Greater Seattle Property Sale Price

Final Project MSDS 430 Alisher Siddikov

(1) An introduction to your project explaining why the problem you chose is interesting or relevant to you. You should explain the problem in context and detail. In particular, you should explain any variables or formulas used in the problem.

- I am using King County (Greater Seattle) property sale price data and obtained from
- https://www.kaggle.com/harlfoxem/housesalesprediction. It has about 20 property features/details for 21613 residential property transactions between May 2014 and May 2015.
 I'm interested in knowing if the house sale price correlates to additional amenities such as the number of bedrooms, sq. ft. of living space, and other features.
- Here is the variable explanations:
 - o id Unique ID for each home sold
 - o date Date of the home sale
 - o price Price of each home sold
 - bedrooms Number of bedrooms
 - bathrooms Number of bathrooms, where .5 accounts for a room with a toilet but no shower
 - o sqft_living Square footage of the apartments interior living space
 - sqft lot Square footage of the land space
 - o floors Number of floors
 - waterfront A dummy variable for whether the apartment was overlooking the waterfront or not
 - o view An index from 0 to 4 of how good the view of the property was
 - o condition An index from 1 to 5 on the condition of the apartment,
 - grade An index from 1 to 13, where 1-3 falls short of building construction and design,
 7 has an average level of construction and design, and 11-13 have a high quality level of construction and design.
 - o sqft above The square footage of the interior housing space that is above ground level
 - sqft_basement The square footage of the interior housing space that is below ground level
 - yr_built The year the house was initially built
 - yr_renovated The year of the house's last renovation
 - zipcode What zipcode area the house is in
 - o lat Lattitude
 - o long Longitude
 - sqft_living15 The square footage of interior housing living space for the nearest 15 neighbors
 - sqft_lot15 The square footage of the land lots of the nearest 15 neighbors
- Since there are a lot of features, I was able to down select property features from 21 to 9 (reduced columns by 57%) and able to remove outliers (reduced rows by 5%). I have the following variables:

- date
- price
- o bedrooms
- bathrooms
- sqft_living
- waterfront
- o view
- o geo indicators: latitude and longitude
- Here is the conclusion of my analysis:

According to the linear regression model, the property sale price is changed by additional amenities such as the number of bedrooms, bathrooms, living space, waterfront, and views: Formula/Charts: Linear Regression Model

- Each one-unit increase in bedrooms causes a decrease of \$25,490 in the price.
- Each one-unit increase in bathrooms causes an increase of \$12,946 in the price.
- Each waterfront property causes an increase of \$52,312 in its price.
- Each one-unit increase in the view of a property causes an increase of \$43,819 in its price.
- Each square-footage increase in the area causes an increase of \$174 in the price.

Price:

Formula/Charts: pairplot, displot, histogram, mean, median, skewness, kurtosis

- Most expensive property was sold at a price of \$7.7M million
- Around 2014 and 2015 at King County (greater Seattle Area), the most frequently sold properties were at price range of \$300k and \$400k.
- After \$400k price, the property availability decreases for each \$100k price increase.

Waterfront:

Formula/Charts: stripplot, violinplot, boxplot

- Waterfront properties are more expensive. However, fewer waterfront properties are sold.
- Most common non-waterfront property price is between \$250k and \$450k.

View:

Formula/Charts: stripplot, violinplot, boxplot

- The highest view score which is 4 had waterfront properties.
- However, view 4 is more expensive than waterfront properties.

Bedrooms:

Formula/Charts: plot hist, plot bar, violin plot

- As we can see that 3-bedroom houses were most commonly sold followed by 4 bedrooms.
- Builders can make a new building with more 3 and 4 bedroom's to attract more buyers.
- So now we know that 3 and 4 bedrooms were the highest selling.
- Most of the bedrooms were sold between the price range of \$200k and \$600k.

