Flashlight: Property Assessment Visualization for the City of Boston

Tyler Brown, Sicheng Hao, Nischal Mahaveer Chand, Sumedh Sankhe

Summary

As a new home-buyer, it's easy to find out about your home but hard to get an understanding of your neighborhood. Flashlight makes it easier for you to see your potential neighborhood in Boston. This discrepancy is due to current real estate websites emphasizing individual properties rather than individual neighborhoods. Our group communicates the differences between Boston neighborhoods using an interactive data visualization called Flashlight.

Our dataset includes Property Assessment history from 2014-2017 [1] using Boston's Open Data Hub. We enriched the property assessment data with coordinates from Open Addresses [2], and neighborhood boundaries from Zillow [3]. These combined datasets provide unique insights to new home-buyers in Boston. As open data becomes more prevalent in cities across the United States, we can scale our insights and models.

Our prime focus of this project is to provide information that other major housing websites do not, which is property assessment value and interior detail. Property assessment value does not relate to the property's selling price directly, but as the tax value. Assessment value has a powerful influence on home buyer's financial statements. Interior detail is the information which is hard to get when viewing a property from outside. The interior condition of properties in Boston are widely distributed due to the long history of the city. Interior condition determines how much money and time a new owner will need to spend after buying the property. Since our data is a legitimate source from the government website [1], we are going to focus on how to visualize those two aspects of Boston housing.

Methods

We used methods for collecting, preparing, modeling, and presenting our data. Each step of the process is detailed here.

0.1 Data Collection

We started with Boston's Property Assessment data from 2014-2017 [1]. This dataset "[g]ives property, or parcel, ownership together with value information, which ensures fair assessment of Boston taxable and non-taxable property of all types and classifications."[1]. We wanted to use this information because it helps us capture changes in Boston properties over time. For example, a remodeled property would change it's property tax assessment value we have this variable available to us.

After starting with the Property Assessment dataset, we brought in additional datasets to increase the value of our data collection. Neighborhoods in Boston were not named or geographically demarcated in the Property Assessment dataset so we brought in Neighborhood Boundaries from Zillow [3] to make this distinction. Additionally, geographic coordinates for each assessed property's address were occasionally not coded correctly or included at all for 2017 so we had to bring in those values using Open Addresses [2]. Once neighborhood names, boundaries, and missing coordinates were available, we were able to proceed to data preparation.

0.2 Data Preparation

There were a number of steps involved in data preparation. Transformation of data is considered to be a part of data preparation. We detail notable parts of our data preparation by elaborating on data audits, geocoding missing addresses, and working with GeoJSON in Python.

0.2.1 Data Audits

The purpose of a data audit is to answer questions related to data quantity and quality. We started with our Property Assessment dataset by checking for the quantity of populated items within each variable. About 73% of variables were less than 70% populated. We were able to disregard these variables for our modeling purposes. Data quality checks are not as easily automated but value added.

Analyzing data quality helped us understand data problems up front such as having a non-unique primary key about 0.3% of the time, latitude and longitude were missing or corrupted about 35% of the time, and the ratio of unique addresses concatenated with coordinates to unique coordinates were about $\frac{3}{1}$. We also found that the Property Assessment data did not map to defined neighborhoods in Boston. Understanding these shortcomings with a data audit allowed our group to plan remediation steps early in our analysis.

0.2.2 Geocoding Missing Addresses

During the data audit we found about 35% of addresses within the Property Assessment data were not matched to any coordinate pair. Our team work to mitigate this deficiency by leveraging the a "free and open global address collection" called the OpenAddresses [2] project. There are several strategies one can take when Geocoding (mapping address strings to coordinate pairs) addresses. The simplest would be to use Google Maps Geocoding API [4].

