Coursera - IBM Data Science Capstone Project

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Github code: https://github.com/Brian-Lee/Coursera_Capstone/blob/master/brians_capstone_project.ipynb

1. Introduction

If I were to open a Starbucks, where should I locate it? Clearly, the location is one of the most important business decisions for this venture. Is there a science to locating a Starbucks? Can we create a machine learning model to predict where a Starbucks is likely to be located? I'd like to find out.

If a reliable model can be made, it could be used in the process of opening a store. It could be used as a final sanity check, or at the beginning stage, to select a promising location. If a trustworthy model predicts with a high degree of confidence that a Starbucks should be located in an area, but there is not one there yet, perhaps that is an opportunity.

Any person interested in opening a Starbucks should be interested in these results. This includes me, other potential franchisees, and the Starbucks corporation itself, which operates many of its own stores. Starbucks competitors might also be interested as they could possibly gain competitive insights. I also believe others might be interested in this procedure, as it might be applied to predicting the location of other entities, based on the same sort of data.

The main purpose of this project is to prove the concept of predicting Starbucks locations in general. I suspect it may work better or worse depending on the locations chosen for training and prediction, the radius size, and the specific features used in the model.

2. Data

Foursquare (https://foursquare.com) is a company that crowdsources location data, tying latitude-longitude coordinates (and other things) with public venues, including many businesses, such as Starbucks locations. After generating a corpus of geographic coordinates, the features for the Starbucks location classifier will come from JSON venue data returned by the Fourquare API ‘explore’ endpoint. I will use venue category names (such as 'bar', 'Chinese restaurant', 'coffee shop') as features to classify an area as either an area with a Starbucks, or an area without one. I will use the venue name (e.g. 'Starbucks') to determine whether the venue is a Starbucks. An area containing a Starbucks contains at least one venue named 'Starbucks' (case insensitive) within the radius supplied to the Foursquare API's explore' endpoint.

Once I have labelled data, I will use sklearn.model_selection.train_test_split to generate training and testing sets. I will also generate a separate validation set. Then I will use Python scikit-learn classifiers to generate predictive models.

An area will be a circular area with a given radius. I used a radius of 300m for this project. Within that radius, the Foursquare API will return venues. The larger the radius, the more venues that could be anticipated, and the higher likelihood of a Starbucks, but a larger radius is also less useful for business use.

The quality of the Foursquare venue data is good, but not perfect. I noticed venues returned as "SUBWAY" separately from other venues returned as "Subway." I cleaned venue category names received by the API by altering the case. I also noticed that the crowdsourced latitude-longitude coordinates for Starbucks locations often include duplicative results, slightly offset. For instance, there could be a cluster of tightly packed coordinates returned as Starbucks locations, giving the impression of many Starbucks next to each other. I suspect this reflects different geographic coordinates representing a single Starbucks venue. Additionally, there are areas (for instance in my validation area in Illinois) where no venues are reported within the radius. In some cases, it can be seen that some venues (such as churches) are in fact located nearby.

The areas chosen for training/testing and validation data contain a mix of areas with Starbucks and those without. I selected a geographic rectangle in San Francisco for training/testing. With a reasonably small radius, most points will have true labels of 0 (or not near a Starbucks). In order to balance the classes for better binary classification performance, I added a large number of additional geographic points to the training set. These additional coordinates come from the Kaggle dataset (https://www.kaggle.com/starbucks/store-locations) containing the latitude and longitude coordinates of 25,600 worldwide Starbucks locations. The idea was that these added points should have true labels of 1 (near a Starbucks), and most do. However, I discovered that they do not all. To that end, the best balancing would be a ratio of about 2:1. The fact that these added points don't all appear to have labels of 1 is distressing. Perhaps that is a sign that something is wrong, or perhaps it is due to different data sources not agreeing on exactly where a current Starbucks venue is located. In any event, my training data is comprised of a grid of points inside a rectangle in San Francisco, combined with double that number of points located throughout California.

