Machine Learning Nanodegree Capstone

Predicting Facebook Check-In Behavior – Kaggle Competition.

# Project Overview

This project is based on the Kaggle competition begun by Facebook to predict where a person is most likely to check in next. From the competition

The goal of this competition is to predict which place a person would like to check in to. For the purposes of this competition, Facebook created an artificial world consisting of more than 100,000 places located in a 10 km by 10 km square. For a given set of coordinates, your task is to return a ranked list of the most likely places. Data was fabricated to resemble location signals coming from mobile devices, giving you a flavor of what it takes to work with real data complicated by inaccurate and noisy values. Inconsistent and erroneous location data can disrupt experience for services like Facebook Check In.[[1]](#footnote-1)

I chose a Kaggle competition because of the community around each project. It seemed to me to offer much more education benefit in the developmental stages of a skill to be involved in a larger project with other ideas being floated around instead of creating an entirely unique project.

The dataset provided by Facebook for this competition is completely fabricated and includes a hypothetical “grid” of x,y coordinates, a timestamp, an ID of the check in location, and an undefined “accuracy” measure. In total, the training dataset is 29,118,021 data points. In my estimation, each of these data points is meant to represent an interaction with the Facebook mobile app and returns the equivalent of a GPS coordinate (the x,y value), a timestamp, the location of their next check in (place\_id), and a GPS accuracy measurement of unknown units.

# Problem Statement

The challenge is to predict, given only an x,y coordinate, a timestamp, and an accuracy measurement, where the user will check in next. This is a classification problem of a very large scale as evidenced in table 1:

Table 1 - Unique values of each feature in the feature dataset

|  |  |
| --- | --- |
| Measurement | Number of Unique Values in Dataset |
| X Coordinate | 100001 |
| Y Coordinate | 100001 |
| Timestamp | 786239 |
| Accuracy Measurement | 1025 |

Using the data from Table 1, there are 8.059 x 1018 possible combinations of feature data to relate to 108390 unique places. The sheer size of this dataset makes this a challenging problem and as such I made some decisions and observations about this project before beginning.

## A Note on the Problem:

There are many ways to tackle this problem, however the most effective ways will most likely require the data to be read from a data store and use some in-storage reduction techniques such as MapReduce. That is beyond the scope of this course and while I realize this would most likely be a more realistic approach to solving this problem, for simplicity I will remain working from in-memory solutions. As such, the algorithms will be simplistic, the accuracy will suffer, and the overall usefulness of the solution will be tempered by the fact that simplistic algorithms such as a Nearest-Neighbors analysis will most likely not give highly accurate or reliable results.

All of this being said, my goal is to create a functional, memory efficient approach to solving this problem that will provide *some* useful insights. This approach will most likely not compare well to solutions that have more computational power or a more sophisticated data delivery approach but is an interesting educational experience regardless.

## Hypothetical Solution

This problem is a classic example of a classification problem with the true challenge coming from the vagueness of some of the features, namely timestamp and accuracy, the size of the dataset, and the number of targets. I will approach the problem in four stages:

1. Read in, format, and transform data into useable variables stored in memory, erasing any transient variables used in the process to preserve memory
2. Perform data exploration with basic statistics and graphical measures to understand the distribution of the dataset. This being a geographically related dataset there will also be a “location” graphical aspect to see if there are concentrations of features in specific geographic (x,y) areas.
3. Implement various classification machine learning algorithms with an eye toward efficiency and compare their results to find the best possible algorithm for this problem.
4. Select the appropriate machine learning algorithm based on the tests and tune the algorithm to provide the best possible result.

The problem will be judged based on the accuracy of check-in place\_id predictions. The metric used for these predictions will most likely be the built in SciKit Learn accuracy\_score as the F1 score used in previous projects during this course, to my understanding, is for binary classification problems which this problem most certainly is not.

Ideally the algorithm will return multiple possible check-in locations with a weight of which is most likely, as per the problem definition provided by Facebook. For purposes of defining the problem completely and easing computational load, I will return one possible place\_id and the accuracy score will check the result against the true place\_id.

# Data Exploration

As previously discussed, the dataset is constructed of 4 features and 1 target. The 4 features are x coordinate, y coordinate, timestamp, and accuracy. The target data is a place\_id which is a randomly generated number associated with a hypothetical geographic (or business) location.

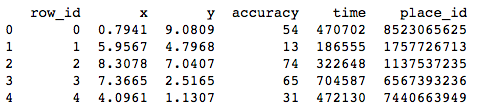


Figure 1 - Sample of dataset

## X Coordinate and Y Coordinate

These can reasonably be correlated to GPS coordinates but have been normalized to a 10 by 10 grid with five significant digits, values on both of these can range from 0.0000 to 10.0000.

## Time

The time feature appears to be a random figure ranging from 1 to 786239, this precludes it from being a machine timestamp such as Epoch time or Unix time. It could be seconds, which would equate to 9.1 days, more likely the timestamp is in minutes which equates to an even 546 days. Considering the volume of interactions, neither of these solutions is entirely satisfactory. If we consider the timestamp to be seconds, that would equate to 3.2 million check-ins per day in this 10km square, where as if it is considered to be minutes that would equate to 53330 check-ins per day. The former case seems like too much volume while the latter seems like it could be too little. Without an understanding of the density of this hypothetical population area, I will have to make an educated guess as to which to choose. Considering how large of a number of check-ins would have to occur for this to be seconds, I will assume that it is minutes.