The Google Maps Geocoding API has a free usage tier which maxes out at 2,500 requests per day [4]. Our data required geocoding an order of magnitude more coordinates so this approach was out of the question. We resolved the issue by creating 'address hashes' for each address in the OpenAddress and Property Assessment dataset with missing coordinates. An 'address hash' was a string concatenated of concatenated values for street number, street name, city, and zip code. We excluded unit number as a simplifying assumption because we expected all unit numbers to be at the same property. Once 'address hash' had been computed for both datasets we performed an inner join.

In some cases, this join generated a many-to-many relationship between addresses in both datasets due to our exclusion of unit numbers. We resolved this issue by grouping and taking the first coordinate pair. Subsequent iterations of our analysis can be improved by adding robustness to our geocoding procedure.

0.2.3 Working with GeoJSON and Python

To create the graphical interface for the map, we used Leaflet [5, 6] - a library to show interactive maps. The team looked at a number of ways to plot the boundaries of each region on the map, and decided that the best way would be to use GeoJSON [7] - a format for encoding a variety of geographic data structures. We used Zillow's shapefiles [3] to use as the base to extract region boundaries and convert them to GeoJSON.

Unfortunately, R did not have a robust GeoJSON library and did not offer the features we had in mind. We switched to Python for converting the shapefile to GeoJSON files. We then realised that there was no way to map the original data to the neighborhood regions which had been defined by Zillow. To counter this, we mapped each point on the map to a region by checking if the latitude and longitude of a point were inside a particular region polygon. The mean interior score of each region was used to fill the polygons, and multiple points were clustered in higher zoom levels to reduce overplotting. Finally, depending on the zoom level, either the regions or the points are shown.

0.3 Data Modeling

We used data modeling to help our user understand the differences between neighborhoods as well as the differences between individual properties. Two scores were generated, one as a descriptive statistic assessing the interior of each property, and the other projected change in property assessment value for this upcoming year.

0.3.1 Projected Change to Property Assessment Value

We were able to create a representation of how property assessment value would change in the next year. When we considered how physical features of the property play an important role in the value of a property, our model was more influenced more significantly by market conditions, and surrounding neighborhoods. The Property Assessment data did not include these market relationships. We decided to create a simple linear model at first by using previous evaluations to predict for the year 2017.

A more important prediction would be to predict how the price per square foot changes per region. We could apply the same linear model to predict price per sqft. First, the price per sqft was calculate for every property parcel identification number (PID) [1]. We grouped by the region and the mean price per sqft was calculated for that particular region by year.

Next, a linear regression model was created with 3 variables and 1 response variable, the variables included the valuations for the year 2014 through 2016 which predicted the evaluations for the year 2017. With an RMSE of $5.45/sqft and a MAE of $4.477/sqft the model performed unexcitingly. Considering all the variables were linearly related to the response variable. The above model was applied to predict the price per sqft for the year 2018 taking into considerations the values from 2015 through 2017. Since there was no way to gauge the performance of this model with real data as of now it would be interesting to see the performance. An interesting problem would be to gauge how housing evaluations are done and how neighborhoods end up having such diverse scores even when they are next to each other.

0.3.2 Interior Score as a Descriptive Statistic

We combined all the columns that are related to the interior characteristics of properties into a single column called the interior score. One of the project goals was to help users understand their prospective properties better, not only from the neighborhood, but also from inside. This is the kind of information which was barely accessible for potential homebuyers. Since all interior characteristic data columns are ordinal, we simply scaled them to 1, 2 and so on, according to what the group felt were high valued characteristics, with 1 being the lowest. The interior score is the sum of all such columns. Also, the score is exponentiated by a power of 2.5 to make the interior score normally distributed (approximately).

0.4 Data Presentation

We use Shiny Dashboard [8] to present our data. The dashboard has two parts, a interface to filter data and the map itself. Filters can be used to look at specific data points on the map. The map, rendered using Leaflet, shows the regions upon startup. Each region is filled using the mean interior score for that region. Hovering over any region brings up a small dialog showing statistics, like mean, max, and min interior scores, property count, and the projected value change for 2018 in price per square feet. Zooming in hides the polygon layer and show marker clusters and the ploygon boundaries. The clusters help with the overplotting problem. Each cluster shows the number of properties in the highlighted ploygon when hoving over the cluster. When a cluster is clicked, or the map is zoomed, the clusters split to show a higher level of detail and exposing individual property markers. When a property marker is clicked, it brings up a popup with property details and statistics for that property.

