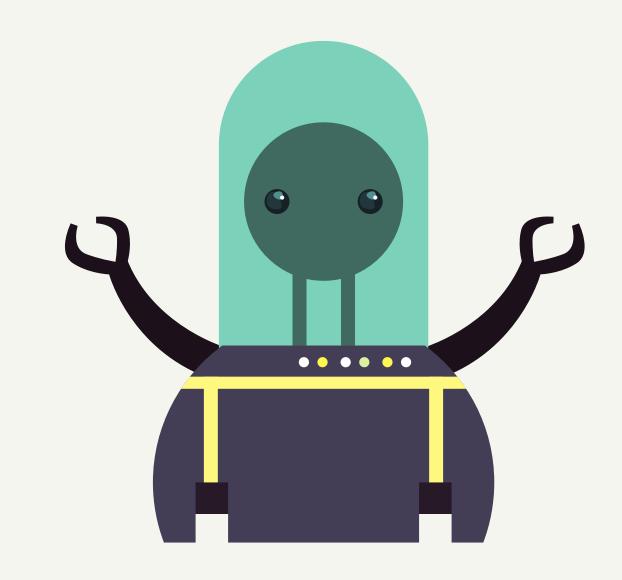
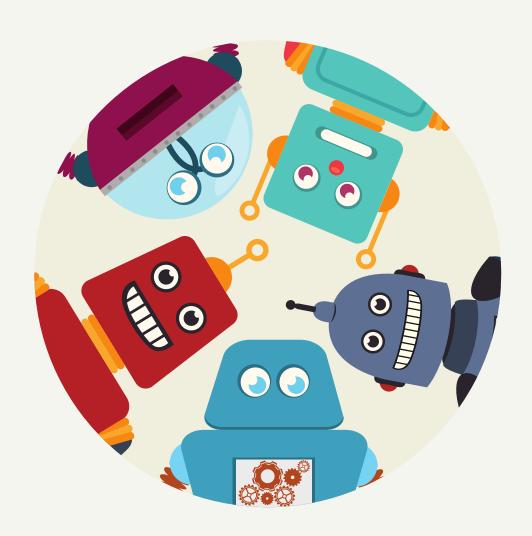
## Auction Fraud Detection

"Human or Robot"

Springboard School of Data

by Gabrielle Wald



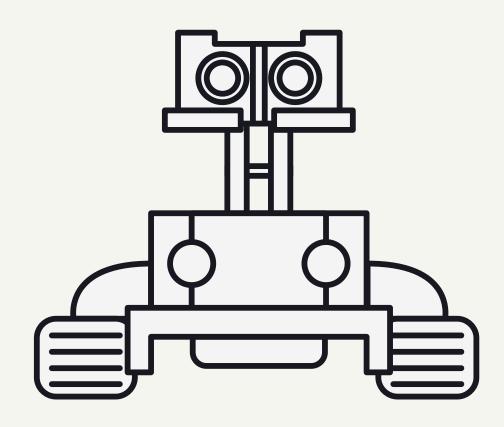


## Introduction

## 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



What we want to solve

 Prevent customer churn and improve satisfaction.



Assumption

 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.

## Significance of the Project

#### For customers

 Customer satisfaction and experience improves.



#### For website owners

- Customer churn decreases.
- Clients stay on website, improves profitability.

## Data Understanding



## 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

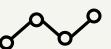
There are two datasets:

- bidder dataset (train and test)
  - bid dataset
- Over 7 million bids (data points)



#### Challenge

- Obfuscated fields for privacy
  - Unique identifiers



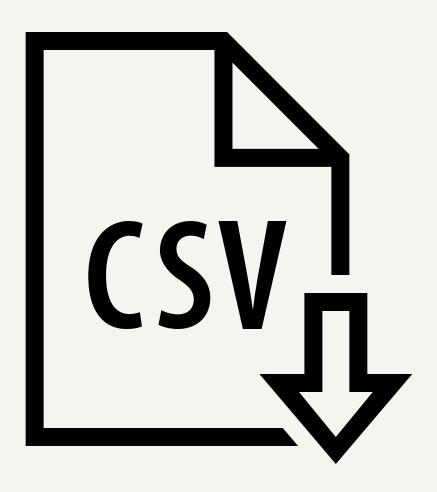
#### Data Wrangling

- Merge on bidder\_id
- Performed EDA to identify patterns and inform feature engineering.
- Dataset prepared for modeling at bidder level (1984 rows)



