copy-of-s22229759-sfds-cw01-resit

June 22, 2024

1 Software for Data Science - Coursework 01 - Resit

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ATTESTATION: I confirm that the material contained within the submitted coursework is my own work

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3 TITLE - Exploratory Data Analysis of House Sales in King County (USA)

The report documented in this notebook is an exploration of the sales of residential house properties in King county between 2014 and 2015, using the house prices dataset that describes the sale of individual properties in King Country, USA. For more information on this dataset, see for example: https://www.kaggle.com/datasets/harlfoxem/housesalesprediction/data.

The objective of the report is to perform the preprocessing steps required to explore the dataset using statistical and visualisation techniques available in *Python* (and it's associated library packages).

4 INTRODUCTION

When we model the linear relationship between a set of features and a single target variable, the model is called simple linear regression. For this use-case, we want to predict the sale price of residential house properties and a set of intrinsic housing and neighbourhood features, such as bedrooms, bathrooms and zipcodes. However, the objective of the report is to perform the preprocessing steps required to explore the dataset using statistical and visualisation techniques available in *Python*.

Although, the focus of this report is not entirely centered on scientific data models such as regression, classification or clustering, we will be using some of these techniques to guide our analysis while performing the actual exploration of the data with descriptive statistics and visualisation charts.

5 DATA EXPLORATION

In order to perform data analysis on the dataset, we need to setup the development environment. Since we will be performing the data analysis in *Python*, we will first import the relevant modules to ingest, wrangle, visually analyse the data with modules like *Pandas*, *Seaborn* and *MatplotLib*.

[1]:
```
# import python libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
%matplotlib inline
```

5.1 Data Ingestion

We will ingest the dataset from *Google Drive* for the following reasons; * First, since we're working in *Google Colab*, it makes sense to store the dataset in an integrated repository for faster retrieval * Secondly, it provides an enormous storage capacity to store large datasets without any impact on local resources.

[2]:
```
# mount Google Drive (with permission)
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[3]:
```
# get the storage location on Google Drive
source_path = '/content/drive/My Drive/Colab Notebooks/SfDS/Assessments/CW 01/
↪Datasets'

# list the files and folders
print('\nList of files and folders on: ', source_path)
!ls '/content/drive/My Drive/Colab Notebooks/SfDS/Assessments/CW 01/Datasets'
```

```
List of files and folders on:  /content/drive/My Drive/Colab
Notebooks/SfDS/Assessments/CW 01/Datasets
house_data.csv  Housing_1.txt  Housing_2.txt  Housing_Data_Dictionary.txt
```

To ingest the dataset, we will use the *pandas.read_csv()* [1] method read a comma-separated values (csv) file into dataframe

[4]:
```
# load the dataset
df = pd.read_csv(source_path + '/house_data.csv')
```

After loading a dataset for analysis, it is often customary to review it to understand the structure of the data.

To kick-off the preliminary analysis of the data, we will begin by reviewing the dimensionality with *pandas.shape* [2]

[5]:
```
# preview the data structure
df.shape
```

[5]: (21615, 21)

Next, we will use the *pandas.info()* [3] method to get a concise summary of the dataset, including the index datatype and columns, as well as, the non-null values and memory usage

[6]:
```
# preview the data attributes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21615 entries, 0 to 21614
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21615 non-null  int64
 1   date           21615 non-null  object
 2   price          21609 non-null  float64
 3   bedrooms       21615 non-null  int64
 4   bathrooms      21615 non-null  float64
 5   sqft_living    21615 non-null  int64
 6   sqft_lot       21615 non-null  int64
 7   floors         21615 non-null  float64
 8   waterfront     21615 non-null  int64
 9   view           21615 non-null  int64
 10  condition      21615 non-null  int64
 11  grade          21615 non-null  int64
 12  sqft_above     21615 non-null  int64
 13  sqft_basement  21615 non-null  int64
 14  yr_built       21615 non-null  int64
 15  yr_renovated   21615 non-null  int64
 16  zipcode        21615 non-null  int64
 17  lat            21615 non-null  float64
 18  long           21615 non-null  float64
 19  sqft_living15  21611 non-null  float64
 20  sqft_lot15     21615 non-null  int64
dtypes: float64(6), int64(14), object(1)
memory usage: 3.5+ MB
```

Since we will be performing further exploratory analysis on the data, it makes sense to create a data dictionary that describes the structure of the dataset so we can refer to it later on.

1. ***id*** (discrete, ordinal) - Unique ID for each home sold
2. ***date*** (discrete, ordinal) - Date of the home sale
3. ***price*** (continuos, ordinal, target) - Price of each home sold
4. ***bedrooms*** (discrete, ordinal) - Number of bedrooms
5. ***bathrooms*** (discrete, ordinal) - Number of bathrooms, where .5 accounts for a room with a toilet but no shower
6. ***sqft_living*** (discrete, ordinal) - Square footage of the apartments interior living space
7. ***sqft_lot*** (discrete, ordinal) - Square footage of the land space
8. ***floors*** (discrete, ordinal) - Number of floors

9. ***waterfront*** (discrete, nominal) - A dummy variable for whether the apartment was overlooking the waterfront or not
10. ***view*** (discrete, ordinal) - An index from 0 to 4 of how good the view of the property was
11. ***condition*** (discrete, ordinal) - An index from 1 to 5 on the condition of the apartment,
12. ***grade*** (discrete, ordinal) - 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.
13. **sqft_above** (discrete, ordinal) - The square footage of the interior housing space that is above ground level
14. ***sqft_basement*** (discrete, ordinal) - The square footage of the interior housing space that is below ground level
15. ***yr_built*** (discrete, ordinal) - The year the house was initially built
16. ***yr_renovated*** (discrete, ordinal) - The year of the house's last renovation
17. ***zipcode*** (discrete, nominal) - What zipcode area the house is in
18. ***lat*** (continuos, nominal) - Lattitude
19. ***long*** (continuos, nominal) - Longitude
20. ***sqft_living15*** (continuos, ordinal) - The square footage of interior housing living space for the nearest 15 neighbors
21. ***sqft_lot15*** (continuos, ordinal) - The square footage of the land lots of the nearest 15 neighbors

Source: https://info.kingcounty.gov/assessor/esales/Glossary.aspx

5.2 Data Overview

After loading a dataset, it is important to explore various aspects of the data to gain insights into its structure, characteristics, and potential issues that might need to be resolved before proceding with further analysis. Then, we we shall consider further preprocessing steps to handle the duplicate missing and/or extreme values.

However, in this section, we will perform a general review of the data by taking a samples of the first and last observations of the data. Next, we will take a deeper look into the data attributes of the dataset. We will also peep to see if there are missing entries in the data.

[7]:
```
# preview the data
# NB: the pandas.head() method previews the first 10 observations of the data
df.head(10)
```

[7]:

	id	date	price	bedrooms	bathrooms	sqft_living	\
0	7129300520	20141013T000000	221900.0	3	1.00	1180	
1	6414100192	20141209T000000	538000.0	3	2.25	2570	
2	5631500400	20150225T000000	180000.0	2	1.00	770	
3	2487200875	20141209T000000	604000.0	4	3.00	1960	
4	1954400510	20150218T000000	510000.0	3	2.00	1680	
5	7237550310	20140512T000000	1225000.0	4	4.50	5420	
6	1321400060	20140627T000000	257500.0	3	2.25	1715	
7	2008000270	20150115T000000	291850.0	3	1.50	1060	
8	2414600126	20150415T000000	229500.0	3	1.00	1780	
9	3793500160	20150312T000000	323000.0	3	2.50	1890	

