Team 10 - Spam Call Detection and Analysis

Problem

What Are The Problems?

- Assuming we know that incoming call is spam, how do we determine the type of spam call?
- How can we forecast when the next spam call will be made provided previous complaint data?
- Are there higher geographical concentrations of received and made spam calls in the US?
- How can we develop an interactive visual interface to showcase spam call data?

Why Is It Important And Why Should We Care?

- Research studies have show that spam calls have the following drastic effects:
  - Contribute to fraud and the swaying of public opinions in political elections
  - Cause millions in financial losses every year

Our Approaches

What Are Our Approaches?

- *Model Development:*
  - **Spam Call Classifier:** predicts probabilities of each type of spam call using date and time of issue, and area code of the caller and recipient.
  - **Forecasting Future Spam Calls:** estimates potential next call by predicting date range using area code of the caller and recipient, and type and method of spam call.
- *Visualization:*
  - **Prediction module:** provides users functionality to add call details to generate visualizations showing percentage distributions of the likelihood of each type of spam call.
  - **Exploration module:** generates geographical visualization of spam call frequency aggregated by area code and filtered by types of spam call.

How Do They Work?

- *Spam Call Classifier:*
  - **Data Preprocessing** - Convert date and location into easily usable values
  - **One Hot Encoding** - Transform categorical data (phone numbers, area codes, spam call types, etc.) into features usable for a predictive model
  - **Random Forest Classifier** - Build classifier based on transformed data to perform the predictions
- *Forecasting Future Spam Calls:*
  - **Categorical Binning** - Translates issue dates into categories representing date intervals
  - **One Hot Encoding** - Transforms categorical features into boolean measures
  - **TruncatedSVD** - Dimensionality reduction of feature space
  - **Random Forest Classification** - Predict transformed categories by majority vote
- *Visualization Application Technologies:*
  - **Flask** - Web Framework in Python for simplifying development of API and web application
  - **D3.js / Bootstrap** - Javascript libraries for data visualizations and web components
  - **Lime** - Python library using linear models to offer explanations for predictions
- *Web App Backend Approach:*
  - All data provided is converted into **JSON** format and is fed into d3.js to produce the visualizations

Why Can We Solve The Problem?

- We are provided in-depth information about each spam call reported to the FCC.
- We can use this knowledge to study common trends of spam call perpetrators.
- Provides us ability to construct preventive measures against spam calls

What Is New In Our Approach?

- Most approaches to combat against spam calls are reactive. Previously proposed solutions include:
  - Whitelisting and blacklisting phone numbers
  - Reporting and blocking spam calls
- We propose a **proactive** solution by informing users of the predicted call type.
- This motivates us to develop model that **predicts defining characteristics** of calls based on previous reports.

Data

How Did We Get Our Data?

- Our data is found in the FCC Open Data repository made publicly available here: https://opendata.fcc.gov/Consumer/CGB-Consumer-Complaints-Data/3xyp-aqkj

What Are Characteristics Of Our Data?

- *Characteristics of dataset:*
  - Time of issue
  - Spam call type and method
  - Caller phone number
  - Recipient location
- *Preprocessing required:*
  - Convert time to ISO format
  - Recipient location -> area code
  - Imputation of missing values, dropping of invalid rows
- Dataset ~ **300MB** post-processing

Experiment

How Did We Evaluate Our Results?

- *For both predictive models:*
  - Created test and training sets assuming 20-80 split to measure model performance
  - For classifier, evaluated the mean confidence of our class predictions to determine how confident model is in distinguishing between classes
- *For prediction module:*
  - Qualitatively evaluated that interface and visuals are intuitive and easy to understand
  - Ensured that API response time was optimized to avoid negative user experience
- *For exploration module:*
  - Qualitatively evaluated the interface and visuals are intuitive and easy to understand
  - Ensured that number of spam calls was roughly proportional to population distribution as a sanity check

What Are Our Results?

