Predicting the Foursquare rating of Taco Bell restaurants

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INTRODUCTION

Background

Taco Bell is an American fast food chain which serves Mexican and Tex-Mex foods. According to scrapehero.com, there are currently 7,117 locations in the United States with 824 locations in California. In 2019, there were 7,363 locations worldwide, an increase of 1,467 locations from 5,896 locations in 2010. That is an average increase of 163 locations per year.

Meanwhile, consumers are often guided by where they eat based on the ratings of the restaurants they go to. Thus, having a location with a higher rating is lucrative.

In other words, when opening a new Taco Bell restaurant, the owner might be interested in opening the restaurant at a location that is biased towards a higher rating.

Problem

How does a Taco Bell restaurant's location affect its rating? In this project, our goal is to determine whether or not a restaurant's location has an impact on its Foursquare venue rating and if so give the relationship.

Interest

This problem is clearly of interest to entrepreneurs looking to invest in a new Taco Bell. However, the methods in this project can easily extend to other franchises, in which case the problem would be of interest to any potential franchise owner.

Data

Data Source

We will be using Foursquare API which provides rich information on venues in a specific location and details on each venue. See link for all the response fields.

The columns we collect are the Foursquare ID (used to pull the rating), restaurant name, latitude, longitude, city, and Foursquare rating.

For this particular project, we gather entries for Taco Bell locations surrounding three areas, Los Angeles (34.0522°N, 118.2437°W), Orange County (33.7175°N, 117.8311°W), and the midpoint between the two (33.8849°N, 118.0374°W)

Data Cleaning

Because we're interested in predicting the ratings, we drop locations which do not have a rating from the dataset.

We also only keep locations whose name is strictly "Taco Bell." Explicitly, we drop three listings for "Taco Bell/Pizza Hut" and three listings for "Taco Bell/KFC."

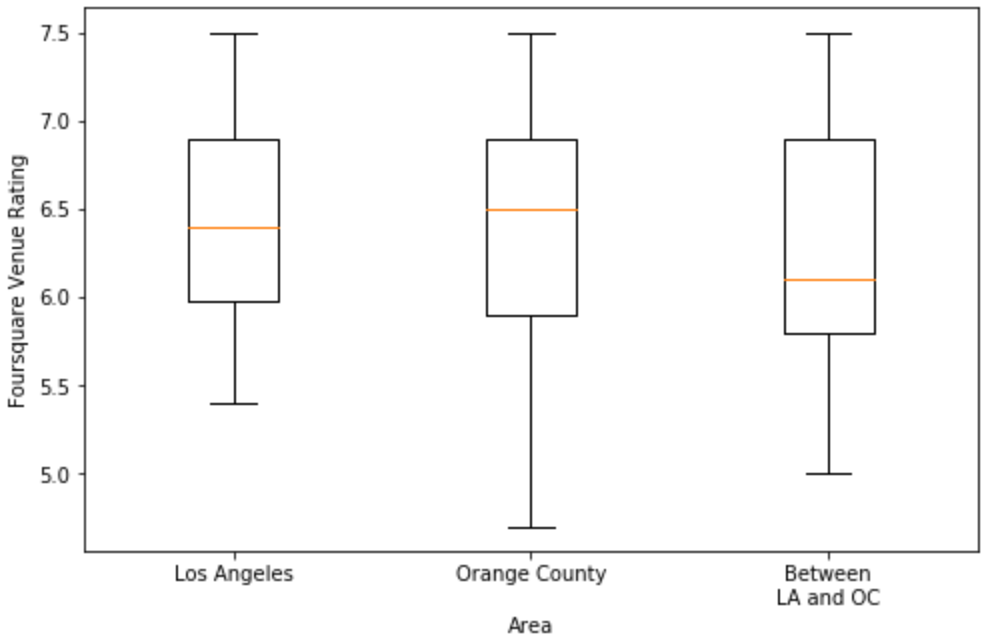
Finally, when combining data from the three locations, we drop the duplicates.

