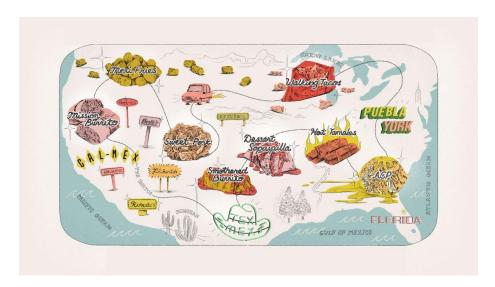
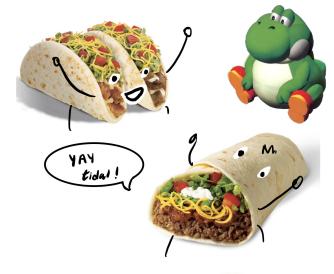


Goldman Sachs: Problem



Design a product to visualize various data on restaurants that sell tacos and burritos in order to understand trends across the united states

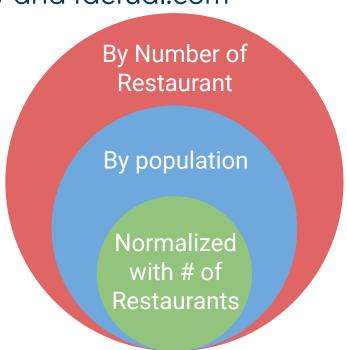




Goldman Sachs: Approach



- 1. Clean up the data
- 2. Acquire additional data via census.gov and factual.com
 - a. Population of People per state
 - b. Ratio of people to restaurants
 - c. Ratio of taco and burrito-serving restaurants to all restaurants in a state
- 3. Create a visual to help compare properties and correlations



Goldman Sachs: Results



Created a python interactive interface with various filtration.



By Number of Restaurant By population Normalized with # of Restaurants

Goldman Sachs: Conclusion



Based on our findings, we now know that:

- California and Texas have highest count of places that sell tacos or burritos
- Alaska has the most places that sell tacos or burritos per person
- The southwestern region has the highest percentage of restaurants that serve tacos and burritos!

If we had more time, we would have:

- Gathered more census data to see where the restaurants are in relation to income, household number, etc.
- Create a GUI to identify a taco or burrito restaurant to go to based on their own personal preferences by answering questions

ConocoPhillips: Problem



Be able to predict when equipment will fail with the data from 107 sensors (very important for run time)

```
1000 Failures

If you will still achieve

59,000 Non-failures
high accuracy score!!!

59,000/60,000=.98333
```

ConocoPhillips: Approach



- 1. Clean up the data
- 2. Identify any correlation in the feature set and visualize (**PCA**, t-SNE, Pearson Correlation)
- 3. Build classifiers (tree based, gaussian, linear)
- 4. Identify important features (**feature importance**, feature extraction and/or engineering)
- 5. Predict on the test set (**weighted model averages**, soft or hard voting, BMA)



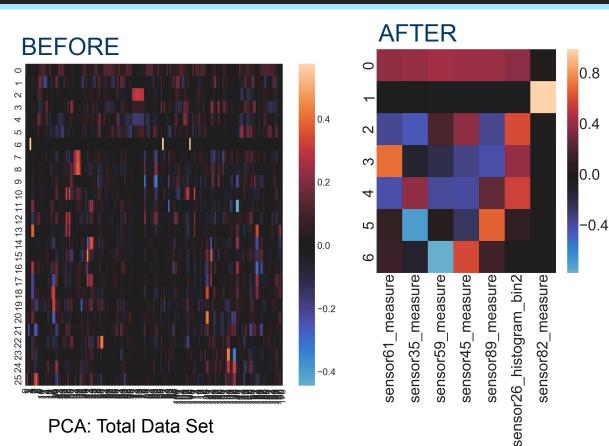


PCA Before Feature Importance



Why PCA?

Good to use over t-SNE and Correlation methods in data that is incomplete or has missing data.



