Using Data & Diagnostics for Obesity Prediction

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Background

Goal

- Predict if a person has obesity based on certain traits

Method

Simple Logistic Regression
K-Nearest Neighbors
Random Forest

Relevance

- Obesity is a dangerous level of weight classification
- Over 100 million Americans classified as such
- Linked with cardiovascular diseases like diabetes
- Decrease of life expectancy by 3 years

Data Cleaning

Missing Value Imputation

- About **8%** of all observations had missing values
- For 11 numeric variables: use **MEAN**
- For 19 categorical variables: factor & use **MODE**

Significant Predictors

FAF: Physical Activity Frequency	**CALC:** Caloric intake
CH2O: Daily Water Intake	**SCC:** Consumption of sweet drinks
FCVC: Frequency of Vegetable Consumption	**CAEC:** Consumption of food between meals
NCP: Number of main meals	**FAVC:** Frequent consumption of high-caloric food
Height	**Gender**
Age	**Family_history_with_overweight**

Simple Logistic Regression

Benefits

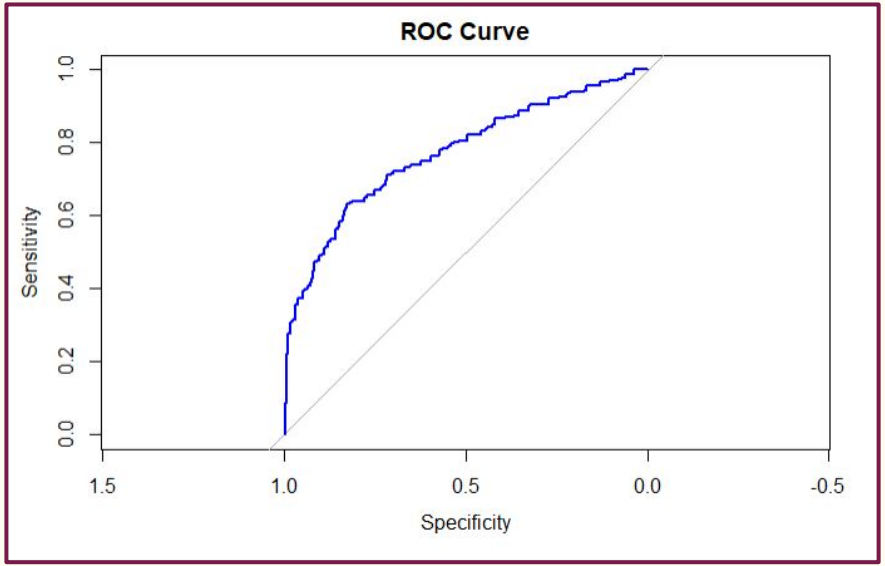
- Simple
- Quick
- Easily Interpretable

Method

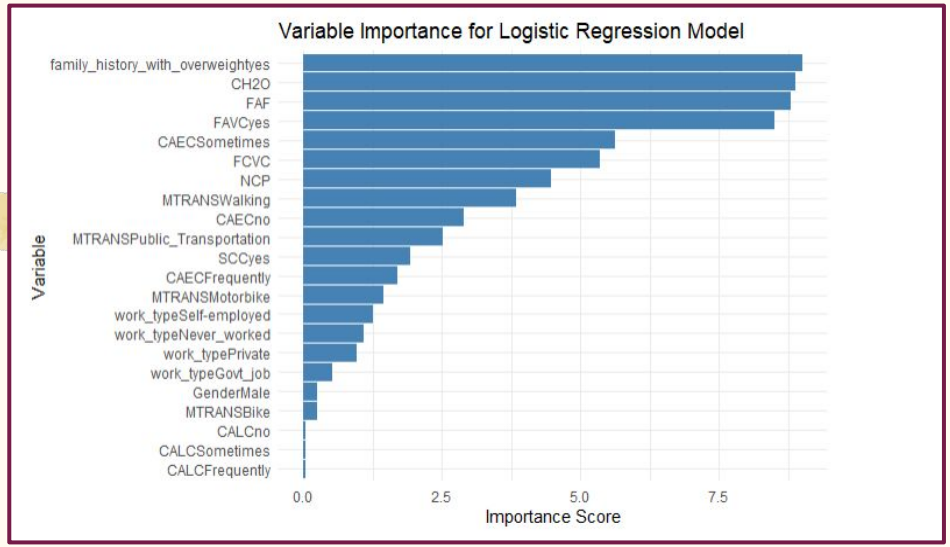
- Generalized linear model function
- Binomial family
- Response variable Obesity Status regressed on significant predictors

