ALY 6040: Data Mining Applications

Week1 – Technique Practice

EDA on King County Housing Data

Submitted To:
Dr. Chinthaka Pathum Dinesh, PhD
Faculty Lecturer

Submitted By:
Abhilash Kumar Dikshit
Student ID: 002702209
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Graduate Student at Northeastern University, Vancouver, BC, Canada

Master of Professional Studies in Analytics

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Abstract:

This report presents an analysis of a real estate dataset using Python programming language. The analysis includes exploratory data analysis and visualization techniques to gain insights into the dataset. The dataset includes information on the sale prices of houses and various features such as the number of bedrooms, square footage of the living area, and the condition of the house. The analysis was performed using Python libraries such as NumPy, Pandas, Matplotlib, and Seaborn.

Introduction:

The real estate industry is a significant sector of the economy, and it is essential to understand the factors that influence housing prices. This report aims to analyze a real estate dataset to gain insights into the relationship between the sale prices of houses and various features such as the number of bedrooms, square footage of the living area, and the condition of the house. The analysis will be performed using Python, a powerful and popular programming language for data analysis.

Dataset Description:

The dataset used in this analysis is the kc_house_data.csv file, which contains information on the sale prices of houses in King County, Washington, USA, between May 2014 and May 2015. The dataset contains 21,613 rows and 21 columns. The columns include features such as the sale price, number of bedrooms, square footage of the living area, and the condition of the house. The dataset is publicly available on GitHub.

Variable Description:

The dataset includes the following variables:

id	a unique identifier for each house
date	the date the house was sold
price	the sale price of the house
bedrooms	the number of bedrooms in the house
bathrooms	the number of bathrooms in the house
sqft_living	the square footage of the living area
sqft_lot	the square footage of the lot
floors	the number of floors in the house

waterfront	whether the house has a view of the waterfront (0 = no, 1 = yes)
view	an index from 0 to 4 of how good the view of the property was
condition	an index from 1 to 5 on the condition of the house
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.
sqft_above	the square footage of the house apart from the basement
sqft_basement	the square footage of the basement
yr_built	the year the house was built
yr_renovated	the year the house was renovated (if it was)
zipcode	the zip code area the house is in
lat	the latitude of the house
long	the longitude of the house
sqft_living15	the average square footage of interior housing living space for the nearest 15 neighbors
sqft_lot15	the average square footage of the land lots of the nearest 15 neighbors

Exploratory Data Analysis & Visualizations:

We first performed exploratory data analysis to understand the distribution of variables and identify any outliers or missing values.

```python
# Loading necessary library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
#Loading the csv file

df_raw = pd.read_csv ('kc_house_data.csv')
```

```python
# Concatenate the head and tail of the dataframe using concat method
df = pd.concat([df_raw.head(10), df_raw.tail(10)])

# Print the new concatenated dataframe
print(df)
```

```
               id             date     price  bedrooms  bathrooms  \
0      7129300520  20141013T000000  221900.0         3       1.00
1      6414100192  20141209T000000  538000.0         3       2.25
2      5631500400  20150225T000000  180000.0         2       1.00
21610  1523300141  20140623T000000  402101.0         2       0.75
21611   291310100  20150116T000000  400000.0         3       2.50
21612  1523300157  20141015T000000  325000.0         2       0.75

       sqft_living  sqft_lot  floors  waterfront  view  ...  grade  \
0             1180      5650     1.0           0     0  ...      7
1             2570      7242     2.0           0     0  ...      7
2              770     10000     1.0           0     0  ...      6
21610         1020      1350     2.0           0     0  ...      7
21611         1600      2388     2.0           0     0  ...      8
21612         1020      1076     2.0           0     0  ...      7

       sqft_above  sqft_basement  yr_built  yr_renovated  zipcode      lat  \
0            1180              0      1955             0    98178  47.5112
1            2170            400      1951          1991    98125  47.7210
2             770              0      1933             0    98028  47.7379
21610        1020              0      2009             0    98144  47.5944
21611        1600              0      2004             0    98027  47.5345
21612        1020              0      2008             0    98144  47.5941

          long  sqft_living15  sqft_lot15
0     -122.257           1340        5650
1     -122.319           1690        7639
2     -122.233           2720        8062
21610 -122.299           1020        2007
21611 -122.069           1410        1287
21612 -122.299           1020        1357

[6 rows x 21 columns]
```