PCA: FI Average

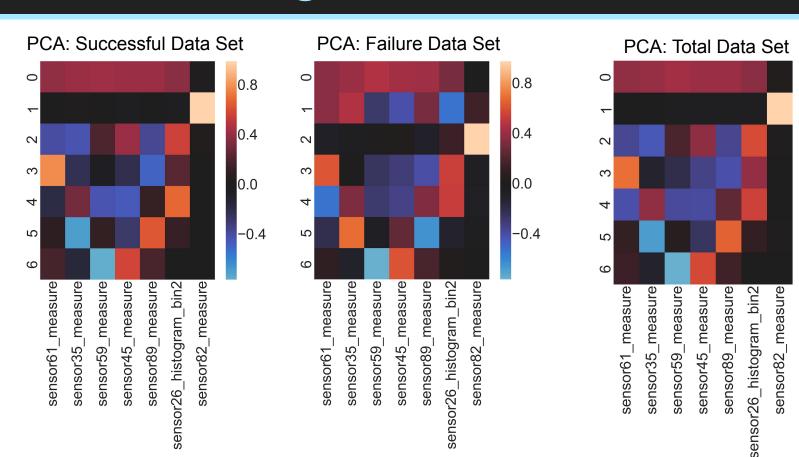


0.8

0.4

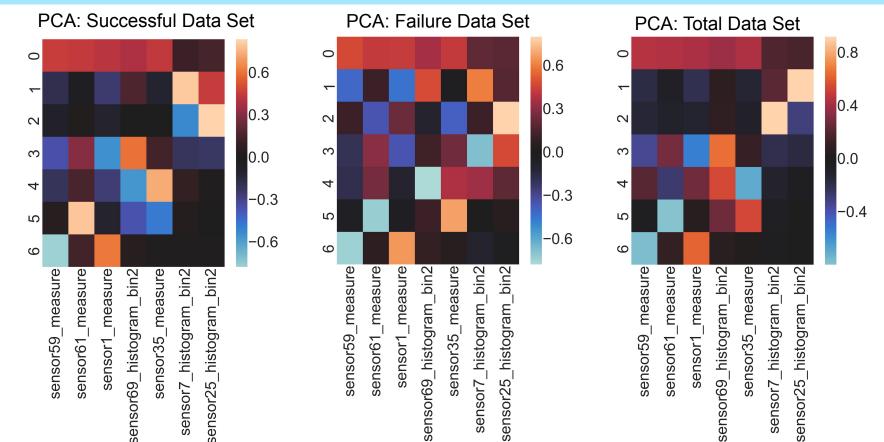
0.0

-0.4



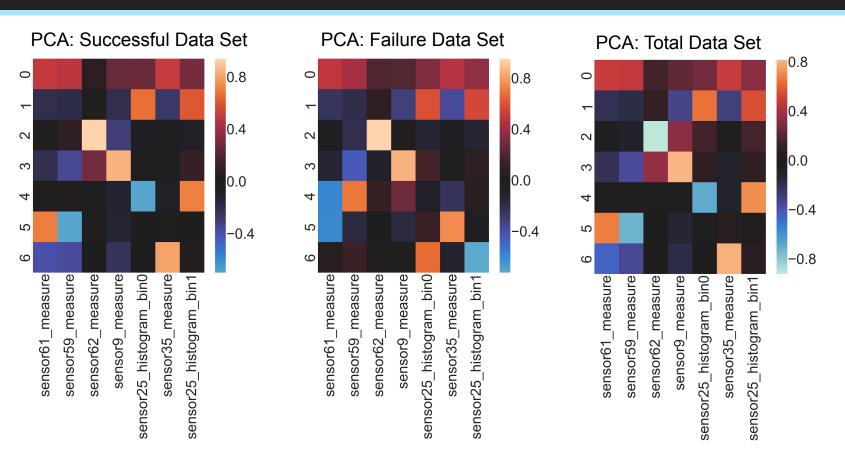
PCA: FI XGboost





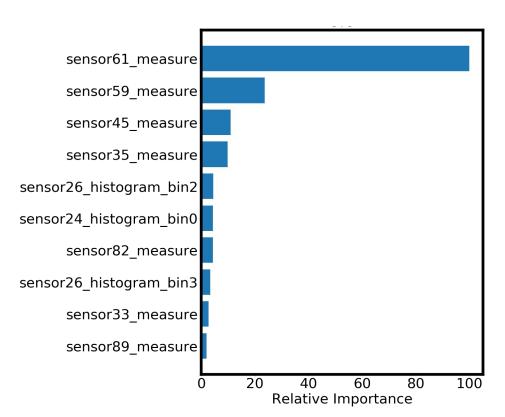
PCA: FI Gradient Boosting





Classification in High Dimension





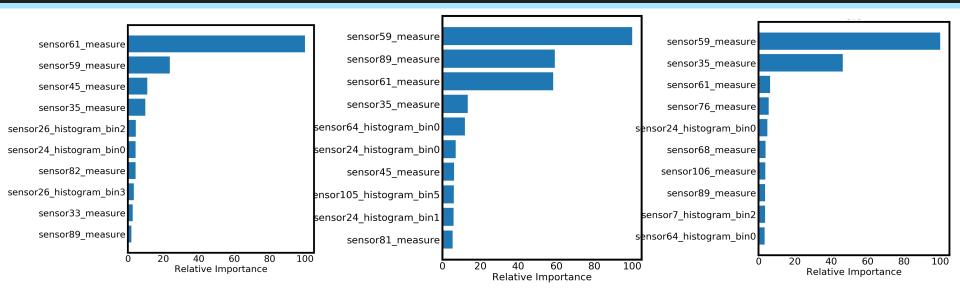
Why Tree Based?

Tree based algorithms handle higher dimensional and sparse data better than most classifiers like Gaussian, naive, linear, etc

