Fighting Depression

Personalized Treatment Recomendation for Patients with Depression

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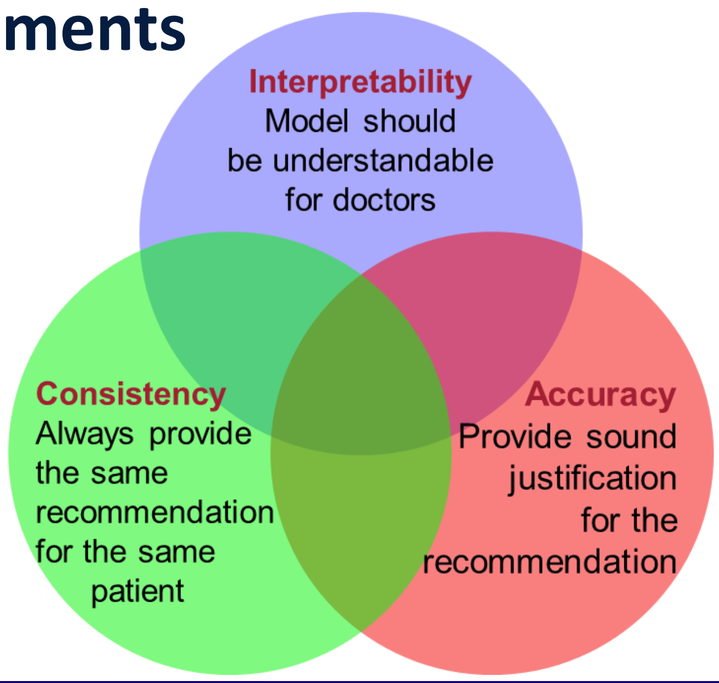
Problem Statement and Objective

According to the CDC, **13.2%** of the US population is on **antidepressants** of which **8.6%** require a **change** in **therapy** because the first prescription resulted in no improvement

The goal is to build a **model** that **recommends** a **treatment** for each user that **maximizes** the probability of **effectiveness** (probability of patient staying on the medication)

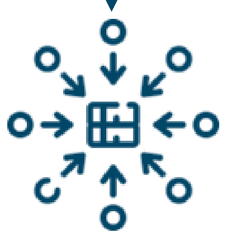
Requirements



Methodology

Patient Prescription Claims

Data Preprocessing

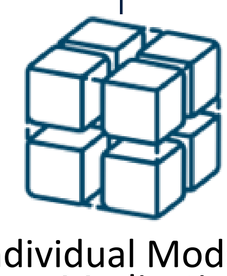


Data Aggregation and Feature Engineering

Propensity Model

Covariate Balance Evaluation

Incorporate Predicted Probabilities as Weights



Individual Models per Medication

Prescription Model Evaluation

Optimal Treatment Recommendation

Connection: Safe File Transfer Protocol (SFTP) to ensure data security

Patient ID	Medication Prescribed	Covariates (Age, Gender, Diagnosis, etc)	Effective (Target Variable)
1	A	…	0
1	B	…	1
2	B	…	1

Raw Data: Paid prescription claims for depression medications

Effectiveness: Measures if a patient stays on the medication

Has been their last medication, they stayed on it for more than 42 days and they have multiple refills for that medication.

Any of the 3 conditions is not satisfied

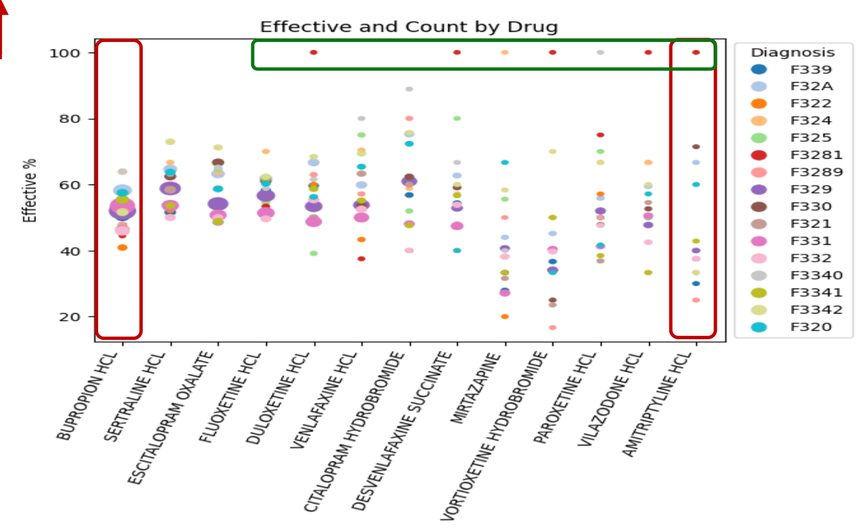
Effectiveness % by medication and diagnosis

