# Predicting Prediabetes and Diabetes with Machine Learning

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National Health and Nutrition Examination Survey 2007 - 2016

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# The Problem

- 10.5% of American population had diabetes as of 2018.
- One in five didn't know it!
- 34.5% of American adults had prediabetes.
- Just over one in ten knew!

# The Problem

Diabetes:

- 7th leading killer of Americans
- Leading cause of end-stage kidney failure, blindness in working-age adults, amputation
- 2- to 4-fold risk of heart attack, stroke
- $327 billion cost

Prediabetes:

- Increased risk of heart attack, stroke, kidney disease
- Increased risk of type 2 diabetes

# Can Machine Learning Help?

- Increasing use in health care as aid in diagnosis, creating tailored treatment
- Leverage health care resources where spread thin
- Gain new insights from health data
- More people who know = earlier treatment, fewer complications, lower cost

# Predict Prediabetes and Diabetes with Machine Learning

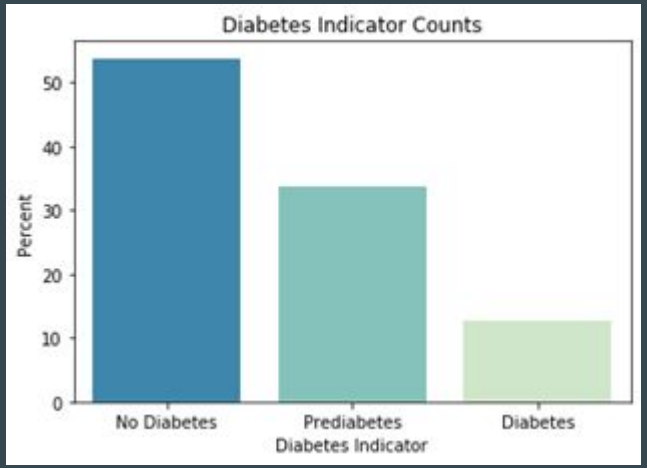
- National Health and Nutrition Examination Survey (NHANES) 2007-2016
- Python machine learning: scikit-learn, XGBoost
- Predict prediabetes using American Diabetes Association diagnostic criteria with blood test results
- Predict diabetes using prescription medication records
- Look for risk factors for prediabetes and diabetes
- Help identify who should get tested

# NHANES

- Two year survey cycles
- Changes in survey content between cycles
- Demographics, socioeconomics, dietary intake, physical examination, laboratory testing, prescription medications, questionnaires on many health-related topics
- 5,000 participants per year
- Oversampling of certain groups to ensure subsample sizes adequate for analysis

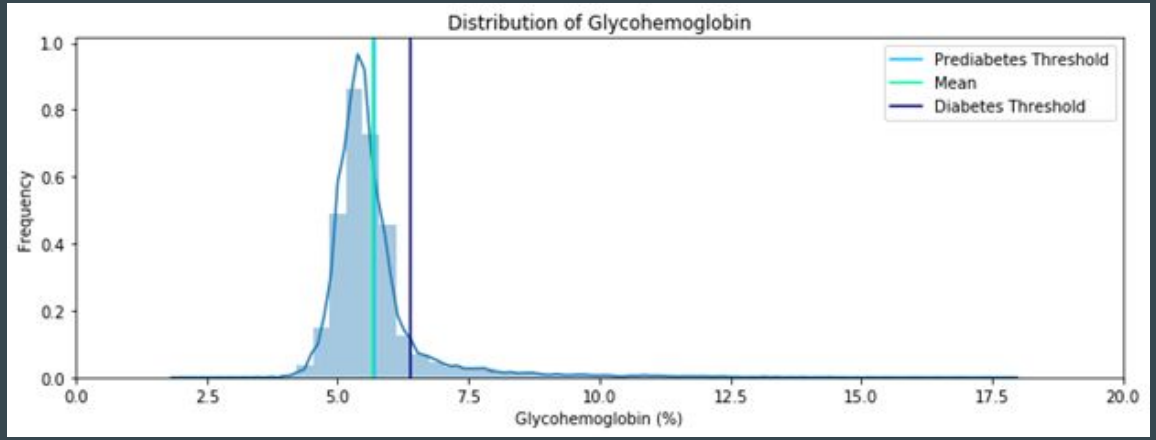
# What does the data say?