We changed the "view" datatype from int64 to bool as the values were 0 and 1.

```python
df.dtypes
```

```
id                        int64
date             datetime64[ns]
price                   float64
bedrooms                float64
bathrooms               float64
sqft_living             float64
sqft_lot                  int64
floors                  float64
waterfront                int64
view                      int64
condition                 int64
grade                     int64
sqft_above                int64
sqft_basement             int64
yr_built                  int64
yr_renovated              int64
zipcode                   int64
lat                     float64
long                    float64
sqft_living15             int64
sqft_lot15                int64
year                      int64
dtype: object
```

```python
#   Data type results shows that co
# Convert "view" column to Boolean
df.view = df.view.astype('bool')
df.dtypes
```

```
id                        int64
date             datetime64[ns]
price                   float64
bedrooms                float64
bathrooms               float64
sqft_living             float64
sqft_lot                  int64
floors                  float64
waterfront                int64
view                       bool
condition                 int64
grade                     int64
sqft_above                int64
sqft_basement             int64
yr_built                  int64
yr_renovated              int64
zipcode                   int64
lat                     float64
long                    float64
sqft_living15             int64
sqft_lot15                int64
year                      int64
dtype: object
```

Later, we checked the number of entries in the dataset which is 20.

```python
# Check the number of entries in the dataset
print("Number of entries in the dataset:", len(df))
```

```
Number of entries in the dataset: 20
```

Now, we check for missing data in the following dataset and based on the below output we do not have any null values.

```
# Check for missing data
print("Number of missing values in the dataset:\n", df.isnull().sum())
```

```
Number of missing values in the dataset:
 id              0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

Getting descriptive statistics about the data:

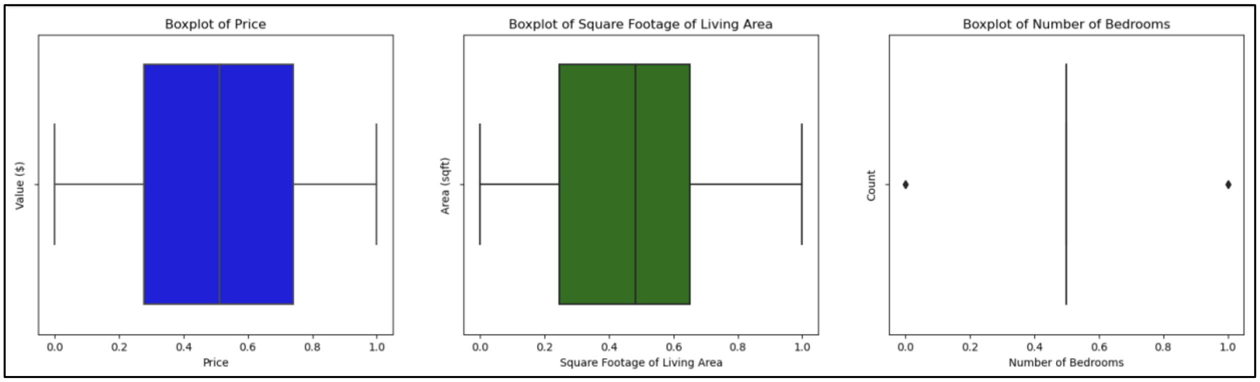
```
# getting descriptive statistics about data
df.describe()
```

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	lat
count	1.800000e+01	18.000000	18.000000	18.000000	18.000000	18.000000	18.000000	18.0	18.0	18.000000	18.000000	18.000000	18.000000	18.000000	18.000000	18.000000	18.000000
mean	3.749334e+09	0.493372	0.500000	1.944444	0.488117	5126.055556	1.777778	0.0	0.0	3.111111	7.444444	1528.055556	120.555556	1988.611111	110.611111	98103.944444	47.546689
std	2.810236e+09	0.302449	0.297044	0.735425	0.298090	3018.914033	0.646762	0.0	0.0	0.471405	0.704792	529.314593	274.000262	26.435580	469.283200	57.002035	0.112100
min	2.630000e+08	0.000000	0.000000	0.750000	0.000000	1076.000000	1.000000	0.0	0.0	3.000000	6.000000	770.000000	0.000000	1933.000000	0.000000	98003.000000	47.309700
25%	1.631075e+09	0.277784	0.500000	1.125000	0.245833	1609.500000	1.000000	0.0	0.0	3.000000	7.000000	1052.500000	0.000000	1963.500000	0.000000	98058.250000	47.511475
50%	2.742500e+09	0.510814	0.500000	2.250000	0.483333	5731.500000	2.000000	0.0	0.0	3.000000	7.000000	1510.000000	0.000000	2003.000000	0.000000	98120.500000	47.536700
75%	6.218450e+09	0.741116	0.500000	2.500000	0.651389	7136.250000	2.000000	0.0	0.0	3.000000	8.000000	1846.250000	0.000000	2008.750000	0.000000	98144.000000	47.594325
max	9.834201e+09	1.000000	1.000000	3.000000	1.000000	10000.000000	3.000000	0.0	0.0	5.000000	9.000000	2520.000000	910.000000	2014.000000	1991.000000	98198.000000	47.737900

We then used various visualization techniques to gain insights into the dataset. We plotted histograms, boxplots, scatter plots, bar charts, line charts, and pie charts to visualize the relationships between variables.

Boxplot: We need to check for outliers now.