In anomaly detection, tree based classifiers, when tuned correctly, can detect anomaly with good accuracy. Especially tree based algorithms with a built in cost function like gradient boosting

Random Seed: Feature Importance



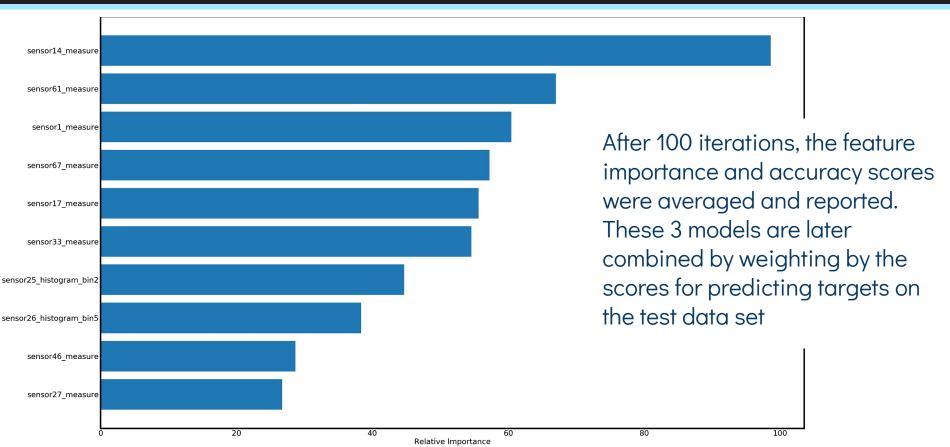


The data is randomly undersampled, so 1000 data points for target=0 and another 1000 data points for target=1 are used in a classifier.

With each random seed, the important features change.