```
   sqft_lot  floors  waterfront  view  …  grade  sqft_above  sqft_basement  \
0      5650     1.0           0     0  …      7        1180              0
1      7242     2.0           0     0  …      7        2170            400
2     10000     1.0           0     0  …      6         770              0
3      5000     1.0           0     0  …      7        1050            910
4      8080     1.0           0     0  …      8        1680              0
5    101930     1.0           0     0  …     11        3890           1530
6      6819     2.0           0     0  …      7        1715              0
7      9711     1.0           0     0  …      7        1060              0
8      7470     1.0           0     0  …      7        1050            730
9      6560     2.0           0     0  …      7        1890              0

   yr_built  yr_renovated  zipcode      lat     long  sqft_living15  \
0      1955             0    98178  47.5112 -122.257         1340.0
1      1951          1991    98125  47.7210 -122.319         1690.0
2      1933             0    98028  47.7379 -122.233         2720.0
3      1965             0    98136  47.5208 -122.393         1360.0
4      1987             0    98074  47.6168 -122.045         1800.0
5      2001             0    98053  47.6561 -122.005            NaN
6      1995             0    98003  47.3097 -122.327         2238.0
7      1963             0    98198  47.4095 -122.315         1650.0
8      1960             0    98146  47.5123 -122.337         1780.0
9      2003             0    98038  47.3684 -122.031         2390.0

   sqft_lot15
0        5650
1        7639
2        8062
3        5000
4        7503
5      101930
6        6819
7        9711
8        8113
9        7570

[10 rows x 21 columns]
```

[8]:
```python
# preview the data
# NB: the pandas.tail() method previews the last 10 observations of the data
df.tail(10)
```

[8]:
```
               id             date     price  bedrooms  bathrooms  \
21605  7852140040  20140825T000000  507250.0         3       2.50
21606  9834201367  20150126T000000  429000.0         3       2.00
21607  3448900210  20141014T000000  610685.0         4       2.50
```

```
21608  7936000429  20150326T000000  1007500.0         4       3.50
21609  2997800021  20150219T000000   475000.0         3       2.50
21610   263000018  20140521T000000   360000.0         3       2.50
21611  6600060120  20150223T000000   400000.0         4       2.50
21612  1523300141  20140623T000000   402101.0         2       0.75
21613   291310100  20150116T000000   400000.0         3       2.50
21614  1523300157  20141015T000000   325000.0         2       0.75

       sqft_living  sqft_lot  floors  waterfront  view  …  grade  \
21605         2270      5536     2.0           0     0  …      8
21606         1490      1126     3.0           0     0  …      8
21607         2520      6023     2.0           0     0  …      9
21608         3510      7200     2.0           0     0  …      9
21609         1310      1294     2.0           0     0  …      8
21610         1530      1131     3.0           0     0  …      8
21611         2310      5813     2.0           0     0  …      8
21612         1020      1350     2.0           0     0  …      7
21613         1600      2388     2.0           0     0  …      8
21614         1020      1076     2.0           0     0  …      7

       sqft_above  sqft_basement  yr_built  yr_renovated  zipcode      lat  \
21605        2270              0      2003             0    98065  47.5389
21606        1490              0      2014             0    98144  47.5699
21607        2520              0      2014             0    98056  47.5137
21608        2600            910      2009             0    98136  47.5537
21609        1180            130      2008             0    98116  47.5773
21610        1530              0      2009             0    98103  47.6993
21611        2310              0      2014             0    98146  47.5107
21612        1020              0      2009             0    98144  47.5944
21613        1600              0      2004             0    98027  47.5345
21614        1020              0      2008             0    98144  47.5941

          long  sqft_living15  sqft_lot15
21605 -121.881         2270.0        5731
21606 -122.288         1400.0        1230
21607 -122.167         2520.0        6023
21608 -122.398         2050.0        6200
21609 -122.409         1330.0        1265
21610 -122.346         1530.0        1509
21611 -122.362         1830.0        7200
21612 -122.299         1020.0        2007
21613 -122.069         1410.0        1287
21614 -122.299         1020.0        1357

[10 rows x 21 columns]
```

5.3 Data Cleaning/Preprocessing

Previewing the dataset provides us with a chance to perform some cleanup to preprecess the data for analysis.

Our first step to cleaning up the data will be to check for duplicate entries in the data. For this, we will use the *pandas.drop_duplicates()* [4] method to remove duplicate entries in the data

[9]:
```
# remove duplicates in the data
df.drop_duplicates()

