Assignment1 : Exploratory Data Analysis and Feature Engineering with the Melbourne Housing Dataset

Objective: The objective of this assignment is to conduct an exploratory data analysis (EDA) and apply feature engineering techniques to enhance the predictive modelling capabilities using the Melbourne Housing dataset.

Module: CS401 Machine Learning

Student Name: Precious Deremo

Student Number: 20325666

Importing all of the necessary mathemeatical functions to visualise the graphs of the housing data.

Read an overview of the practical skills documentation to bring me up to speed on how to approach the assignment

Downloaded the melbourne data

Took notes of missing data/required data

Tried to define what the data means

Used Excel Workbook's Quick Analysis tool to pick out obvious traits of the data and look through its suggestions.

Tried analysing the data on the jupyter notebook by follwing the cs dojo example. Ran into an error : C:\Users\pdere\AppData\Local\Temp\ipykernel_83052\1220715966.py:2: DtypeWarning: Columns (13) have mixed types. Specify dtype option on import or set low_memory=False. mel_housing = pd.read_csv('Melbourne_housing.csv')

https://www.roelpeters.be/solved-dtypewarning-columns-have-mixed-types-specify-dtype-option-on-import-or-set-low-memory-in-pandas/ -> used the dtype solution provided in here and managed to visual the data

This helped me understand the issue more at first -> https://stackoverflow.com/questions/24251219/pandas-read-csv-low-memory-and-dtype-options

```
%matplotlib inline

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import scipy.stats as stats
```

Data Loading and Initial Exploration (20 points):

```
mel_housing = pd.read_csv('Melbourne_housing.csv')
```

```
C:\Users\pdere\AppData\Local\Temp\ipykernel_41760\789277600.py:1:
DtypeWarning: Columns (13) have mixed types. Specify dtype option on
import or set low_memory=False.
  mel_housing = pd.read_csv('Melbourne_housing.csv')
```

1.1 Provide information on the dataset, including the number of rows and columns.

Figured out that there was 34857 rows × 22 columns. Following the csdojo tutorial I decided to use the code provided to see how many type 'h' there was, and found 23980 rows × 22 columns. I noticed in BuildingArea there are values such as inf or NaN which do not seem valuable to the data so I will try to remove these which means I will be removing any data connected to.

I am having difficulties catching the NaN, which is weird since I specified the BuildingArea as a string type so I figured I could display the information along with the inf and see how many columns of that there was.

```
mel_housing
```

```
                  Suburb             Address  Rooms Type Method  
SellerG  \
0            Abbotsford       68 Studley St      2    h     SS  
Jellis   
1          Airport West       154 Halsey Rd      3    t     PI  
Nelson   
2           Albert Park      105 Kerferd Rd      2    h      S  
hockingstuart   
3           Albert Park  85 Richardson St      2    h      S  
Thomson   
4            Alphington       30 Austin St      3    h     SN  
McGrath   
...                 ...                ...    ...  ...    ...  
...   
34852         Reservoir       18 Elinda Pl      3    u     SP  
RW   
34853      Roxburgh Park     14 Stainsby Cr      4    h      S  
Raine   
34854   Springvale South      8 Bellbird Ct      4    h     PI  
Barry   
34855   Springvale South  30 Waddington Cr      3    h      S  
Harcourts   
34856        Westmeadows       42 Pascoe St      4    h      S  
Barry   

             Date  Distance  Postcode  Bedroom  ...  Landsize  
BuildingArea  \
0        3/9/2016       2.5    3067.0      2.0  ...     126.0  
```

```
inf
1         3/9/2016      13.5    3042.0      3.0  ...     303.0
225
2         3/9/2016       3.3    3206.0      2.0  ...     120.0
82
3         3/9/2016       3.3    3206.0      2.0  ...     159.0
inf
4         3/9/2016       6.4    3078.0      3.0  ...     174.0
122
...            ...       ...       ...      ...  ...       ...
...
34852  30/09/2017      12.0    3073.0      3.0  ...       NaN
105.0
34853  30/09/2017      20.6    3064.0      4.0  ...       NaN
225.0
34854  30/09/2017      22.2    3172.0      4.0  ...     534.0
152.0
34855  30/09/2017      22.2    3172.0      3.0  ...     544.0
NaN
34856  30/09/2017      16.5    3049.0      4.0  ...     813.0
140.0

       YearBuilt                     CouncilArea  Latitude Longtitude
\
0            NaN              Yarra City Council -37.80140  144.99580

1         2016.0      Moonee Valley City Council -37.71800  144.87800

2         1900.0       Port Phillip City Council -37.84590  144.95550

3            NaN       Port Phillip City Council -37.84500  144.95380

4         2003.0            Darebin City Council -37.78180  145.01980

...          ...                             ...       ...        ...

34852     1990.0            Darebin City Council -37.69769  145.02332

34853     1995.0               Hume City Council -37.63665  144.92976

34854     1970.0  Greater Dandenong City Council -37.97037  145.15449

34855        NaN  Greater Dandenong City Council -37.97751  145.14813

34856     1960.0               Hume City Council -37.67631  144.89409


                       Regionname  Propertycount      ParkingArea
Price
0           Northern Metropolitan         4019.0          Carport
```

```
NaN
1             Western Metropolitan         3464.0   Detached Garage
840000.0
2            Southern Metropolitan         3280.0   Attached Garage
1275000.0
3            Southern Metropolitan         3280.0            Indoor
1455000.0
4            Northern Metropolitan         2211.0           Parkade
NaN
...                            ...            ...               ...
...
34852        Northern Metropolitan        21650.0           Parkade
475000.0
34853        Northern Metropolitan         5833.0       Underground
591000.0
34854   South-Eastern Metropolitan         4054.0           Carport
NaN
34855   South-Eastern Metropolitan         4054.0   Detached Garage
780500.0
34856        Northern Metropolitan         2474.0   Attached Garage
791000.0

[34857 rows x 22 columns]
```

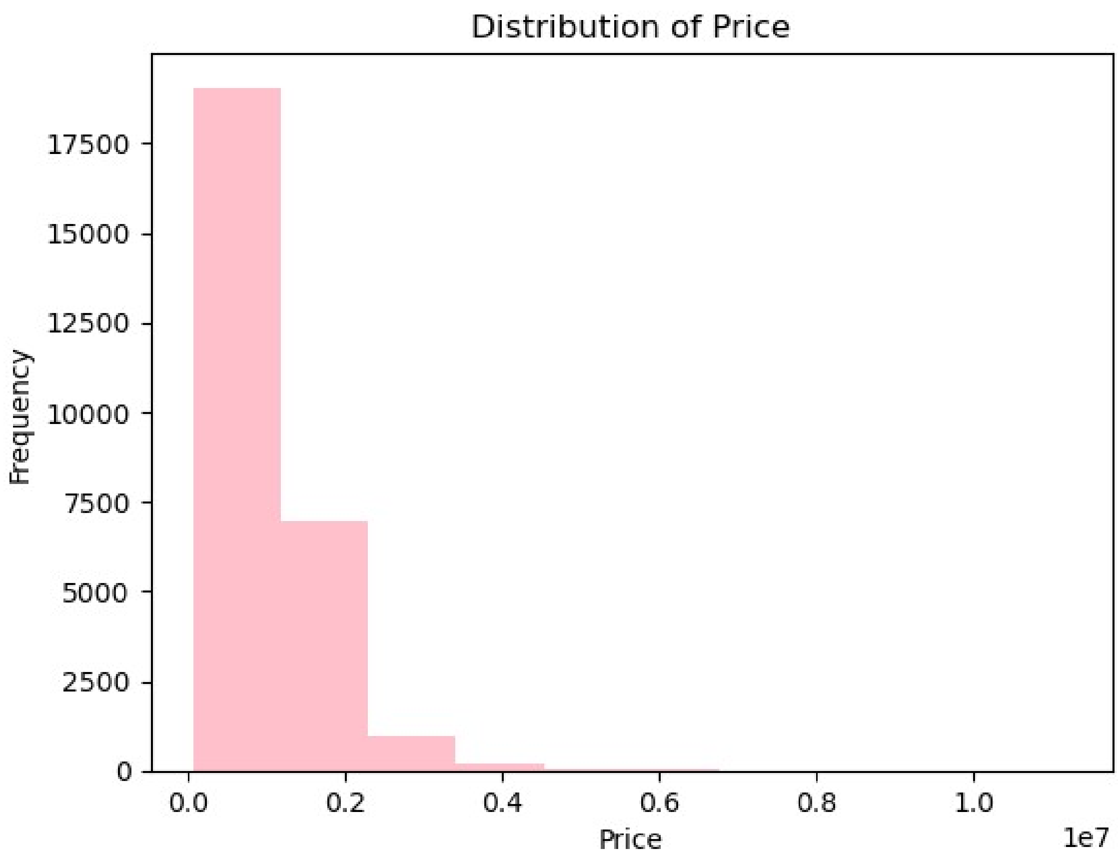
This is the size of the housing data

```
mel_housing.size

766854
```

