Predicting Home Values in Los Angeles' South Bay

Springboard | Milestone Report

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Business Problem:

Home prices in Los Angeles County remain consistently high, which can make purchasing a home difficult for those unfamiliar with the market, the neighborhoods, or the popular home features in those neighborhoods (i.e. number of bedrooms, time of year, proximity to the ocean, etc). Being able to better predict home prices would be a benefit to first-time home buyers, new home builders, or real estate agents. For example, for a first-time home buyer, the decision to put a bid on a home is a big one, and knowing early on whether or not a particular home is over-(or under-)valued would save time, money, and unnecessary stress. Additionally, this kind of information may be useful for a new home builder, as they assess the features that would be important to get the most value for their new build. In this project, I looked at a specific set of neighborhoods in the southwest corner of Los Angeles County, called the South Bay. The project looks at home sales in that area for an approximate 2-year period.

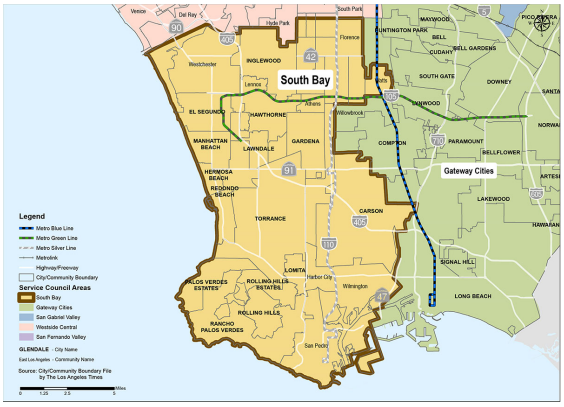


Image: South Bay Area; Source: Metro.net

Potential Client(s):

- *New Home Buyer/Investor:* For someone considering a home purchase, it would be useful to know whether or not a home is worth bidding on - i.e. if the home is undervalued in the market. Additionally, for an individual selling their home, it would be useful to know what might be a suitable asking price.
- *New Home Builders:* Being able to predict the price could help a new home builder determine what features may be important to add to a home to get the highest asking price for the area.
- *Real Estate Agents*: This information would help them to determine what a reasonable listing price could be for a client's home.

Data Collection and Wrangling:

The data was retrieved from Redfin.com. The site allows you to download sales, but limits downloads to 350 properties at a time. Files were downloaded manually from the site in groups of approximately 350 properties, and at 2 different points in time. The resulting .csv files were named according to neighborhood and filtered attributes (i.e. 3 bedroom properties in Redondo Beach).

The original dataset consisted of **19,527 rows and 29 columns in 84 separate files**, representing South Bay home sales for an approximate 2-year period.

Data was merged and cleaned in Python using pandas. The following cleaning steps were taken:

Merging Tables: The 84 files were imported as pandas data frames and merged using *pandas.concat()*. Since data was collected at two different times, the column "collection" was added (Collection 1: 51 csv files, and Collection 2: 33 csv files) to distinguish which date files were pulled from in case that information would be needed in the future. This column was eventually dropped once all data was merged and other cleaning steps were completed.

Dropping Columns: The following columns were dropped from the data frame, because they contained information not useful to solving the problem, the columns were empty, or because the information included was identical down the entire data frame: *'SALE TYPE', 'NEXT OPEN HOUSE START TIME', 'NEXT OPEN HOUSE END TIME', 'STATUS', 'FAVORITE', 'INTERESTED', 'URL', 'SOURCE', 'LOCATION', and 'STATE.'*

Deleting Duplicates: After inspecting the duplicated data, I determined that most were either due to a difference in the 'NEIGHBORHOOD' (a column I added based on the original file name of the downloads), or a difference in the number of days a house was on the market. I replaced the neighborhood columns in the duplicated rows with the city name, and used the max value for days on market when those were the cause of the duplicates.