# check for changes
df.shape
```

[9]:
```
(21615, 21)
```

Next, we will perform a count of missing entries. This will provide guidiance of the next preprocessing steps to take.

For this, we will use the *pandas.isna()* [5] method to extract the observations having missing entries. Next, we will use the *pandas.sum()* [6] method to obtain the count of missing observations in each of the feature coulumns

[10]:
```
# get the count of missing entries
df.isna().sum()
```

[10]:
```
id                0
date              0
price             6
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     4
sqft_lot15        0
dtype: int64
```

A review of missing entries indicate that there are six (6) *price* entries, and four (4) missing *sqft_living15* entries.

In both cases, we will input zero (0) rather than completely delete the observation. For *price*, we can assume that the ownership of the house was transfered rather than sold. Similarly, for *sqft_living15*, we can assume that the property is in an isolated location, completely away from neighbours

[11]:
```
# input zero (0) for missing entries
df['price'].fillna(value=0, inplace=True)
df['sqft_living15'].fillna(value=0, inplace=True)

# check for changes
df.isna().sum()
```

[11]:
```
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
```

Next, we will convert the *bathrooms* and *floors* to a natural integer data types

[12]:
```
# represent the data in their natural data types
df['bathrooms'] = df['bathrooms'].astype(int)
df['floors'] = df['floors'].astype(int)
```

Lastly, we will remove unneccessary identity features, including *id*, *lat*, and *long*.

We leave *zipcode* as it can be used to perform further analysis of house prices within particular locality

[13]:
```
# remove unnecessary columns
df.drop(['id', 'lat', 'long'], axis=1, inplace=True)
```

Now that we have confirmed that the data is well represented with no missing entries. We will check the data again to see it's in order

[14]:
```
# preview the data
df.head()
```

[14]:
```
              date     price  bedrooms  bathrooms  sqft_living  sqft_lot  \
0  20141013T000000  221900.0         3          1         1180      5650
1  20141209T000000  538000.0         3          2         2570      7242
2  20150225T000000  180000.0         2          1          770     10000
3  20141209T000000  604000.0         4          3         1960      5000
4  20150218T000000  510000.0         3          2         1680      8080

   floors  waterfront  view  condition  grade  sqft_above  sqft_basement  \
0       1           0     0          3      7        1180              0
1       2           0     0          3      7        2170            400
2       1           0     0          3      6         770              0
3       1           0     0          5      7        1050            910
4       1           0     0          3      8        1680              0

   yr_built  yr_renovated  zipcode  sqft_living15  sqft_lot15
0      1955             0    98178         1340.0        5650
1      1951          1991    98125         1690.0        7639
2      1933             0    98028         2720.0        8062
3      1965             0    98136         1360.0        5000
4      1987             0    98074         1800.0        7503
```

5.4 Feature Selection & Engineering

Feature selection and engineering is a preparatory step in data modelling used to select and transform variables of interest for further analysis.

For our use-case, we will transform the *date* column into two (2) columns that reflect the month and year the property was sold as *year_sold* and *month_sold* respectively. we will use the transformation to facilitate a time-series of the residential property sales over time

[15]:
```
# format the date column
df['date'] = pd.to_datetime(df['date'])

# engineer new features from the date column
df['yr_sold'] = df['date'].apply(lambda date: date.year)
df['mth_sold'] = df['date'].apply(lambda date: date.month)