1.2 Briefly describe the target variable (e.g., 'Price') and its distribution.

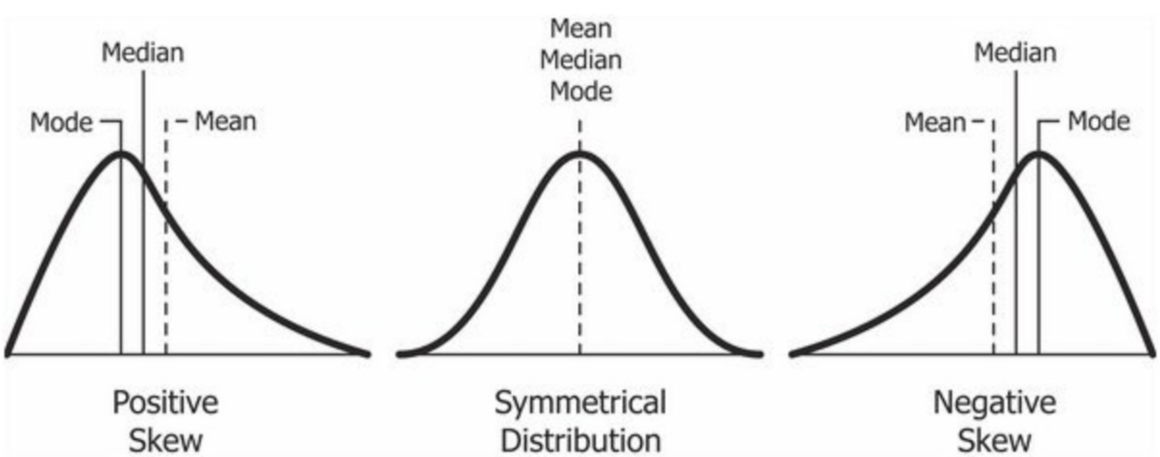
Displaying the distrubution of the Price according the the original state of the data since the goal of this analysis is to determine how to predict the prices of housing.

```
mel_housing['Price'].hist(color='pink', grid=False)
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.title('Distribution of Price')

Text(0.5, 1.0, 'Distribution of Price')
```



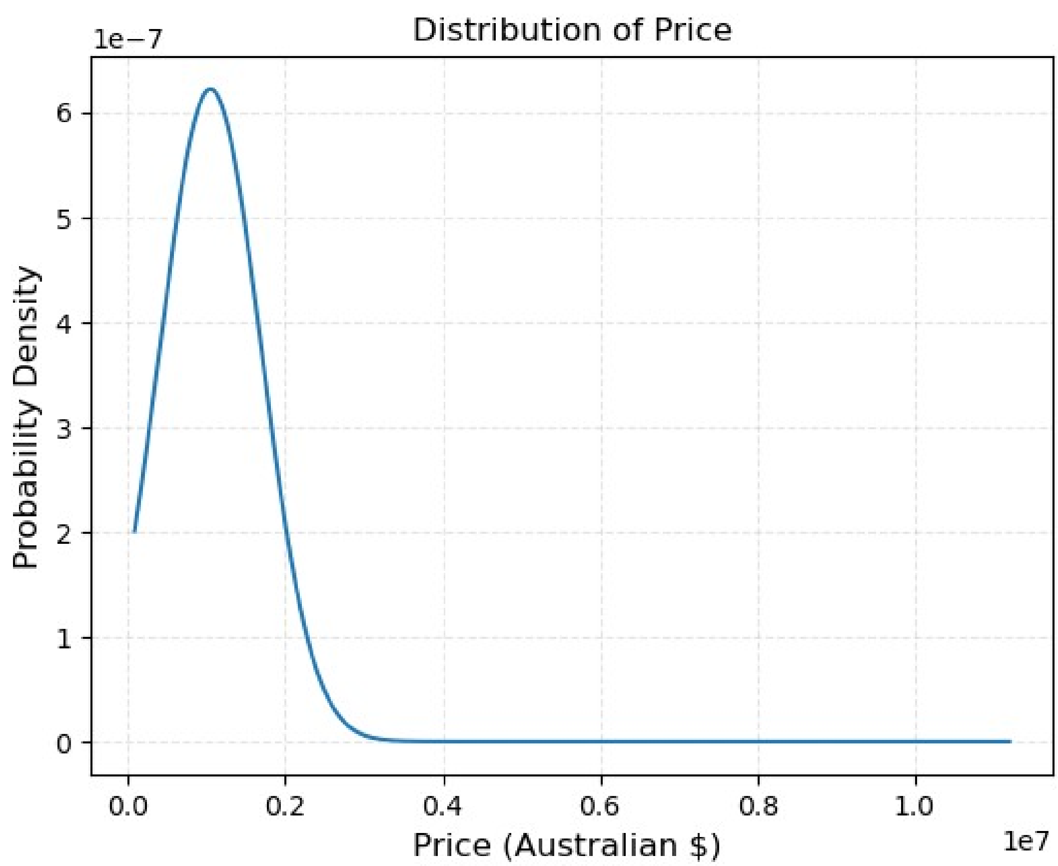
According to the distribution metric, the distribution of Price is positively skewed.

```
from IPython import display
display.Image("dist.png")
```




```
mh_mean = np.mean(mel_housing["Price"])
mh_std = np.std(mel_housing["Price"])
```

```
pdf = stats.norm.pdf(mel_housing["Price"].sort_values(), mh_mean,
mh_std)
# X axis is showing the price in decimals in respect to 1 million
australian dollars
plt.plot(mel_housing["Price"].sort_values(), pdf)
plt.xlabel("Price (Australian $) ", size=12)
plt.ylabel("Probability Density", size=12)
plt.title('Distribution of Price')
plt.grid(True, alpha=0.3,linestyle="--")
plt.show()
```



I displayed the datatypes and was shown objects so I assume I should be displaying the actual types and will be converting them from object to their value types as per this solution https://stackoverflow.com/questions/24251219/pandas-read-csv-low-memory-and-dtype-options

The plan for handling the missing values was to exclude any data relating to them

I searched around for a solution and found https://www.digitalocean.com/community/tutorials/pandas-dropna-drop-null-na-values-from-dataframe

Handling missing data Showcasing how much of the data has invalid values to figure out which values would be good to drop and focus on

```
I switched from the anaconda version of jupyter to the vscode conda
version and everything worked fine. I decided to stick with this for
the time being.
```

I used this solution to get rid of the NaN and inf vals -> https://sparkbyexamples.com/pandas/pandas-drop-infinite-values-from-dataframe/#:~:text=By%20using%20replace()%20%26%20dropna,represented%20in%20NumPy%20as%20np.

1.4 Identify any missing values and outline a plan to handle them

```
mel_housing.isnull().sum()
```

```
Suburb                0
Address               0
Rooms                 0
Type                  0
Method                0
SellerG               0
Date                  0
Distance              1
Postcode              1
Bedroom            8217
Bathroom           8226
Car                8728
Landsize          11810
BuildingArea      21097
YearBuilt         19306
CouncilArea           3
Latitude           7976
Longtitude         7976
Regionname            0
Propertycount         3
ParkingArea           0
Price              7610
dtype: int64
```

```
mel_housing.isnull().sum()/len(mel_housing)*100
```

```
Suburb              0.000000
Address             0.000000
Rooms               0.000000
Type                0.000000
Method              0.000000
SellerG             0.000000
Date                0.000000
Distance            0.002869
Postcode            0.002869
Bedroom            23.573457
Bathroom           23.599277
```

```
Car              25.039447
Landsize         33.881286
BuildingArea     60.524428
YearBuilt        55.386293
CouncilArea       0.008607
Latitude         22.882061
Longtitude       22.882061
Regionname        0.000000
Propertycount     0.008607
ParkingArea       0.000000
Price            21.832057
dtype: float64
```

as distance, postcode and councilarea along with propertycount dont have that much missing data i decided to drop the invalid data within these columns since they werent very important. Keeping the data concise is very important. It seems this data was missing at random

3.1 Handling missing data (e.g., imputation methods)

```
mel_housing = mel_housing.dropna(subset=['Distance', 'Postcode',
'CouncilArea', 'Propertycount'])
mel_housing.isnull().sum()
```

```
Suburb               0
Address              0
Rooms                0
Type                 0
Method               0
SellerG              0
Date                 0
Distance             0
Postcode             0
Bedroom           8214
Bathroom          8223
Car               8725
Landsize         11807
BuildingArea     21094
YearBuilt        19303
CouncilArea          0
Latitude          7973
Longtitude        7973
Regionname           0
Propertycount        0
ParkingArea          0
Price             7610
dtype: int64
```

Printing the column names along with their data types and then changing object to category to show how many categories there are

```python
print(mel_housing.dtypes)
```

```
Suburb             object
Address            object
Rooms               int64
Type               object
Method             object
SellerG            object
Date               object
Distance          float64
Postcode          float64
Bedroom           float64
Bathroom          float64
Car               float64
Landsize          float64
BuildingArea       object
YearBuilt         float64
CouncilArea        object
Latitude          float64
Longtitude        float64
Regionname         object
Propertycount     float64
ParkingArea        object
Price             float64
dtype: object
```