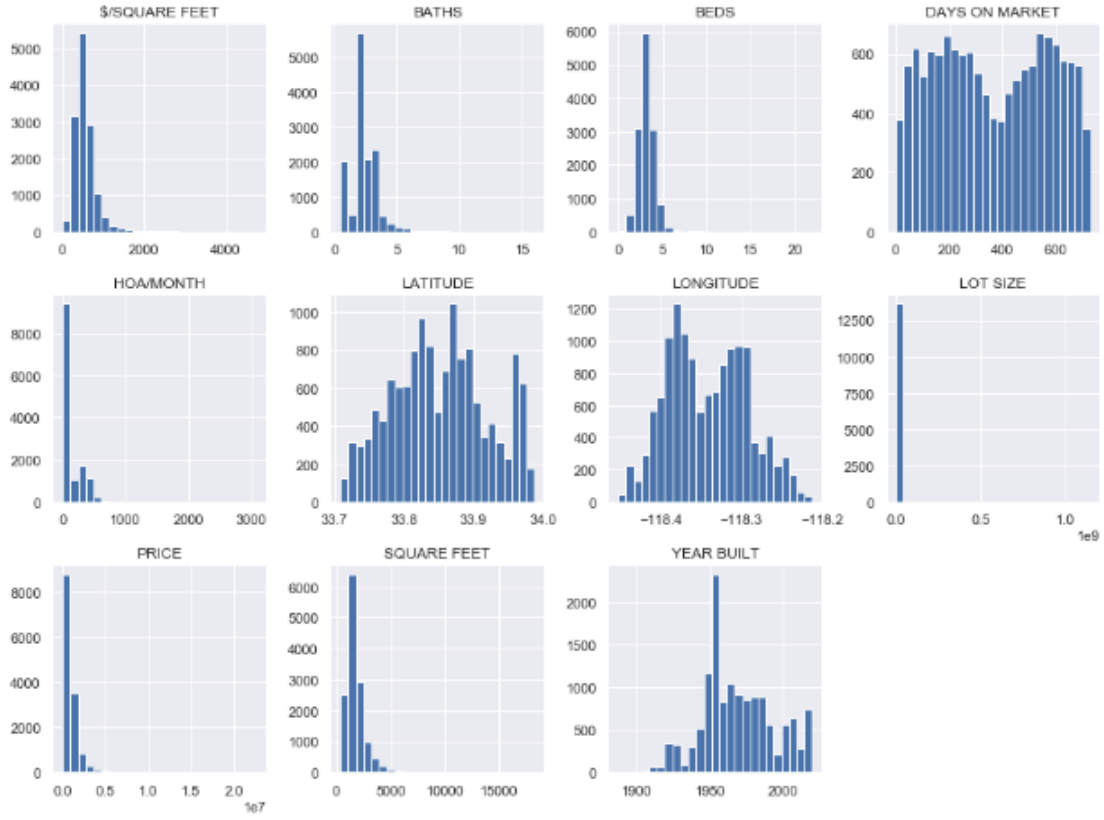
Missing/Incorrect Values:

- **SOLD DATE, PROPERTY TYPE:** I used the .dropna() method to remove properties with no sold date, and dropped all properties other than the following types: *Single Family Home, Townhouse, Condo/Co-op, Mobile/Manufactured Home.*
- **ADDRESS, CITY, ZIP/POSTAL CODES:** I manually looked up missing addresses, city, and zip/postal codes to verify information against other real estate sites and Google. I dropped any records I could not verify. Additionally, I updated any incorrect data, such as a property with a postal code outside of the CA range.
- **PRICE, HOA/MONTH:** I removed any rows in which the price was less than $10,000 (one was a property priced at $25). I filled empty HOA/MONTH values with 0, as having no HOA is not uncommon for some properties.
- **BEDS, BATHS:** I dropped rows with missing information on the number of bedrooms and/or bathrooms. I tried searching the information as well on Redfin and Zillow (another real estate site) to verify but could not find consistent information. I dropped 2 rows of single family homes with beds/baths higher than 10 that I could not verify between Redfin, Zillow, and the LA County Assessor's data.