# remove redundant columns
df.drop(['date'], axis=1, inplace=True)
```

```python
# preview the data
df.head()
```

[15]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	221900.0	3	1	1180	5650	1	0
1	538000.0	3	2	2570	7242	2	0
2	180000.0	2	1	770	10000	1	0
3	604000.0	4	3	1960	5000	1	0
4	510000.0	3	2	1680	8080	1	0

	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated
0	0	3	7	1180	0	1955	0
1	0	3	7	2170	400	1951	1991
2	0	3	6	770	0	1933	0
3	0	5	7	1050	910	1965	0
4	0	3	8	1680	0	1987	0

	zipcode	sqft_living15	sqft_lot15	yr_sold	mth_sold
0	98178	1340.0	5650	2014	10
1	98125	1690.0	7639	2014	12
2	98028	2720.0	8062	2015	2
3	98136	1360.0	5000	2014	12
4	98074	1800.0	7503	2015	2

6 DATA EXPLORATION AND ANALYSIS

Our exloration and analysis of the dataset will include an analysis on descriptive summary statistics, as well as, data visualisation with univariate and bivariate analysis of the residential sale price

6.1 Summary Statistics

We will begin our Exploratory Data Analysis (EDA) with a review of the descriptive summary statistics of tha dataset. Using descriptive summary statistics as a preliminary analysis for a dataset can provide a quick summary of dataset. This is particularly useful for comparing and analysing the central tendencies of features that make up the dataset. In our use-case, we will use the *pandas.describe()* [7] method to retrieve key statistical parameters such as the mean and standard devation

[16]:
```python
# preview the descriptive statistics
# NB: we transpose the data so we can view it in long format
df.describe().T
```

[16]:

	count	mean	std	min	25%
price	21615.0	539931.716771	367226.557551	-20000.0	321000.0
bedrooms	21615.0	3.370854	0.930032	0.0	3.0
bathrooms	21615.0	1.749711	0.734859	0.0	1.0

sqft_living	21615.0	2079.847467	918.433531	290.0	1426.0
sqft_lot	21615.0	15106.445108	41418.631940	520.0	5040.0
floors	21615.0	1.446218	0.551889	1.0	1.0
