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Abstract

Home appraisals are considered an art form.

As there are many variables that can impact a home's market value, the appraisal (or estimation of a home's market value) is simply a 'feeling' at how much a home is worth, given by the appraiser.

Because they are highly regulated, home appraisal professionals go through a rigorous training, continuing education and lengthy on-the-job experience before they become licensed appraisers. This is a must, as home appraisals are routinely relied on for mortgage financing by financial institutions.

However, Zillow's introduction of the Zestimator has now offered reliable real estate pricing; challenging appraisals by moving real estate estimation from a 'feeling' to a science.

Using Machine-Learning Regression and its ability to weight multiple factors, Zillow is able to accurately give the normal homeowner access to a free estimate of their home based on factors private to Zillow's propriety regression.

Introduction

Description of the problem and discussion of the background

The impact of a home's value is based on many factors; square footage, number of bedrooms, number of bathrooms and utility features like garages or a washroom.

But most famously, the three most important factors for a home's value are 'Location! Location! Location!' Considered a Real Estate agent's mantra, this phrase is the belief that a home's location is the greatest variable of a home's value.

This phrase is the basis of our hypothesis:

Can the FourSquare api can be used to enhance Zestimator home prices by Location data analysis?

Targeting our customer base as Home Owners who can use our estimator to more accurately price their homes.

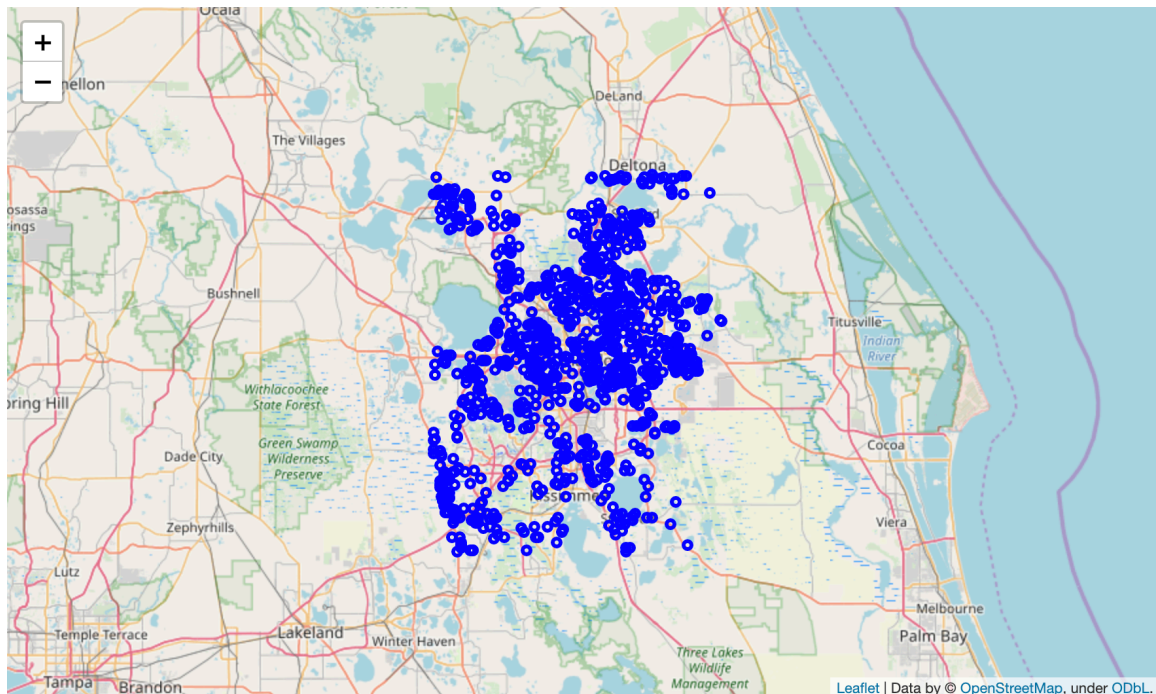
Methodology

How the data will be used to prove our hypothesis

In order to test our Hypothesis, a baseline home regression estimator will need to be built using parsed real estate data (sqft, bedrooms, bathrooms, longitude, latitude) then an additional regression estimator will be created using the real estate data coupled with the location venue data from our FourSquare api. This data will include all available FourSquare data in a suitable radius from each home.

For our housing market; we will choose the Orlando, Florida area.

The two estimators will be compared and if the estimator accuracy is increased by our FourSquare data, then we have proved our hypothesis.



Results

Our cross val score testing showed that the dataframe that was compiled with location data performed better (lower error) than with the standard baseline data.

Results

```
#This is where we compare our estimator accuracies  
print('Final Score for Base Estimator:', initial_score, '// Final Score with Foursquare Data', Final_scores)
```

```
Final Score for Base Estimator: 47538.604896770536 // Final Score with Foursquare Data 42458.85154927293
```

Discussion

Our results show that our Mean Absolutes Error of our Base Estimator is reduced by adding our FourSquare data, so its does show that our hypothesis is correct.

Below, we'll look more closely at each venue's price behavior by performing 'all else the same' testing and iterating through each venue to see the change in value from our Estimator.

For this section we will only use venues that have 3 responses or more to keep things relevant. As using our RandomForestRegressor requires 2 data points per node.

Conclusion

The individual price impact of each venue can be shown in the visualization below.

With the increase in accuracy for our MAE, we can see how our regressor rates each venue in value added or subtracted from our target price estimate.