Bathrooms:

Formula/Charts: plot hist, plot bar, violin plot

- As we can see that 2.5-bathroom houses are most commonly sold followed by 1 bathroom.
- Builders can make a new building with more 2.5 and 1 bathrooms to attract more buyers.
- So now we know that 2.5 and 1 bathrooms are the highest selling.

Living Area:

Formula/Charts: jointplot

- Around 2014 and 2015 at King County (greater Seattle Area), the most frequently sold properties were at living space range of 1500 sqft and 2000 sqft.
- After 2000 sqft, the property availability decreases for each additional 500 sqft increase.
- It makes sense that people would pay for the more living area.
- Most common living area is between 1000 and 2500 sq. ft.
- Most common price range is between \$250k and \$500k.
- As we can see that 2.5-bathroom houses are most commonly sold followed by 1 bathroom.

Time:

Formula/Charts: datetime, pivot_table, plot bar

• The slowest months are during fall and winter seasons. April, June, and July months are the busiest times.

Location:

Formula/Charts: jointplot, folium.Map, Implot

- We can find out ideal locations and here are the denser locations where most of properties are sold.
- There are many properties sold at these latitudes: around 47.7 and between 47.6 and 47.5
- Also, there are many properties sold at these longitudes: between -122.4 to -122.2
- Most of the properties were sold in West Seattle, North Seattle, and close to the waterfront.
- The most expensive neighborhoods were North Seattle, University of Washington, Mercer Island, Medina, Bellevue, Redmond, and properties along the waterfront area.
- Least expensive neighborhoods were South Seattle, further North Seattle, and the properties away from water.

(2) A very brief description of your algorithmic process (your approach) for solving the problem. Your code, of course, should implement this algorithm (thought process).

• I was able to use feature extraction and percentile to extract important features of the dataset and now I have the following features date, price of sold property, number of bedrooms and

bathrooms, square footage of living area, waterfront properties, views, and geographic indicators (latitude and longitude).

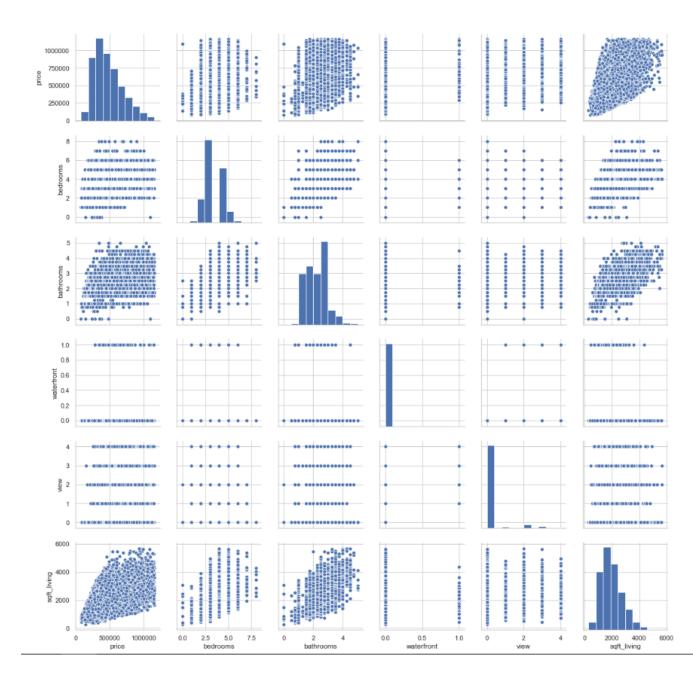
- I was also able to remove extreme outlier values
- After I prepared the data for analysis, I started with correlation analysis and histograms to understand the dataset better. I used the following packages:
 - Seaborn
 - sns.pairplot(house_df4_analysis, kind="scatter")
 - sns.distplot(house_df['price'])
 - sns.violinplot(x='view', y='price', hue = 'waterfront', data = house_df4, scale = 'c ount', split = True)
 - sns.jointplot(x=house_df4['sqft_living'], y=house_df4['price'], kind='reg')
 - sns.lmplot(x='long', y='lat', hue='price_range', data=house_df4, fit_reg=False, he ight=10)
 - Pandas
 - pd.read csv('kc house data.csv')
 - pd.qcut(house_df4.price, 5, labels=["min", "25%", "50%", "75%", "max"])
 - pd.to_datetime(house_df4.date, format='%Y%m%d', errors='ignore')
 - pd.DataFrame(reg.coef_, X.columns, columns=['Coefficient'])
 - NumPy
 - np.round(house_df_analysis.describe())
 - np.percentile(house_df.price, 95)]
 - np.mean(house df.price)
 - np.median(house_df.price)
 - Matplotlib
 - plt.subplots(figsize=(12, 8))
 - plt.xlabel('price without outliers', fontsize = 15)
 - plt.show()
- I also run linear regression model to understand price and property feature correlation relationship
 - o reg = LinearRegression()
 - reg.fit(X, y)
 - pd.DataFrame(reg.coef_, X.columns, columns=['Coefficient'])
- I used bar plot, hist plot, joint plots, boxplot, strip plot, violin plot, and Im plot for further analysis.