- **LOCATION/NEIGHBORHOOD:** I dropped the original “Location” feature as the format of entries did not seem to be standardized. Instead, I created a column called “Neighborhood” based on the neighborhood I looked up on Redfin and the name of the created .csv file.
- **SQUARE FEET, LOT SIZE, $/SQUARE FEET:** I dropped 6 records (SFH & Townhomes) for which I could not verify the square feet information through another source. For Mobile Homes with no square feet information (56), I filled with the average square feet for other mobile homes in the area. Lot size was filled with the median size by property type. $/Square Feet was filled by calculating values from both the Price and Square Feet columns.
- **YEAR BUILT:** The earliest standing home built in Los Angeles was built around 1818. I looked for any properties sold before this date or after 2020 and dropped those records.

The final data frame consisted of **13,631 rows and 18 columns.**

It includes home sales data in South Bay neighborhoods between **February 06, 2018 and January 24, 2020**.



Bar Graphs of South Bay Home Sale Numeric Attributes

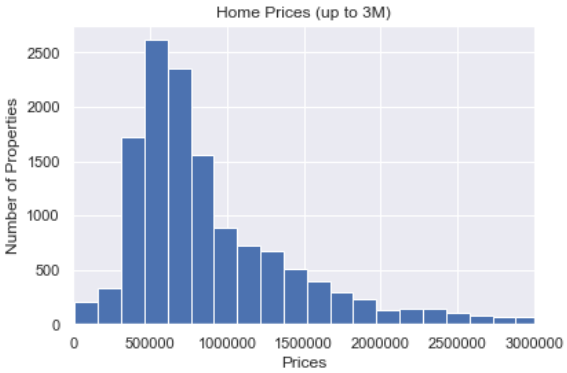
Initial Findings:

With the data cleaned, I turned my attention to looking further at some of the features of this dataset to see how the variables relate to each other, as well as how these variables relate to the price of a home.

Home Prices. To build a model to predict home prices, it would be good to have an understanding of the distribution prices in the area. I created visualizations for prices in a number of ways: overall, by property type, and by neighborhood. There is a large spread in home prices in the data, with a minimum price of $10,000, and the maximum at over $22 million, so I tend to display the median price.

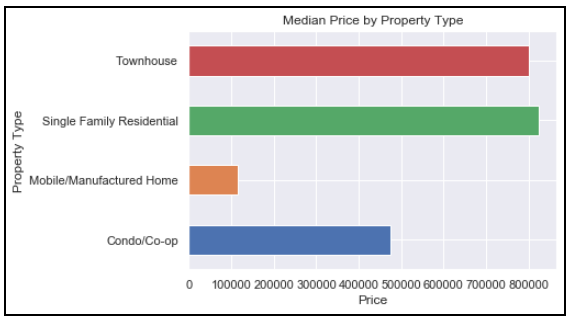
Overall. The histograms below look at the overall distribution of home prices. The histogram on the left displays the all data, while the one on the right zooms in to ignore outlier properties priced higher than $3 million. **It appears that the majority of properties are clustered between about $500,000 and $900,000,** and then begin to taper off around the $1 million mark.