### Data Cleaning

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



#### DATA FIELDS

#### For bidder dataset:

- bidder\_id
- payment\_account
- address
- outcome

#### For the bid dataset:

- bid\_id
- bidder\_id
- auction
- merchandise
- device
- time
- country
- ip
- url

## Exploratory Data Analysis

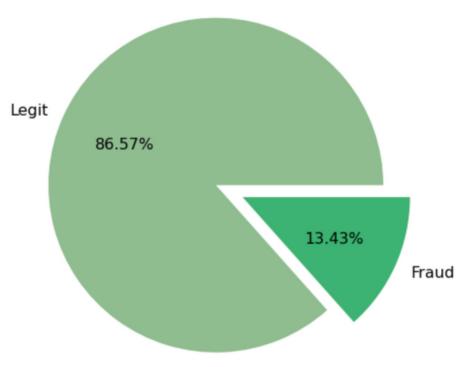
## Initial Assumptions

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



# Human 94.88% Solution of Human vs. Robot Bidders Solution of Human vs. Robot Bidders Froportion of Human vs. Robot Bidders Robot





## First Impressions

- The data is highly unbalanced.
- 12,740 auctions
- 5,729 devices
- 199 countries
- 663,873 unique URLs
- 1,030,950 unique IP addresses

## EDA FINDINGS

Robots vs. Humans

## Initial assumptions held true.

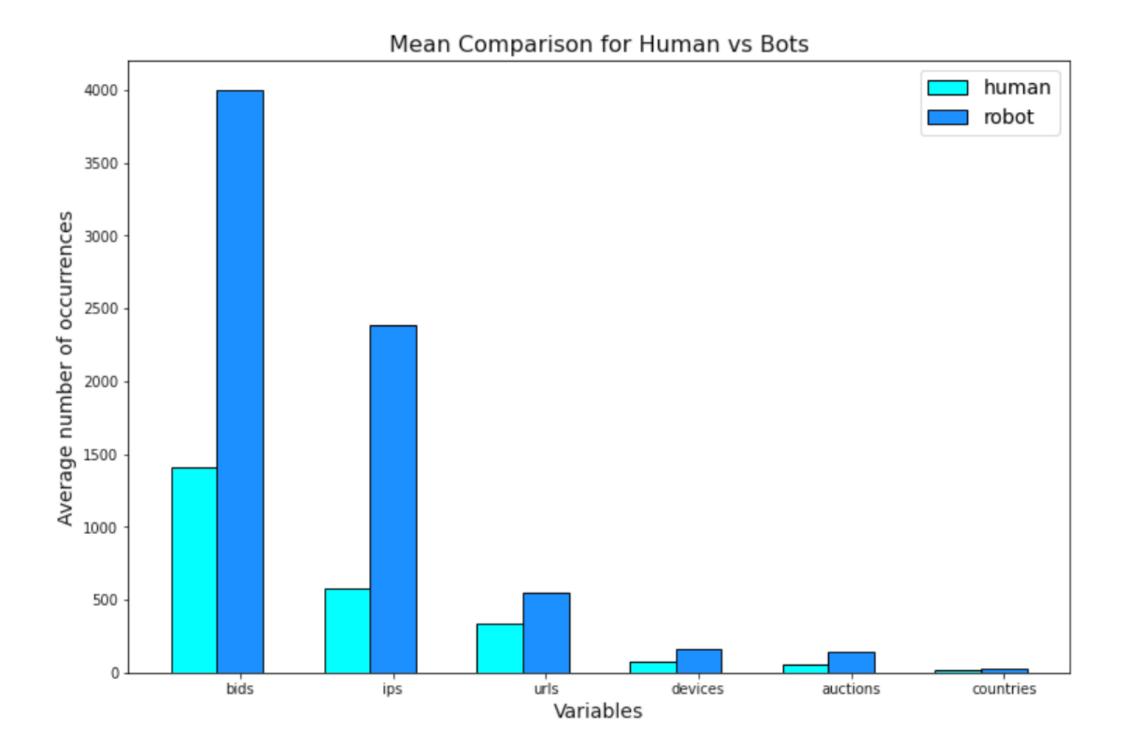
The mean and median number of occurrences between human and robots differ significantly for several variables.