- Indicator based on laboratory results using American Diabetes Association diagnostic criteria
- Distribution similar to National Diabetes Statistics Report



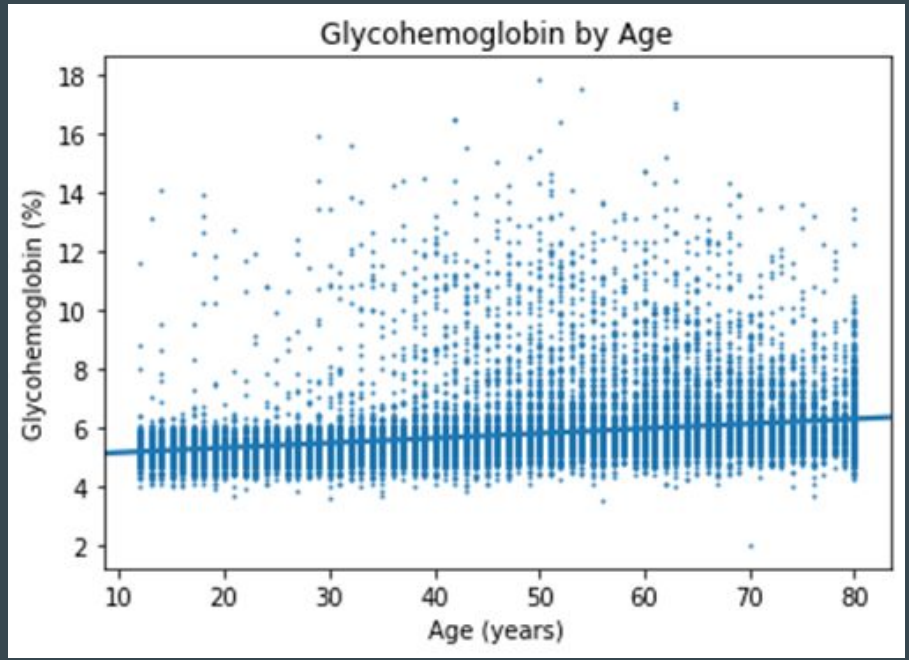
# What does the data say?

- Many features with right skews, long right tails
- Very high outliers
- Data verified, outliers are valid measurements
- Mean glycohemoglobin (long term blood sugar) at prediabetes diagnosis threshold!



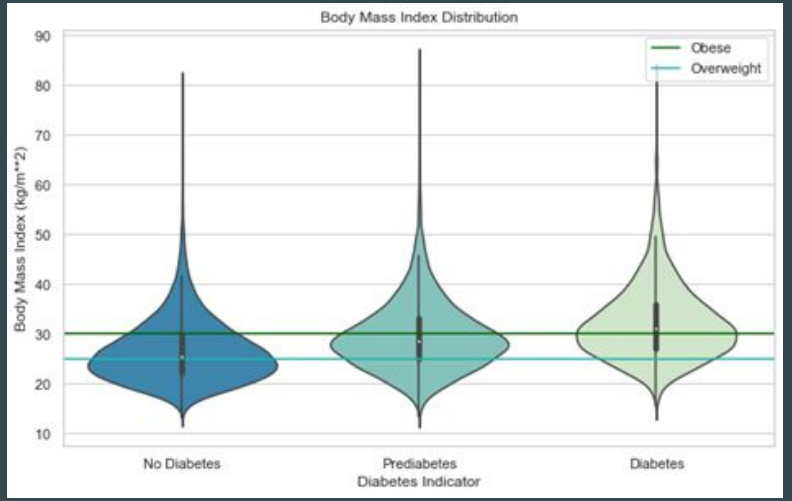
# What does the data say?