Result

- Moderately High AUC
- Sensitivity - Specificity Trade Off
- Decent job at classification



Logistic Regression Interpretation



Significant Variables

1. Family History with Overweight

2. CH2O

3. FAF

Diagnostics

Accuracy = 74.74%

Actual Class \ Predicted Class	Not Obese	Obese
Not Obese	15,902	3,498
Obese	4,591	8,034

K-Nearest Neighbors

Benefits

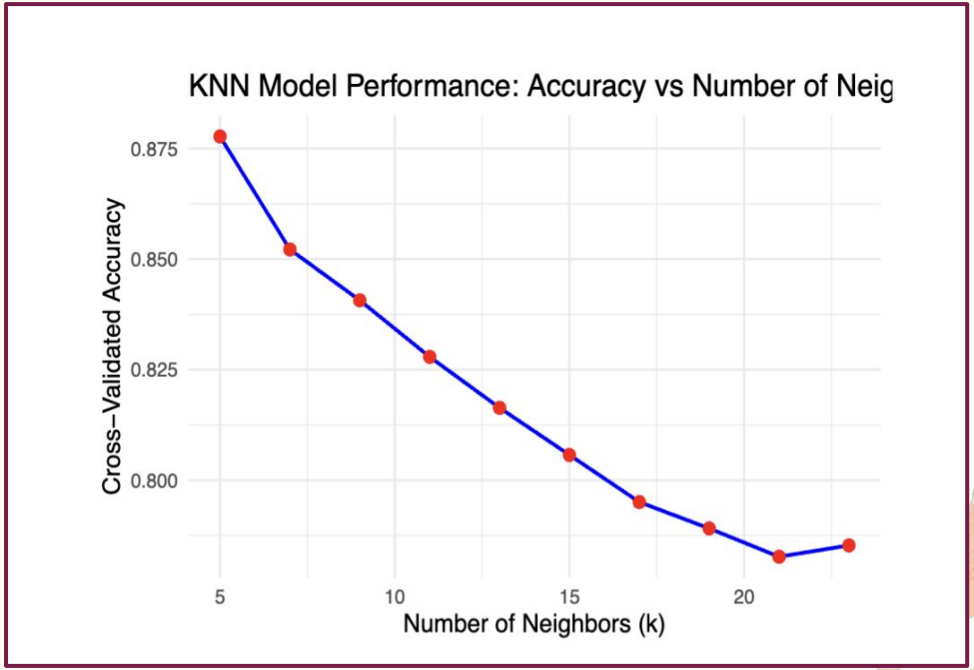
- Intuitive
- Non-Parametric
- Versatile