waterfront	21615.0	0.007541	0.086513	0.0	0.0
view	21615.0	0.234282	0.766285	0.0	0.0
condition	21615.0	3.409484	0.650738	1.0	3.0
grade	21615.0	7.656812	1.175461	1.0	7.0
sqft_above	21615.0	1788.365394	828.077972	290.0	1190.0
sqft_basement	21615.0	291.482073	442.563449	0.0	0.0
yr_built	21615.0	1971.004950	29.372159	1900.0	1951.0
yr_renovated	21615.0	84.394448	401.661476	0.0	0.0
zipcode	21615.0	98077.932917	53.507347	98001.0	98033.0
sqft_living15	21615.0	1986.069350	685.626571	0.0	1490.0
sqft_lot15	21615.0	12768.155216	27302.936333	651.0	5100.0
yr_sold	21615.0	2014.322970	0.467622	2014.0	2014.0
mth_sold	21615.0	6.574231	3.115320	1.0	4.0

	50%	75%	max
price	450000.0	645000.0	7700000.0
bedrooms	3.0	4.0	33.0
bathrooms	2.0	2.0	8.0
sqft_living	1910.0	2550.0	13540.0
sqft_lot	7620.0	10687.5	1651359.0
floors	1.0	2.0	3.0
waterfront	0.0	0.0	1.0
view	0.0	0.0	4.0
condition	3.0	4.0	5.0
grade	7.0	8.0	13.0
sqft_above	1560.0	2210.0	9410.0
sqft_basement	0.0	560.0	4820.0
yr_built	1975.0	1997.0	2015.0
yr_renovated	0.0	0.0	2015.0
zipcode	98065.0	98118.0	98199.0
sqft_living15	1840.0	2360.0	6210.0
sqft_lot15	7620.0	10083.5	871200.0
yr_sold	2014.0	2015.0	2015.0
mth_sold	6.0	9.0	12.0

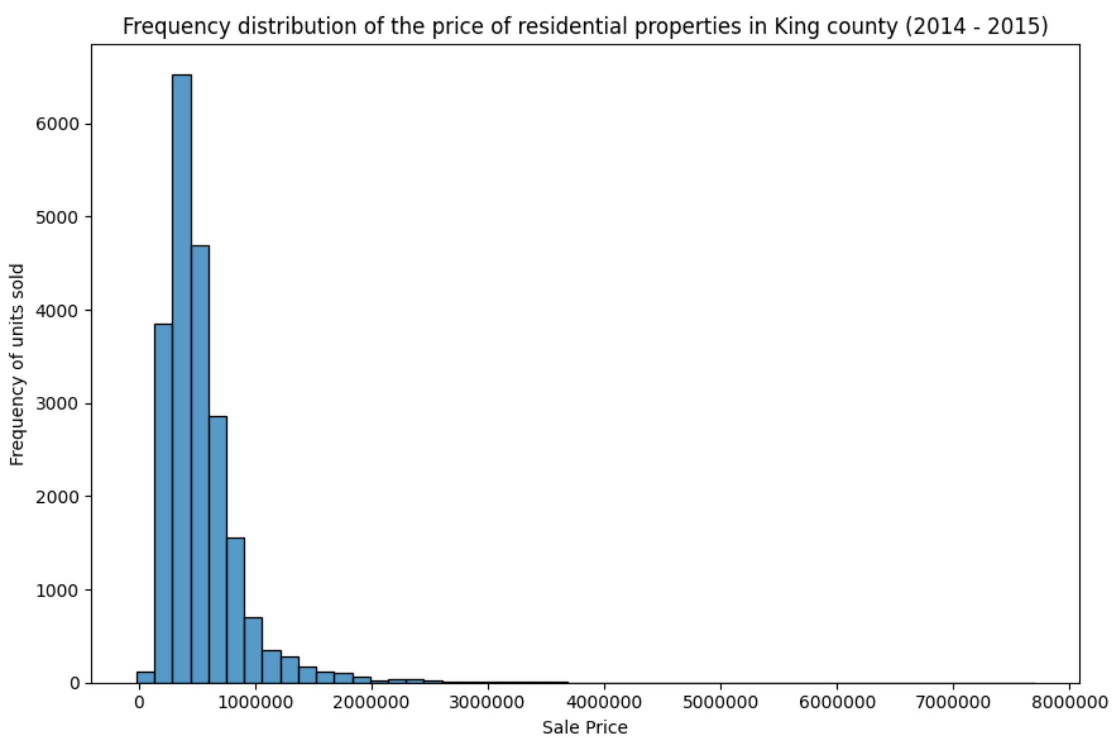
6.2 Data Visualisation

Univariate Analysis of Sale Price

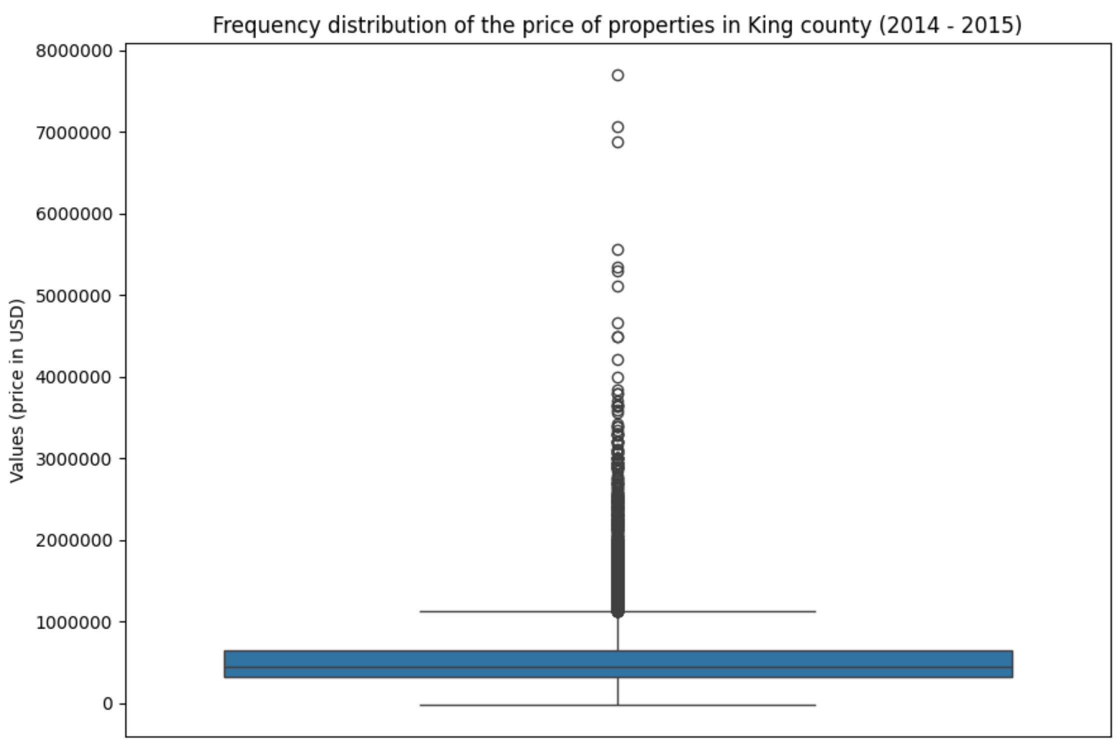
Univariate analysis is an essential technique in Exploratory Data Analysis (EDA) that helps to uncover patterns and anomalies (for example, outliers) about individual variables (in this case, the target variable, *price*) in a dataset.

Since it focuses on a single variable at a time, it can serve as a fundamental step in examining in understanding central tendencies, dispersions, and distributions of an individual variable before diving into more complex multivariate analysis

[17]:
```
# create a figure for the plot
plt.figure(figsize=(9,6))

