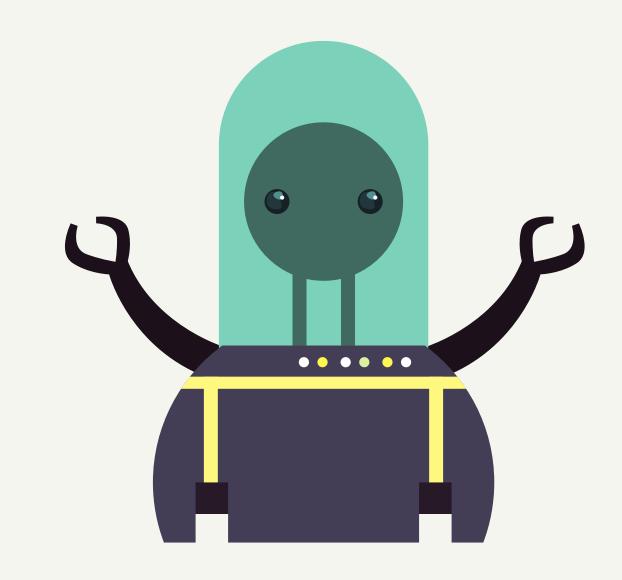
## Auction Fraud Detection

"Human or Robot"

Springboard School of Data

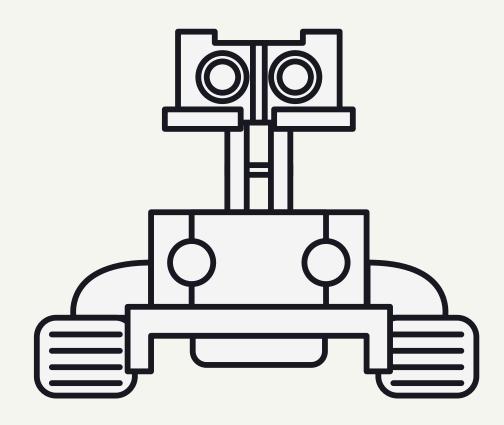
by Gabrielle Wald



## Background

#### Overview of the project

- Auction website
- Frustrated human bidders
- Inability to win auctions vs. their software-controlled accounts
- Customer base is plummeting
- Rebuild customer happiness by eliminating computer generated bidding from their auctions.



## The Problem





 We want to prevent customer churn and improve satisfaction.  We assume the problem can be improved by eliminating robots from the website.

## Goal

Identify users that are "robots", so they can be removed from the auction site.

## Importance

#### customers

• Improve customer satisfaction and experience.



#### website owners

 Decrease customer churn and improves profitability

## Data Source

This project is part of an Engineering competition created by Facebook and Kaggle in 2015.

- 1. The data was retrieved from the Kaggle website in csv format.
- 2. One of the richest data of its kind.
- 3. Great potential for feature engineering.



#### About the Data

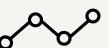
Two datasets:

- bidder (train and test) and bid datasets
  - Over 7 million bids (data points)
    - 1984 unique bidders



#### Challenge

- Obfuscated fields for privacy
  - Unique identifiers



#### Data Wrangling

- Merge on bidder\_id
- Performed EDA to identify patterns and inform feature engineering.



#### Data Cleaning

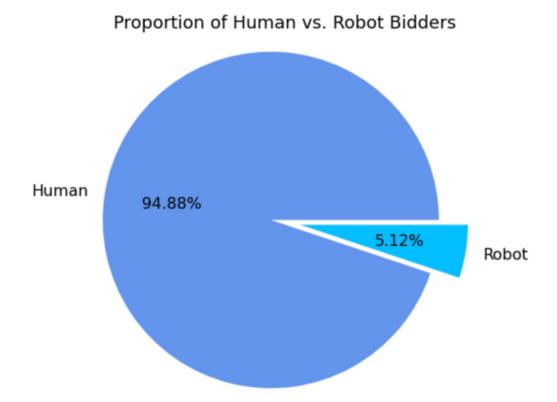
- 29 missing data points were dropped (mapped to human data).