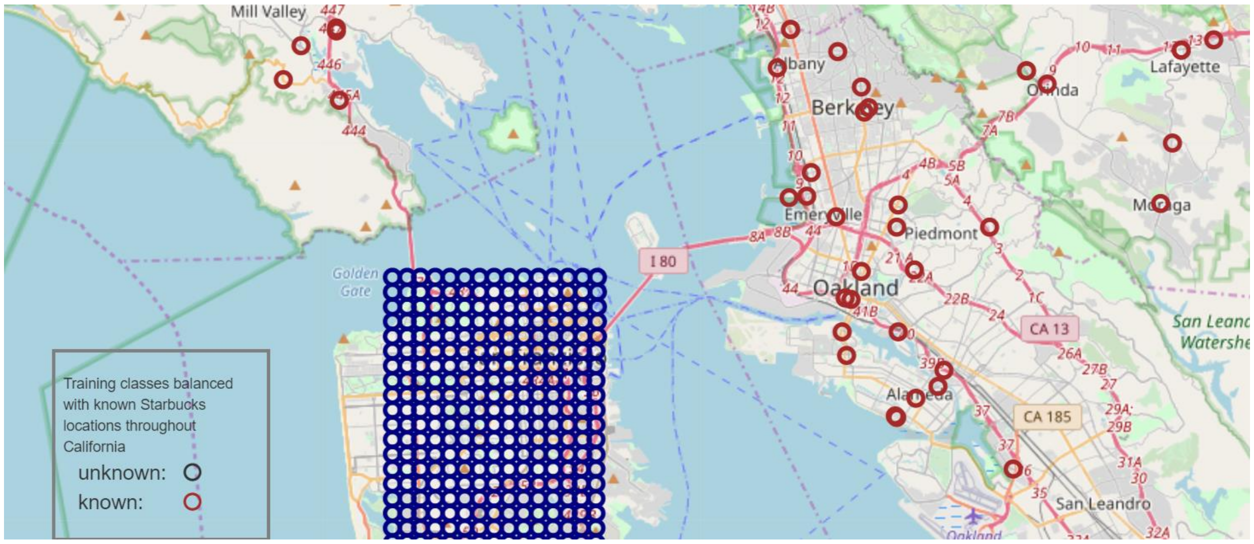


Figure 1: Zoomed map showing some of the training/testing data points, with navy circles representing grid coverage coordinates, and brown circles representing coordinates intended to balance the resulting classes.

The foursquare API returns the names of venues as well as the names of the categories of the venues. Here is an example of the resulting pandas DataFrame:

```
venues.tail()
```

	Point Name	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Distance	Venue Category
31714	point01754	37.668025	-122.468802	Sleep number	37.668014	-122.468470	29	Mattress Store
31715	point01754	37.668025	-122.468802	Wells fargo atm drive-thru	37.669537	-122.469406	176	ATM
31716	point01754	37.668025	-122.468802	Bobaville	37.667318	-122.468920	79	Bubble Tea Shop
31717	point01754	37.668025	-122.468802	Shoe palace	37.669360	-122.467000	217	Shoe Store
31718	point01754	37.668025	-122.468802	Fitness usa - daly city	37.665693	-122.469456	265	Gym

```
venues['Venue Category'].value_counts()
```

```
Coffee Shop                     1620
Pizza Place                     1028
Mexican Restaurant              1019
Sandwich Place                  1013
```

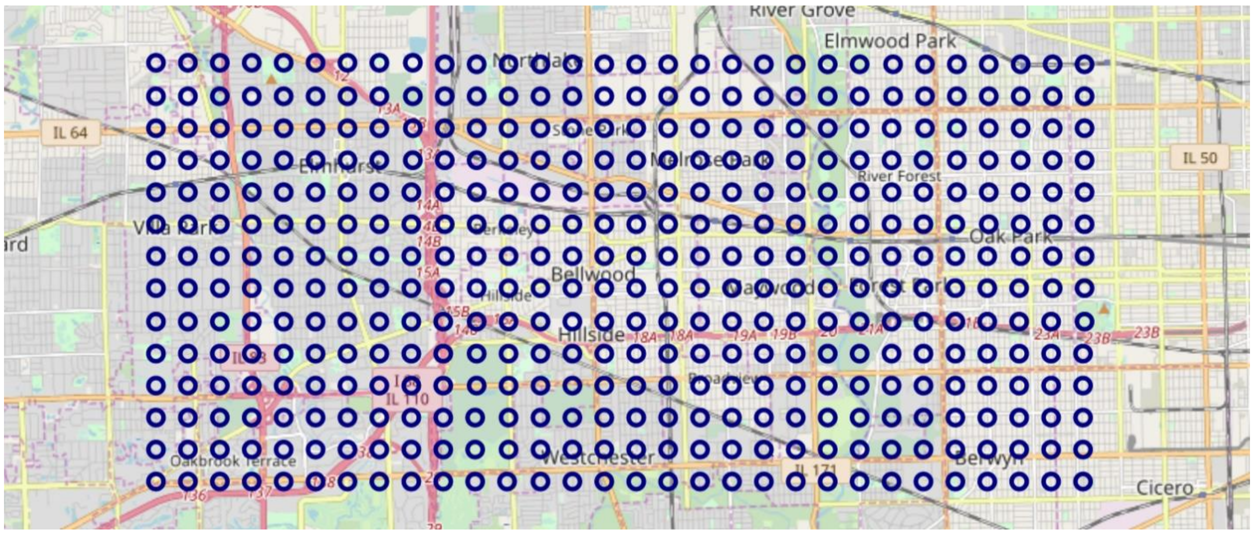
In order to keep my feature-space down, I used the category names, but not the venue names. The category names were one-hot encoded and normalized. Multiple rows for a given coordinate set were combined, resulting in a feature DataFrame such as the following:

```
X.tail()
```