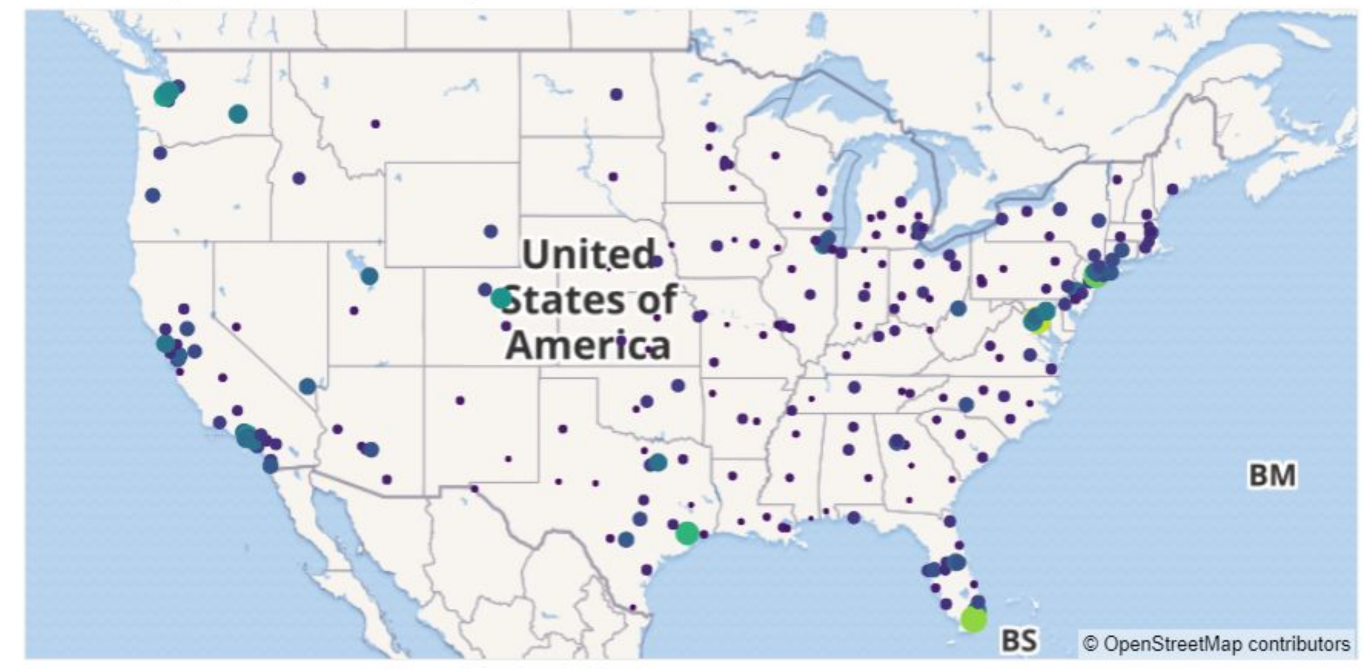
- *For predictive models:*
  - *Classifier Performance:* Test set accuracy of **~ 70%**
    - ~ 70% of predictions have confidence > 60%
  - *Forecast Model Performance:* Test set accuracy of **~ 50%**
    - Assumes length of intervals = ~ 1 year
- *For prediction module:*
  - Interface intuitive and simple for predicting type of spam call and why
  - Average API response times **< 20s** on tested configurations which is sufficient for demo purposes
- *For exploration module:*
  - States in Northeastern US region and other states including Texas, Florida, and California have largest proportion of spam calls and also have the largest populations, validating the visualization
  - States in US Midwestern region has smallest proportion with respect to population distribution
  - Interface allows users to easily explore spam calls by type and geography across US with configuration for region size and colour intensity

How Do Our Methods Compare To Other Methods?

- To directly compare the performance of our method against others, we would need to implement it in a real-time system
- Our method does have some inherent advantages over others:
  - Only uses information known at time-of-call
  - Should be straightforward to extend methodology to regions outside of US, given data
  - Offers both a determination of type of spam call and an explanation why, which is not done by other methods
  - Visual explanation of predictions reduces blackbox effect of models and can be extended to other applications outside of spam call detection

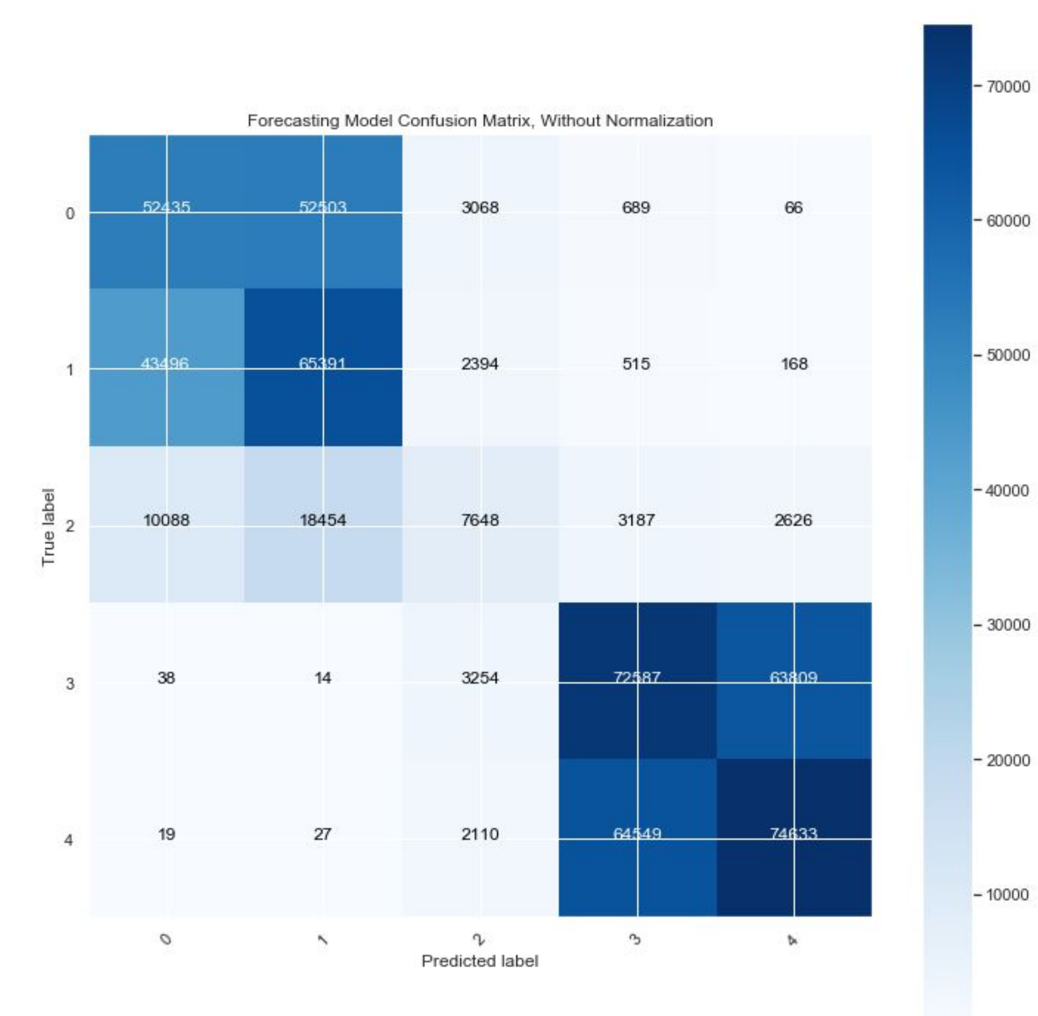
Source Locations of Spam Calls by Frequency Aggregated By Area Code