Method

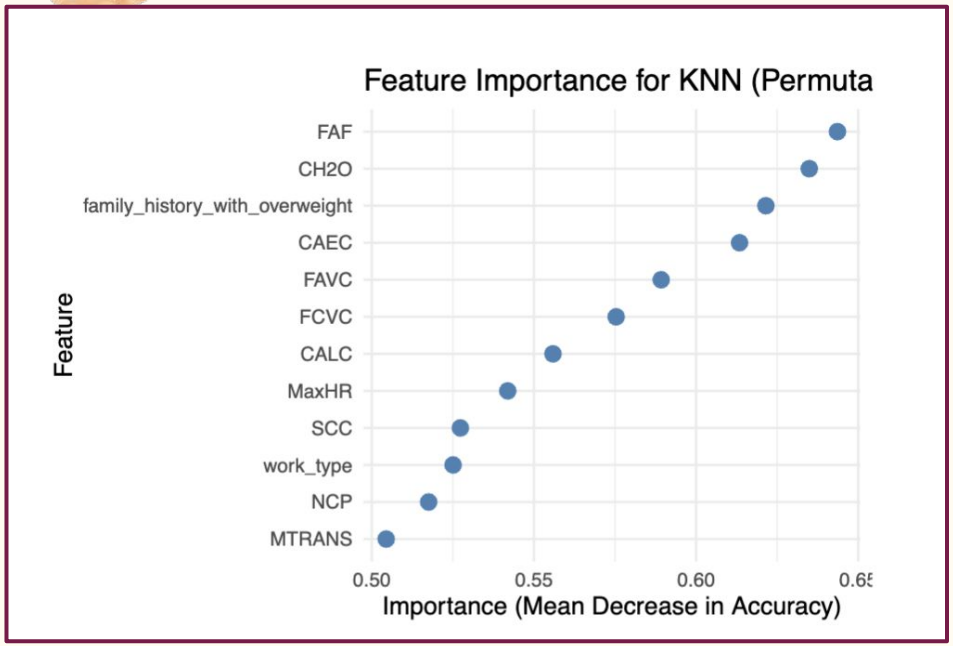
- Cross-validation from k = 5 to 23
- Accuracy primary metric

Result

- Highest accuracy at k = 5
- Accuracy declined with k increase
- Importance of optimizing k for bias and variance balance



KNN Interpretation



Significant Variables

1. FAF

2. CH2O

3. Family History with Overweight

Diagnostics

Training Accuracy = 92.84%

		Predicted Class: Not Obese	Predicted Class: Obese
Actual Class	Not Obese	18,101	1,009
Actual Class	Obese	1,282	11,622

Random Forest

Benefits

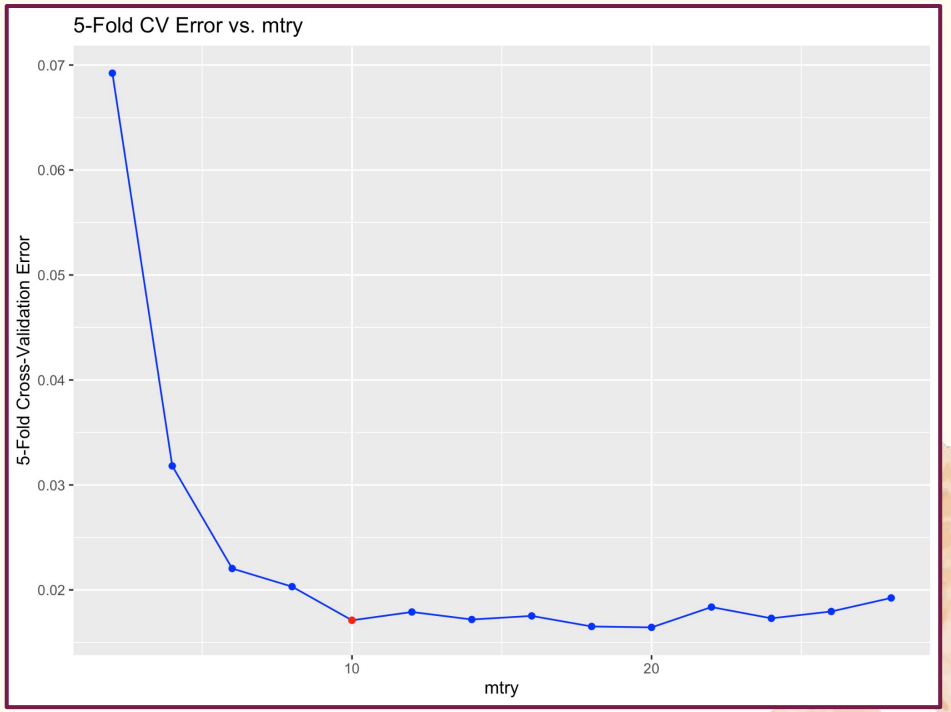
- Improved Accuracy
- Feature Importance