	ATM	Acai House	Accessories Store	Acupuncturist	Adult Boutique	Afghan Restaurant	African Restaurant	Airport	Airport Lounge	Airport Service	...	Zoo	Zoo Exhibit	no venue	number_of_venu
1749	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
1750	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
1751	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
1752	0.125000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	
1753	0.033333	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	

5 rows × 526 columns

I wanted to validate the results on a separate geographic area, with a naturally occurring distribution of classes. I chose a rectangular area in Illinois, near Chicago, with a decent number of Starbucks locations according to Google Maps.



3. Methodology

I ran some Random Forests and Support Vector Machines on the full set of features, initially getting training set accuracies as high as 1, and test-set accuracies as high as 96% or so. Ultimately, I decided that I should remove the venue entries that represent actual Starbucks locations, even though they were deidentified, with only the venue category name ("coffee shop") in the training data. When I removed those data rows, my performance dropped a fair bit, but I believe these results are more transferrable to a real-world situation.

When I got the venue category names (used to create one-hot features) for the validation set, I discovered that I had a slightly different set of features. There were a few (3) venue category types that did not occur in my training/testing set, and a few dozen (~30) that occurred in the validation data that did not occur in the training/testing data. I could have retrained my model with a superset of features that would satisfy both regimes, but I chose instead to reformat my validation features to fit my trained model. I added three dummy columns to the validation data, and threw out 30 columns, resulting in a feature set of 452. I felt this approach was a good approach to test the generalizability and durability of the trained model. Ultimately, I increased the size of the training area, resulting in over 500 features. I also added a few engineered features, which tend to rise to the top of the feature importances. Some of the important engineered features are sums of other features, for instance, "rssj", which increments for each feature with "restaurant", "store", "shop", or "joint" (e.g. "Burger Joint") in its name. This is an attempt to aggregate a host of similar type venues into a single feature.

I checked for strong correlations (> 0.7) between features, as that can degrade training of some models. I removed those features first and re-ran my models. I then used recursive feature elimination to try to ascertain the best number of features to use.

I tried different hyperparameters for Random Forests (max-depth from 3-20, number of estimators from 1-100). Ultimately, I used 100 estimators (probably overkill) and a max-depth of 6. Max-depths over 15 showed signs of overfitting, as the training scores were much higher than the testing and validation scores. I attempted to gain insight into the classifier by visualizing a model with just one estimator and a depth of only 4. I ran Random Forests with a wide range of features, from over 500 to just 1.

I tried several kernels for SVM: Radial Basis Function, Linear, Polynomial, and Sigmoid. I ran the Support Vector Machines with 500 features, and one extra promising SVM with a Radial Basis Function with just 50 features.

For feature reduction, I first used the approach of removing highly correlated (>0.7) features. After that, I gradually and recursively removed the features with the lowest feature importances. When I thought I had an insight, I created a few features to exploit that, such as a feature that just represents the total number of venues in an area.

In the hopes of gaining insights, I plotted my data on maps, and superimposed Foursquare results for "Starbucks" searches. My data includes rectangular areas of points which can be classified as either "0: not near Starbucks" or "1: near Starbucks" Also, irregularly spaced points drawn from the Kaggle "starbucks/store-locations.csv" file, which we could guess will have labels of 1, but in practice only some do. Those points can be classified with either label. Finally, I added locations of Starbucks returned from a Foursquare search. These points are not classified but are shown in red to inspire understanding. We would like to see our green circles (class 1 points) clustered closely with red circles. Away from red circle markers, we'd like to see mostly blue circle markers. We can zoom in or out on the Folium map in order to try to identify venues, venue clusters, geographic features etc. that we would expect to influence the likelihood of a Starbucks location in the area.