Filtering will help users pin down on the type of properties to view on the map, and then the map will help users determine which neighborhood would most suit their needs.

Results

0.5 Shiny App

Our project is deployed on Shiny Server: "https://sichenghao1992.shinyapps.io/DS5110/"

0.6 Interesting Findings

1. The rise in evaluations can be seen to grow very fast from 2014 to 2016, but the evaluations for the year 2017 have been low considering the rise they have witnessed for the past 3 years, if the same trend follows into 2018 then the evaluations will change only slightly for the year 2018.

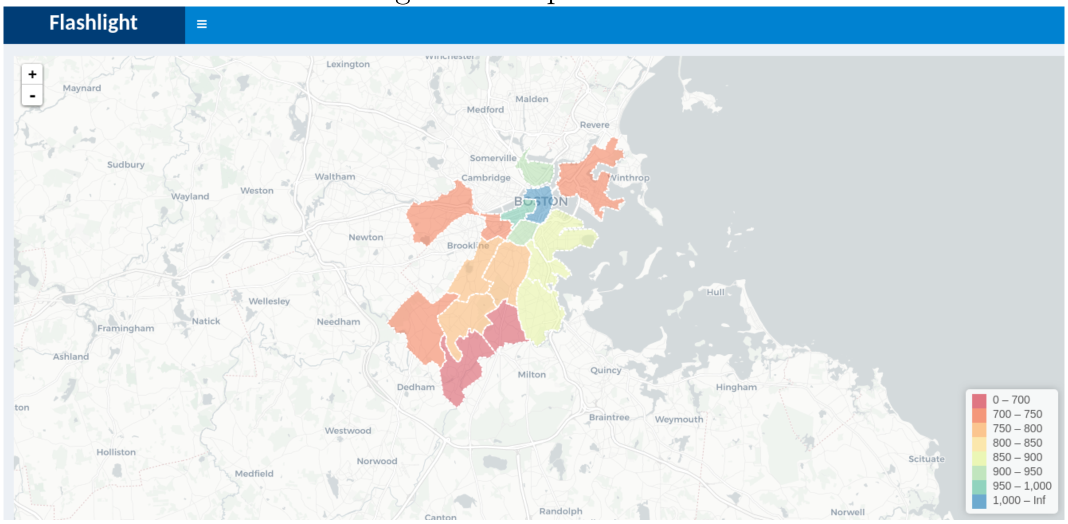
2. The best region in the interior score is Central. Mattapan and Hyde Park have the lowest interior score. This is also the intuition of Boston housing by some long-time Boston residents.

Discussion

1. One huge surprise was finding how inaccurate the coordinates for properties were from government websites. Since we only include actual coordinates for the properties, not all properties are on the interactive map.

2. Since our model is only based on assessment values from the year 2014 to the year 2017, the projected values for assessment may be misrepresent. With more data in the future, our model could preform better.

Figure 1: Map Overview



Statement of Contributions

Together everyone achieves more.

- **Tyler Brown:**
- **Sicheng Hao:** Data transformation, Shiny App data filter.
- **Nischal Mahaveer Chand:** Map visualization, Finding region for each property in map, Geocoding data to find missing latitude and longitude.
- **Sumedh Sankhe:** Data cleaning and transformation, data audit to apply machine learning models to predict assessment values for 2018, linear regression for price per sqare feet for all regions, initial tests to geocode data using Google's Geocoding API.

Appendices

https://github.com/sichenghao1992/DS5110Project

Above is our working repository.

References

[1] C. of Boston, "Property assessment - datasets - analyze boston." https://data.boston.gov/dataset/property-assessment. (Accessed on 10/26/2017).