#### Bids

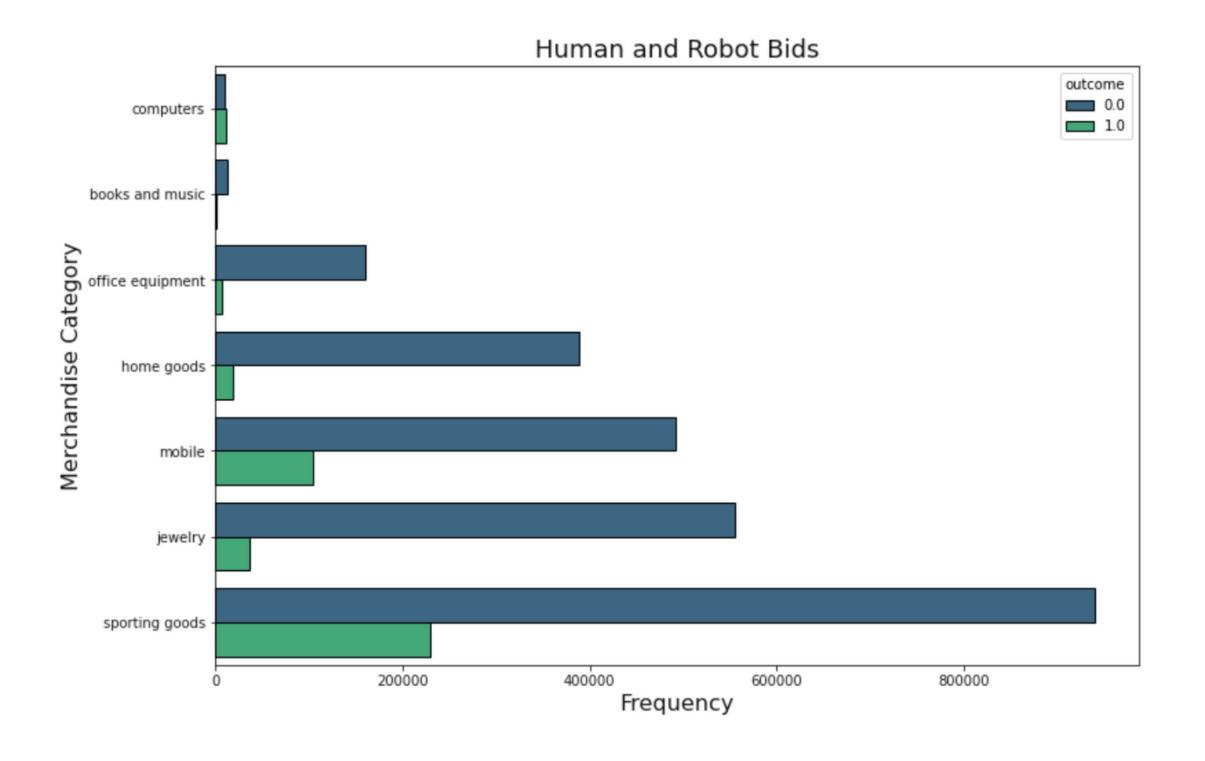
- ROBOT
  - $\circ$  Mean = 4,004, Median = 716.
- HUMAN
  - Mean = 1443, Median = 14