(3) Any relevant results such as tables, graphs, etc. along with their purpose and description.

• Statistical description of data (outliers has not yet removed at this stage).

	price	bedrooms	bathrooms	waterfront	view	sqft_living
count	21613.0	21613.0	21613.00	21613.0	21613.0	21613.0
mean	540182.0	3.0	2.00	0.0	0.0	2080.0
std	367362.0	1.0	1.00	0.0	1.0	918.0
min	75000.0	0.0	0.00	0.0	0.0	290.0
25%	321950.0	3.0	2.00	0.0	0.0	1427.0
50%	450000.0	3.0	2.00	0.0	0.0	1910.0
75%	645000.0	4.0	2.00	0.0	0.0	2550.0
max	7700000.0	33.0	8.00	1.0	4.0	13540.0
median	450000.0	3.0	2.25	0.0	0.0	1910.0

• Correlation and histogram analysis



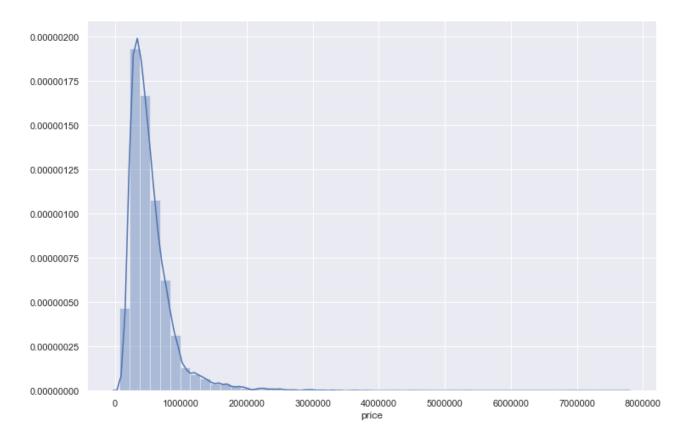
Linear Regression Analysis

bedrooms -25490.210923 bathrooms 12945.978668 waterfront 52312.229508 view 43819.312150 sqft_living 174.350976

- Each one-unit increase in bedrooms causes a decrease of \$25,490 in the price.
- Each one-unit increase in bathrooms causes an increase of \$12,946 in the price.
- Each waterfront property causes an increase of \$52,312 in its price.
- Each one-unit increase in the view of a property causes an increase of \$43,819 in its price.
- · Each square-footage increase in area causes an increase of \$174 in the price.