3.2 Encoding categorical variables (e.g., one-hot encoding or label encoding)

Encoding categorical variables

```python
objtocat = ['Suburb', 'Address', 'Type', 'Method', 'SellerG',
'CouncilArea','Regionname', 'ParkingArea']
for colname in objtocat:
    mel_housing[colname] = mel_housing[colname].astype('category')

mel_housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 34854 entries, 0 to 34856
Data columns (total 22 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Suburb         34854 non-null  category
 1   Address        34854 non-null  category
 2   Rooms          34854 non-null  int64
 3   Type           34854 non-null  category
 4   Method         34854 non-null  category
 5   SellerG        34854 non-null  category
 6   Date           34854 non-null  object
 7   Distance       34854 non-null  float64
```

```
 8   Postcode       34854 non-null  float64
 9   Bedroom        26640 non-null  float64
 10  Bathroom       26631 non-null  float64
 11  Car            26129 non-null  float64
 12  Landsize       23047 non-null  float64
 13  BuildingArea   13760 non-null  object
 14  YearBuilt      15551 non-null  float64
 15  CouncilArea    34854 non-null  category
 16  Latitude       26881 non-null  float64
 17  Longtitude     26881 non-null  float64
 18  Regionname     34854 non-null  category
 19  Propertycount  34854 non-null  float64
 20  ParkingArea    34854 non-null  category
 21  Price          27244 non-null  float64
dtypes: category(8), float64(11), int64(1), object(2)
memory usage: 5.7+ MB

C:\Users\pdere\AppData\Local\Temp\ipykernel_20140\1286130307.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  mel_housing[colname] = mel_housing[colname].astype('category')
```

Bringing in a new variable to hold the age of the housing property in order to get rid of other useless data such as YearBuilt, this is to make it easier for people to see how long the housing property has been around

```
# Remove false BuildingArea
mel_housing = mel_housing[mel_housing['BuildingArea']!=0]

# Remove false YearBuilt (Melbourne Founded 1835)
mel_housing = mel_housing[mel_housing['YearBuilt']> 1835]

# Adding feature for house age
mel_housing['PropertyAge'] = 2023 - mel_housing['YearBuilt']
mel_housing
```

```
                 Suburb          Address  Rooms Type Method
SellerG  \
1          Airport West    154 Halsey Rd      3    t     PI
Nelson
2           Albert Park   105 Kerferd Rd      2    h      S
hockingstuart
4            Alphington     30 Austin St      3    h     SN
McGrath
5            Alphington       6 Smith St      4    h      S
```

```
Brace
6           Alphington  5/6 Yarralea St      3    h      S
Jellis
...                ...              ...    ...  ...    ...
...
34851        Noble Park       5 Blaby St      3    h     PI
C21
34852         Reservoir     18 Elinda Pl      3    u     SP
RW
34853     Roxburgh Park   14 Stainsby Cr      4    h      S
Raine
34854  Springvale South    8 Bellbird Ct      4    h     PI
Barry
34856       Westmeadows     42 Pascoe St      4    h      S
Barry

             Date  Distance  Postcode  Bedroom  ...  BuildingArea
YearBuilt  \
1        3/9/2016      13.5    3042.0      3.0  ...           225
2016.0
2        3/9/2016       3.3    3206.0      2.0  ...            82
1900.0
4        3/9/2016       6.4    3078.0      3.0  ...           122
2003.0
5        3/9/2016       6.4    3078.0      3.0  ...           263
1930.0
6        3/9/2016       6.4    3078.0      3.0  ...           inf
2013.0
...           ...       ...       ...      ...  ...           ...
...
34851  30/09/2017      22.7    3174.0      3.0  ...         130.0
1959.0
34852  30/09/2017      12.0    3073.0      3.0  ...         105.0
1990.0
34853  30/09/2017      20.6    3064.0      4.0  ...         225.0
1995.0
34854  30/09/2017      22.2    3172.0      4.0  ...         152.0
1970.0
34856  30/09/2017      16.5    3049.0      4.0  ...         140.0
1960.0

                          CouncilArea  Latitude  Longtitude  \
1          Moonee Valley City Council -37.71800   144.87800
2           Port Phillip City Council -37.84590   144.95550
4                Darebin City Council -37.78180   145.01980
5                Darebin City Council -37.77070   145.03180
6                Darebin City Council -37.78540   145.03250
...                               ...       ...         ...
34851  Greater Dandenong City Council -37.96900   145.18226
```

```
34852           Darebin City Council -37.69769   145.02332
34853              Hume City Council -37.63665   144.92976
34854  Greater Dandenong City Council -37.97037   145.15449
34856              Hume City Council -37.67631   144.89409

                         Regionname  Propertycount      ParkingArea
Price  \
1          Western Metropolitan         3464.0  Detached Garage
840000.0
2         Southern Metropolitan         3280.0  Attached Garage
1275000.0
4         Northern Metropolitan         2211.0          Parkade
NaN
5         Northern Metropolitan         2211.0      Underground
2000000.0
6         Northern Metropolitan         2211.0    Outdoor Stall
1110000.0
...                         ...            ...              ...
...
34851  South-Eastern Metropolitan      11806.0           Indoor
627500.0
34852       Northern Metropolitan      21650.0          Parkade
475000.0
34853       Northern Metropolitan       5833.0      Underground
591000.0
34854  South-Eastern Metropolitan       4054.0          Carport
NaN
34856       Northern Metropolitan       2474.0  Attached Garage
791000.0

       PropertyAge
1              7.0
2            123.0
4             20.0
5             93.0
6             10.0
...            ...
34851         64.0
34852         33.0
34853         28.0
34854         53.0
34856         63.0

[15543 rows x 23 columns]
```

Keeping the data concise as i do not need yearbuilt, method, latitude and longitude as from face value there is not enough contextual data for me to deem them very important

```
mel_housing =
mel_housing.drop(['YearBuilt','Method','Latitude','Longtitude'], axis
= 1)
mel_housing
```

```
                  Suburb            Address  Rooms Type         SellerG  \
1           Airport West     154 Halsey Rd      3    t          Nelson
2            Albert Park    105 Kerferd Rd      2    h  hockingstuart
4             Alphington      30 Austin St      3    h         McGrath
5             Alphington        6 Smith St      4    h           Brace
6             Alphington   5/6 Yarralea St      3    h          Jellis
...                  ...               ...    ...  ...             ...
34851         Noble Park        5 Blaby St      3    h             C21
34852          Reservoir      18 Elinda Pl      3    u              RW
34853      Roxburgh Park   14 Stainsby Cr      4    h           Raine
34854  Springvale South     8 Bellbird Ct      4    h           Barry
34856        Westmeadows      42 Pascoe St      4    h           Barry

             Date  Distance  Postcode  Bedroom  Bathroom  Car
Landsize  \
1        3/9/2016      13.5    3042.0      3.0       2.0  1.0
303.0
2        3/9/2016       3.3    3206.0      2.0       1.0  0.0
120.0
4        3/9/2016       6.4    3078.0      3.0       2.0  1.0
174.0
5        3/9/2016       6.4    3078.0      3.0       2.0  4.0
853.0
6        3/9/2016       6.4    3078.0      3.0       2.0  2.0
208.0
...           ...       ...       ...      ...       ...  ...       ..
.
34851  30/09/2017      22.7    3174.0      3.0       1.0  6.0
569.0
34852  30/09/2017      12.0    3073.0      3.0       1.0  1.0
NaN
34853  30/09/2017      20.6    3064.0      4.0       2.0  2.0
NaN
34854  30/09/2017      22.2    3172.0      4.0       2.0  2.0
534.0
34856  30/09/2017      16.5    3049.0      4.0       2.0  6.0
813.0

      BuildingArea                     CouncilArea  \
1              225      Moonee Valley City Council
2               82       Port Phillip City Council
4              122            Darebin City Council
5              263            Darebin City Council
6              inf            Darebin City Council
...            ...                             ...
```

```
34851        130.0  Greater Dandenong City Council
34852        105.0           Darebin City Council
34853        225.0              Hume City Council
34854        152.0  Greater Dandenong City Council
34856        140.0              Hume City Council

                       Regionname  Propertycount      ParkingArea
Price  \
1          Western Metropolitan         3464.0  Detached Garage
840000.0
2         Southern Metropolitan         3280.0  Attached Garage
1275000.0
4         Northern Metropolitan         2211.0          Parkade
NaN
5         Northern Metropolitan         2211.0      Underground
2000000.0
6         Northern Metropolitan         2211.0    Outdoor Stall
1110000.0
...                         ...            ...              ...
...
34851  South-Eastern Metropolitan       11806.0           Indoor
627500.0
34852       Northern Metropolitan       21650.0          Parkade
475000.0
34853       Northern Metropolitan        5833.0      Underground
591000.0
34854  South-Eastern Metropolitan        4054.0          Carport
NaN
34856       Northern Metropolitan        2474.0  Attached Garage
791000.0

       PropertyAge
1              7.0
2            123.0
4             20.0
5             93.0
6             10.0
...            ...
34851         64.0
34852         33.0
34853         28.0
34854         53.0
34856         63.0

[15543 rows x 19 columns]
```