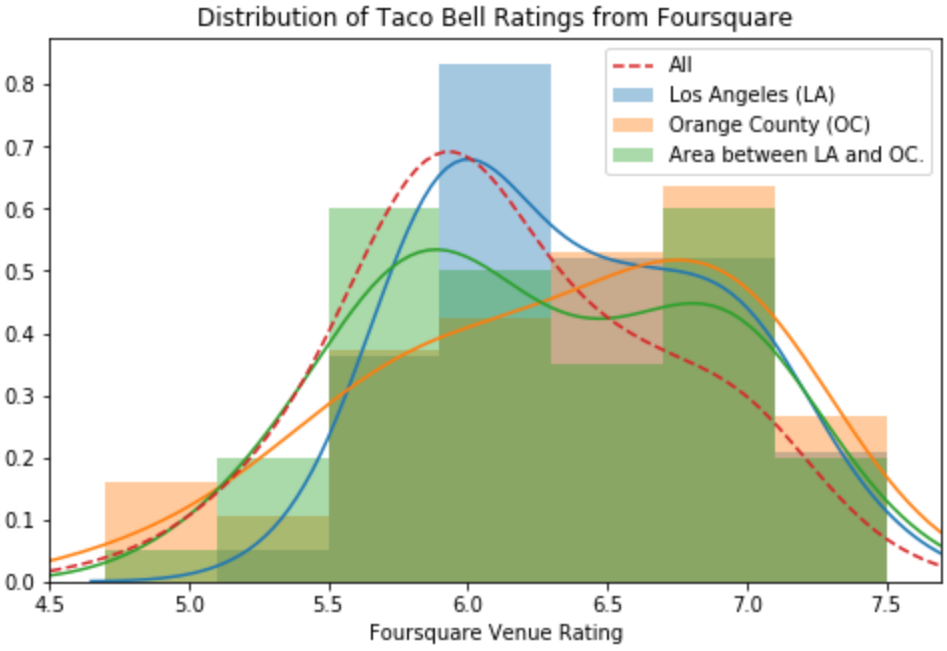
Feature Selection

While there are many location features that exist in practice (e.g., next to freeway, near mall) and can be incorporated with the appropriate queries or additional sources, we keep the scope of this project simple by only taking the geographical coordinates (latitude and longitude) as features.

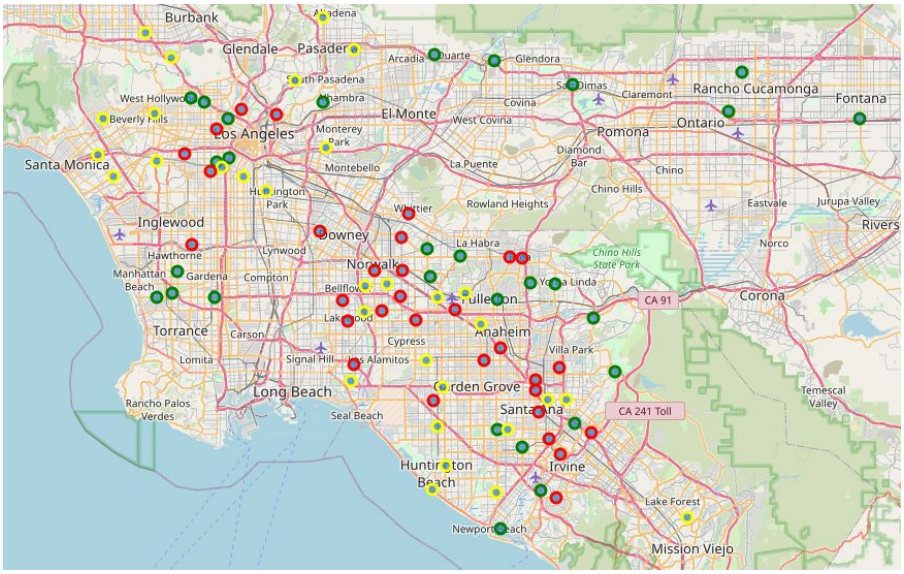
Exploratory Data Analysis

After cleaning the datasets, the three areas have 44, 45, and 49 locations, respectively. Although the separate datasets have various locations in common, it is still reasonable to plot and compare their distributions (see boxplots and histograms).





We can also look at how the ratings are distributed across the map (a larger map can be found at the end of the report). Locations with ratings less than or equal to 5.8 are shown as red markers while ratings greater than or equal to 6.4 are shown as green markers. The rest use yellow markers (a rating between 5.9 and 6.3). The cutoffs 5.8 and 6.4 were determined by taking the 33rd and 66th percentile of all the ratings, respectively.