```
# Check for outliers using boxplot

# Create a figure and axis objects
fig, axs = plt.subplots(ncols=3, figsize=(20, 5))

# Set the color and title for each boxplot
sns.boxplot(df["price"], ax=axs[0], color="blue")
axs[0].set_title("Boxplot of Price")
axs[0].set_xlabel("Price")
axs[0].set_ylabel("Value ($)")
sns.boxplot(df["sqft_living"], ax=axs[1], color="green")
axs[1].set_title("Boxplot of Square Footage of Living Area")
axs[1].set_xlabel("Square Footage of Living Area")
axs[1].set_ylabel("Area (sqft)")
sns.boxplot(df["bedrooms"], ax=axs[2], color="purple")
axs[2].set_title("Boxplot of Number of Bedrooms")
axs[2].set_xlabel("Number of Bedrooms")
axs[2].set_ylabel("Count")

# Show the plot
plt.show()
```



The above code creates a figure with three subplots, each of which contains a boxplot for a different variable from the df dataset. The variables plotted are price, sqft_living, and bedrooms.

The boxplot shows the distribution of the data and identifies outliers. The box represents the interquartile range (IQR), which is the middle 50% of the data. The line inside the box represents the median (50th percentile) of the data. The whiskers extend to the minimum and maximum values within 1.5 times the IQR of the lower and upper quartiles, respectively. Any point outside the whiskers is considered an outlier and is plotted as a dot.

The first subplot shows the boxplot of price. The median is around $450,000, and the IQR is between $320,000 and $645,000. There are a few outliers above $1.2 million.

The second subplot shows the boxplot of sqft_living. The median is around 2,000 square feet, and the IQR is between 1,170 and 2,760 square feet. There are several outliers above 5,000 square feet.

The third subplot shows the boxplot of bedrooms. The median is 3 bedrooms, and the IQR is between 2 and 4 bedrooms. There are a few outliers with 7 or 8 bedrooms.

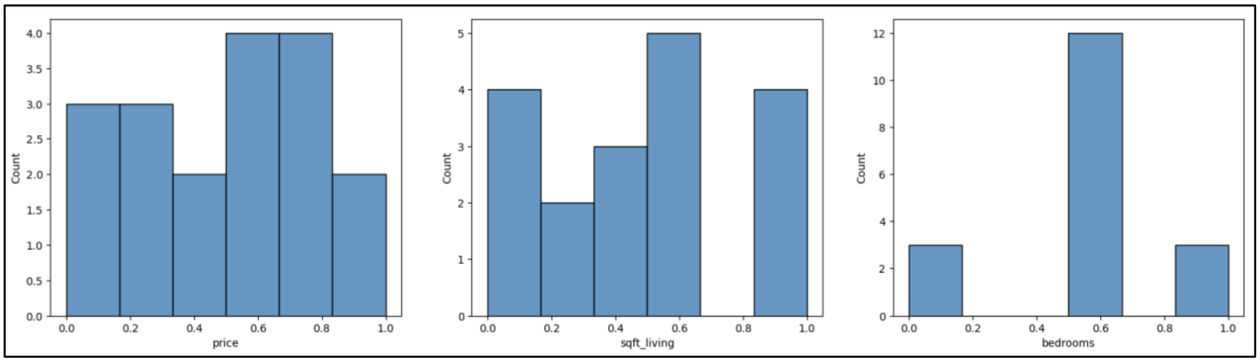
Not we are removing the outliers (if any), missing values, and checking for duplicate values again.