1.3 Display summary statistics and data types of the features.

```
mel_housing.describe()
```

```
                Rooms     Distance      Postcode       Bedroom
Bathroom  \
count  15543.000000  15543.00000  15543.000000  15543.000000
15542.000000
mean       3.108473     11.15479   3117.082481      3.090330
1.670634
std        0.986302      6.94583    115.296813      1.008559
0.735059
min        1.000000      0.00000   3000.000000      0.000000
0.000000
25%        2.000000      6.30000   3047.000000      2.000000
1.000000
50%        3.000000     10.10000   3101.000000      3.000000
2.000000
75%        4.000000     14.00000   3155.000000      4.000000
2.000000
max       12.000000     48.10000   3978.000000     30.000000
12.000000

                  Car      Landsize  Propertycount         Price
PropertyAge
count  15291.000000  13709.000000   15543.000000  1.207800e+04
15543.000000
mean       1.704205    531.397768    7519.586116  1.077308e+06
57.630380
std        1.000952   1053.382858    4302.386291  6.714684e+05
36.765601
min        0.000000      0.000000     129.000000  8.500000e+04     -
83.000000
25%        1.000000    204.000000    4442.000000  6.320000e+05
23.000000
50%        2.000000    470.000000    6763.000000  8.852500e+05
53.000000
75%        2.000000    658.000000   10331.000000  1.320000e+06
83.000000
max       26.000000  42800.000000   21650.000000  9.000000e+06
173.000000
```

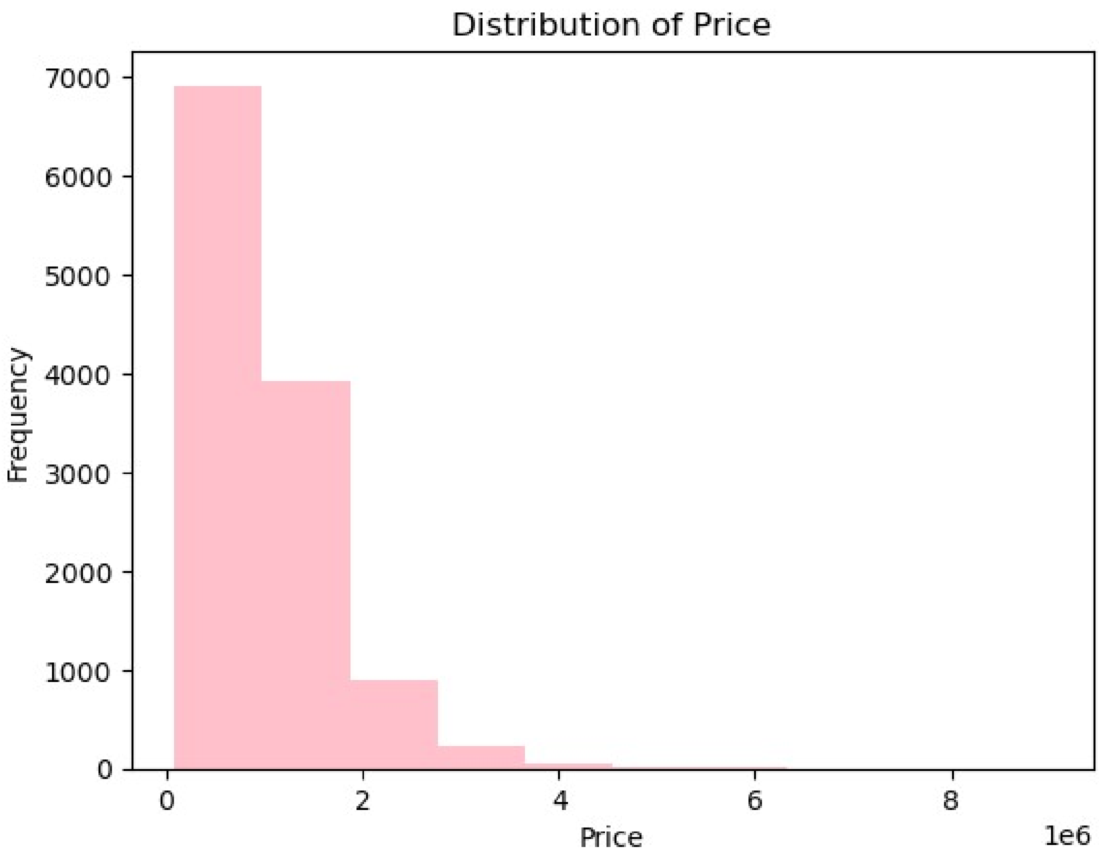
Exploratory Data Analysis (EDA) (30 points):

Distribution of Price after i had refined the data

2.1 Visualize the distribution of numeric variables using histograms and box plots.

```
mel_housing['Price'].hist(color='pink', grid=False)
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.title('Distribution of Price')
```

```
Text(0.5, 1.0, 'Distribution of Price')
```



Finding the correlation between Price and some numerical data in order to calculate which values depend on which Price.

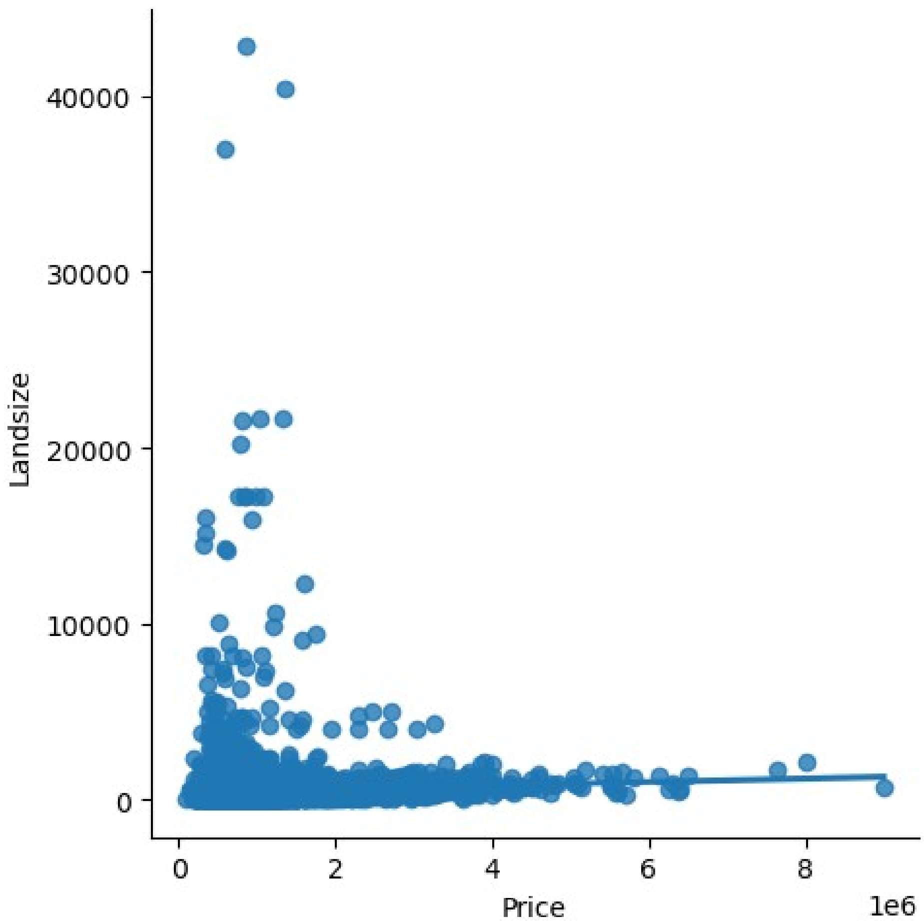
```
print('Correlation of Price and Landsize is ',
mel_housing['Price'].corr(mel_housing['Landsize']))
print('Correlation of Price and Propertycount is
',mel_housing['Price'].corr(mel_housing['Propertycount']))
print('Correlation of Price and Distance is ',
mel_housing['Price'].corr(mel_housing['Distance']))
print('Correlation of Price and PropertyAge is ',
mel_housing['Price'].corr(mel_housing['PropertyAge']))
```

```
Correlation of Price and Landsize is  0.05957442097897617
Correlation of Price and Propertycount is  -0.05908207218928333
Correlation of Price and Distance is  -0.23229107807731325
Correlation of Price and PropertyAge is  0.33996565172632415
```

