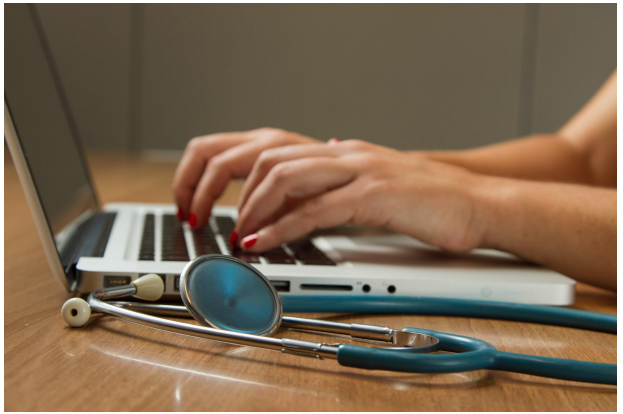
Predicting Congestive Heart Failure

Brandon Ryu, Douglas Hilton, Stephen Kita

Why Healthcare Analytics

- Common interest in helping patients
- Career Opportunities
  - $11.5 Billion market in 2019
  - $40.8 Billion market projected in 2025
  - Compound Annual Growth Rate: 23.55%
  - Growing opportunities for data scientists
- Meaningful Use
  - Increase in volume
  - Increase in interoperability



Why Congestive Heart Failure?

Prevalence

- 6.2 Million adults in US
  - 10% of patient population
- 13.4% of deaths in 2018 mentioned heart failure
- $30.7 Billion to treat CHF in 2012

Survival Rate

- ~50% 5 year survival rate
- 5 year survival rates per stage (2007 study, 2000 subjects)
  - Stage A: 97%
  - Stage B: 95.7%
  - Stage C: 74.6%
  - Stage D: 20%

Difficulty

- Hard to clearly diagnose with few labs
  - Acute Kidney Failure: diagnosed with few labs

Data Source

MIMIC IV v0.4

- Medical Information Mart for Intensive Care (MIMIC)
- Beth Israel Deaconess Medical Center (Boston, MA)
- Intensive Care Unit (ICU) and Emergency Department (ED) patients from 2008~2019
- Ethics course requirement

Tables

Used 8 of 34 total tables

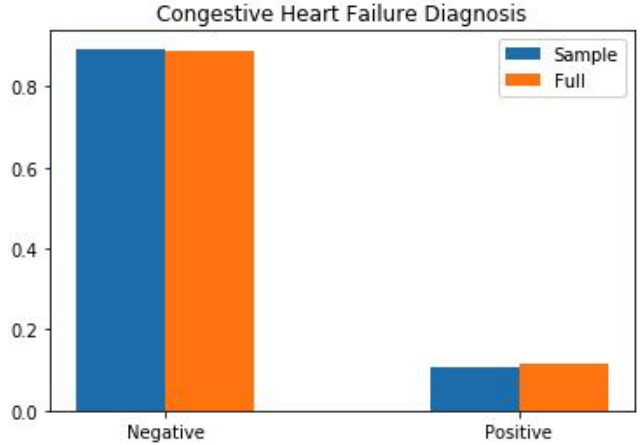
- Patients (sub_id)
- Admissions (sub_id, adm_id)
- Diagnoses (adm_id, diag_id)
- Labevents (adm_id, lab_id)
- Chartevents (adm_id, event_id)
- Dictionaries (lab_id, event_id, diag_id)

Rows

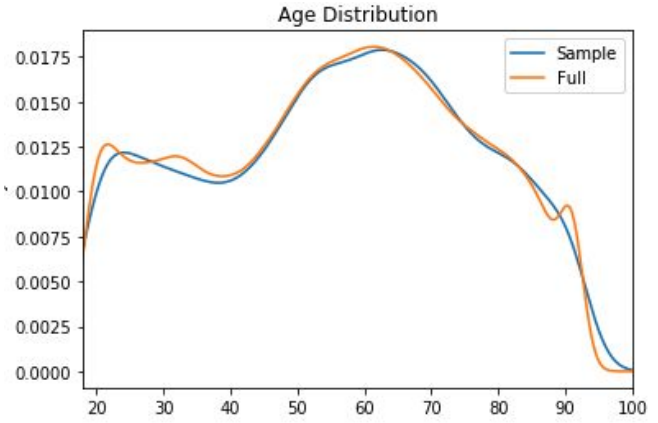
- 260,000 total patients
  - 200,000 adult patients
- 530,000 hospital admissions
  - 460,000 adult admissions
- 500,000,000 events