[2] OpenAddresses, "Openaddresses." https://openaddresses.io/. (Accessed on 12/09/2017).

Figure 2: Map Overview with Filters

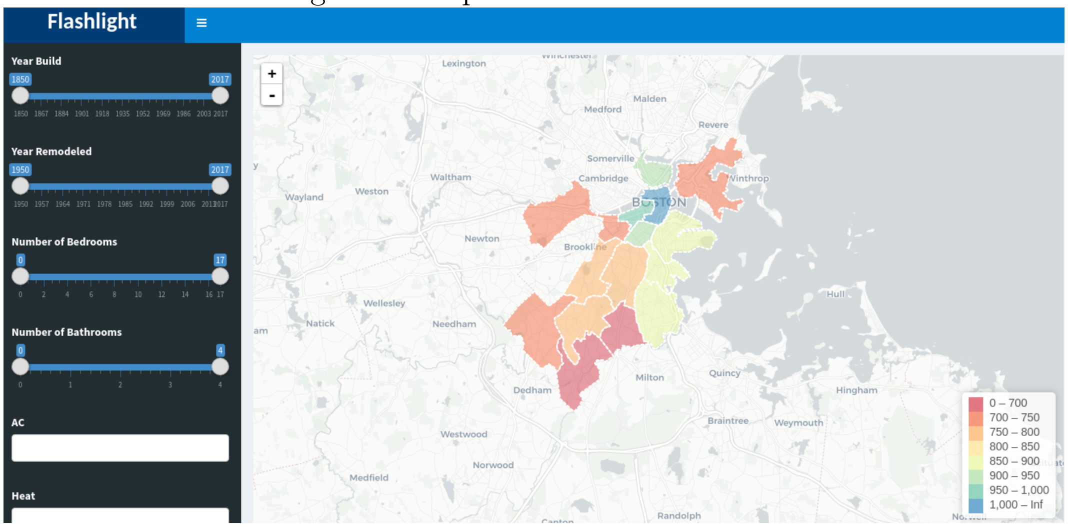


Figure 3: Labels for each Boston Neighborhood

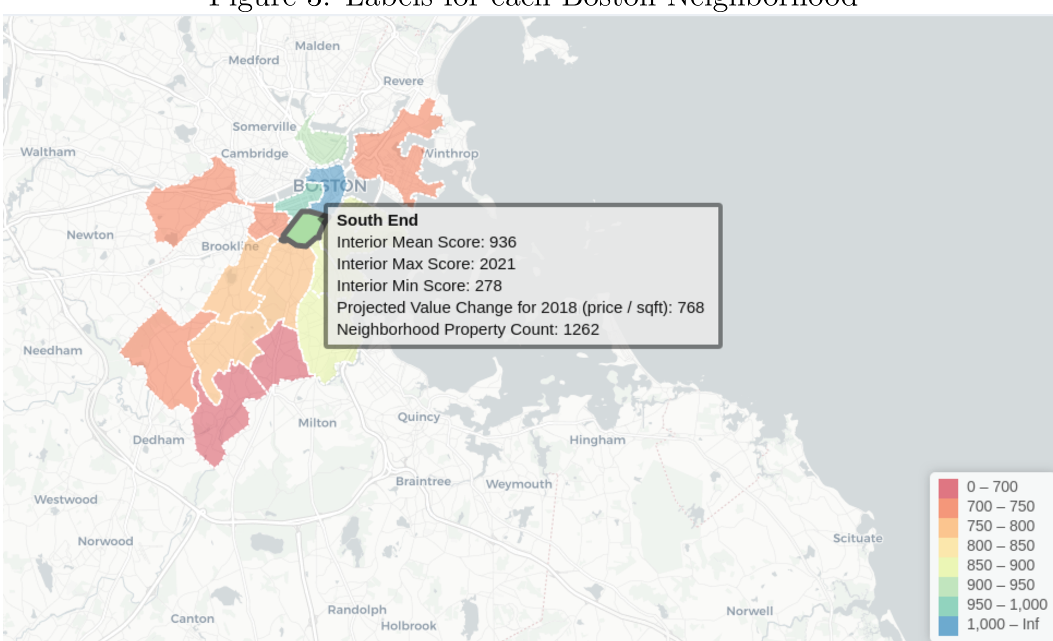


Figure 4: Increase Zoom to see Property Location Clusters

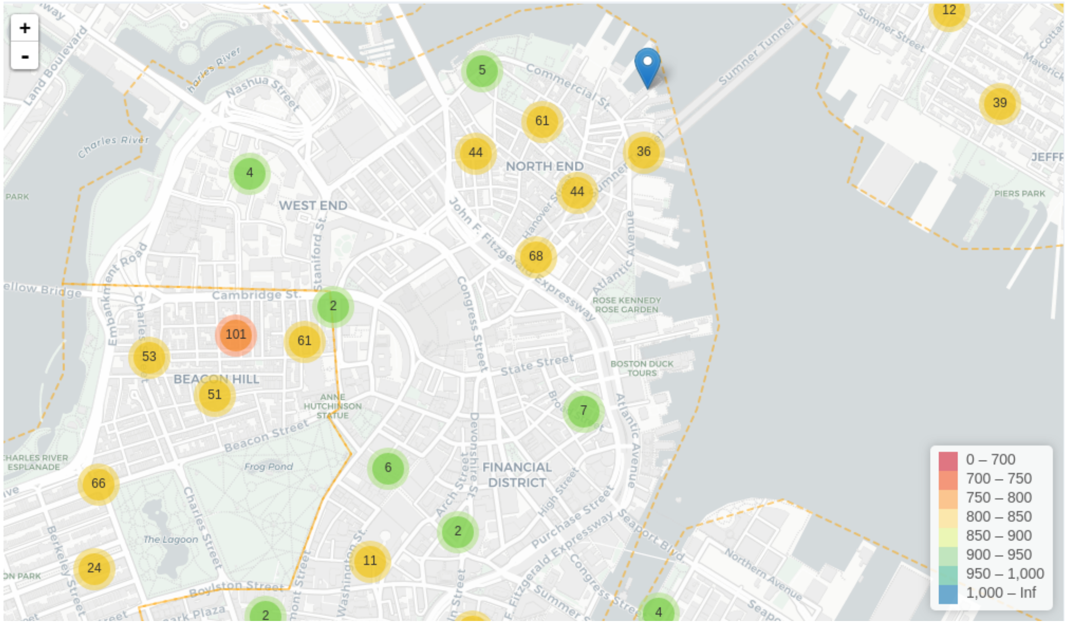


Figure 5: Labels for each Assessed Property