4. Results

I got the best performance from a Support Vector Machine (SVM) trained on 500 features. The validation accuracy is suspiciously high at 0.95:

```
-----SVM (with rbf kernel)-----
SVM (with rbf kernel) Train accuracy = 0.8132573057733429
SVM (with rbf kernel) Train ROC AUC = 0.8980169971671388
SVM (with rbf kernel) Test accuracy = 0.8091168091168092
SVM (with rbf kernel) Test ROC AUC = 0.8797108512020793
SVM (with rbf kernel) Validation accuracy = 0.95
SVM (with rbf kernel) Validation ROC AUC = 0.8595297768230099

SVM (with rbf kernel) Average of Test and Validation accuracy: 0.8795584045584046
SVM (with rbf kernel) Average of Test and Validation ROC AUC score: 0.8696203140125446
```

I also got good performance from an SVM using a polynomial kernel:

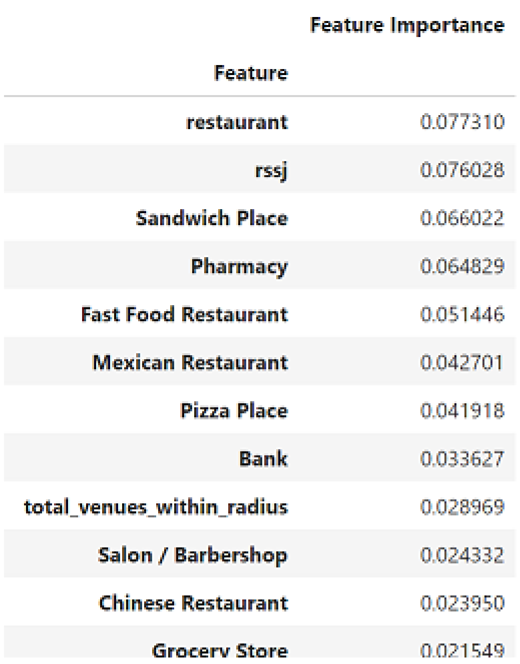
```
-----SVM (with poly kernel)-----
SVM (with poly kernel) Train accuracy = 0.8980755523877405
SVM (with poly kernel) Train ROC AUC = 0.9534549119862137
SVM (with poly kernel) Test accuracy = 0.8005698005698005
SVM (with poly kernel) Test ROC AUC = 0.8557667316439246
SVM (with poly kernel) Validation accuracy = 0.9380952380952381
SVM (with poly kernel) Validation ROC AUC = 0.7728845924334646

SVM (with poly kernel) Average of Test and Validation accuracy: 0.8693325193325193
SVM (with poly kernel) Average of Test and Validation ROC AUC score: 0.8143256620386946
```

The Random Forest with all 526 features did well:

```
-----RF_all_features_1-----
RF_all_features_1 Train accuracy = 0.8503207412687099
RF_all_features_1 Train ROC AUC = 0.9405871379160383
RF_all_features_1 Test accuracy = 0.811965811965812
RF_all_features_1 Test ROC AUC = 0.8927550357374918
RF_all_features_1 Validation accuracy = 0.8725981620718463
RF_all_features_1 Validation ROC AUC = 0.8725981620718463

RF_all_features_1 Average of Test and Validation accuracy: 0.8422819870188292
RF_all_features_1 Average of Test and Validation ROC AUC score: 0.882676598904669
RF_all_features_1 Num Features: 526
```

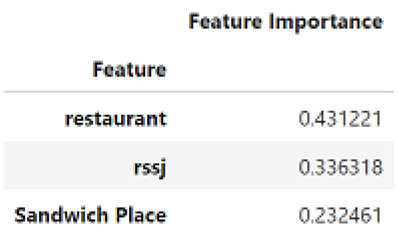


Feature	Feature Importance
restaurant	0.077310
rssj	0.076028
Sandwich Place	0.066022
Pharmacy	0.064829
Fast Food Restaurant	0.051446
Mexican Restaurant	0.042701
Pizza Place	0.041918
Bank	0.033627
total_venues_within_radius	0.028969
Salon / Barbershop	0.024332
Chinese Restaurant	0.023950
Grocery Store	0.021549