- Clear upward trend in glycohemoglobin with increasing age
- Proportion in diabetic range (>= 6.5%) higher over 30 years old
- Several teens in diabetic range



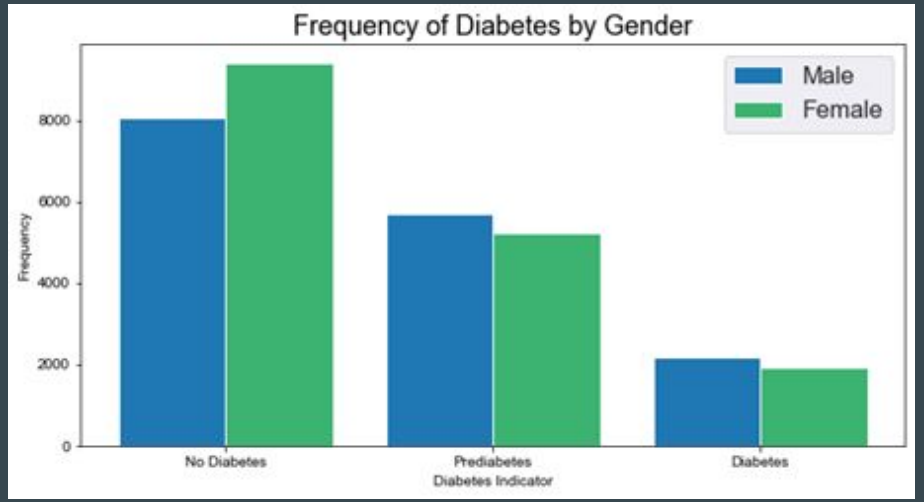
# What does the data say?

- Many features have a clear trend upward from healthy blood sugar through prediabetes to diabetes.



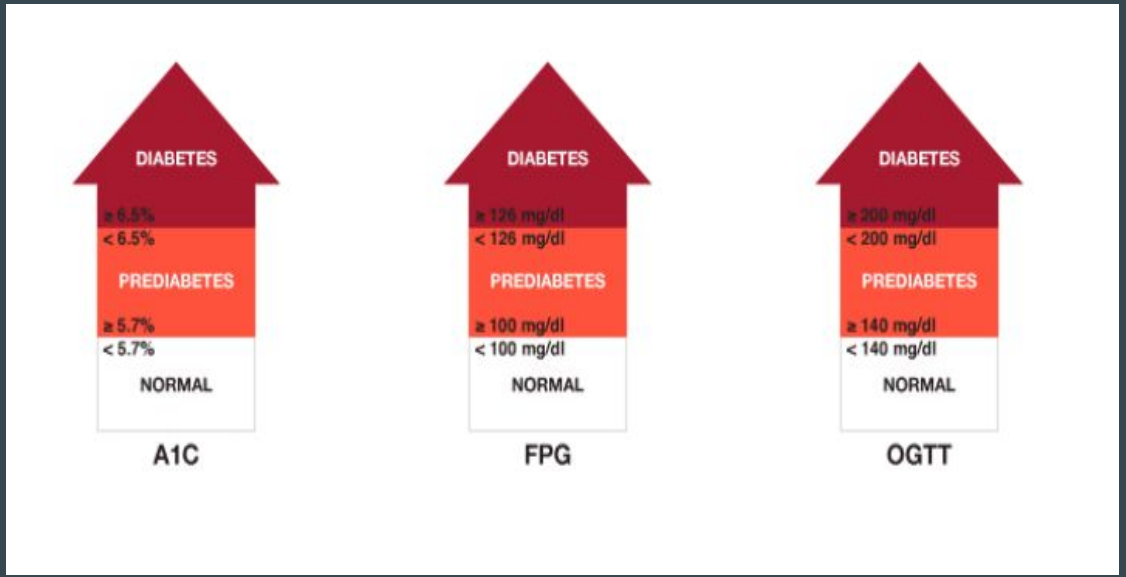
# What does the data say?