#### IP Addresses

- ROBOT
  - Mean = 2,388, Median = 290.
- HUMAN
  - Mean = 581, Median = 11

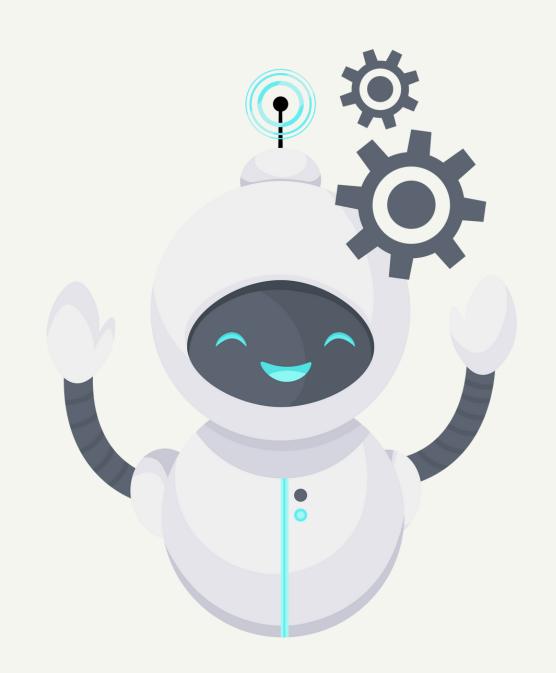


New features will highlight these differences in behaviors.



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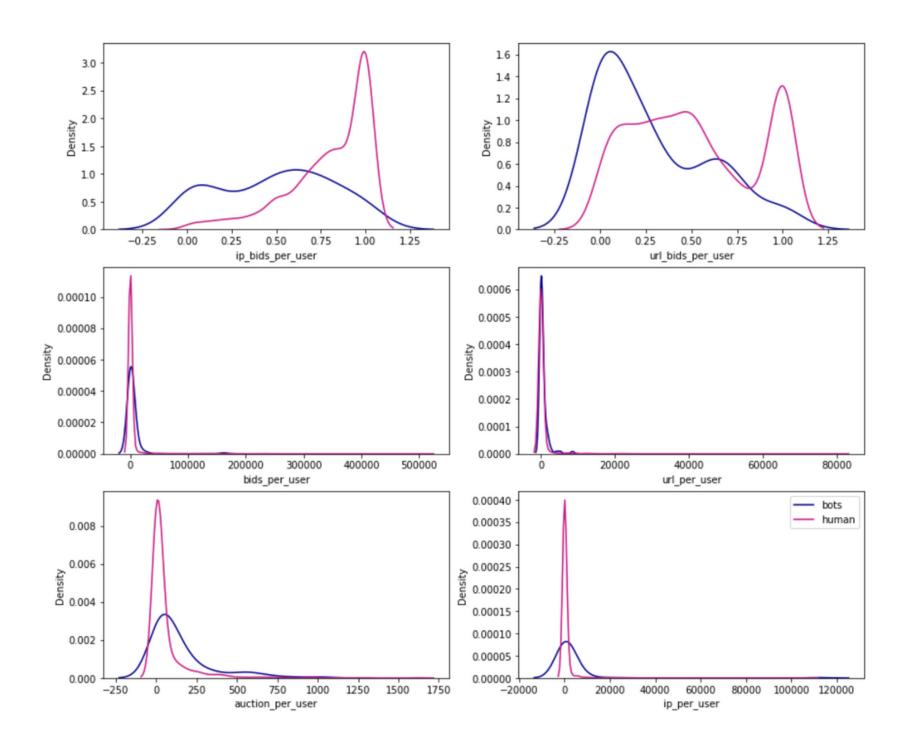
## Feature Engineering



### 16 Features Created

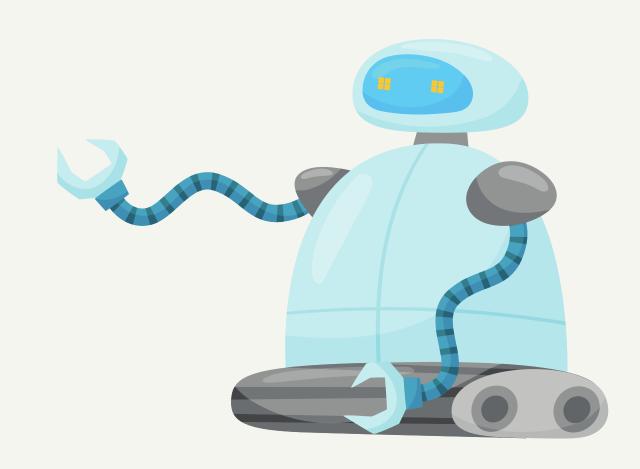
#### Some of the Features:

- 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



## Advanced Analytics & Insights

Machine Learning



## 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;

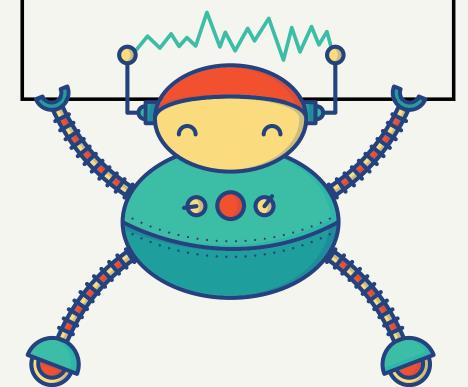
• True Negatives: 374

• False Positives: 0

• False Negatives: 19

• True Positives: 4

RANDOM FOREST CLASSIFIER



Accuracy is 0.94;

• True Negatives: 366

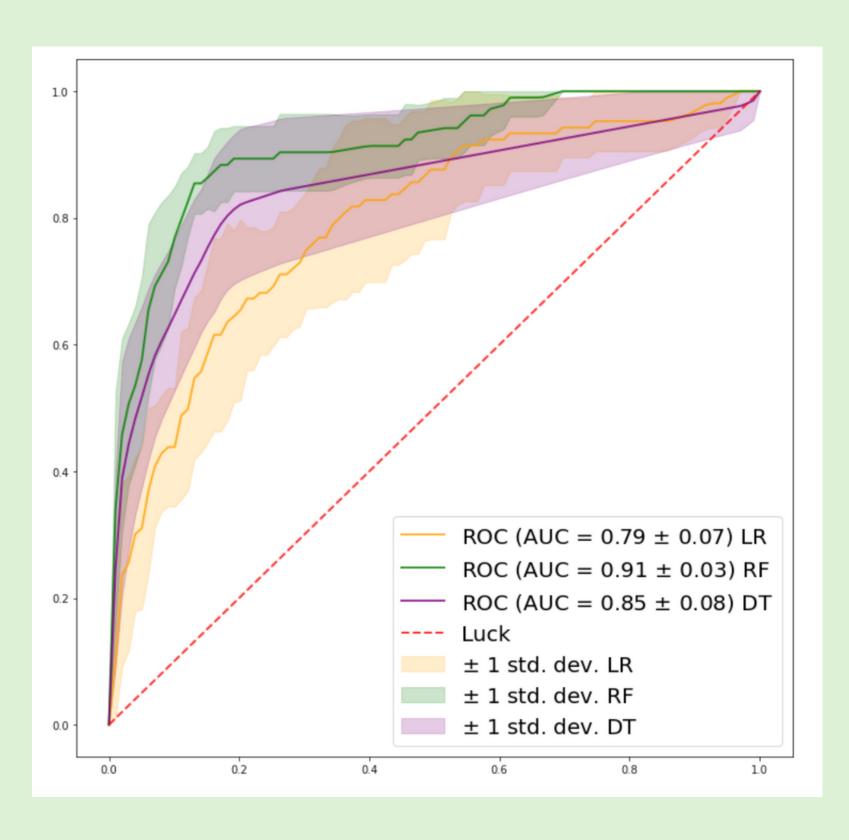
• False Positives: 8

• False Negatives: 15

• True Positives: 8

DECISION TREE

CLASSIFIER



## Evaluation

ROC - AUC Curve

 Random Forest has the highest AUC value:

0.91 +/- 0.03

## Misclassification

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

## **Possible Solution**

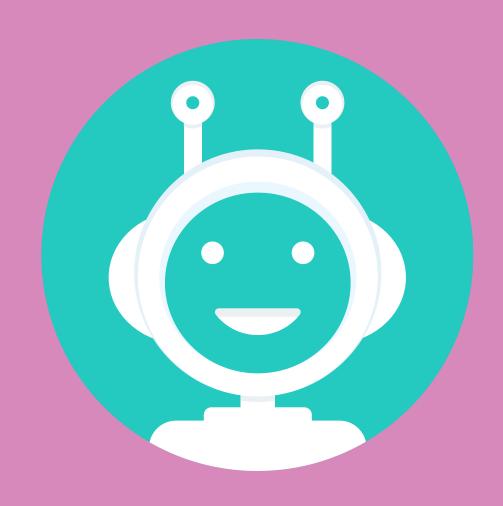
CAPTCHA is one approach to manage with type I error.



## Conclusion &

Suggestions for future improvement





## 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!