Random Forests do well with very few features:

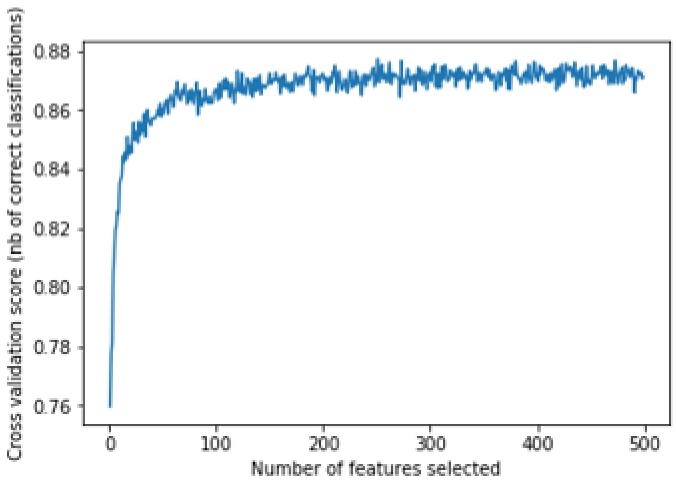
```
-----Random Forest #13-----
Random Forest #13 Train accuracy = 0.7947255880256593
Random Forest #13 Train ROC AUC = 0.8866215386866416
Random Forest #13 Test accuracy = 0.7492877492877493
Random Forest #13 Test ROC AUC = 0.8414879792072775
Random Forest #13 Validation accuracy = 0.8768946174961213
Random Forest #13 Validation ROC AUC = 0.8768946174961213

Random Forest #13 Average of Test and Validation accuracy: 0.8130911833919353
Random Forest #13 Average of Test and Validation ROC AUC score: 0.8591912983516994
Random Forest #13 Num Features: 3
```

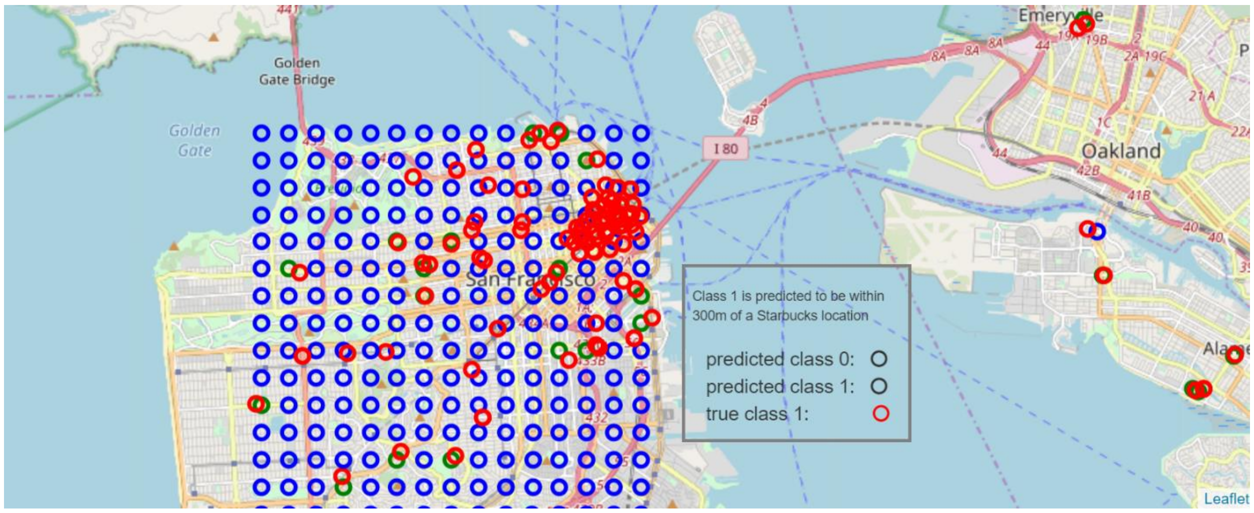


Feature	Feature Importance
restaurant	0.431221
rssj	0.336318
Sandwich Place	0.232461