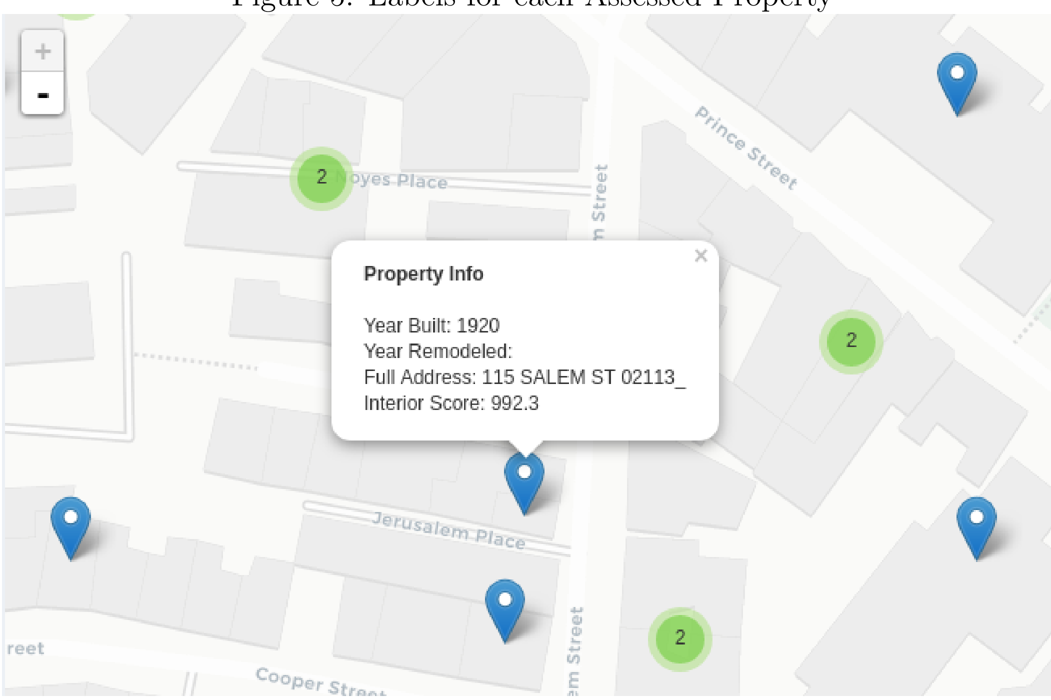
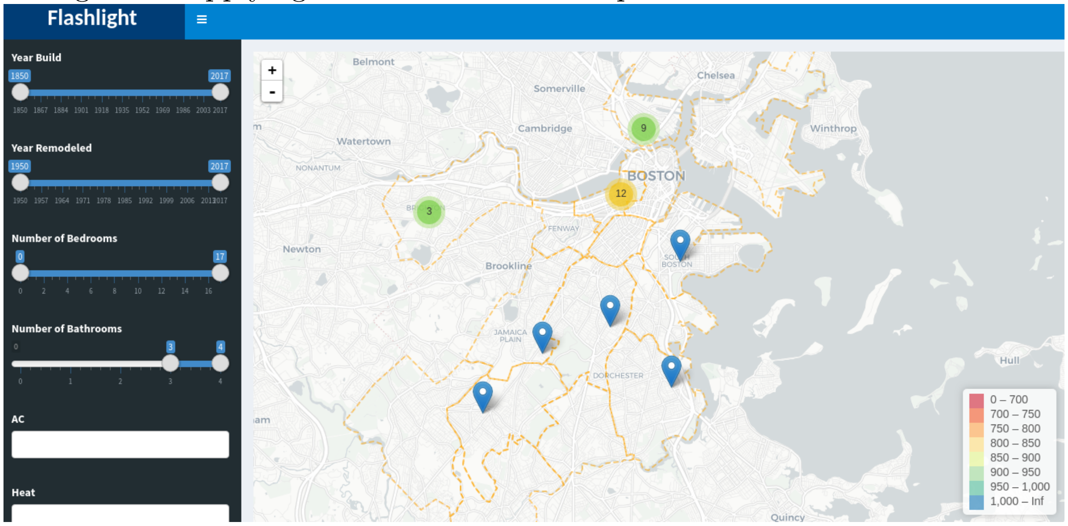


Figure 6: Applying a Filter to Find a Properties with >= 3 Bathrooms



[3] Zillow, "Zillow neighborhood boundaries." https://www.zillow.com/howto/api/neighborhood-boundaries.htm. (Accessed on 12/09/2017).

[4] Google, "Google maps geocoding api." https://developers.google.com/maps/documentation/geocoding (Accessed on 12/09/2017).

[5] Mapbox, "Leaflet - a javascript library for interactive maps." http://leafletjs.com/. (Accessed on 12/10/2017).

[6] RStudio, "Leaflet for r." https://rstudio.github.io/leaflet/. (Accessed on 12/10/2017).

[7] I. E. T. F. (IETF), "Rfc 7946 - the geojson format." https://tools.ietf.org/html/rfc7946, Aug 2016. (Accessed on 12/10/2017).

[8] RStudio, "Shiny dashboard." https://rstudio.github.io/shinydashboard/. (Accessed on 12/10/2017).