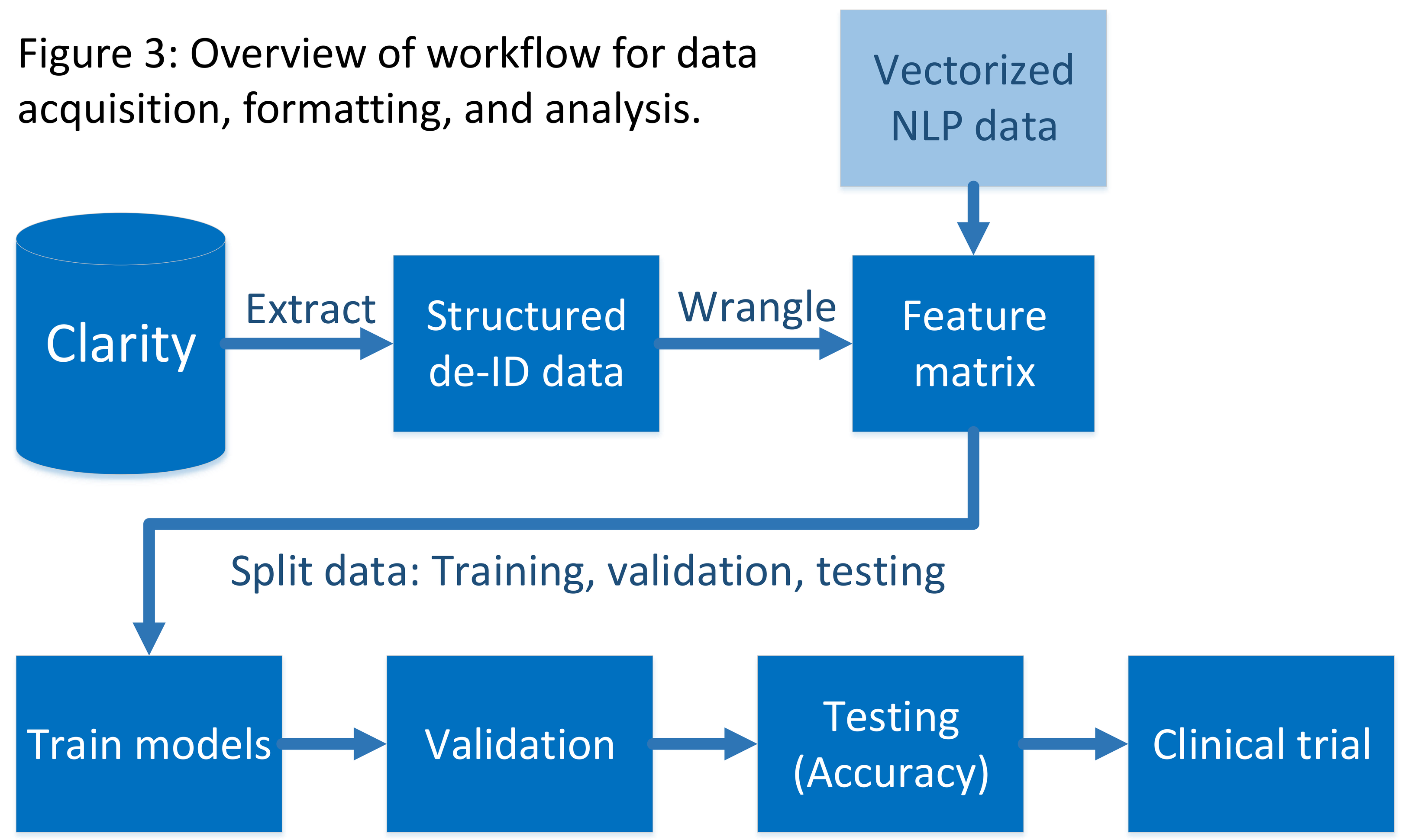
Figure 2: Feature matrix for data analysis. Rows represent encounters. Columns represent demographic data and the presence/absence of clinical elements including medications and diagnoses.

Major Challenges

- Noisy EHR data- missing values, nonsensical dates, etc.
- Project done in parallel with NLP analysis, requiring both de-identified and identified data with different permissions for different team members, jittered dates, and post-hoc data mapping
- Mapping ICD codes to SNOMED, given codes are not 1:1
- How to handle data across time

Pipeline

Figure 3: Overview of workflow for data acquisition, formatting, and analysis.



Conclusions and Future Directions

- Project progress to date has focused on data acquisition, data wrangling, and feature engineering.
- Next steps will be to perform supervised machine learning, evaluating accuracy in predicting which patients would benefit from more intensive resources following an encounter with the health system.
- Once accuracy is assessed and deemed clinically valuable, we aim to expose our algorithm to clinicians through a client-facing application (e.g. through SMART on FHIR) to assist in planning follow-up care and resource allocation.

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