Map Template Source: Wikipedia

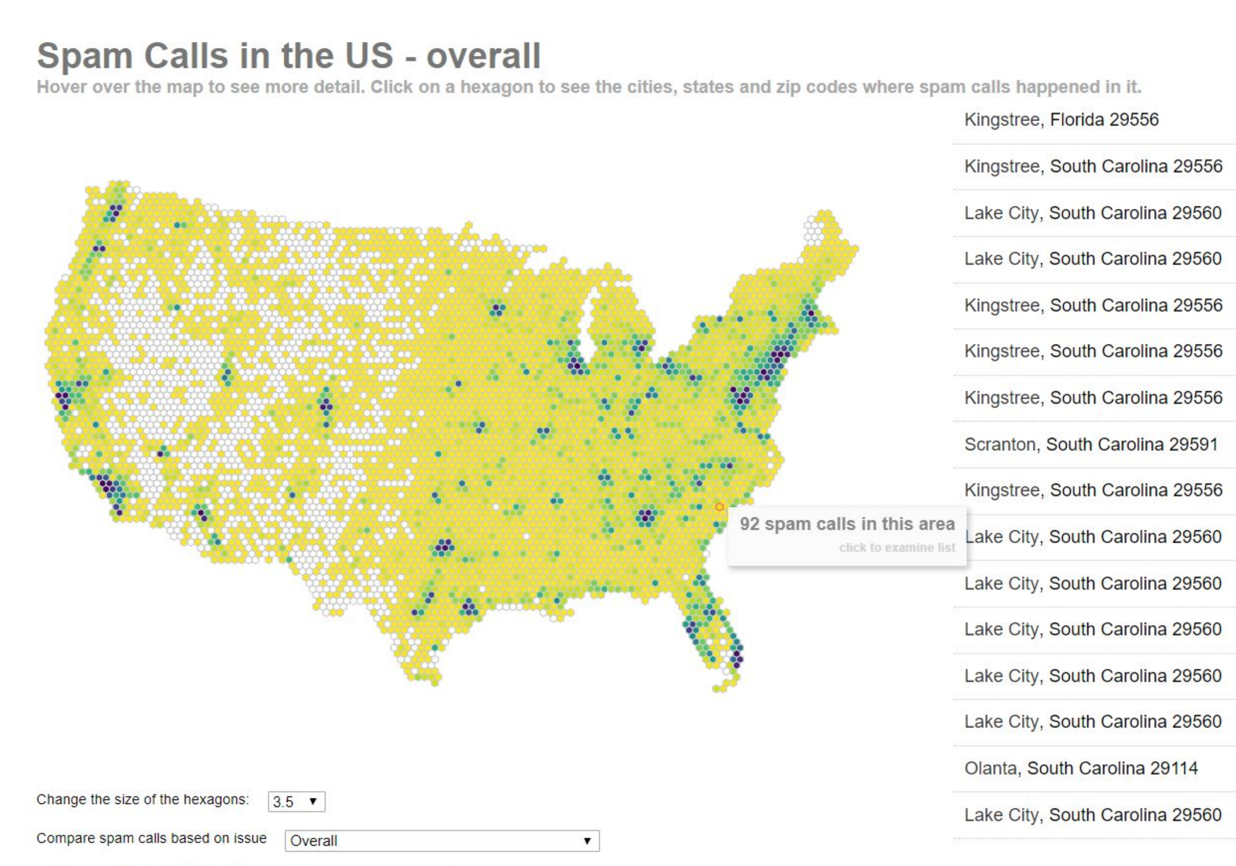


Confusion Matrix of Forecast Predictive Model

(Categories represent ~1 year time intervals from min date to max date of data)



Exploration Module of Web Application



Prediction Module of Web Application