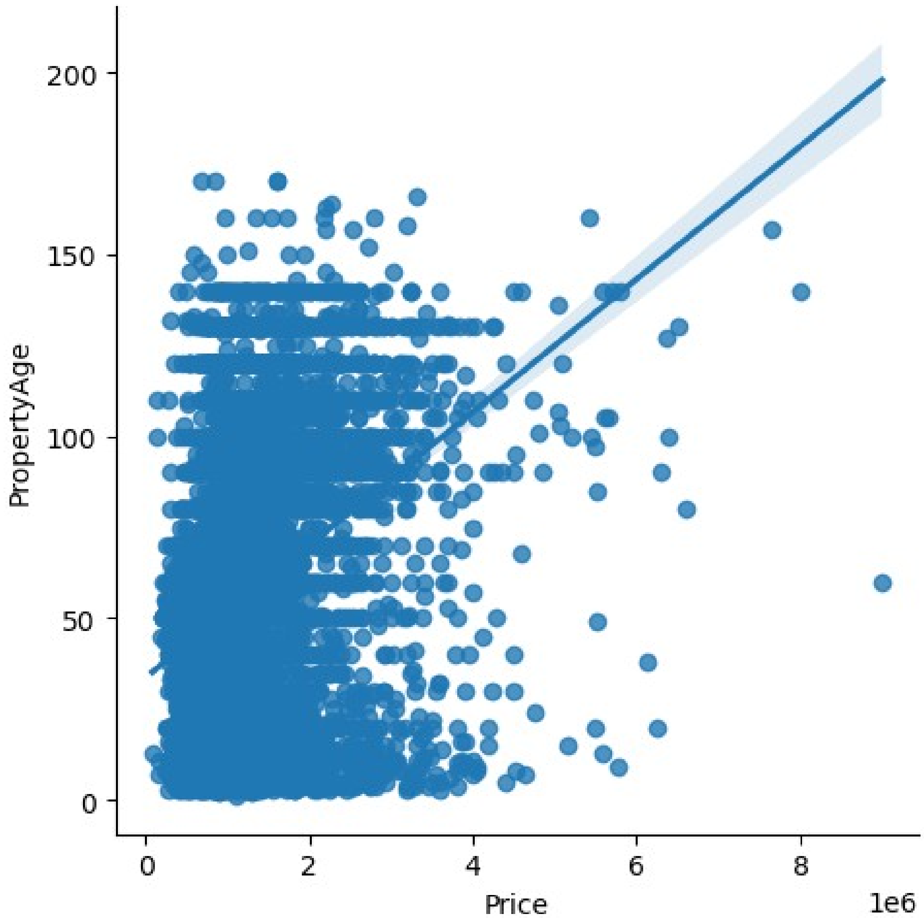
Wanted to graph the lines of best fit for price, landsize and propertyage to view where the average data values lie and identify any of the possible ouytliers for this data.

2.2 Explore relationships between features and the target variable using scatter plots and correlation matrices.

```
sns.lmplot(x="Price", y="Landsize", data=mel_housing)

c:\Users\pdere\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)

<seaborn.axisgrid.FacetGrid at 0x1e89d9fb290>
```




```
sns.lmplot(x="Price", y="PropertyAge", data=mel_housing)

c:\Users\pdere\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)

<seaborn.axisgrid.FacetGrid at 0x1e88eea3290>
```



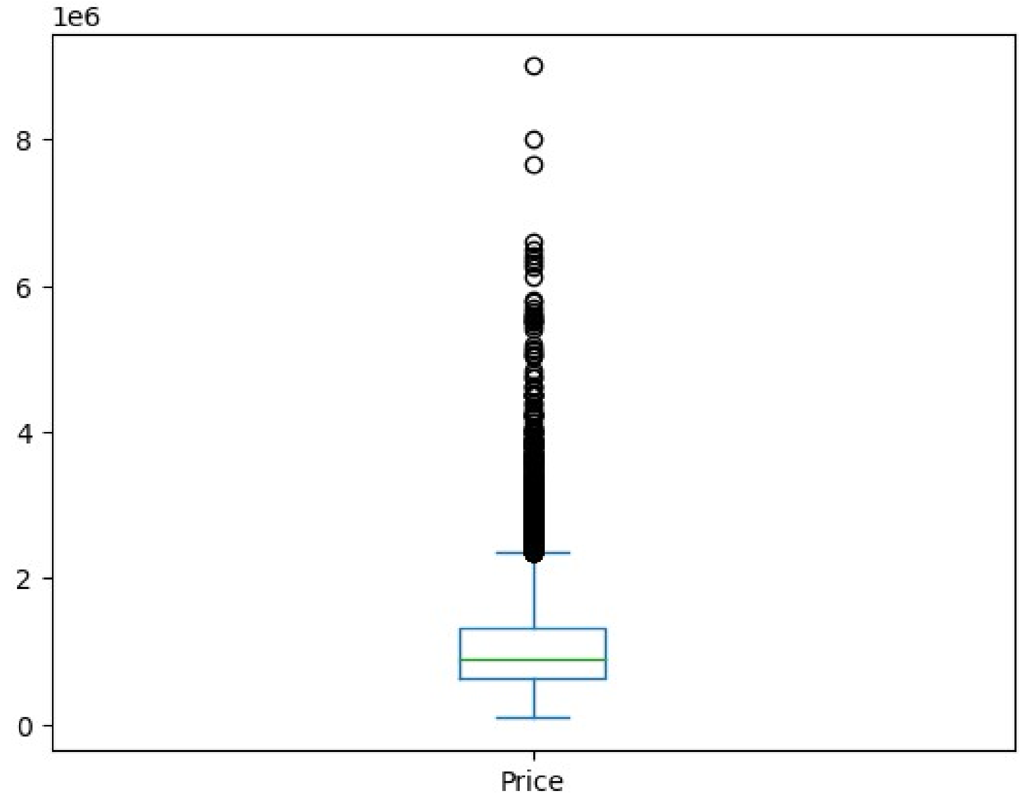
Box Plots I needed to look up the definition as i have never made a box plot before but this is to further visualise the outliers of the numerical values from the data set provided.

2.3 Examine categorical variables with bar plots and frequency tables.

2.4 Identify potential outliers and discuss their impact on the dataset.

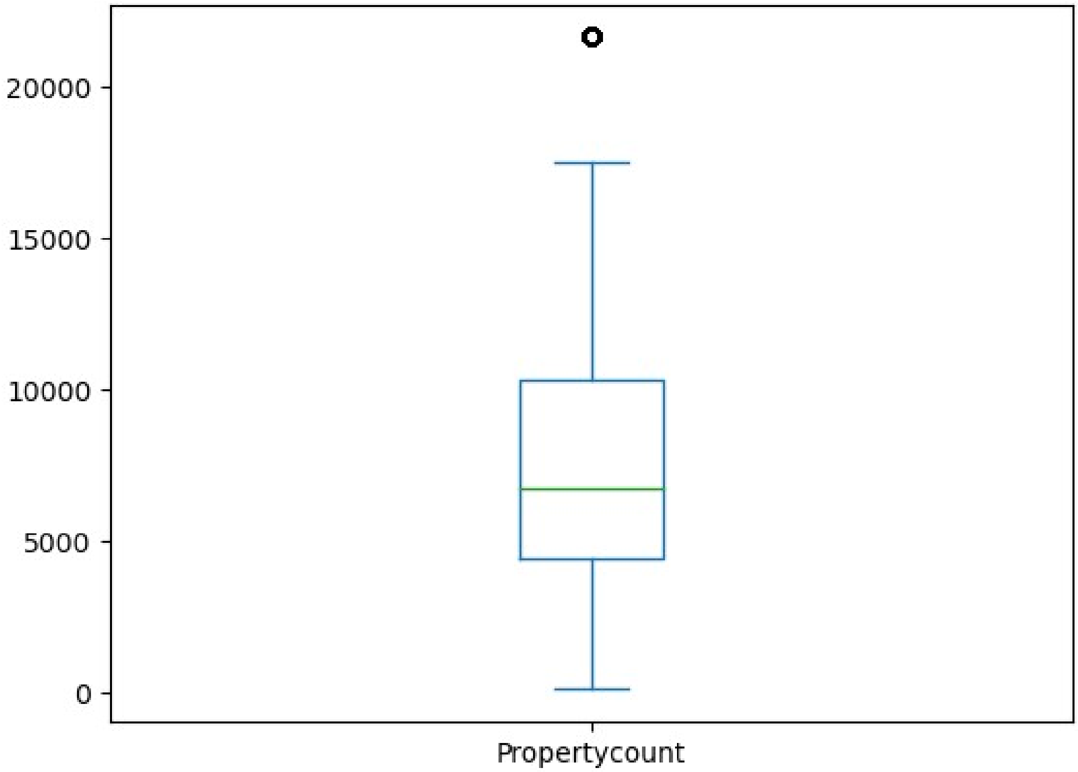
```
mel_housing['Price'].plot(kind = 'box')
```

```
<Axes: >
```