Why analyze the data beyond the existing timestamps? The time measure is completely linear and does not account for the cyclical nature of how people frequent businesses. Traffic at some businesses will be higher on a Monday, while others will be higher on a Saturday night. By converting the timestamps to a cyclical Day:Hour feature regardless of the year, month, week or even the minute, it reduces the timestamp data significantly from 786239 values to 168 (7 days, 24 hours). This pseudo-feature reduction (not in the strict sense) will make the timestamp a much more useful feature without sacrificing granularity. Most interactions with businesses occur within certain time blocks where, hypothetically, 12:45pm is not much different in interactions than 12:50pm and probably somewhat different than 1:45 pm. Thus we can assume that the 12:00 pm hour and the 1:00 pm hour can be treated as two individual times. If accuracy is lost by this reduction, it could be possible to create time blocks of 15 or 30 minutes to increase the amount of data

## Accuracy

This feature is left entirely up to interpretation. No explanation of the feature was provided at all including units or if a high number was either subjectively “good” or “bad”. With this in mind, to simplify the analysis of this data, I will filter all of the data removing all data points with outside of one standard deviation from the mean accuracy measurement. Accuracy will then be removed entirely as a feature. This decision is two fold, one it will remove noisy data, two it will reduce the number of features significantly, making computation easier.

# Statistics and Visualization

## Visualizing Check Ins by Day, Time, and Location

|  |  |
| --- | --- |
|  |  |

Figure 2 - Check In Volume by Day of the Week and Hour of the Day

After breaking down time into a more manageable, cyclical measurement of day of the week (0-6) and hour of the day (0-23). From this point forward we will add 1 to all measurements to make them easier to talk about, this making our values from 1-7 and 1-24. We can see that although some patterns to arise, suggesting that day 2 has slightly more check-in volume than other days and that between hours 1 and 13 during the day check-in volume is higher, the amount of variation in the data is so small as to suggest that there are no high significant variations in behavior in the day of the week, or hour of the day.

Next, an analysis of the physical space was performed to see if there was more check-in density from different blocks in the hypothetical test space.

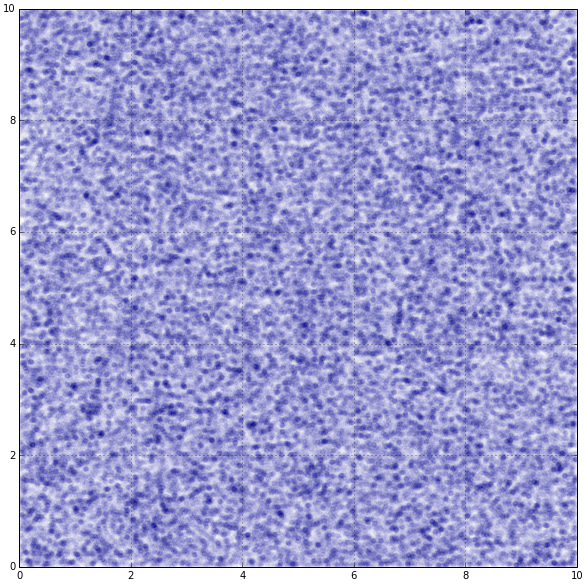


Figure 3 - x,y coordinates of 500,000 randomly sampled check-in data points

Sampling 500,000 check-in data points randomly from the full set and plotting them reveal that there are no large patterns of check-in behavior based on location. Figure 3 appears to be a fairly consistent Gaussian distribution of data points.

## Accuracy analysis

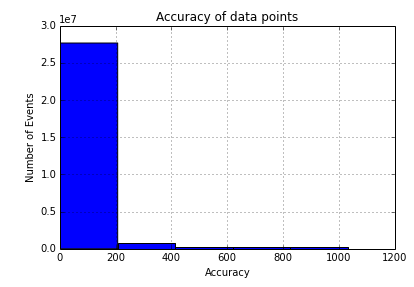


Figure 4 - Accuracy of each event in data set

Accuracy is the least useful feature in this dataset as it is not defined and has no effect on user behavior, simply on the accuracy of correlation between their GPS coordinate and their following check-in. With that in mind, I will remove noisy data and remove the feature entirely from the dataset. Only data within one standard deviation of the mean will be retained for the remainder of this problem.

Table 2 - Statistical analysis of accuracy feature

|  |  |
| --- | --- |
| Mean | 82.85 |
| Standard Deviation | 114.75 |
| Minimum Accuracy | -31.90 (0) |
| Maximum Accuracy | 197.60 |

# Algorithms and Techniques

To baseline performance of this modified data, the k nearest neighbors classifier technique built into SK-Learn was used using 1 nearest neighbor and an accuracy score was calculated using the built in *score* function. The data was split into an 80% training 20% testing set and the results were as follows:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Samples | Train Time (s) | Predict Time (s) | Predict/Train Time Ratio | Mean Accuracy Score (%) |
| 10000 | 0.014 | 0.183 | 13.07142857 | 0.90 |
| 100000 | 0.233 | 8.226 | 35.30472103 | 2.11 |
| 1000000 | 11.642 | 345.175 | 29.64911527 | 14.39 |
| 2000000 | 74.217 | 942.868 | 12.70420524 | 21.36 |
| 5000000 | 554.941 | 3184.24 | 5.737979353 | 30.49 |

Here, I am using the score function built into K Nearest Neighbors. This function returns the accuracy of the prediction, the course on Kaggle uses a metric derived from precision. I have made this decision intentionally to ease computational difficulty.

1. Kaggle, <https://www.kaggle.com/c/facebook-v-predicting-check-ins>, (May 25, 2016) [↑](#footnote-ref-1)