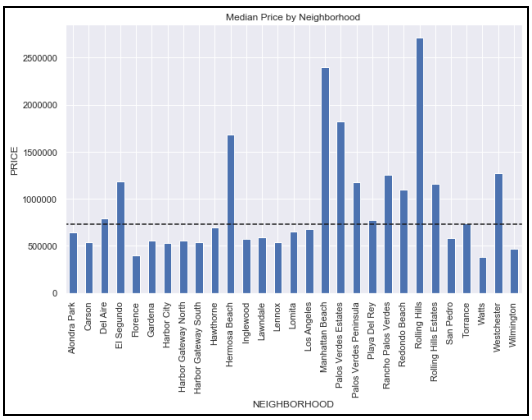
South Bay Home Prices: Overall Distribution



South Bay Home Prices: Capped at $3M

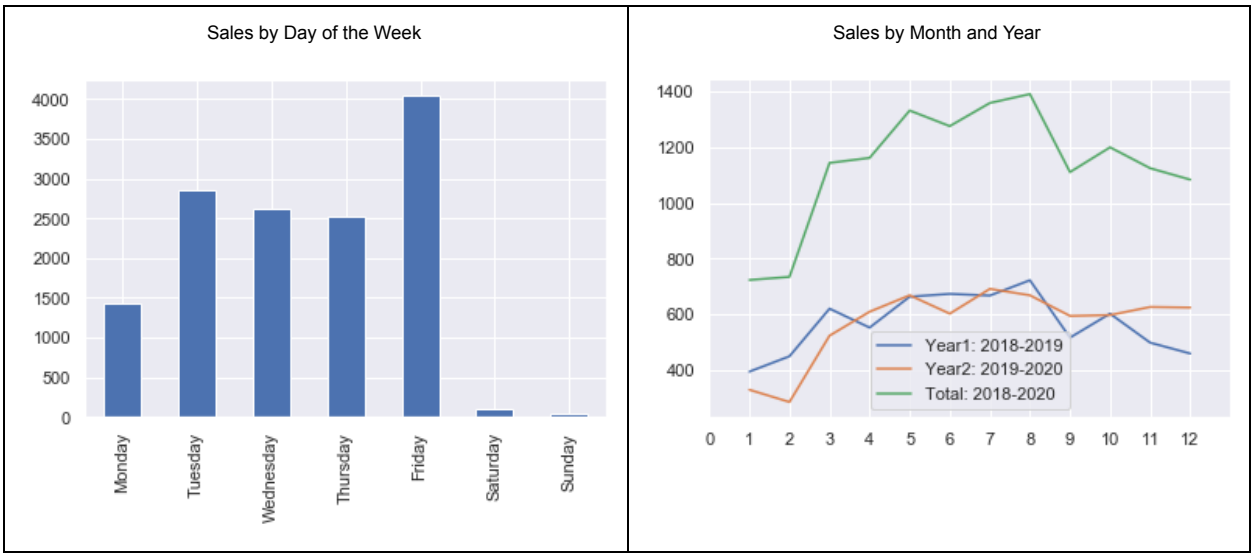
Property Type. When looking at median prices by home type, **single family homes and townhomes appear to have sold for a median price of about $800,000**, while the median price of a Condo/Co-op, or Mobile/Manufactured home is significantly less. This may be due to the difference in square feet between these home types, or some other factors. We may explore this further in the future.





Neighborhood. **Three neighborhoods appear to have the highest median home prices: Rolling Hills, Manhattan Beach, Palos Verdes Estates, and Hermosa Beach.** We may look further at what similarities exist between these three neighborhoods that affect home prices.

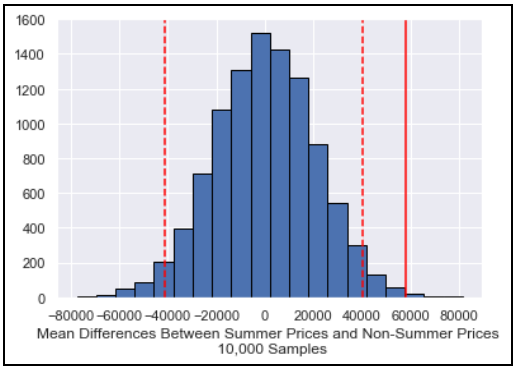
Timing of Home Sales. When are the most frequent time periods for home sales? Analyzing the data by the "SOLD DATE" column, I was able to group the data first by days of the week, and then by months of the year. **More homes were counted as "Sold" on Friday than any other day of the week**, though it is unclear what constitutes a home as being considered "Sold" (close date, contract date, etc.). Further, in looking at sales by month of the year**, it appears that overall, more homes were sold in the summer months in this data set.** Home sales were highest in July and August, and lowest in the months of January and February.