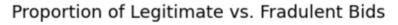
## Exploratory Data Analysis

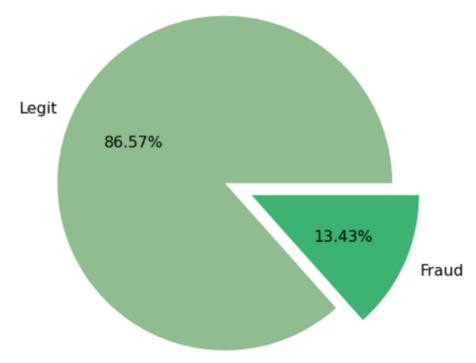
## Initial Assumptions

- 1. Total number of bids
- 2. Number of bids per auction
- 3. Number of distinct IP addresses
- 4. Merchandise category
- 5. Number of devices









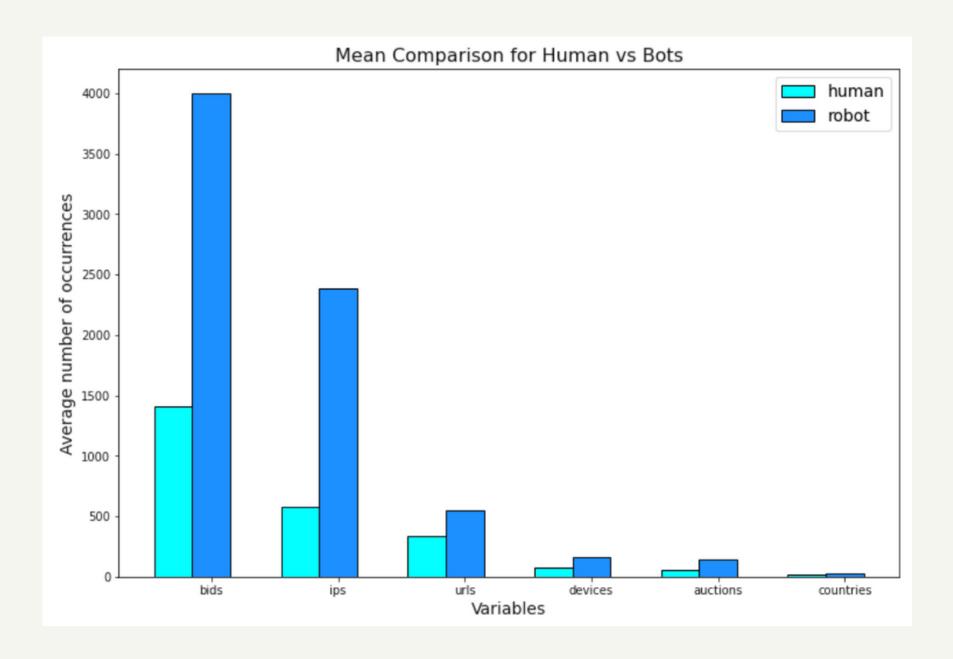
# The data is highly unbalanced at the bidder and bid levels