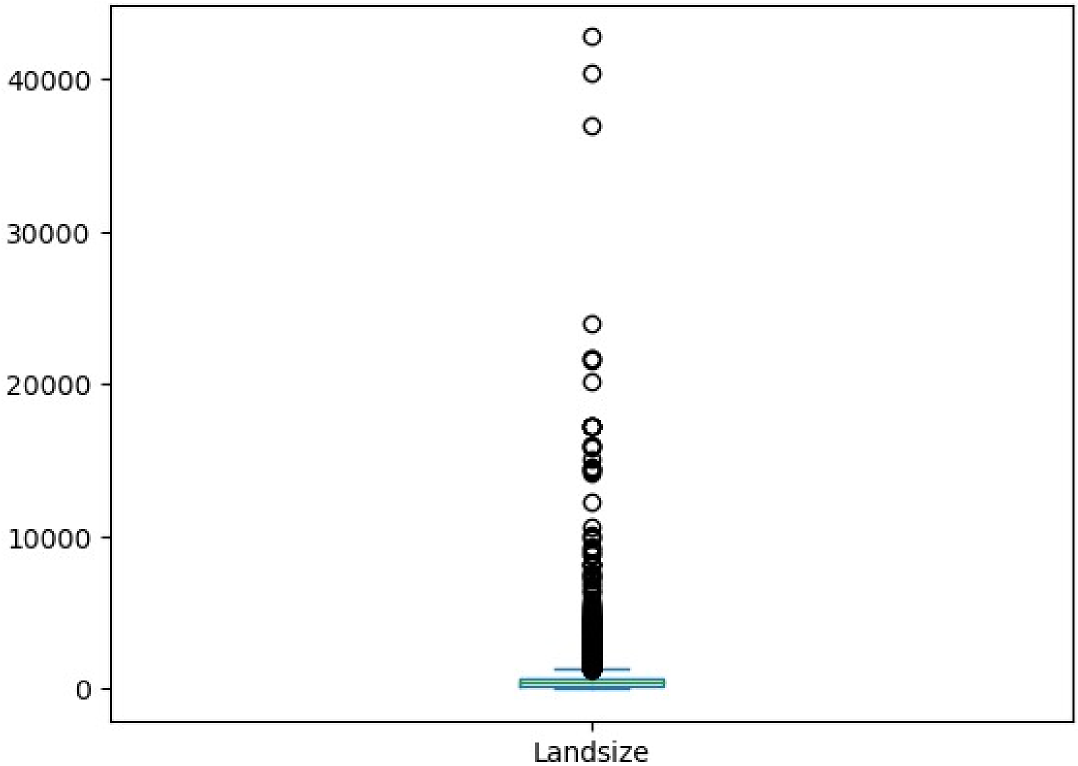

```
mel_housing['Propertycount'].plot(kind = 'box')
```

```
<Axes: >
```



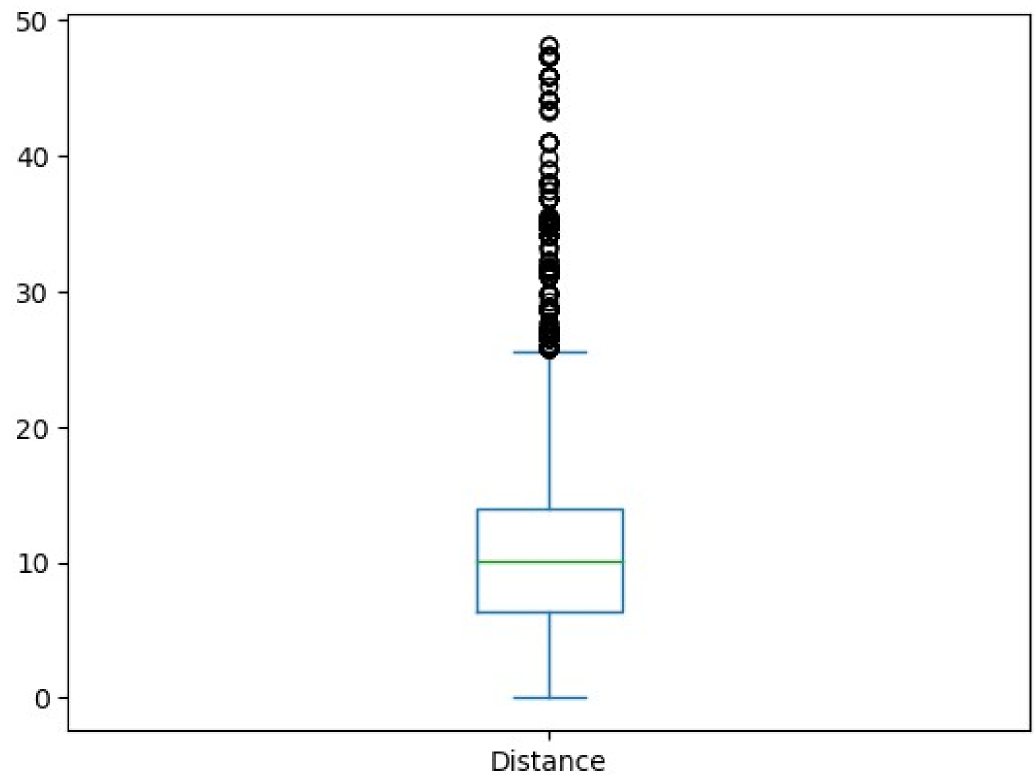

```
mel_housing['Landsize'].plot(kind = 'box')
```

```
<Axes: >
```




```
mel_housing['Distance'].plot(kind = 'box')
```

```
<Axes: >
```



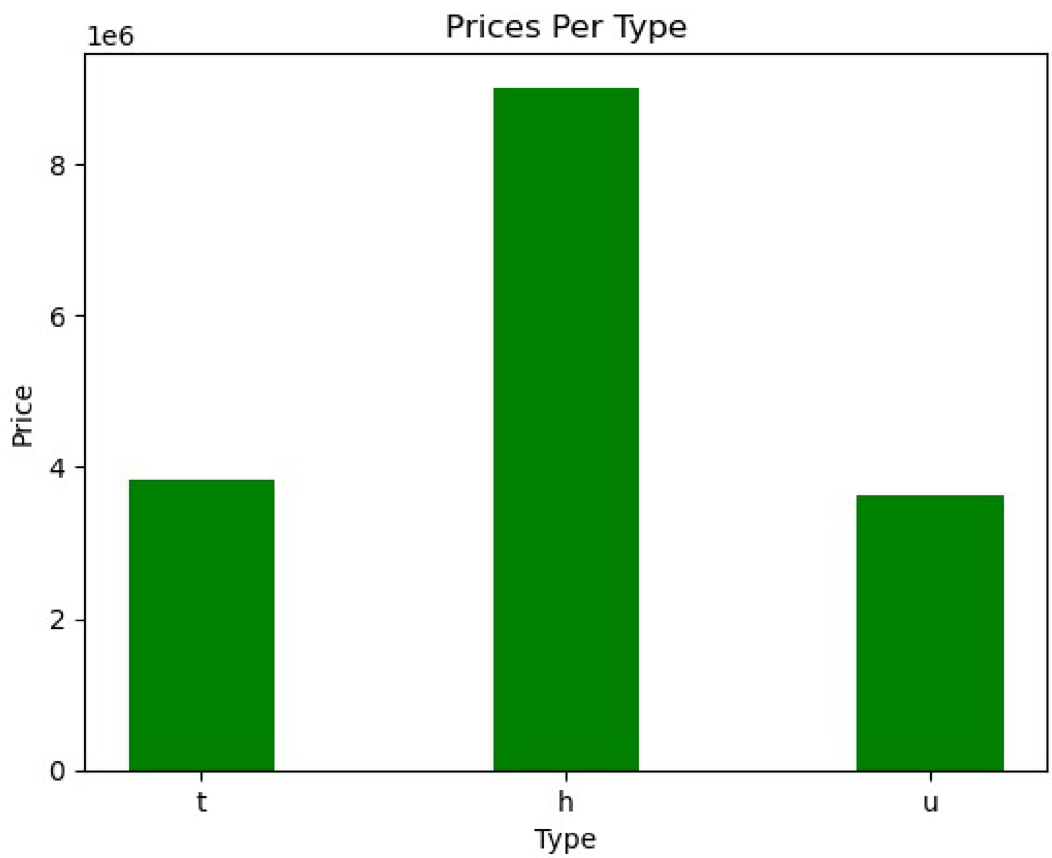
Bar plots of prices per regionname as i found there were 8 regions all together which made it easier to graph rather than the SellerG which had way to many names

['Nelson', 'hockingstuart', 'McGrath', 'Brace', 'Jellis', ..., 'Ace', 'Leased', 'Avion', 'Weston', 'Craig'] Length: 306 Categories (388, object): ['@Realty', 'A', 'AIME', 'ASL', ..., 'iProperty', 'iSell', 'iTRAK', 'voglwalpole']

I identified the types, although there is no data to explain the letter representatives, it seems that type 'h' has the highest value when it comes to housing in melbourne, which will be great to look at throughout some of the analysis

Feature Engineering (40 points):

```
print(mel_housing['Type'].unique())

['t', 'h', 'u']
Categories (3, object): ['h', 't', 'u']

plt.bar(mel_housing['Type'],mel_housing['Price'],color='green',width=
0.4)
plt.title('Prices Per Type')
plt.xlabel('Type')
plt.ylabel('Price')
plt.show()
```




```
pd.crosstab(mel_housing['Price'], mel_housing['Type'])
```