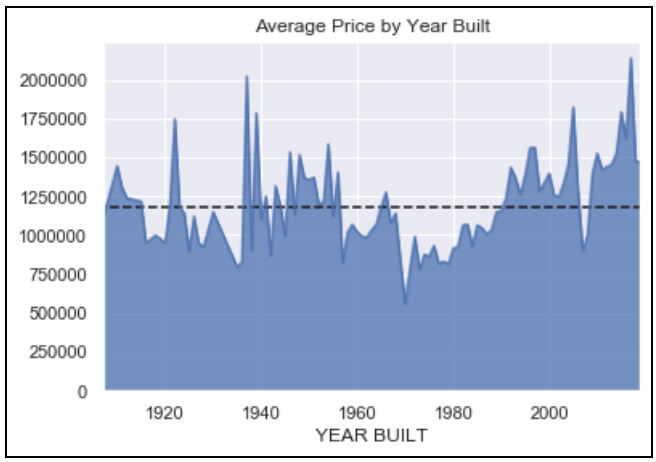
Summer vs. Non-Summer. Is there a "hot time" to buy a home? From initial data, it looked like the *number* of home sales in the summer months was greater than non-summer months. Could the increase in sales be due to a difference in price in the summer months vs. other months? I sought to answer the question: **Is there a difference in average home price for homes that sell in the summer vs. non-summer months?** I defined "summer" months as June, July, and August, and "non-summer" months as the other 9 months in the year. Then, I got values for the average price in each group, as well as the difference in means.

Mean Price, Summer: $1,034,713.47
Mean Price, Not Summer: $976,924.60
Difference in Mean Prices: $57,788.87

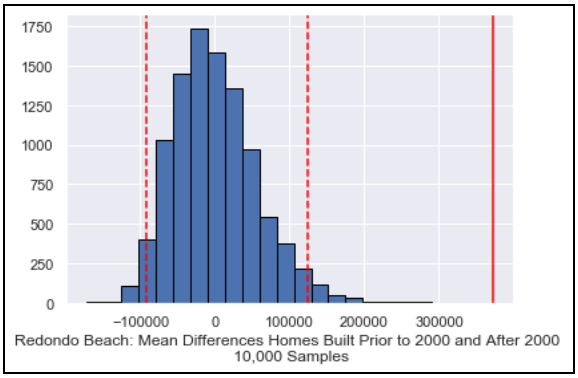
If the prices of the two groups were the same, we would expect the difference in mean to be closer to 0. We set the null hypothesis to be that there is no difference in the two groups, and chose a significance level of 0.05. I used Bootstrap Inference to simulate resampling our data, shifted the means of the groups so that the average prices were equal in both groups, and ran our experiment 10,000 times to see how likely it would be to get the mean difference observed above. **The p-value from this test was 0.0019, so we would reject the null hypothesis. There may, then, be a difference in price between summer and non-summer prices.**

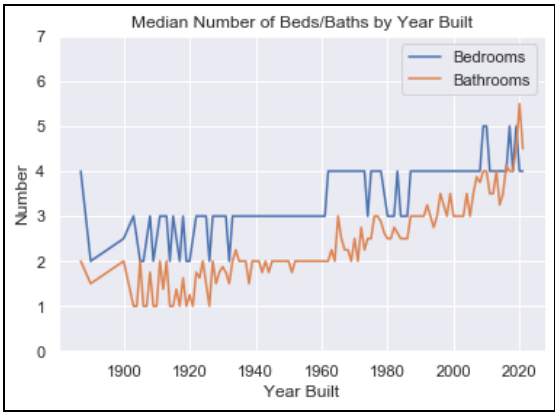


Newer vs. Older Homes. Are newer homes really all the rage? To control for the fluctuation in prices between neighborhoods, I chose one neighborhood to look at in more depth - Redondo Beach. I split the homes then into those that were built prior to 1970 and those built after 1970. I chose this year as it seemed that this was about when prices began to steadily increase.