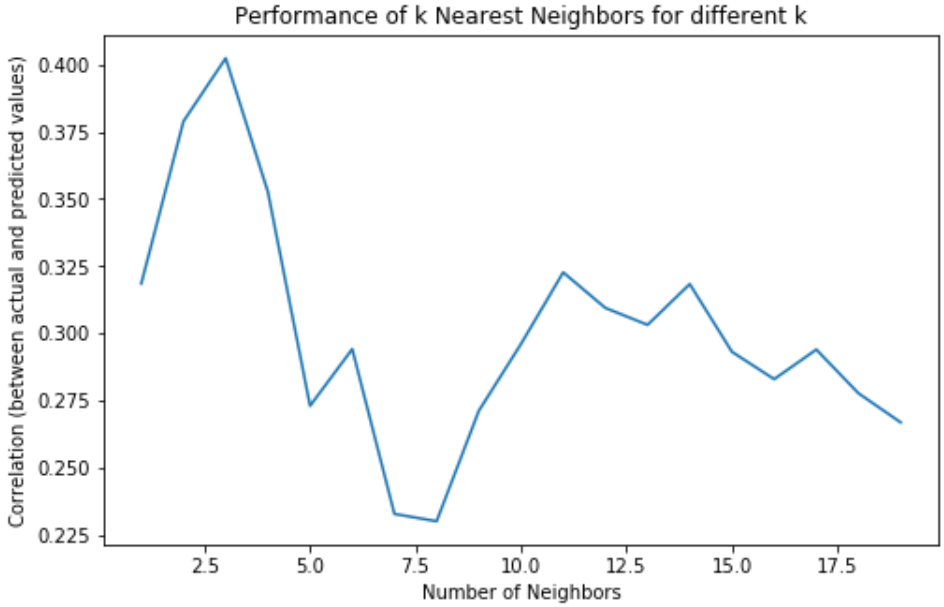


At a glance, the map and color-coded ratings suggest that there is a correlation between location and rating.

Predictive Modeling

Given the map and problem, the primary model to implement is a k-nearest neighbors regression.

Because we're using geographical coordinates we set the metric to `haversine`. We then use the training set to search for an optimal value of k (the number of nearest neighbors) where we perform validation via leave one out. Leave one out works best for the k-nearest neighbors regressor, because using other forms of cross validation is prone to leaving holes in the map and results in very poor prediction.



As one can see from the figure, the optimal value of k occurs at $k = 3$. Note, however, that this value is unstable and may change with a different split (more explicitly, $k = 2$ may show as an optimal value of k for a different random split of the training and test set).

With the value of k=3, we apply the model to the training set and look at it's performance on the test set. To calculate performance, we first perform a linear regression on the actual and predicted values on the training set. We obtain that

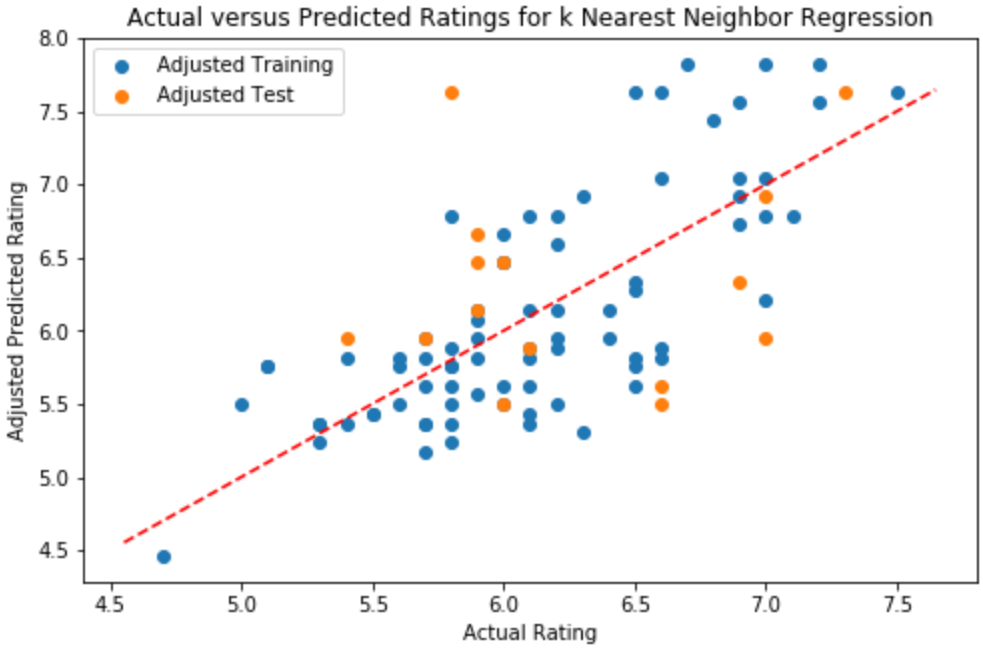
$$predicted\_rating \sim 0.517 * actual\_rating + 2.927,$$

with a correlation coefficient $r = 0.7557$. We use this regression to transform the

predicted values towards the actual values. In other words, we have the transformation

$$T(predicted\_rating) = (predicted\_rating - 2.927)/0.517 .$$

In short, we define an adjusted predicted rating as the application of the transformation to the output of the k nearest neighbor regression. The adjusted predicted rating has a mean squared error of 0.2927 (average squared error on the training data). Similarly, the adjusted predicted rating has a mean square prediction error of 0.0882 (average squared error on the test data). The adjusted predicted ratings are plotted on the next page against their respective actual ratings.



For reference, predicting the average rating (across the training data) has a mean squared error of 0.3260 and a mean squared predicted error of 0.0632.