Data Processing

- Aggregate
  - First hospital admission with CHF diagnosis for patients with CHF
  - Random hospital admission for patients without CHF
  - Loss due to age
  - Loss due to lack of labs



- Full Data vs Current, Future Samples
  - Positive Diagnosis
    - 10.7% vs 11.4%, 11.9%
  - Patients
    - 257.4k vs 11.5k, 8k



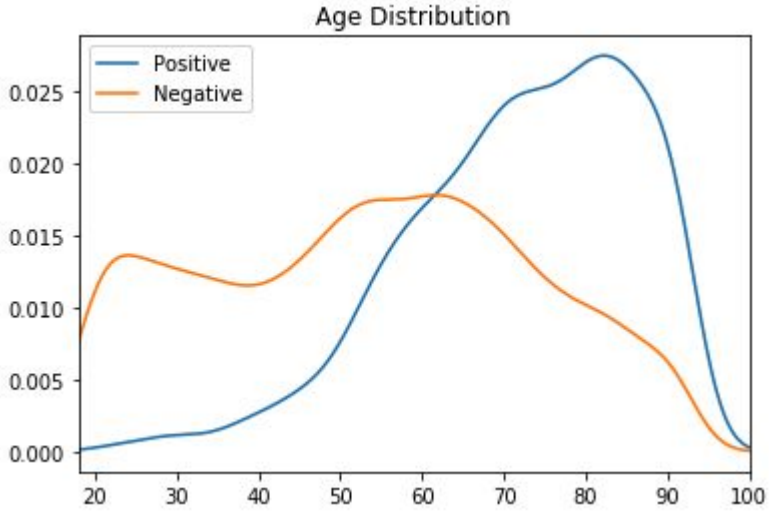
Feature Engineering

- Labs Events
  - > 120m records
  - 1625 different tests
  - Lots of missingness
- Grab most relevant labs
  - 20 most common
  - 5 known to be related
- Aggregate
  - Min
  - Mean
  - Max
  - Abnormal %
  - Above Max
  - Below Min
- 150 Total Lab Event Features

	itemid	label	fluid	category	loinc_code
115	50868	Anion Gap	Blood	Chemistry	1863-0
212	50882	Bicarbonate	Blood	Chemistry	1963-8
222	51464	Bilirubin	Urine	Hematology	5770-3
282	50893	Calcium, Total	Blood	Chemistry	2000-8
442	50902	Chloride	Blood	Chemistry	2075-0
511	50911	Creatine Kinase, MB Isoenzyme	Blood	Chemistry	6773-6
512	50912	Creatinine	Blood	Chemistry	2160-0
634	50920	Estimated GFR (MDRD equation)	Blood	Chemistry	NaN
723	50931	Glucose	Blood	Chemistry	6777-7
761	51221	Hematocrit	Blood	Hematology	4544-3
771	51222	Hemoglobin	Blood	Hematology	718-7
1008	50960	Magnesium	Blood	Chemistry	2601-3
1013	51248	MCH	Blood	Hematology	785-6
1014	51249	MCHC	Blood	Hematology	786-4
1016	51250	MCV	Blood	Hematology	787-2
1189	50970	Phosphate	Blood	Chemistry	2777-1
1211	51265	Platelet Count	Blood	Hematology	777-3
1233	50971	Potassium	Blood	Chemistry	2823-3
1279	51274	PT	Blood	Hematology	5902-2
1307	51277	RDW	Blood	Hematology	788-0
1312	51279	Red Blood Cells	Blood	Hematology	789-8
1373	50983	Sodium	Blood	Chemistry	2951-2
1494	51003	Troponin T	Blood	Chemistry	6598-7
1506	51006	Urea Nitrogen	Blood	Chemistry	3094-0
1598	51301	White Blood Cells	Blood	Hematology	804-5

Feature Engineering

- Additional Features
  - Comorbidities
  - Time in Emergency Department
  - Age
  - Gender
  - Ethnicity
  - Insurance
- Lots of data cleaning
  - Text parsing
  - Bad data entry
  - Differing mapping systems
- Standardize the data
- Check for multicollinearity
  - 173 total features
  - Variance Inflation Factor checks
  - Reduce features to 110-120 depending on the sample