Size determined by the number of prescriptions

Most Prescribed Medications aren't the **most effective**

Medications prescribed based on **consistency**

Specific medications show **higher effectiveness** across diagnosis



What? Probability of a patient receiving each medication on their first visit

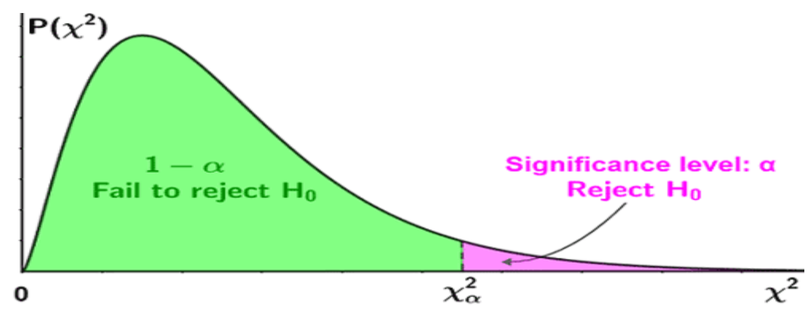
Why? Counteract assignation bias implicit in the data. Reduces the likelihood that observed effects are due to differences in patients rather than the medication

How? Grouping patients based on predicted probabilities so feature distributions in each group are independent of medication.

Covariate Balance

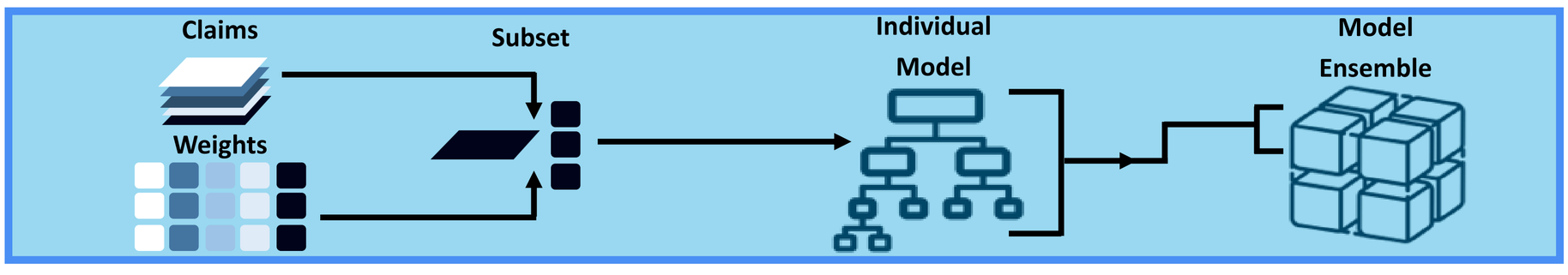
Null Hypothesis (Ho): Feature distribution is independent of the medication

Alternative Hypothesis (H1): Feature distribution is dependent on the medication



Feature	% Groups Accepted
Gender	90%
Diagnosis	90%
Provider	80%

For **each medicine**, build a **model** using the patients who were given that medicine and the corresponding **weights** from the previous model. Helps the model consider other medicines



For any patient, these models estimate how effective each medication will be and choose the highest one

Results

96% **Probability** of the model giving something other than the medications known to be ineffective

5% Mean Average Difference: Between models predictions andnaive effectiveness

14% Predicting the same effective medication as the doctor naive