- Data analysis found relationship between diabetes and gender.
- Also high blood pressure, activity level, triglycerides, body mass index, serum iron, marital status, and asparate aminotransferase (AST)



# Machine Learning Approach

- Two groups of models
- Group 1: multiclass classification with target determined by laboratory results and American Diabetes Association classifications.




https://www.diabetes.org/a1c/diagnosis

# Machine Learning Approach

- Group 2: binary classification with target defined by participant medication use for diabetes
- Logistic Regression and tree based models due to very high dimensionality

https://www.diabetes.org/diabetes/medication-management

# Preprocessing

- Hundreds of features
- Duplicate features, different units
- Highly (nearly perfectly) correlated features
- Some features not collected entire ten years
- Some features moved during ten years
- Self-reported continuous features with code values above data range: “don’t know”, “refused to answer”
- IterativeImputer to fill nulls
- Dummy variables for categoricals
- StandardScaler for Logistic Regression continuous features

# Group 1 Results

- XGBoost performed best.
- No model was a strong predictor of prediabetes.
- All had better precision with diabetes.

**Summary of pre-tuning results:**

| Model | Accuracy (test) | Accuracy (5-fold cv train) | Precision | Recall/Sensitivity | Specificity | F1-Score | ROC AUC |
|---|---|---|---|---|---|---|---|
| Logistic Regression | .715 | 71.7 (.274) | .58 | .63 | .77 | .60 | .74 |
| Decision Tree | .597 | 60.1 (.381) | .45 | .46 | .72 | .46 | .60 |
| Random Forest | .674 | 67.3 (.540) | .55 | .47 | .80 | .50 | .74 |
| Adaboost | .705 | 70.5 (.317) | .59 | .53 | .81 | .56 | .73 |
| Gradient Boosting | .717 | 72.0 (.262) | .60 | .56 | .81 | .58 | .76 |
| XGBoost | .712 | 71.7 (.457) | .60 | .55 | .81 | .57 | .77 |