# draw a histogram showing the distribution of sale price
sns.histplot(df['price'], bins=50)

# add labels and title
plt.xlabel('Sale Price')
plt.ylabel('Frequency of units sold')
plt.title('Frequency distribution of the price of residential properties in␣
 ↪King county (2014 - 2015)')

# show complete scale on x-axis
formatter = ticker.ScalarFormatter(useOffset=False)
formatter.set_scientific(False)
plt.gca().xaxis.set_major_formatter(formatter)

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



[18]:
```
# create a figure for the plot
plt.figure(figsize=(9,6))

# draw a box-plot showing the distribution of sale price
sns.boxplot(df['price'])

# make the x axis label invisible
plt.xticks([])

# add labels and title
plt.ylabel('Values (price in USD)')
plt.title('Frequency distribution of the price of properties in King county␣
 ↪(2014 - 2015)')

# show complete scale on y-axis
formatter = ticker.ScalarFormatter(useOffset=False)
formatter.set_scientific(False)
plt.gca().yaxis.set_major_formatter(formatter)

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



From the frequency distribution indicated by the histogram sale prices above, we could see clearly that properties above 1,000,000 USD were outliers (less than 5% of the total units sold). Also, we could see that the median price of a residential property in King county was approximately 500,000 USD

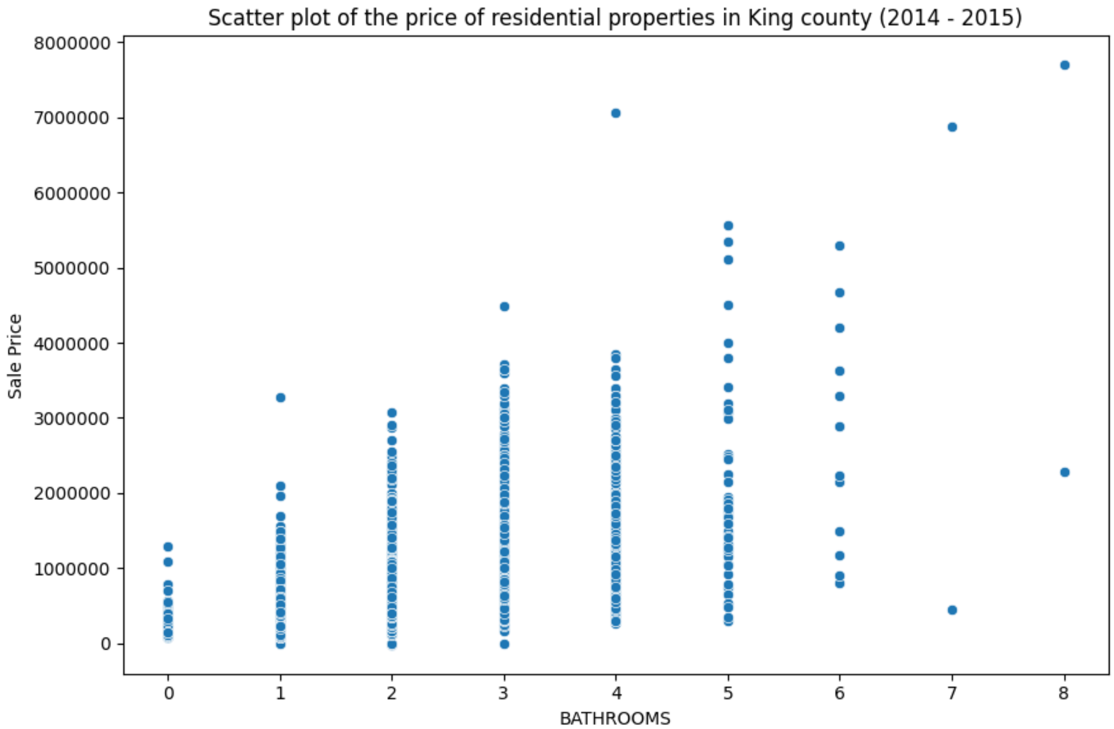
Bivariate Analysis of Sale Price with Highly Correlated Features

Multivariate analysis deals with the interactions and relationships among three or more variables. Whilst in multivariate analysis, more than one parameter is varied simultaneously, bivariate analysis, on the other hand, simultaneously compares two variables.

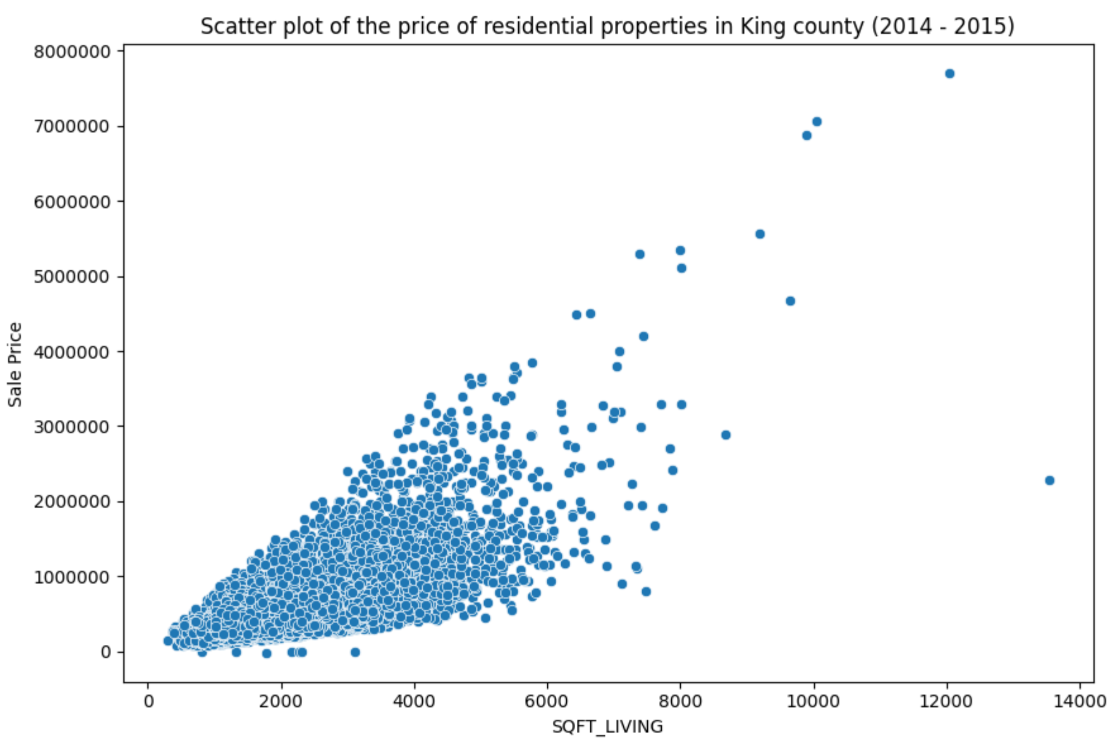
For our use-case, we will consider an analysis of *price* with features where the correlation coefficient is greater than 0.5. In addition, we will also consider the bivariate analysis of *price* with time-series a feature like *yr_built*

[19]:
```
# calculate the correlation to the target
for feature in df.columns.values:
    related = df['price'].corr(df[feature])

