

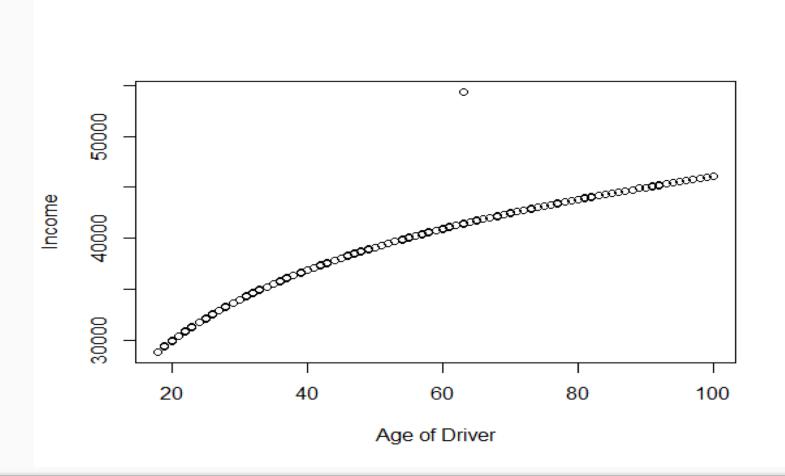
## **Claim Fraud Detection**

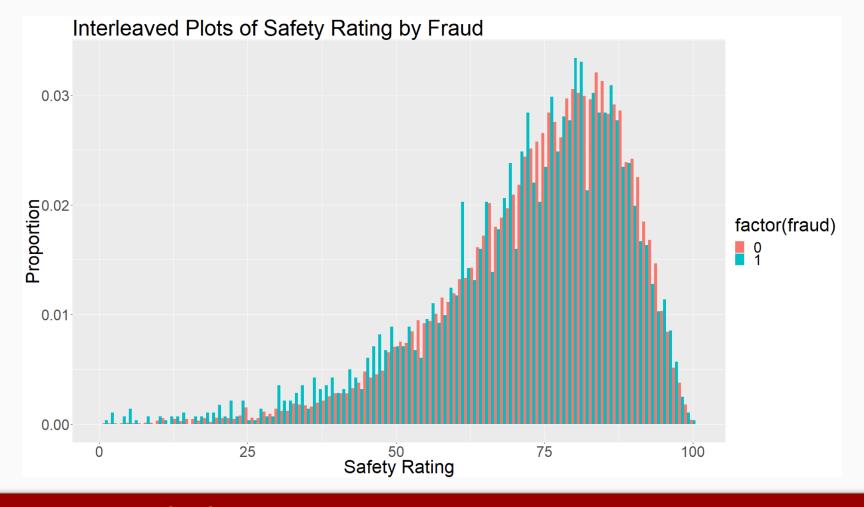
The Magnificent Six

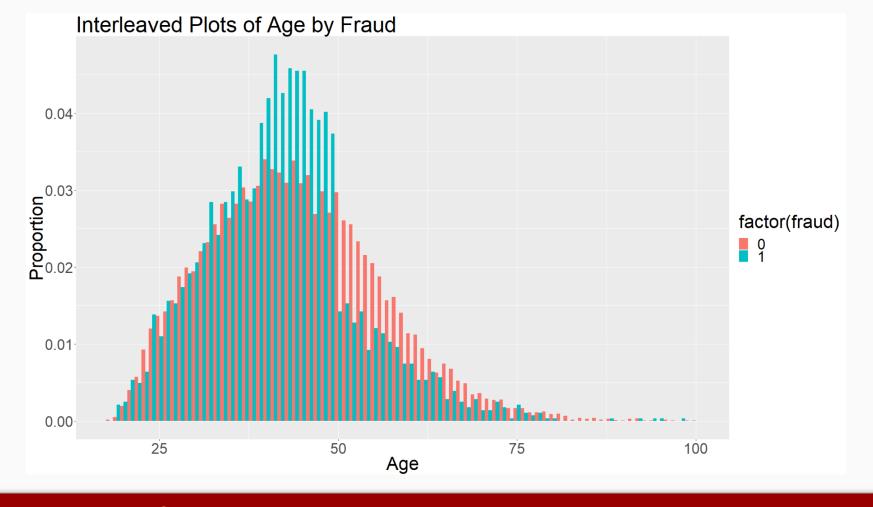