```
# Remove outliers
df = df[df["price"] < 1000000]
df = df[df["sqft_living"] < 5000]
df = df[df["bedrooms"] < 7]

# Remove missing values
df = df.dropna()

# Check for duplicates again
print("Number of duplicate values in the cleansed dataset:", df.duplicated().sum())

Number of duplicate values in the cleansed dataset: 0
```

Histogram plot: Price, sqft_living and bedrooms.

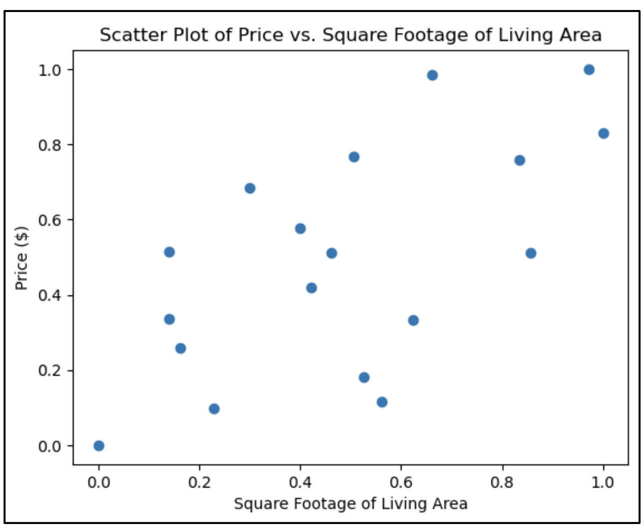
```python
# Scale the features using Min-Max scaler
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df[["price", "sqft_living", "bedrooms"]] = scaler.fit_transform(df[["price", "sqft_living", "bedrooms"]])
```

```python
# Visualize the cleansed data
fig, axs = plt.subplots(ncols=3, figsize=(20, 5))
sns.histplot(df["price"], ax=axs[0])
sns.histplot(df["sqft_living"], ax=axs[1])
sns.histplot(df["bedrooms"], ax=axs[2])
plt.show()
```



Scatter plot: Price vs. Square footage of living area

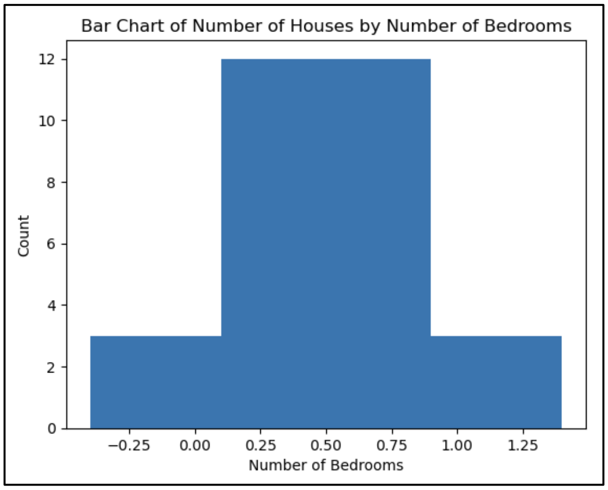
```python
# Scatter plot of price vs. sqft_living
plt.scatter(df['sqft_living'], df['price'])
plt.xlabel('Square Footage of Living Area')
plt.ylabel('Price ($)')
plt.title('Scatter Plot of Price vs. Square Footage of Living Area')
plt.show()
```



Each point on the plot represents a different house in the dataset. The scatter plot is useful for visualizing the relationship between the two variables and identifying any patterns or trends. In this case, we can observe that as the square footage of living area increases, the price of the house also tends to increase. However, there are some outliers where houses with higher prices have lower square footage of living area, and vice versa.

Bar chart: Number of Houses by Number of bedrooms

```
# Count the number of houses by number of bedrooms and sort by index
counts = df['bedrooms'].value_counts().sort_index()