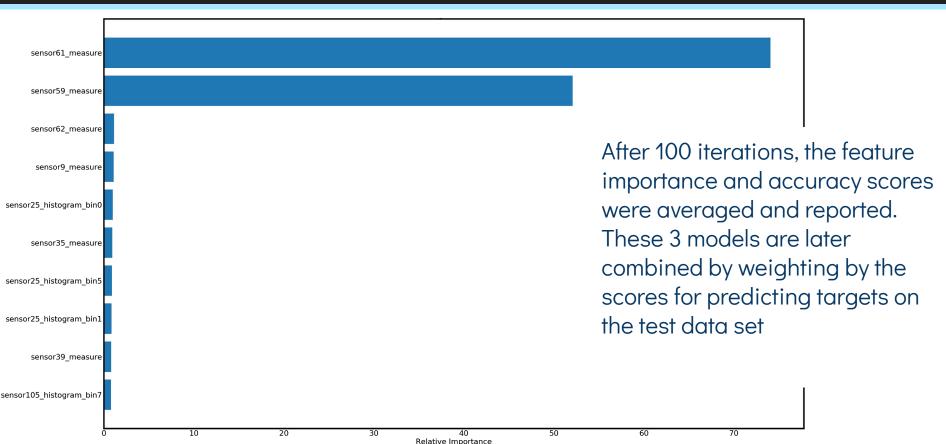
Feature Importance: Random Forest (t)





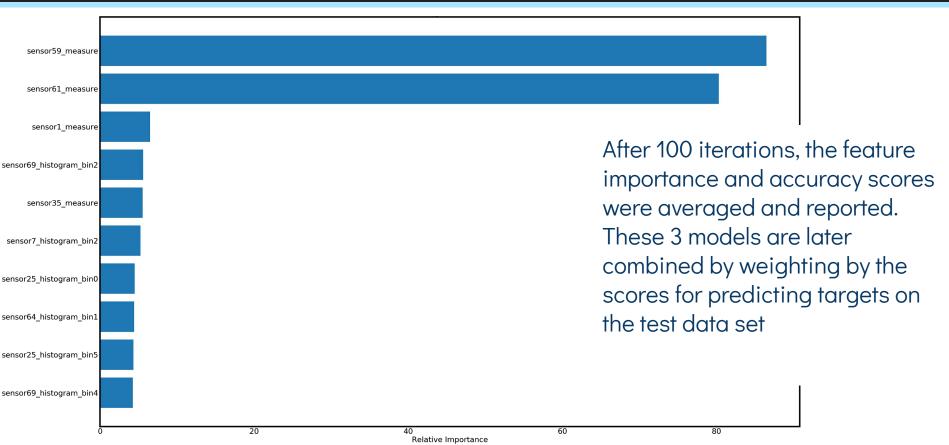
Feature Importance: GBoosting





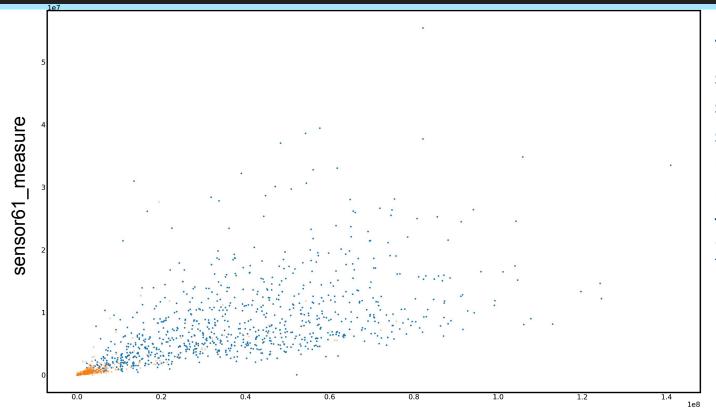
Feature Importance: XGboosting





Visualizing Two Naughty Features





The scatter plot shows the data does seem to be somewhat separable by the two most important features from GBoost and XGBoost classifiers.

ConocoPhillips: Conclusion



Using PCA and feature importance, relative features to detecting the target were identified.

By random undersampling, the classifiers were fit and weighted based on **accuracy scores**. The voting classifier doesn't give us full control over the weighting and BMA is unnecessary for models so similar, especially considering tree based classifiers aren't based on a normal distribution.