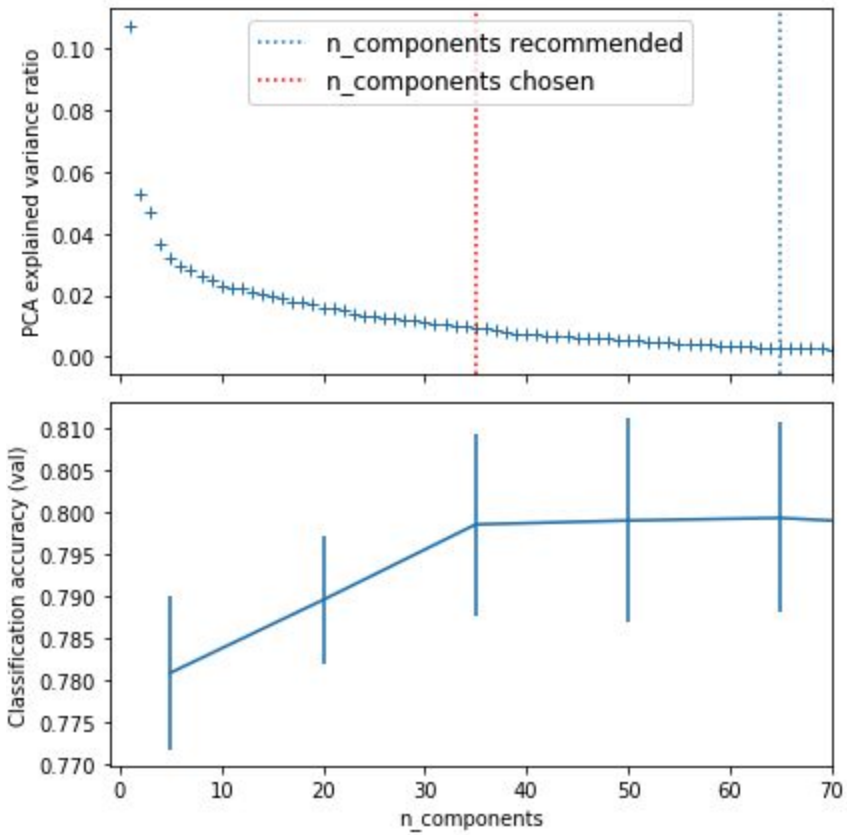
Imputation Methods/Missing Data

- Data is Missing At Random
  - The reason the lab data is missing is because doctors don't need it
  - They either assume it's normal or they can infer based on other lab results
- Normal value imputation
  - Generate 50 normally distributed values around the middle of the normal range
  - Gives a very small chance of an abnormal value
- KNN imputation
  - sqrt(N) Nearest Neighbors
  - More likely to return abnormal values

Feature Selection

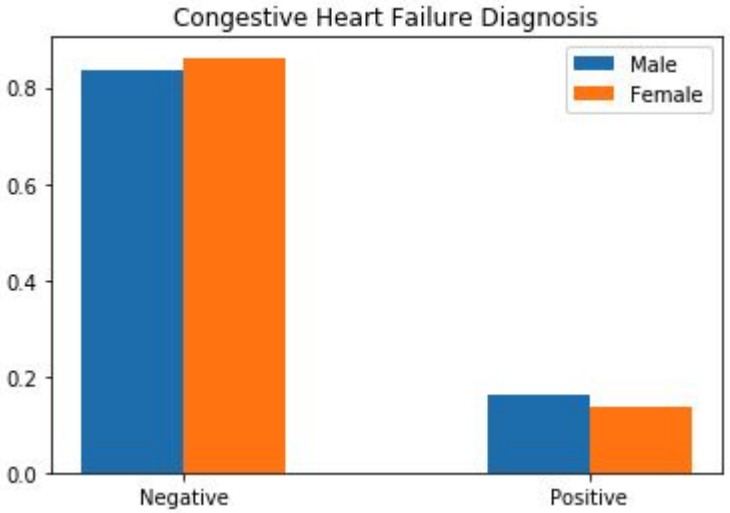
- Principal Component Analysis
  - Reduced feature set from 110 to 35
  - Harder to interpret
  - No better than other models

- Recursive Feature Elimination
  - Reduced feature set from 110 to 36, 60, 101
  - Made model less complex, for the most part