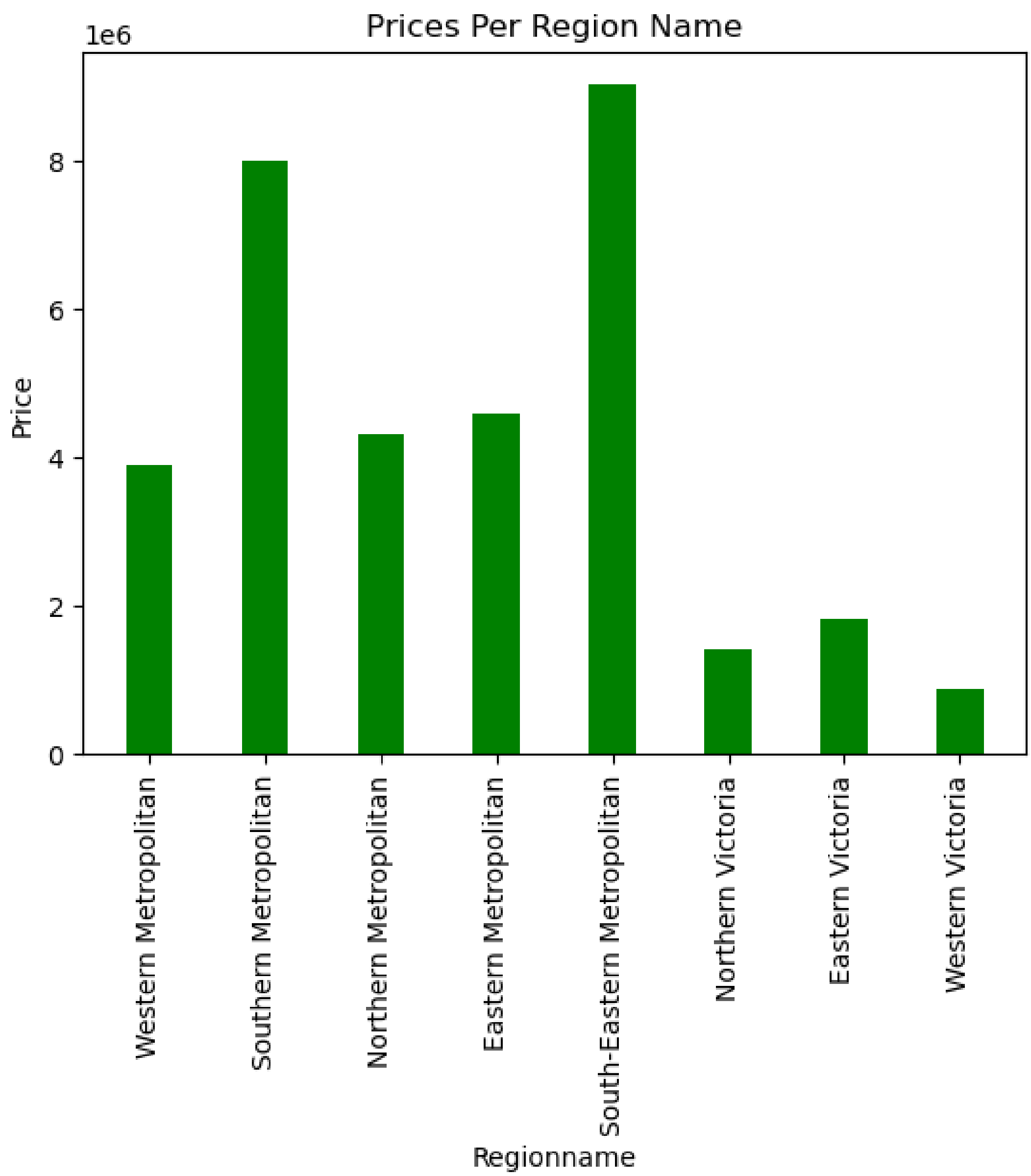
```
Type        h  t  u
Price
85000.0     0  0  1
131000.0    1  0  0
145000.0    1  0  0
160000.0    0  0  1
170000.0    0  0  1
...        .. .. ..
6500000.0   1  0  0
6600000.0   1  0  0
7650000.0   1  0  0
8000000.0   1  0  0
9000000.0   1  0  0

[2104 rows x 3 columns]
```

Regionname is another category i looked at to help further delve into predicting the house pricing. I wanted to make a box plot for this to identify the regions with the highest and lowest prices.

```
print(mel_housing['Regionname'].unique())
```

```
['Western Metropolitan', 'Southern Metropolitan', 'Northern
Metropolitan', 'Eastern Metropolitan', 'South-Eastern Metropolitan',
'Northern Victoria', 'Eastern Victoria', 'Western Victoria']
Categories (8, object): ['Eastern Metropolitan', 'Eastern Victoria',
'Northern Metropolitan', 'Northern Victoria', 'South-Eastern
Metropolitan', 'Southern Metropolitan', 'Western Metropolitan',
'Western Victoria']
```

```
plt.bar(mel_housing['Regionname'],mel_housing['Price'],color='green',w
idth= 0.4)
plt.xticks(rotation = 90)
plt.title('Prices Per Region Name')
plt.xlabel('Regionname')
plt.ylabel('Price')
plt.show()
```



Frequency Table for Price and Region Names as I want to visualise this set of data to check the frequency of the prices per region as i am only foc on a few categories to make it simpler for myself

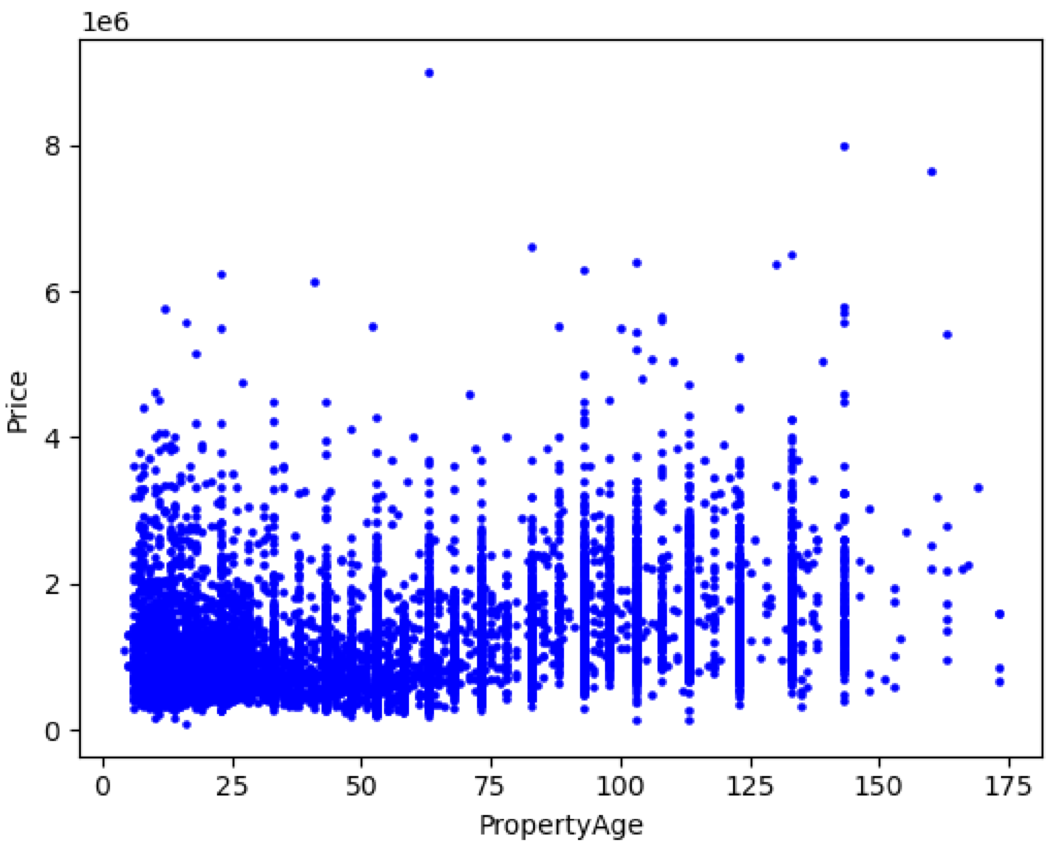
```
pd.crosstab(mel_housing['Price'], mel_housing['Regionname'])

Regionname  Eastern Metropolitan  Eastern Victoria  Northern
Metropolitan  \
Price

85000.0                        0                 0
0
131000.0                       0                 0
```

```
0
145000.0                       0                 0
1
160000.0                       0                 0
0
170000.0                       0                 0
0
...                          ...               ...
...
6500000.0                      0                 0
0
6600000.0                      0                 0
0
7650000.0                      0                 0
0
8000000.0                      0                 0
0
9000000.0                      0                 0
0

Regionname  Northern Victoria  South-Eastern Metropolitan  \
Price
85000.0                     0                           0
131000.0                    0                           0
145000.0                    0                           0
160000.0                    0                           0
170000.0                    0                           0
...                       ...                         ...
6500000.0                   0                           0
6600000.0                   0                           0
7650000.0                   0                           0
8000000.0                   0                           0
9000000.0                   0                           1

Regionname  Southern Metropolitan  Western Metropolitan  Western
Victoria
Price

85000.0                         0                     1
0
131000.0                        1                     0
0
145000.0                        0                     0
0
160000.0                        1                     0
0
170000.0                        0                     1
0
...                           ...                   ...
...
```

```
6500000.0                                1                      0
0
6600000.0                                1                      0
0
7650000.0                                1                      0
0
8000000.0                                1                      0
0
9000000.0                                0                      0
0

[2104 rows x 8 columns]
```