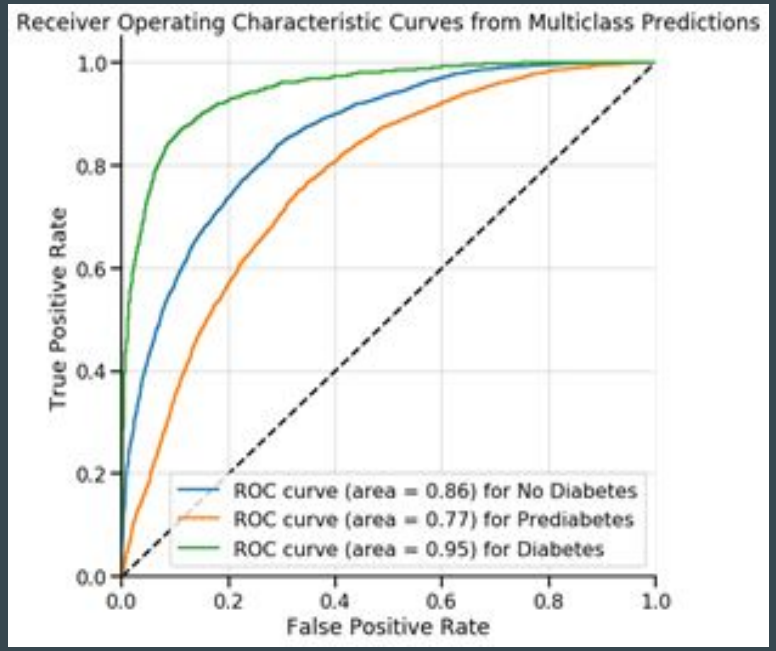
**Post-tuning:**

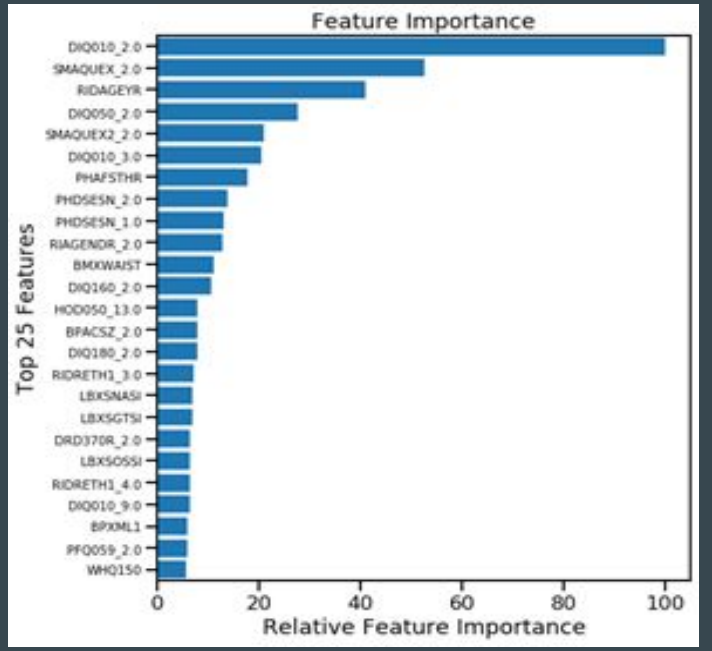
| Model | Accuracy (test) | Accuracy (5-fold cv train) | Precision | Recall/Sensitivity | Specificity | F1-Score | ROC AUC |
|---|---|---|---|---|---|---|---|
| Random Forest | .702 | 70.7 (.584) | .57 | .60 | .78 | .59 | .76 |
| XGBoost | .728 | 72.8 (.529) | .61 | .59 | .81 | .60 | .77 |

**Note: Accuracy is for overall model. All other measures are for Prediabetes class.**

**As this is medical data, reported Sensitivity & Specificity in addition to Precision & Recall.**

# XGBoost Model



# Group 2 Results

- XGBoost again outperformed other models except Gradient Boosting.
- Better precision than Group 1 diabetes results

**Summary of results pre-tuning:**

| Model | Accuracy (test) | Accuracy (5-fold cv train) | Precision | Recall/Sensitivity | Specificity | F1-Score | ROC AUC |
|---|---|---|---|---|---|---|---|
| Logistic Regression | .935 | 93.8 (.723) | .75 | .88 | .95 | .81 | .97 |
| Decision Tree | .928 | 92.0 (.576) | .77 | .78 | .96 | .77 | .87 |
| Random Forest | .917 | 91.7 (.703) | .85 | .57 | .98 | .69 | .97 |
| Adaboost | .942 | 94.1 (.575) | .82 | .81 | .97 | .81 | .97 |
| Gradient Boosting | .953 | 95.4 (.324) | .81 | .92 | .96 | .86 | .98 |
| XGBoost | .952 | 95.5 (.537) | .82 | .89 | .96 | .85 | .98 |