## Outline

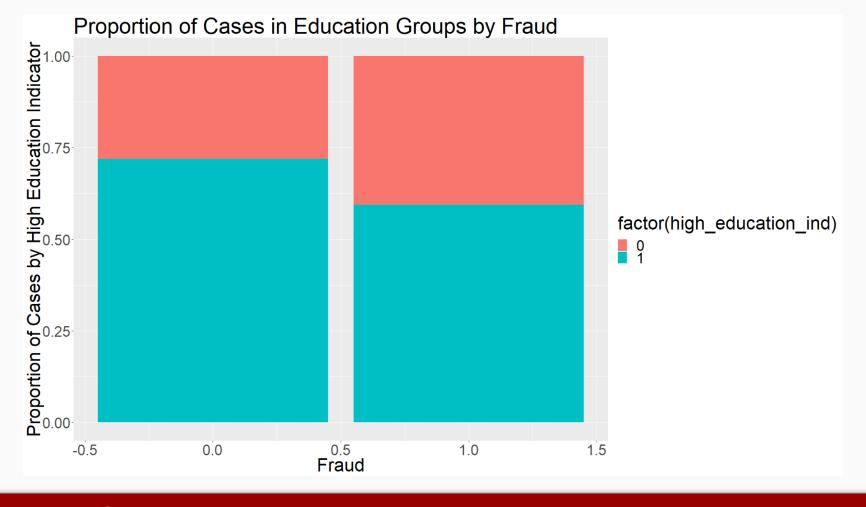
- Introduction
- Preprocessing
  - Data cleaning
  - Feature engineering
  - Feature selection
- Prediction
  - Stacking
  - Modeling
- Conclusion