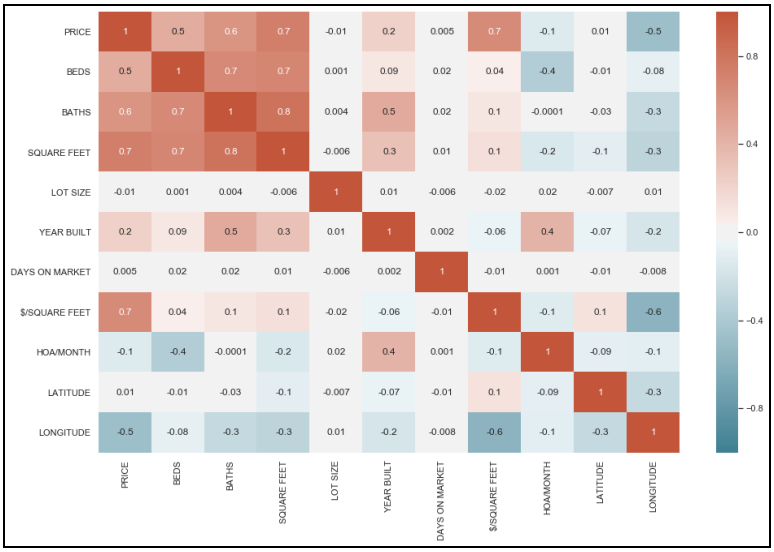
Again, I chose a Bootstrap test like the one above to compare the differences between these two groups. Running this test 10,000 times, **we ended up with a p-value of 0.0 for a significance level of 0.05. With this information, we would *reject* the null hypothesis that there is no difference in average price between homes built before 2000 and those built after in this particular neighborhood of Redondo Beach.**



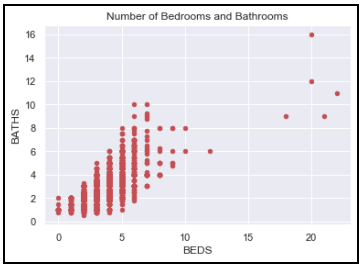


Bedrooms and Bathrooms. I also wanted to see whether or not features like bedrooms or bathrooms are increasing with the year the home is built. This was plotted looking at single family homes. The median number of bedrooms and bathrooms both seem to be increasing over time, although it appears that the number of bathrooms has more of an increasing trend (albeit a slight one).

Correlation Matrix. As we look further into the factors that affect price, let's look at a correlation matrix of all of the numerical features. We would expect that features like bedrooms, bathrooms, and square feet of a home are all positively correlated with price, and they indeed are. Also of note is the negative correlation between price and longitude. It may stand to reason that as homes get closer to the beach, the price increases. This is something we may look at further in the future.



As we saw earlier, the year a home is built is also slightly positively correlated with both the number of bedrooms and bathrooms. Looking at a scatter plot, we can also see that the number of bedrooms and bathrooms are positively correlated as we would expect - so the more bedrooms a home has, the more bathrooms it would also likely have.



Other Considerations & Future Discovery:

For both of the Bootstrap tests done above, there are other factors that could be at play to explain the difference in pricing data. For instance, the recession in 2008 could have helped to bring down the average prices in the group. It may make sense to look at homes built pre-recession and post recession, which may have yielded a different result.

Additionally, in our test of home prices vs sale date -- home prices tend to go up over time in general, so the difference could be due to prices simply rising over time. In future tests, we will need to control for some other factors.