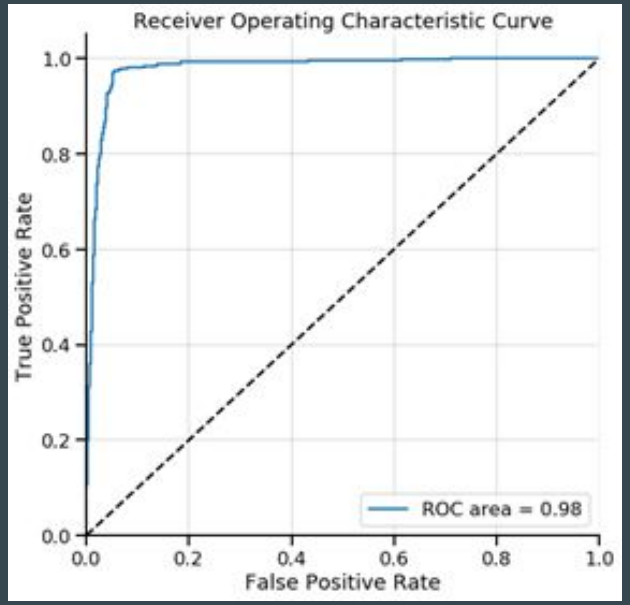
**Post-tuning:**

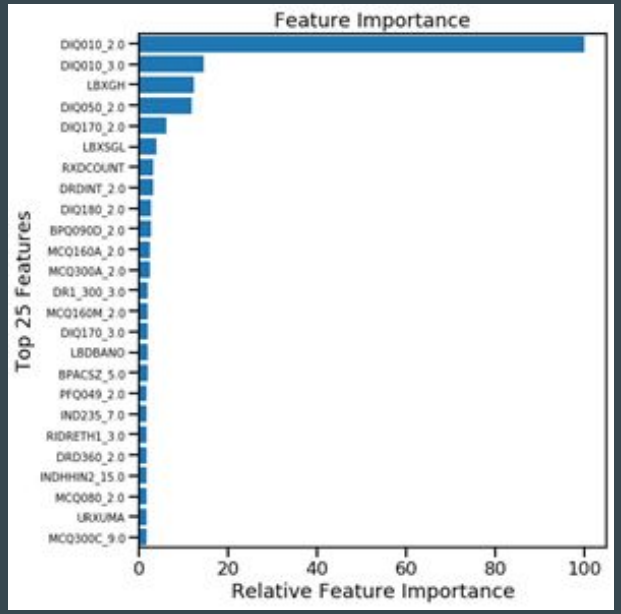
| Model | Accuracy (test) | Accuracy (5-fold cv train) | Precision | Recall/Sensitivity | Specificity | F1-Score | ROC AUC |
|---|---|---|---|---|---|---|---|
| Random Forest | .948 | 95.4 (.448) | .78 | .93 | .95 | .85 | .98 |
| XGBoost | .951 | 95.7 (.596) | .81 | .89 | .96 | .85 | .98 |

**Note: Accuracy is for overall model. All other measures are for positive class: Diabetes.**

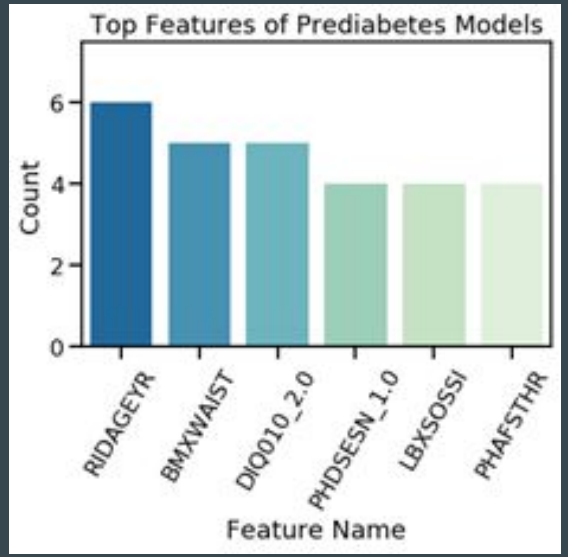
**As this is medical data, reported Sensitivity & Specificity in addition to Precision & Recall.**

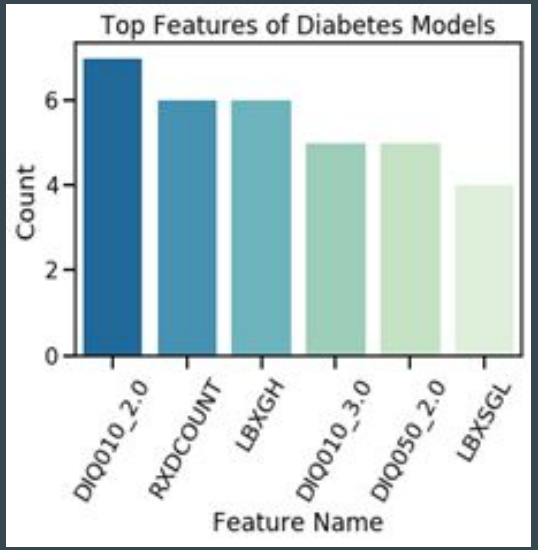
# XGBoost Model



# Most Important Features Overall



# Conclusion

- XGBoost performed best on data
- 60% precision predicting prediabetes in group 1
  - 33.7% of sample
- 80% precision predicting diabetes in group 2
  - 15.8% of sample
- Class imbalance
- More feature overlap between healthy and prediabetes than healthy and diabetes
- Group 2 included diagnostic labs as features
- Noise in features
- Novel important feature: Osmolality for prediabetes

# Future Work

- More feature engineering
  - Noisy features
  - Imputation for categoricals
  - Dummy definition for tree models
  - Class imbalance
  - Additional correlated features
  - Outliers
- Stacked models