## EDA FINDINGS

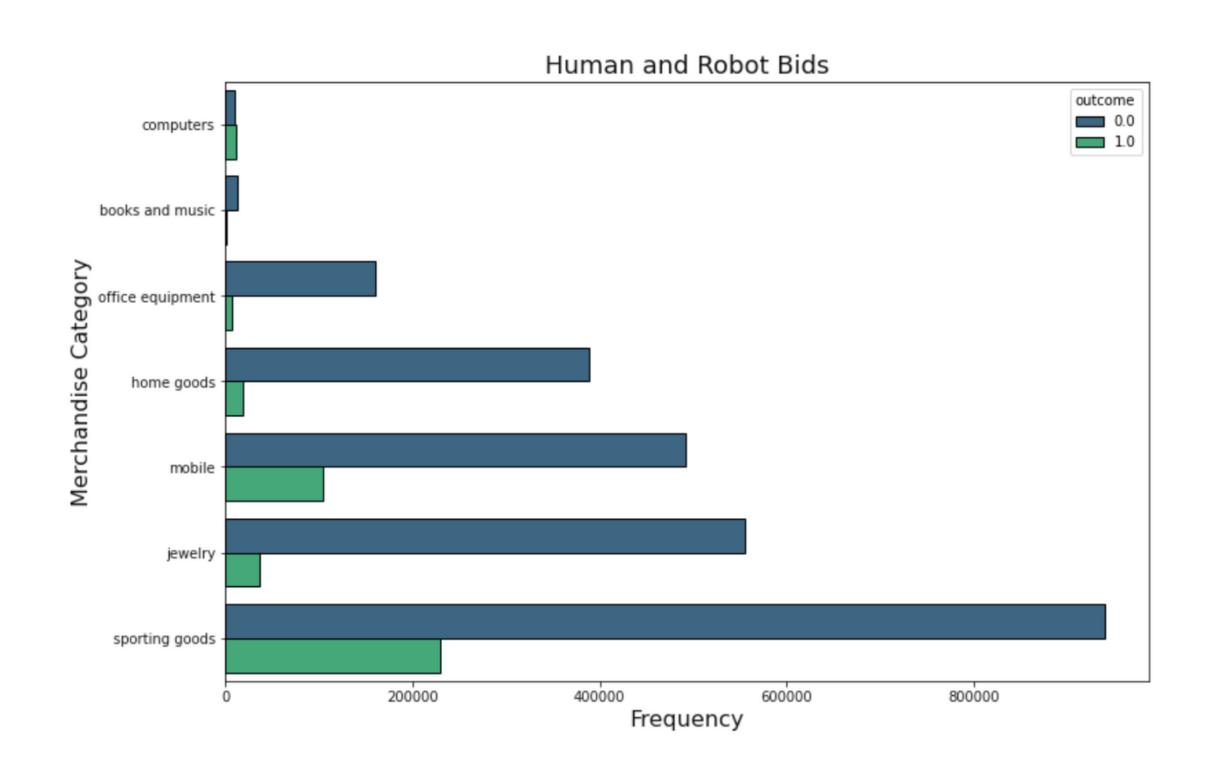
Robots vs.
Humans

#### Initial assumptions held true.

The mean and median number of occurrences between human and robots differ significantly for several variables.



## Merchandise Category Distribution Differs for Humans and Robots

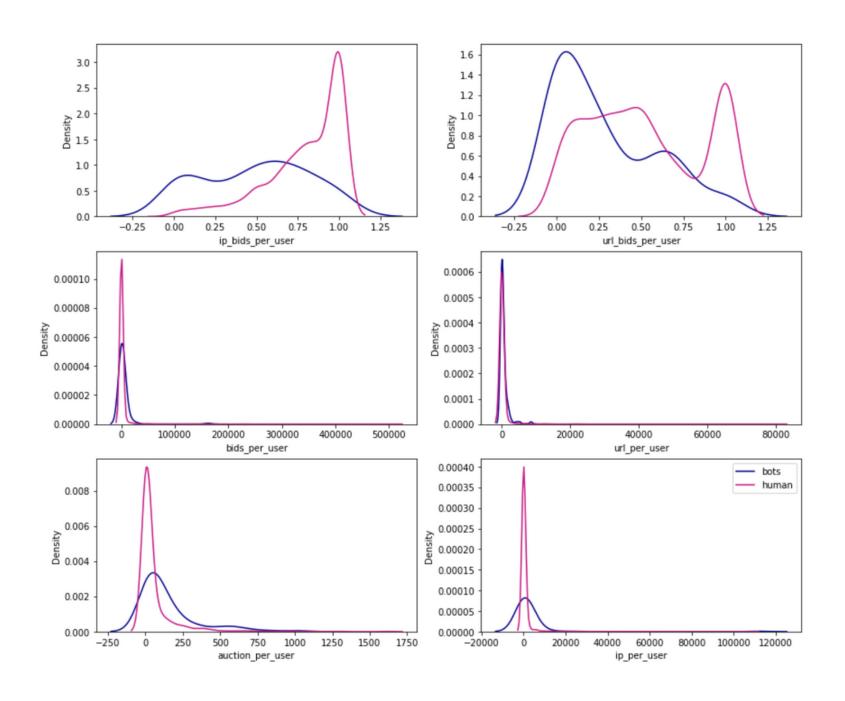


#### 16 Features Created

#### Some of the Features:

- Mean/median number of bids per auction per user
- Number of unique auctions per user
- Proportion of unique ip addresses to bids per user
- Mean number of auctions for each country per user
- Mean/median number of IP addresses per auction per user