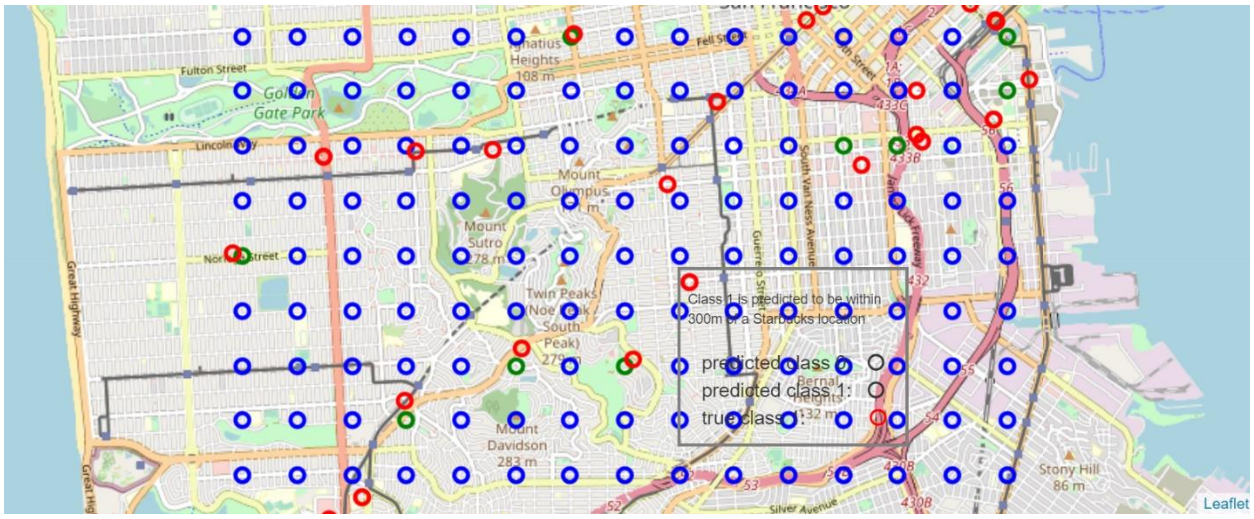
The Random Forests do marginally better with more features:



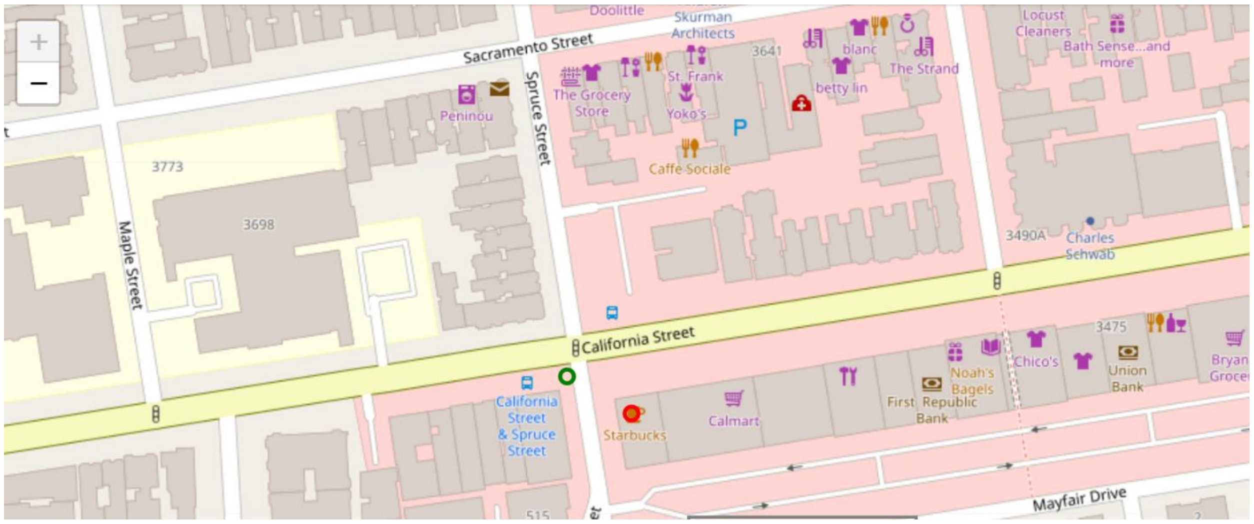
Here is a zoomed map of the training/testing geographic area showing class 0 predictions (blue circles), class 1 predictions (green circles) and coordinates returned by the Foursquare API search endpoint for the query “Starbucks” (red circles):