    # exclude correlation coefficients <= 0.5
    if related > 0.5 and feature != 'price':
        # show the correlation
        print("%s: %f" % (feature, related))

        # create a figure for the plot
        plt.figure(figsize=(9,6))

        # draw a scatter plot showing the distribution of sale price
        sns.scatterplot(x=df[feature], y=df['price'])

        # add labels and title
        plt.xlabel(str.upper(feature))
        plt.ylabel('Sale Price')
        plt.title('Scatter plot of the price of residential properties in King␣
 ↪county (2014 - 2015)')

        # show complete scale on both axes
        formatter = ticker.ScalarFormatter(useOffset=False)
        formatter.set_scientific(False)
        plt.gca().xaxis.set_major_formatter(formatter)
        plt.gca().yaxis.set_major_formatter(formatter)

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

```
bathrooms: 0.509923
```

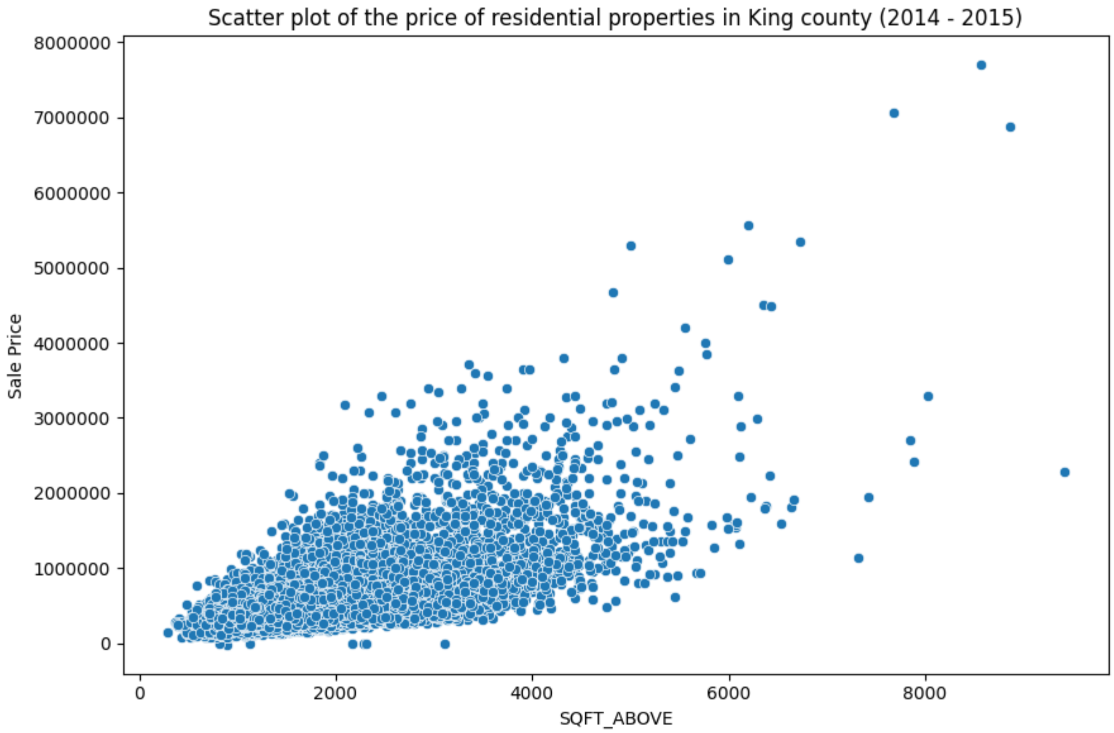


`sqft_living: 0.701829`

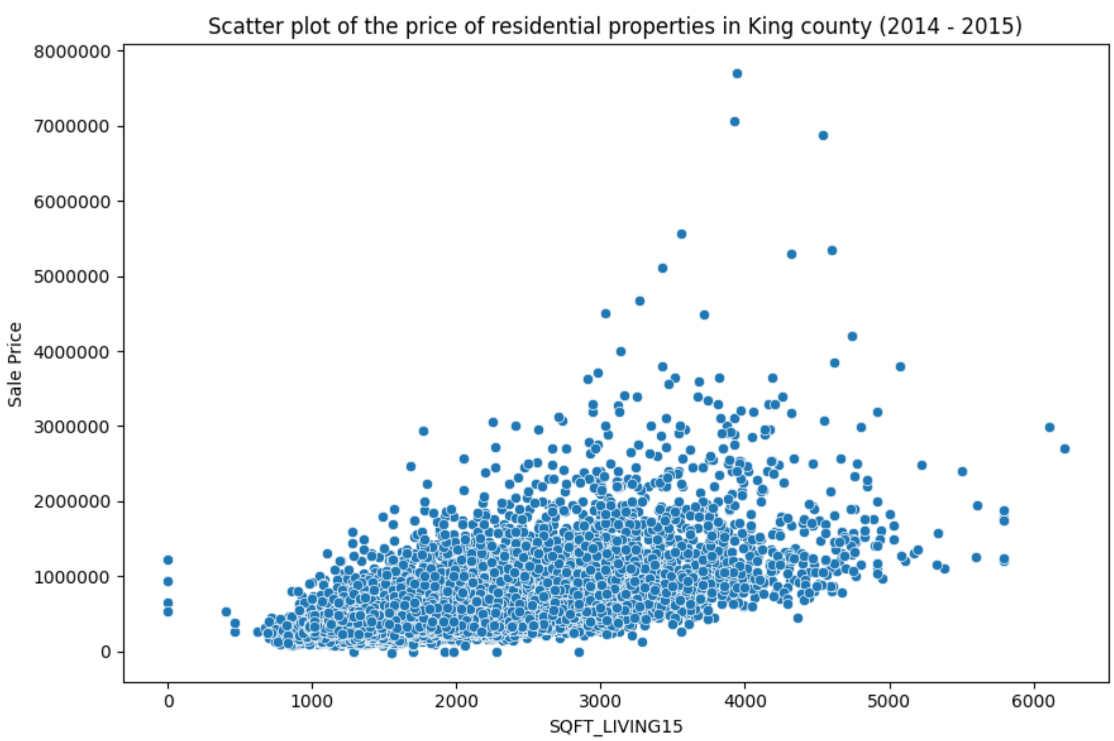


grade: 0.667283

sqft_above: 0.605315

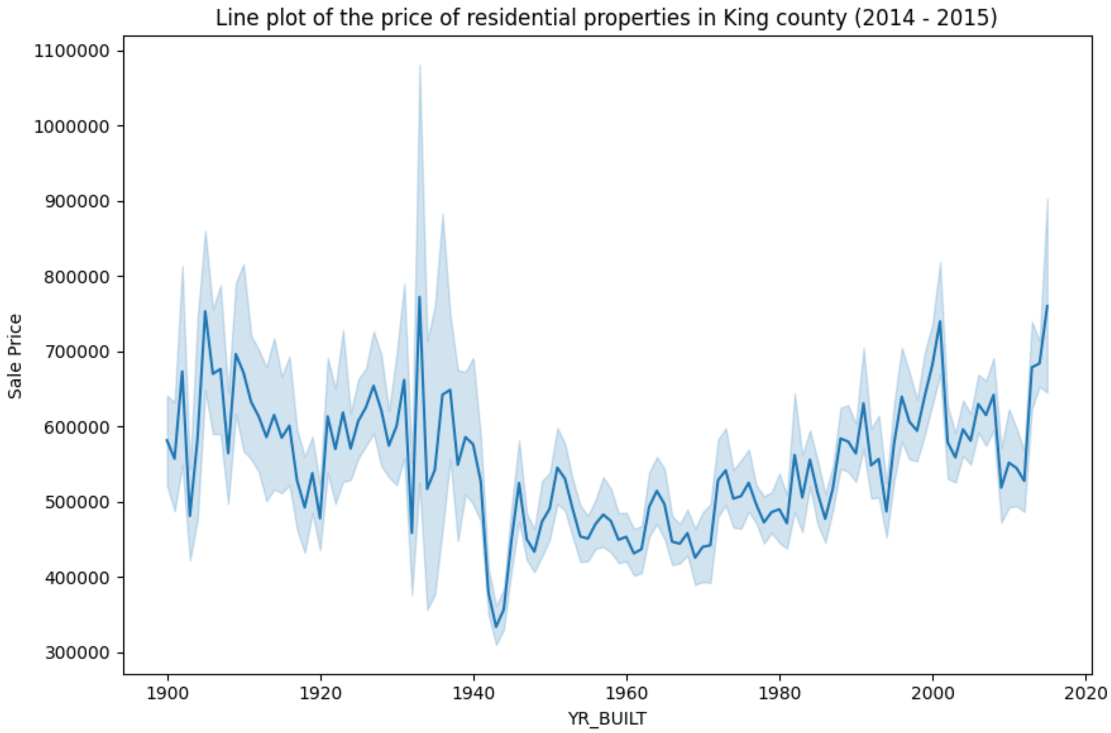


sqft_living15: 0.584154



From the bivariate analysis depicted in the scatter plots above, we could see there is a direct linear relationship between sale price and highly correlated features, such as *bathrooms* and *grade*. This is an indication that these features can easily be modelled with linear machine learning models like linear regression