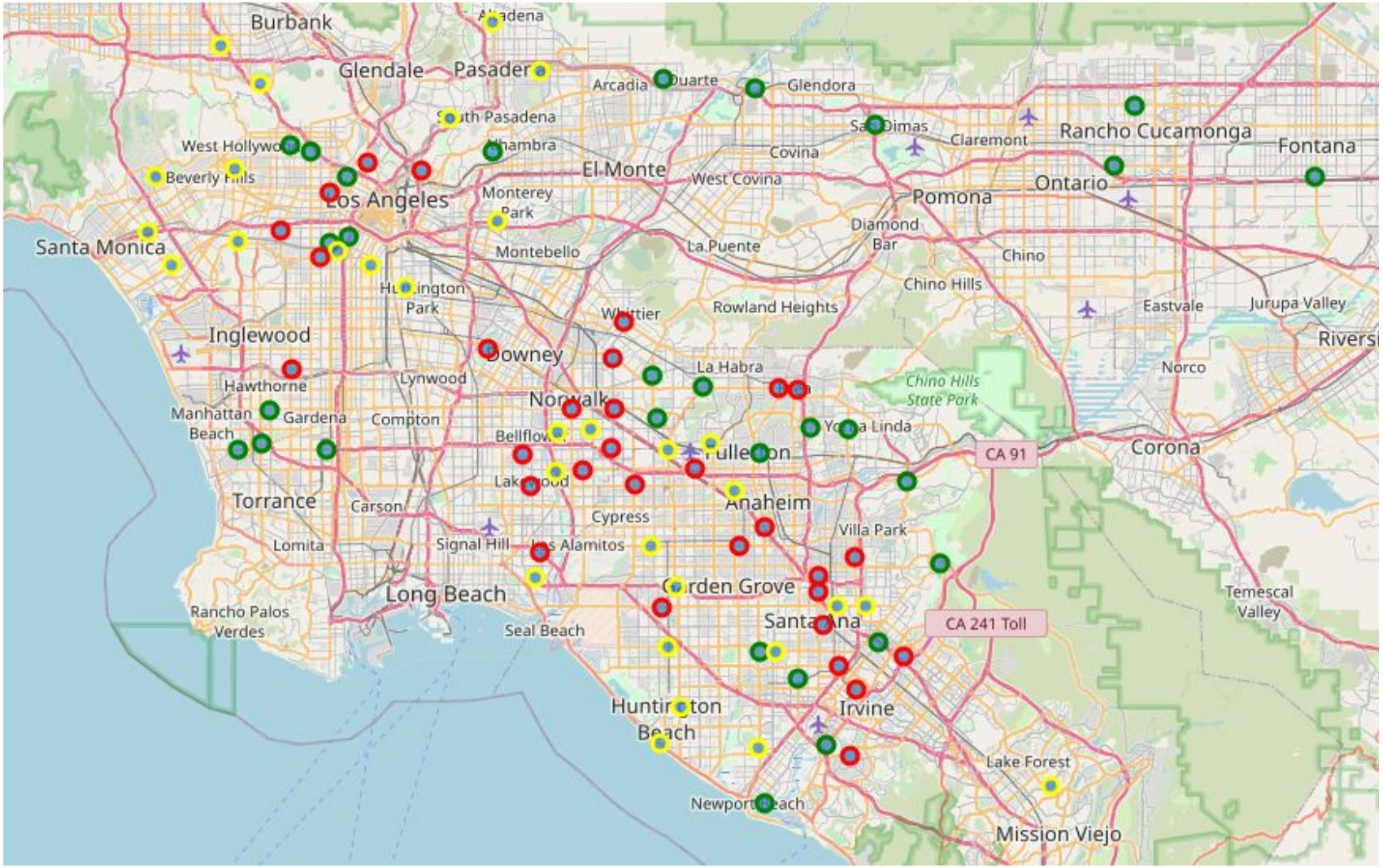
Conclusion

We have shown in this project that there is a correlation between the geographical location of a Taco Bell and its Foursquare rating. However, this leaves many questions such as “Why is this the case?” and “What geographical features can be added that would potentially improve the model or reveal its shortcomings?” Perhaps there exist confounding factors such as users in a particular area have particular behavior when it comes to rating restaurants.

As such, evidence is in favor of a (Taco Bell) location having an impact on its Foursquare venue rating, but inconclusive without further exploration.

Future

In the conclusion we raised some questions which are worth pursuing. In addition to those questions, gathering more data, both for more Taco Bell locations and across other restaurants and other franchises may help bring light to the question of whether or not a Taco Bell restaurant location impacts its Foursquare rating.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Glendale
Pasadena
Arcadia
Glendora
West Hollywood
Beverly Hills
Los Angeles
El Monte
West Covina
Covina
Claremont
Rancho Cucamonga
Fontana
Ontario
Pomona
Monterey Park
Diamond Bar
Santa Monica
Montebello
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Chino Hills
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