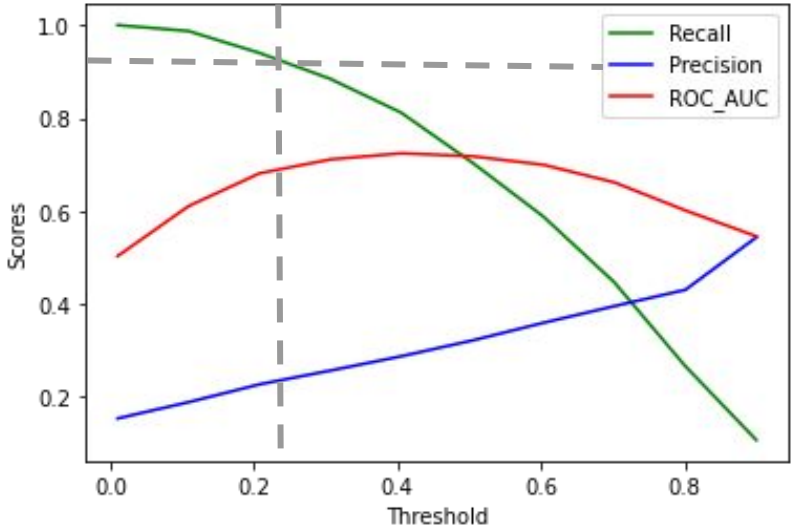
Final Samples for Models

- Current Predictions
  - 11.5k Patients (1.3k Positive Diagnosis)
  - Logistic: 36 Features
  - Random Forest: 101 Features
  - XGBoost: 60 Features
- Gender Based Models
  - Male
    - 8.6k Patients (1.4k Positive Diagnosis)
    - Logistic: 63 Features
  - Female
    - 8.7k Patients (1.2k Positive Diagnosis)
    - Logistic: 77 Features
- Future Predictions
  - 8k Patients (0.9k Positive Diagnosis)
  - All Models: 78 Features



Modeling Objective

- Predict Chronic Heart Failure:
  1. Current visit (present)
  2. Within 1 yr (future)
  3. Differences b/t Male/Female
- Interpretable Models:
  - Logistic Regression
- Accurate Models:
  - Random Forest
  - Gradient Boosting (XGB)
- Tuning:
  - Area Under Curve (AUC)
  - Adjust threshold for 95% Recall



Modeling Results

	Present Model *(11.5K patients, 11.4% with disease)*			**Future Model** *(8K patients, 11.9% with disease)*		
Score	**Logistic** *(36 features)*	**Random Forest** *(101 features)*	**XG Boost** *(60 features)*	**Logistic** *(78 features)*	**Random Forest** *(78 features)*	**XG Boost** *(78 features)*
Recall	*95%*	*95%*	***95%***	*95%*	***95%***	*95%*
ROC/AUC	68%	70%	**71%**	65%	**71%**	66%
Accuracy	49%	52%	**55%**	44%	**55%**	46%
Precision	22%	23%	**24%**	21%	**25%**	21%
F1 Score	36%	37%	**38%**	34%	**39%**	35%

Feature Importance

	Present			Future		
Top Features	**Logistic**	**Random Forest**	**XGBoost**	**Logistic**	**Random Forest**	**XGBoost**
#1	**Atherosclerosis**	**Insurance Medicare**	**Below Min Bicarbonate**	**Arrhythmia**	**Atherosclerosis**	**Atherosclerosis**
#2	Age	Above Max Urea Nitrogen	Abnormal % Chloride	Ethnicity (Other)	Diabetes	Age
#3	Max Bicarbonate	Age	Abnormal % Calcium	Atherosclerosis	Age	Mean Urea Nitrogen
#4	Min Urea Nitrogen	Abnormal % Urea Nitrogen	Below Min Phosphate	Above Max Red Blood DW	Hypertension	Above max Urea Nitrogen
#5	Min Red Blood DW	Abnormal % Troponin T	Below Min Creatine Kinase	Age	Above Max Urea Nitrogen	Hypertension

Demographic Comparisons (Present)

	Logistic Regression	
Score	**Female** *(77 features)*	**Male** *(63 features)*
Recall	*95%*	*95%*
ROC/AUC	72%	71%
Accuracy	55%	54%
Precision	22%	26%
F1 Score	36%	41%

Top Features	Female	Male
#1	Age	Atherosclerosis
#2	Diabetes	Age
#3	Hypertension	Max Bicarbonate
#4	Max Anion Gap	Max Anion Gap
#5	Max Bicarbonate	Ethnicity Asian (-)

Conclusion

Challenges

Dataset was:

- Sparse
- Messy
- Complicated

Model Outcomes

Predicting present

- Similar to doctors
  - max/min labs

Gender

- Female: diabetes
- Male: atherosclerosis

Predicting Future

- Similar accuracy
- More comorbidities

Applications

- Decision support tool for doctors
  - Additional tests
- Early warning tool for patients
  - Lifestyle changes

Future Work

- Compare Ethnicities
- Ensemble different models
  - Sklearn voting classifier
- Incorporate different tables
  - Prescriptions
  - Chartevents
- Predict expire from CHF (severity)