Method

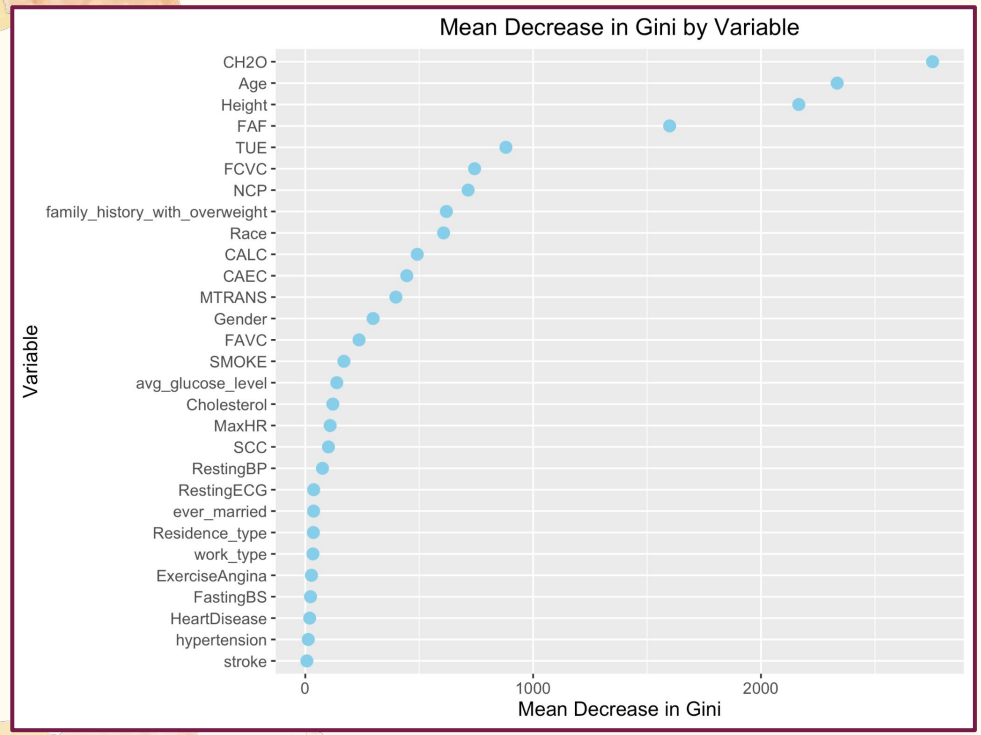
- Bootstrap sampling
- Mtry: Range of number of variables considered at each split from 2 to 29
- Fixed at 5 trees

Result

- Validation Error decreased with mtry increase
- Slowed at mtry = 10, used to balance complexity and performance



Random Forest Interpretation



Significant Variables

1. CH20

2. Age

3. Height

Diagnostics

Training Accuracy = 99.9%

Actual Class \ Predicted Class	Not Obese	Obese
Not Obese	19,524	30
Obese	7	12,453

Improved Model

Best Predictors

- CH2O, FAF, Family History with Overweight, Age, Height

Best Model

- Random Forest (mtry = 4, trees = 5)

Diagnostics

- **Training Accuracy =** 98.2%
- **Testing Accuracy =** 93.4%

Actual Class \ Predicted Class	Not Obese	Obese
Not Obese	19,331	388
Obese	200	12,095

Takeaways

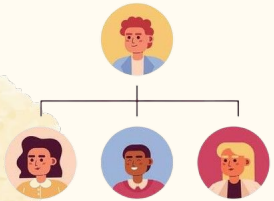
Model Comparison

- **Logistic Regression:** Fast and easy, low accuracy
- **KNN:** Moderate speed and setup, improved accuracy
- **Random Forest:** Slowest and most complicated, high accuracy

Predictor Interpretation

- **CH2O:** Appetite controller, calorie replacement, metabolism boost
- **FAF:** Reduces fat accumulation, calorie burn
- **Family History:** Genetic predisposition, shared lifestyle
- **Age:** Metabolic slowdown, decreased activity level, increase fat mass
- **Height:** Shortness increases BMI





Conclusion

Goal

- Able to predict obesity of person using age, height, family history with overweight, water intake, and physical activity

Possible Improvements

- **Feature Transformation** (Interaction)
- **Advanced Models** (XGBoost)

Future Questions

- How can generative AI models improve obesity prediction?
- Can this model be adapted for real-life healthcare settings?

Thank You!