#### Features distribution for human vs. bots



## Binary Classification

Predicting a class: "human" or "robot"

#### **Evaluation Metrics**

- Recall
- AUC

#### **Models applied**

- Logistic Regression
- Random Forest Classifier
- Decision Tree Classifier

## Models Summary

Accuracy is 0.94;

• True Negatives: 372

• False Positives: 2

• False Negatives: 22

• True Positives: 1

LOGISTIC REGRESSION

Accuracy is 0.95;

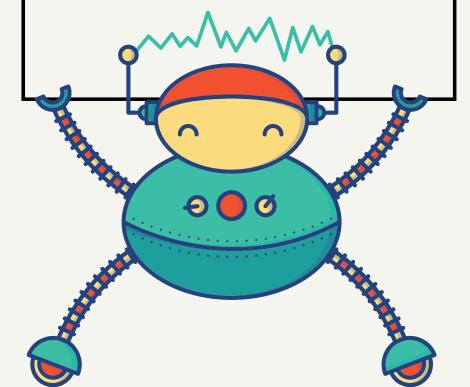
• True Negatives: 374

• False Positives: 0

• False Negatives: 19

• True Positives: 4

RANDOM FOREST CLASSIFIER



Accuracy is 0.94;

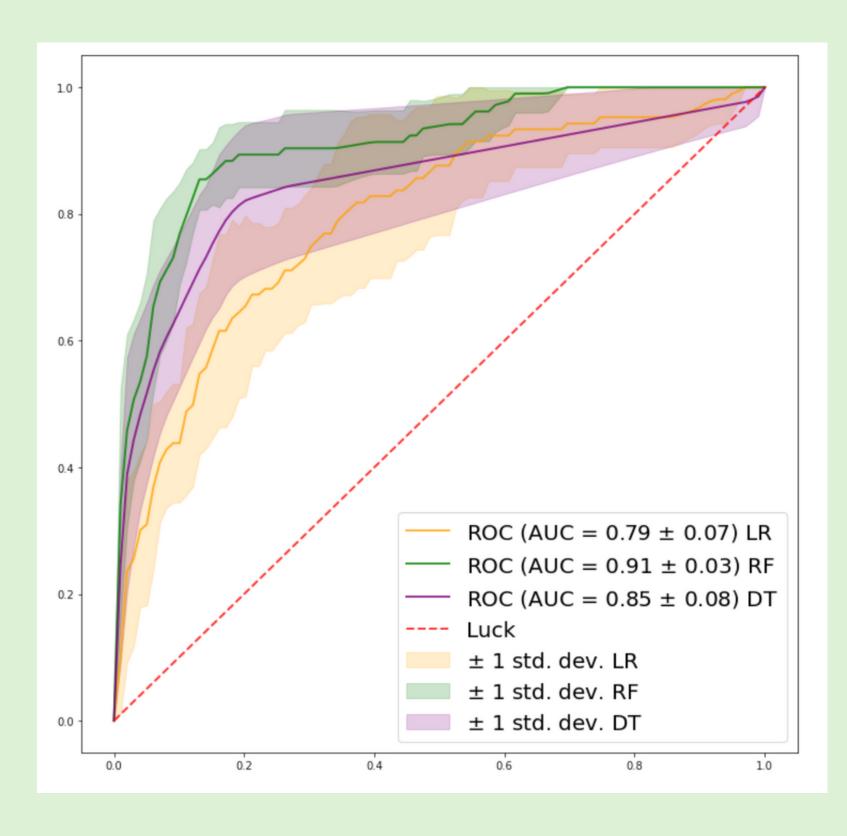
• True Negatives: 366

• False Positives: 8

• False Negatives: 15

• True Positives: 8

DECISION TREE CLASSIFIER

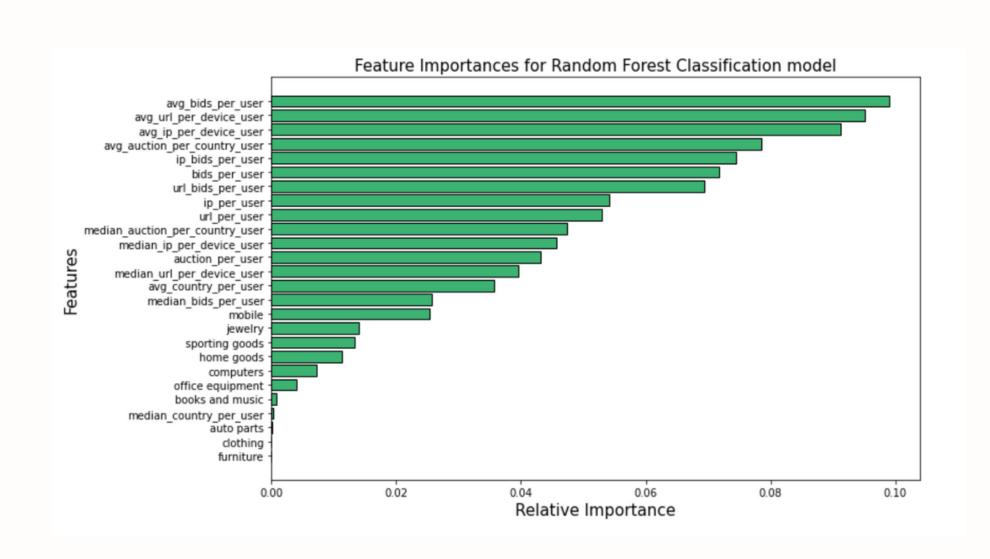


#### Evaluation

ROC - AUC Curve

Random Forest has the highest
 AUC value: 0.91 +/- 0.03

## Features Distinguishing human from robots behavior



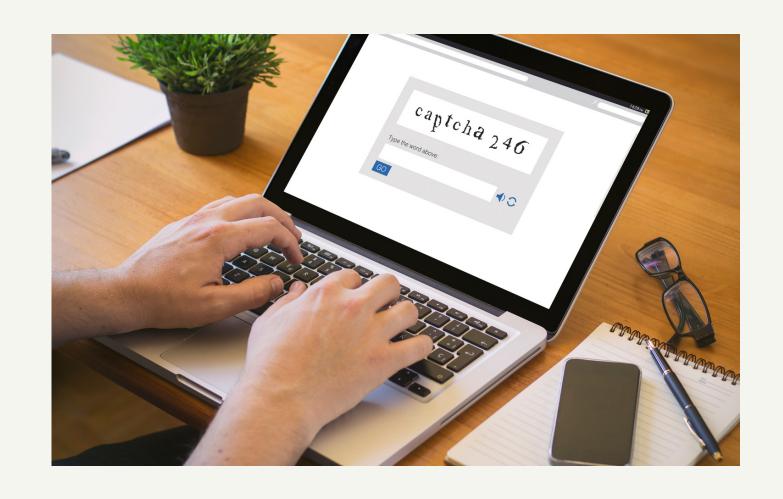
- 1. Average bids per user
- 2. Url per device for each user
- 3. Average ip address per device for each user

#### Misclassification

Type I error - False Positive (Human classified as robot) is better than type II error - False Negative (Robot classified as human).

**Possible Solution** 

CAPTCHA is one approach to manage type I error.





#### Conclusion

- 1. Decision Tree classifier has the highest recall.
- 2. Random Forest classifier has the highest AUC.
- 3. Neither has a high success rate identifying robots.
- 4. Models are not ready to go into production.
- 5. Small sample size (Test set has 397 users, 23 labeled robots).

## Next Steps

- 1. Create new features from the time column like:
  - a. Maximum number of bids made within a 20 minute span;
  - b. Median time between a user's bid and that user's previous bid;
  - c. Number of simultaneous bids
- 2. Try XGBoost, Support Vector Machine and Naive Bayes.
- 3. Require more data.

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# Questions?

Thank you!