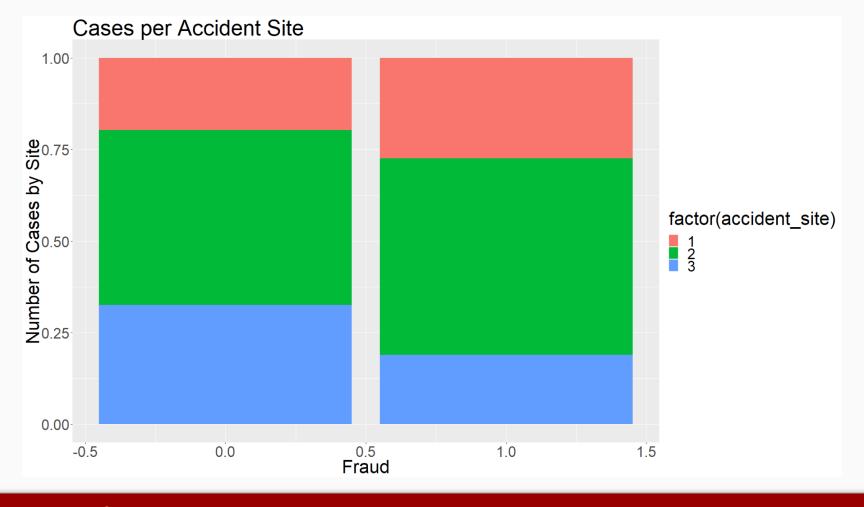
# Introduction



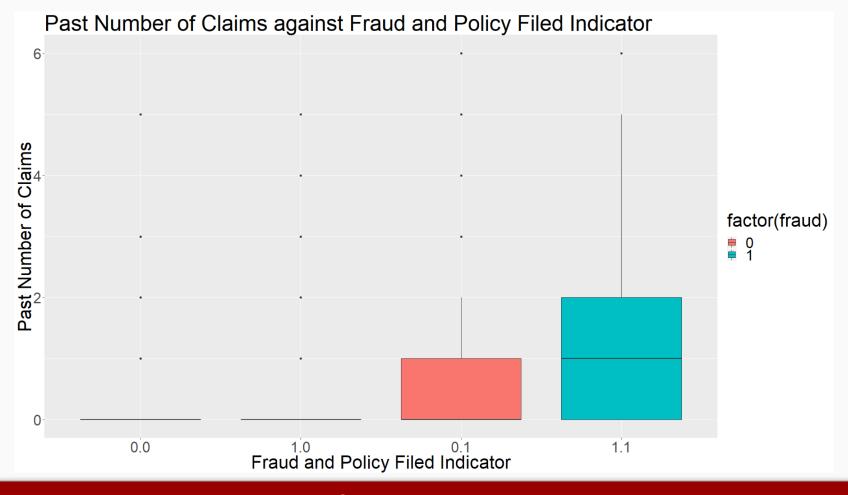








Proportion of cases per Accident Site by Fraud



# Preprocessing

- Data Cleaning
- Feature Engineering
- Feature Selection

## Preprocessing - Data Cleaning

#### NAs

- Train data (fraud=0): delete
- Train data (fraud=1) & Test data: impute (Random Forest)

#### Special variables: Zip code

- NAs: impute (kNN)
- Add city, state, longitude and latitude

#### Highly correlated variables

Age and Income (0.98)

## Preprocessing - Feature Engineering

#### Categorical variables

- Count
- Supervised ratio

$$SR_i = \frac{P_i}{N_i + P_i}$$

WOE

$$WOE_i = \log\left(\frac{P_i/TP}{N_i/TN}\right)$$

- Continuous variables
  - Transform into categorical variables

## Preprocessing - Feature Selection

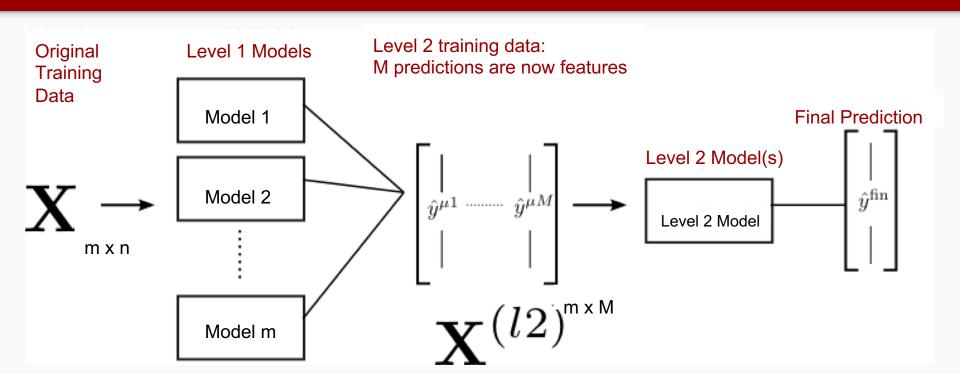
#### Variable Importance

- Random Forest
- Chi-squared Test
- Kruskal Test

## Prediction

- Stacking
- Model

# Prediction - Stacking (General Outline)



#### Prediction - Model Considered

Penalized Logistic Regression (LASSO, SCAD, MCP)