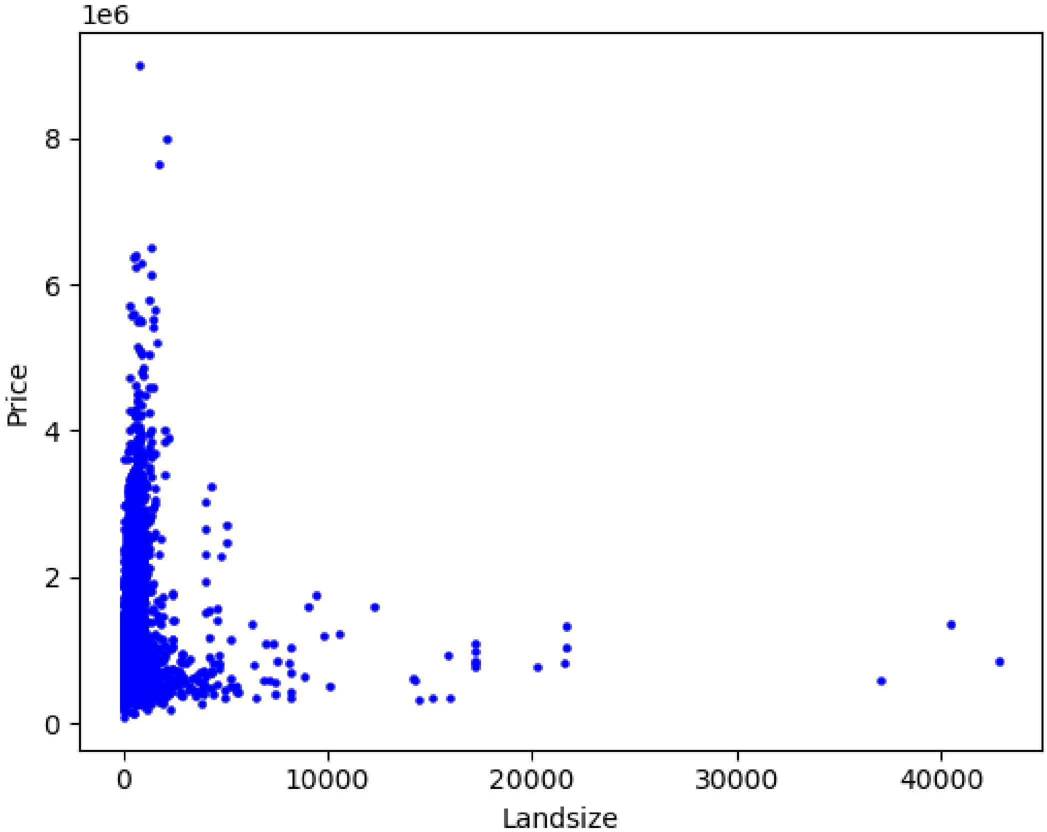
3.3 Creating interaction features or polynomial features

```
mel_housing.plot.scatter(x = 'PropertyAge', y = 'Price', s = 5, c =
'blue')

<Axes: xlabel='PropertyAge', ylabel='Price'>
```

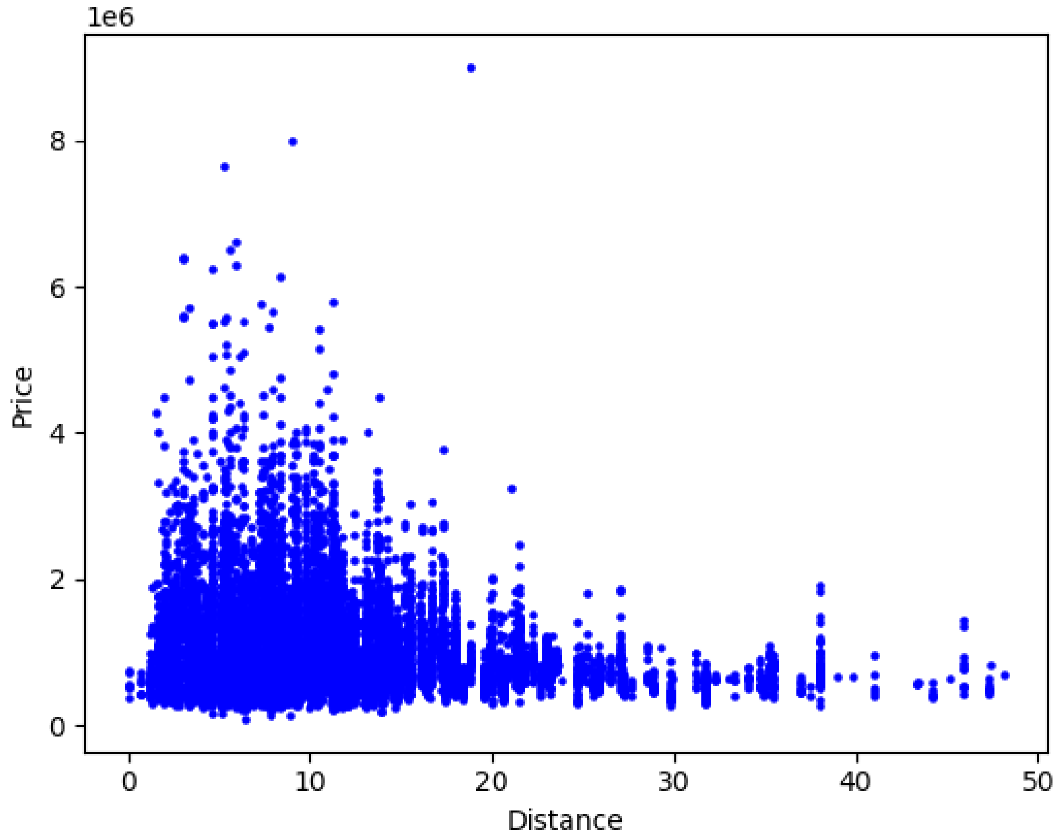



```
mel_housing.plot.scatter(x = 'Landsize', y = 'Price', s = 5, c =
'blue')
```

```
<Axes: xlabel='Landsize', ylabel='Price'>
```




```
mel_housing.plot.scatter(x = 'Distance', y = 'Price', s = 5, c =
'blue')

<Axes: xlabel='Distance', ylabel='Price'>
```



Conclusion and Recommendations (10 points):

Summarize the key findings from the EDA and feature engineering processes

Key findings from the melbourne housing dataset I found where that normally as the distance decreases the price increases.Similarly, the higher the property age the higher the price was which I find stange as in Ireland, normally older properties are cheaper compared to newer properties here. The price can be grouped by Region names and Type to provide a clearer overview of where exactly the price increase may occur according to historical trends. In the case for Regions in Melbourne housing, South Eastern Metropolitan had the highest price for housing so it seems that will also increase as the years go by. All the data is relative to 2023 as that is the current year I am analysing it.

Feature Engineering methods I used were one hot encoding to assign some of the column names as type category to figure out how i can relate them to price and organise the data a bit more, deleting minimal missing random values as it would not impede on my analysis and I wanted to use those values to help predict price, creating graphs for visual analysis to plot the out a plan for the data, I got rid of invalid values that were not to many and seemed like outliers in the grand scheme of analysing.

In conclusion, I surmise that using regionname, type, distance, landsize, propertyage we can predict the future price of melbourne housing. I believe these values are important enough in the data. This data is easy enough to read and understand with some given context about Type. This data is easy enough to graph.

```
mel_housing[["Regionname","Type","Distance","Landsize","PropertyAge","
Price"]]
```

```
                       Regionname Type  Distance  Landsize  
PropertyAge  \
1            Western Metropolitan    t      13.5     303.0  
7.0
2           Southern Metropolitan    h       3.3     120.0  
123.0
4           Northern Metropolitan    h       6.4     174.0  
20.0
5           Northern Metropolitan    h       6.4     853.0  
93.0
6           Northern Metropolitan    h       6.4     208.0  
10.0
...                           ...  ...       ...       ...             ..
.
34851  South-Eastern Metropolitan    h      22.7     569.0  
64.0
34852       Northern Metropolitan    u      12.0       NaN  
33.0
34853       Northern Metropolitan    h      20.6       NaN  
28.0
34854  South-Eastern Metropolitan    h      22.2     534.0  
53.0
34856       Northern Metropolitan    h      16.5     813.0  
63.0

           Price
1       840000.0
2      1275000.0
4            NaN
5      2000000.0
6      1110000.0
...          ...
34851   627500.0
34852   475000.0
34853   591000.0
34854        NaN
34856   791000.0

[15543 rows x 6 columns]
```