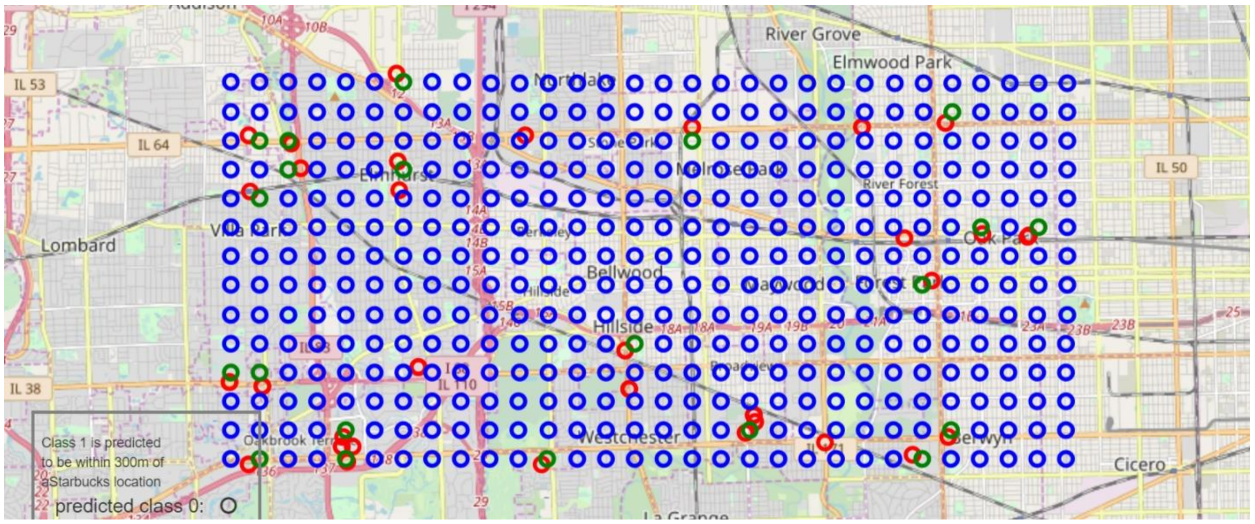
Here is a closer zoom-in:


Class 1 is predicted to be within 300m of a Starbucks location
predicted class 0: ○
predicted class 1: ○
true class 1: ○
Leaflet

Here is a single correctly predicted Starbucks location at the corner of Spruce and California Street zoomed in the max amount:



Here is a zoomed map of the validation geographic area showing class 0 predictions (blue circles), class 1 predictions (green circles) and coordinates returned by the Foursquare API search endpoint for the query “Starbucks” (red circles):



5. Discussion

Removing highly correlated features did not seem to help the Random Forest models very much. In fact, removing even on the order of 500 features only helped marginally. I would generally prefer the far simpler models, even at the expense of a bit of accuracy.

I would like to analyze the performance of polynomial and RBF SVMs with more variations, especially the addition and subtraction of features. I would like to apply Principle Component Analysis (PCA) for feature reduction. I would also like to train on something like 20-1000 times as much training data and see how well the models work on a wide variety of new geographic areas. In particular it would be nice to see how well these models predict qualitatively different regions, for example, rural areas.

It might be worth altering the radius of 300m as well.

6. Conclusion

The dominant features appear to be closely related to general business density, however, there seems to be an emphasis on food-type venues. It is worth noting, though, that venue categories such as restaurants, fast food, and sandwich places (Subway is the second most common venue after Starbucks) make up a disproportionate quantity of business venues in general.

At a certain point, I was worried that this entire exercise would boil down to the simplistic proposition, “Starbucks are located where there are a lot of businesses.” I was pleased to discover that my engineered feature “total_venues_within_radius” had a lower importance than 8 (or so depending on the exact model) other features, including “Bank” and “Pharmacy.” Also, “Chinese Restaurant” and “Clothing Store” have higher incidences than “Bank” or “Pharmacy”, and yet have less predictive power for Starbucks locations. In the case of “Clothing Store”, it has much less predictive importance. Even the venue category “Coffee Shop” has a higher incidence than “Bank” or “Pharmacy”, but much lower feature importance. It should be noted that this category only includes venues other than Starbucks. When I ran the models with the Starbucks venue rows included but deidentified as Starbucks, the feature “Coffee Shop” became the top feature, and the accuracy went up to about 96%.