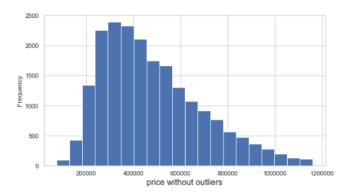
Price chart with outliers

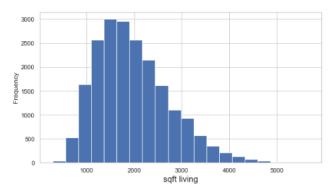
Skewness of price: 4.021716 Kurtosis of price: 34.522444 Average price paid = \$ 540182 Median price paid = \$ 450000



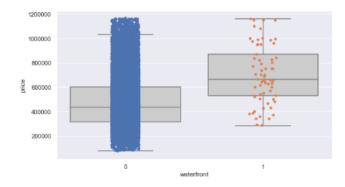
• Price chart with outliers

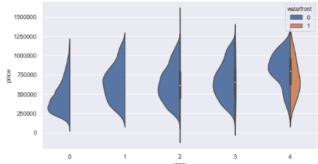
Skewness of price: 0.793138 Kurtosis of price: 0.129848 Average price paid = \$ 479105 Median price paid = \$ 438400



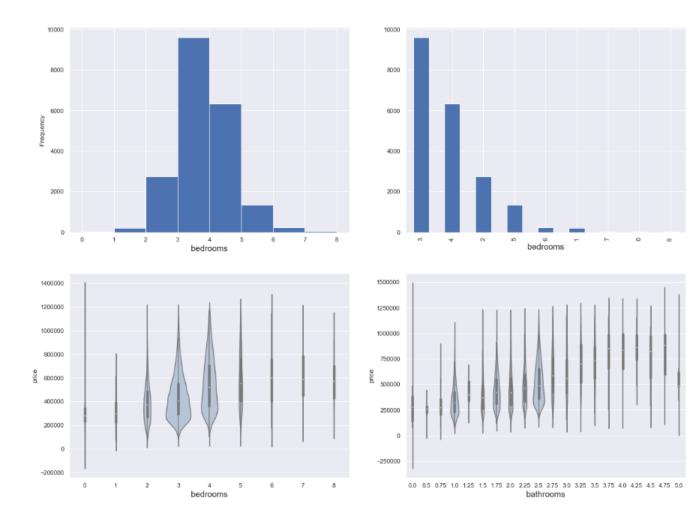


Price vs. Waterfront & View

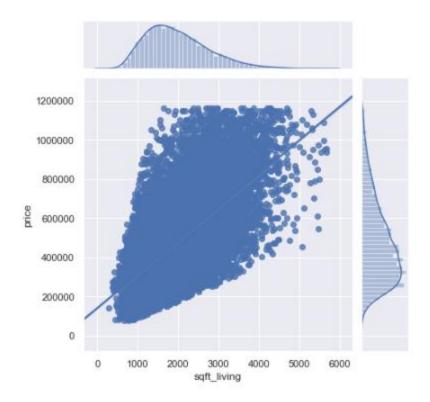




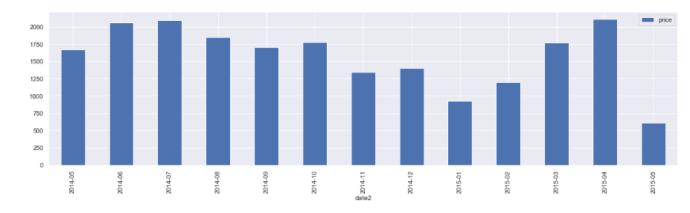
• Price vs. Bedrooms & Bathrooms



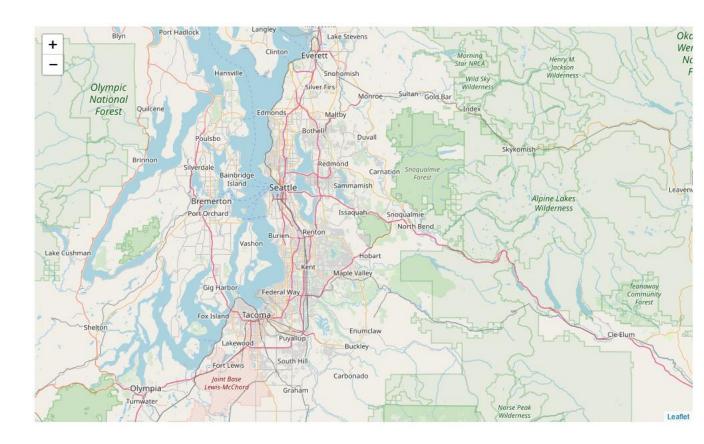
Price vs. Living Room

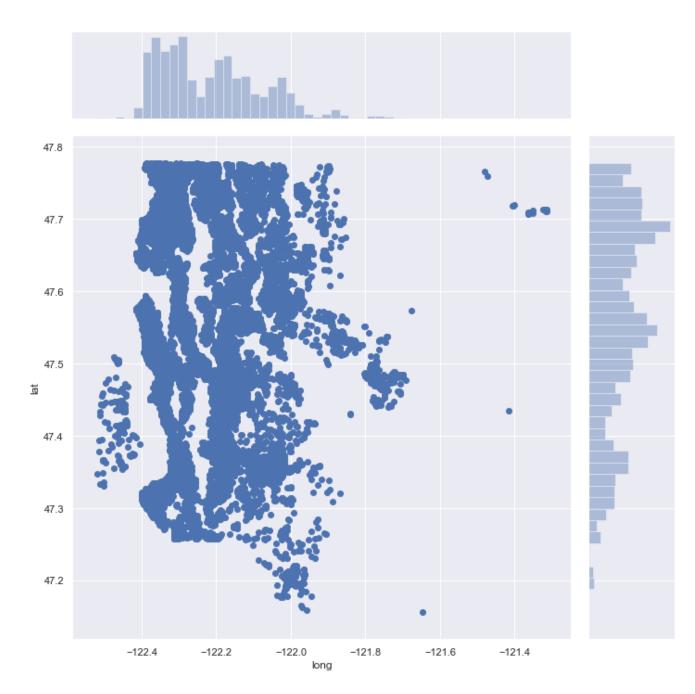


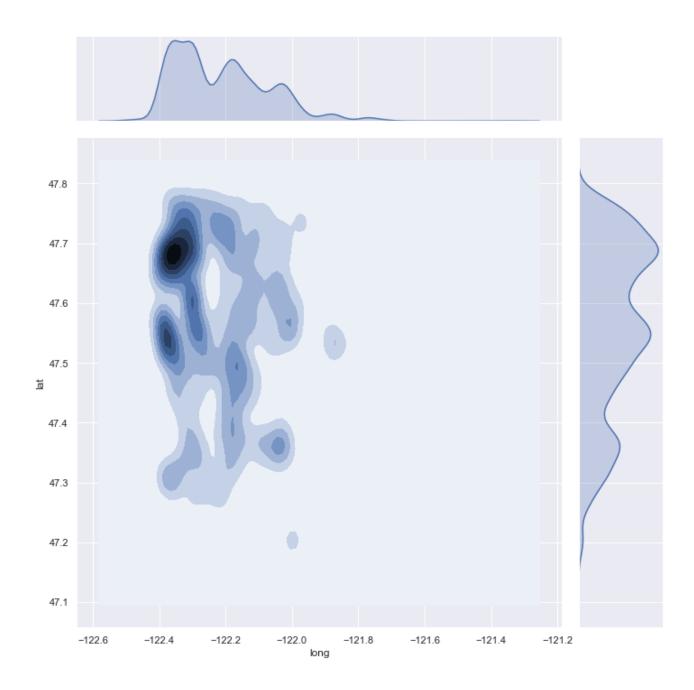
• Price vs. Date



Price vs. Location (density)







• Price vs. Location (Heatmap)