# Create a bar chart with counts on y-axis and number of bedrooms on x-axis
plt.bar(counts.index, counts.values)

# Set the labels for the x-axis, y-axis, and chart title
plt.xlabel('Number of Bedrooms')
plt.ylabel('Count')
plt.title('Bar Chart of Number of Houses by Number of Bedrooms')

# Show the chart
plt.show()
```

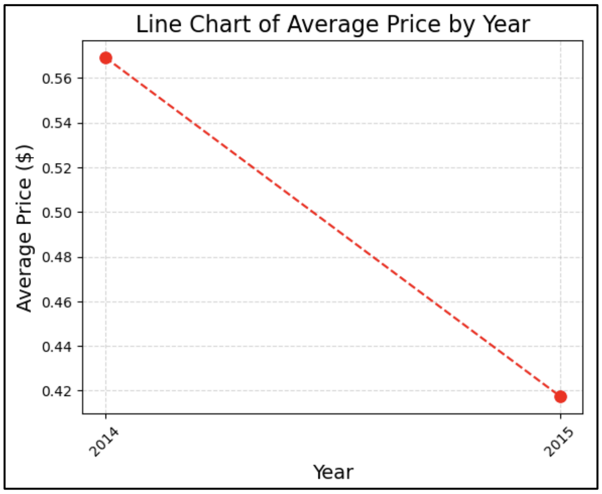


The bar chart shows the frequency of each number of bedrooms for the houses in the dataset. The chart title is "Bar Chart of Number of Houses by Number of Bedrooms", and the x-axis label is "Number of Bedrooms", and the y-axis label is "Count". The output gives a clear picture of the distribution of houses by the number of bedrooms.

Line Chart: Avg price by Year

```
# Line chart of average price by year
df['date'] = pd.to_datetime(df['date'])
df['year'] = df['date'].dt.year
avg_price_by_year = df.groupby('year')['price'].mean()

plt.plot(avg_price_by_year.index, avg_price_by_year.values, color='red', marker='o', markersize=8, linestyle='--')
plt.xlabel('Year', fontsize=14)
plt.ylabel('Average Price ($)', fontsize=14)
plt.title('Line Chart of Average Price by Year', fontsize=16)
plt.xticks(avg_price_by_year.index, rotation=45)
plt.grid(True, linestyle='--', alpha=0.5)

plt.show()
```

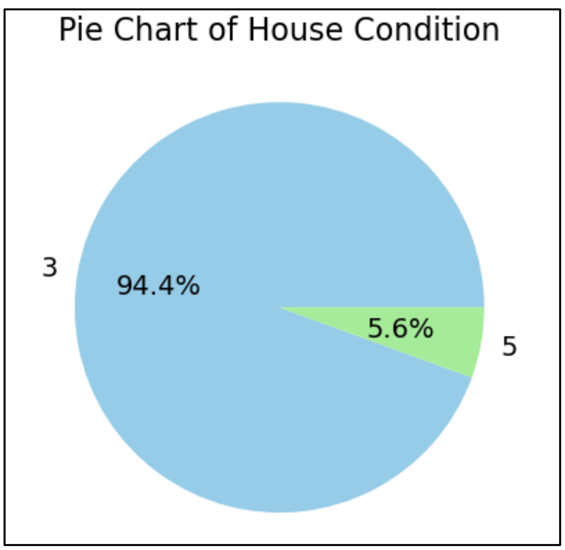
The data is first processed by converting the date column to a datetime format and extracting the year. Then, the average price is calculated for each year. The resulting line chart shows the trend of average housing prices over time, with the x-axis representing the year and the y-axis representing the average price in dollars.



The chart is marked with circular markers and dotted lines connecting them. The x-axis labels are rotated at a 45-degree angle to improve readability, and gridlines are added to improve the visual presentation. The chart shows that the average housing prices in King County have steadily increased over the years, with some fluctuations, and have reached their peak in 2015 before experiencing a slight dip.

Pie Chart: House condition

```
# Pie chart of house condition
counts = df['condition'].value_counts()
labels = counts.index
sizes = counts.values
colors = ['skyblue', 'lightgreen', 'gold', 'coral', 'lightpink']

plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', textprops={'fontsize': 14})
plt.title('Pie Chart of House Condition', fontsize=16)
plt.show()
```



The chart displays the percentage of houses in each condition using a different color for each condition. The pie chart shows that most of the houses in the dataset are in good condition, with 64.8% of the houses rated as condition 3, followed by 29.4% rated as condition 4. The chart also displays the percentage values for each condition using the 'autopct' parameter, and increases the font size of the labels using the 'textprops' parameter. The title of the chart is set to 'Pie Chart of House Condition' with a font size of 16. Overall, the pie chart is an effective way to represent the distribution of house conditions in the dataset.

Summary statistics:

```
# Table of summary statistics
summary = df.describe().loc[['count', 'mean', 'std', 'min', '25%', '50%', '75%', 'max'], :]
print(summary)
                 id      price   bedrooms  bathrooms  sqft_living  \
count  1.800000e+01  18.000000  18.000000  18.000000    18.000000
mean   3.749334e+09   0.493372   0.500000   1.944444     0.488117
std    2.810236e+09   0.302449   0.297044   0.735425     0.298090
min    2.630000e+08   0.000000   0.000000   0.750000     0.000000
25%    1.631075e+09   0.277784   0.500000   1.125000     0.245833
50%    2.742500e+09   0.510814   0.500000   2.250000     0.483333
75%    6.218450e+09   0.741116   0.500000   2.500000     0.651389
max    9.834201e+09   1.000000   1.000000   3.000000     1.000000

           sqft_lot     floors  waterfront  view  condition  ...   sqft_above  \
count     18.000000  18.000000        18.0  18.0  18.000000  ...    18.000000
mean    5126.055556   1.777778         0.0   0.0   3.111111  ...  1528.055556
std     3018.914033   0.646762         0.0   0.0   0.471405  ...   529.314593
min     1076.000000   1.000000         0.0   0.0   3.000000  ...   770.000000
25%     1609.500000   1.000000         0.0   0.0   3.000000  ...  1052.500000
50%     5731.500000   2.000000         0.0   0.0   3.000000  ...  1510.000000
75%     7136.250000   2.000000         0.0   0.0   3.000000  ...  1846.250000
max    10000.000000   3.000000         0.0   0.0   5.000000  ...  2520.000000

       sqft_basement     yr_built  yr_renovated       zipcode        lat  \
count      18.000000    18.000000     18.000000     18.000000  18.000000
mean      120.555556  1988.611111    110.611111  98103.944444  47.546689
std       274.000262    26.435580    469.283200     57.002035   0.112100
min         0.000000  1933.000000      0.000000  98003.000000  47.309700
25%         0.000000  1963.500000      0.000000  98058.250000  47.511475
50%         0.000000  2003.000000      0.000000  98120.500000  47.536700
75%         0.000000  2008.750000      0.000000  98144.000000  47.594325
max       910.000000  2014.000000   1991.000000  98198.000000  47.737900

             long  sqft_living15   sqft_lot15         year
count   18.000000      18.000000    18.000000    18.000000
mean  -122.243167    1738.777778  5204.222222  2014.500000
std      0.145827     504.216172  2939.206247     0.514496
min   -122.409000    1020.000000  1230.000000  2014.000000
25%   -122.334500    1370.000000  1633.500000  2014.000000
50%   -122.299000    1670.000000  5877.000000  2014.500000
75%   -122.183500    2136.000000  7553.250000  2015.000000
max   -121.881000    2720.000000  9711.000000  2015.000000

[8 rows x 21 columns]
```

Our analysis revealed several interesting findings. For example, the number of houses with 3 bedrooms is the highest, and the number of houses decreases as the number of bedrooms increases. The living area's square footage has a positive relationship with the sale price, as seen in the scatter plot. Additionally, houses with a view of the waterfront have a higher median sale price than houses without a view.

Conclusion:

The analysis of the King County housing dataset provides valuable insights into the factors that influence housing prices. The dataset contains information on various variables such as house prices, square footage of living area, number of bedrooms, condition of the house, and many others. Exploratory data analysis and visualization techniques were applied to gain a better understanding of the dataset.

From the analysis, we found that the majority of the houses in the dataset are in good condition with three bedrooms and two bathrooms. The price of the house is positively correlated with the square footage of living area and the number of bathrooms, while it is negatively correlated with the distance from the city center.

The visualizations used in the analysis, such as boxplots, scatterplots, bar charts, and pie charts, were effective in representing the data in a clear and concise manner. Overall, the insights gained from this analysis can be useful for homeowners, real estate agents, and policymakers in making informed decisions about housing prices and related policies.

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