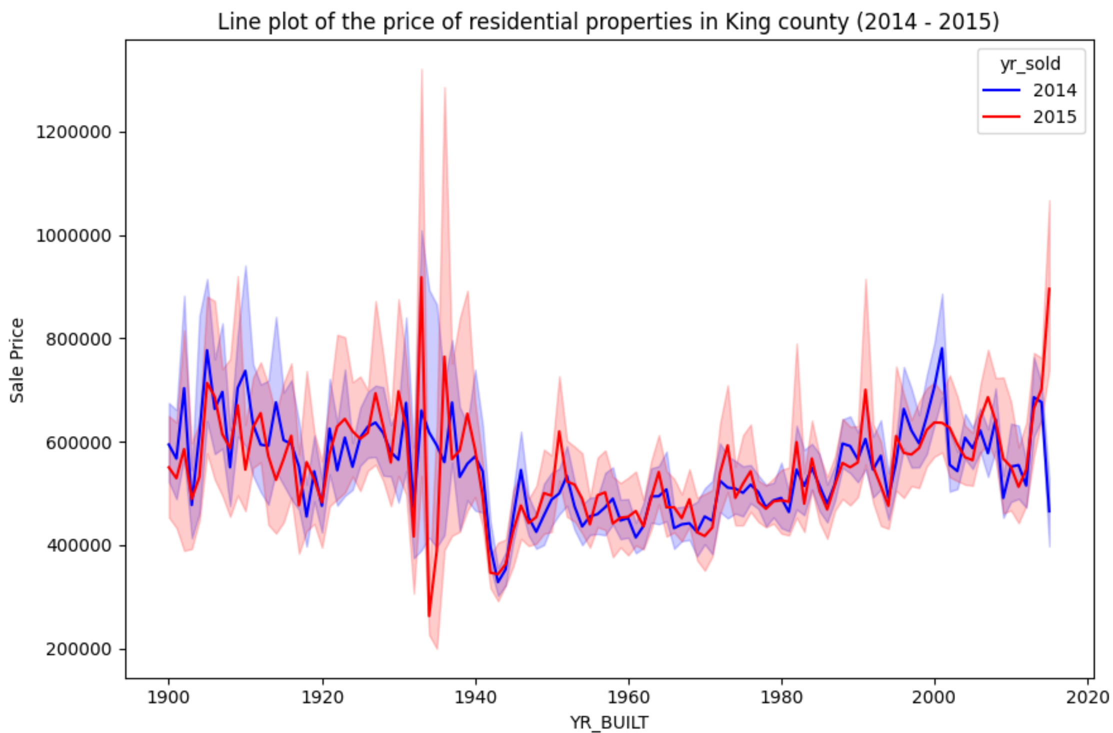
[20]:
```
# create a figure for the plot
plt.figure(figsize=(9,6))

# draw a scatter plot showing the distribution of sale price
sns.lineplot(data=df, x=df['yr_built'], y=df['price'])

# add labels and title
plt.xlabel(str.upper('yr_built'))
plt.ylabel('Sale Price')
plt.title('Line plot of the price of residential properties in King county␣
 ↪(2014 - 2015)')

# show complete scale on both axes
formatter = ticker.ScalarFormatter(useOffset=False)
formatter.set_scientific(False)
plt.gca().xaxis.set_major_formatter(formatter)
plt.gca().yaxis.set_major_formatter(formatter)

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



From the time-series line plot, we could see that the sale price residential properties spiked just after the 1900, 1930 and 2010. However, it deeped strongly in the early 1940's

[55]:
```
# create a figure for the plot
plt.figure(figsize=(9,6))

# draw a scatter plot showing the distribution of sale price
sns.lineplot(data=df, x=df['yr_built'], y=df['price'], hue=df['yr_sold'],␣
↪palette=['blue','red'])

# add labels and title
plt.xlabel(str.upper('yr_built'))
plt.ylabel('Sale Price')
plt.title('Line plot of the price of residential properties in King county␣
↪(2014 - 2015)')

# show complete scale on both axes
formatter = ticker.ScalarFormatter(useOffset=False)
formatter.set_scientific(False)
plt.gca().xaxis.set_major_formatter(formatter)
plt.gca().yaxis.set_major_formatter(formatter)
plt.gca().collections[0].set_path_effects([])
```

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



[57]:
```
x= df.groupby('yr_built')['price'].mean()
x.astype(int)
```

[57]:
```
yr_built
1900    581387
1901    556935
1902    673007
1903    480958
1904    583756
         …
2011    544522
2012    527447
2013    678545
2014    683681
2015    759785
Name: price, Length: 116, dtype: int64
```

As we can see, there were some disparities in the sale prices of residential properties sold in 2014 and 2015. However, there was a steady rise in the sale prices of the properties. This is particularly noticable between 2010 and 2015

7 RESULTS AND DISCUSSION

We make the following observations from the descriptive summary statistics, as well as, the univariate and bivariate analysis.

1. The sale price of most of the residential properties is less than 1,000,000 USD
2. There's a direct linear relationship between strongly correlated features such as *sqft_living*, *grade*, and *sqft_above*. Hence, these features can easliy be modeled with linear machine learning models such as Linear Regression
3. Lastly, we observed that the sale price residential properties spiked just after the 1900, 1930 and early 2000's. However, it deeped strongly in the early 1940's and rose steadily therefter. Although, the reason for these spikes could not be ascertained, there are chances that there would have have been a large margin of profits and losses during these times

8 REFERENCES

[1] *pandas.read_csv()* method, https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.read_csv.html

[2] *pandas.shape*, https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.shape.html

[3] *pandas.info()* method, https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.info.html

[4] *pandas.drop_duplicates()* method, https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.drop_dup

[5] *pandas.isna()* method, https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.isna.html

[6] *pandas.sum()* method, https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.sum.html

[7] *pandas.describe()* method, https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.describe.html