**Discriminant Analysis (LDA, QDA, RDA)** 

**Tree-Based Method (Random Forest, XGBoost)** 

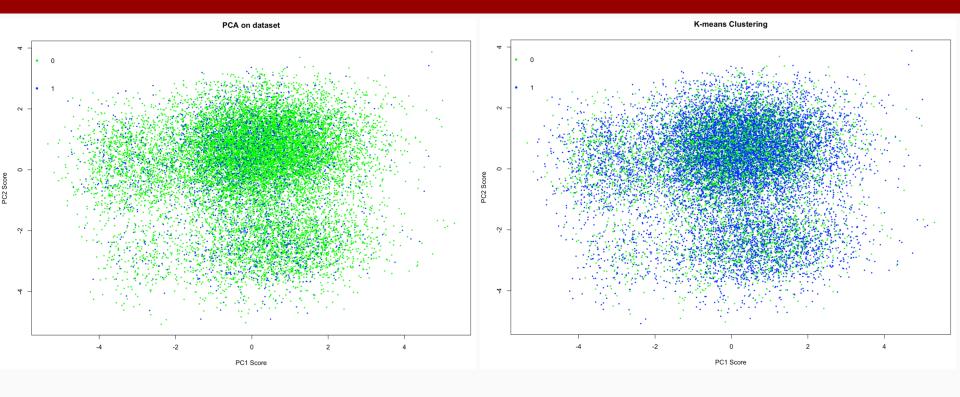
K-Nearest-Neighbors (KNN)

**Generalized Additive Model (GAM)** 

**Clustering Methods** 

**Neural Network (NN)** 

#### Visualization: Principal Component Analysis



#### **Prediction - Model Considered**

Penalized Logistic Regression (LASSO, SCAD, MCP)

**Discriminant Analysis (LDA, QDA, RDA)** 

**Tree-Based Method (Random Forest, XGboost)** 

K-Nearest-Neighbors (KNN)

**Generalized Additive Model (GAM)** 

**Clustering Methods** 

**Neural Network (NN)** 

We use Stacking to build a 3-layer architectures

**First Layer** 

**Second Layer** 

**Third Layer** 

	Penalized Logistic Regression
First Layer	Naive Bayes Classifier
	Linear Discriminant Analysis (LDA)

**Second Layer** 

**Third Layer** 

0.680-0.700

**Third Layer** 

First Layer	
	Generalized Additive Model (GAM)
Second Layer	Regularized Discriminant Analysis (RDA)

0.720-0.730

First Layer

Second Layer

XGBoost

ANN

## Final Prediction AUC

Our group's final prediction on the Kaggle Public Leaderboard had an AUC of 0.74781.

## Conclusion

- Business Insights
- Takeaway
- Suggestions

#### Conclusion

Our findings from this project fall into two categories:

- 1. What the model tells us
- 2. What the modeling process taught us

## Conclusion - Business Insights

#### What the model tells us:

- We found that the following variables are important:
  - Accident Site, Level of Education, Safety Rating, and Past Number of Claims
  - We used the XGBoost variable importance measure to find this
- Fraud was more likely if the accident occurred in a parking lot
- Drivers with lower safety ratings were more likely to commit fraud

- Cast a wide net in researching different methods
  - Our research led us to gradient boosting, a key method in our model.
  - We added several methods to our "toolbox" for future data analysis, even if we did not use them for this project

- Consider a variety of methods to test in cross validation
  - Every method can make predictions, so throw them into the mix for CV
  - Your preferred method may not work for every problem (e.g. SCAD and MCP performed poorly)

- Prediction vs other goals
  - Machine Learning and nonparametric methods perform well, but do not give us easy-to-interpret models.
  - In other settings, we might focus more on variable importance and finding the true model.

- Exploratory data analysis pointed us in the right direction.
  - Summary statistics often do not tell the whole story.
    - Remember Anscombe's Quartet
  - Trust your intuition, but verify.
    - As we might expect, age and income are highly correlated.
    - Safety Rating is related to Past Number of Claims.

## Conclusion - Suggestions

#### Variables which might be useful

- Driver's Criminal History
- Weather on the day of the accident
  - Bad weather might lead to more legitimate accidents
- Time of day of the accident
  - More legitimate accidents may happen during rush hour.
- Whether the accident occurred in the policyholder's home city
  - Perhaps a policyholder is more likely to commit fraud in a situation they can control



# Thank you!

The Magnificent Six