

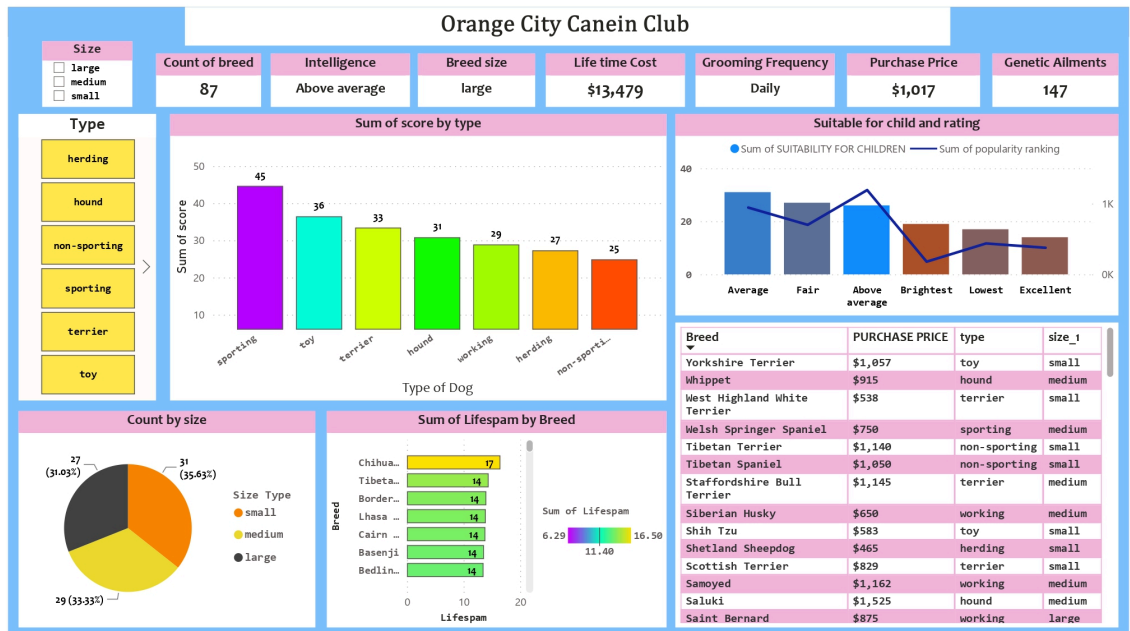
Power Bi dashboard

In [1]: `from IPython.display import Image`

Provide the correct path to your image file

`img_path = '/Users/pritamprabre/Downloads/Dexter_Power BI file_page-Image(filename=img_path)`

Out [1]:



Orange City Canine Club Dataset

This is an demo project where we have the set of data belonging from dog breed with their various parameter such as

- * Type of breed
- * Its intelligence level
- * various expenditures like Purchasing Price, Food cost per year and life time cost

Also we have the ranking and score which defines the dog is sutable for which kind of condition such as family dog or guard dogs.

In [2]: `#importing required libraries`
`import pandas as pd`
`import numpy as np`
`import matplotlib.pyplot as plt`
`plt.get_current_fig_manager().full_screen_toggle()`
`import seaborn as sns`

<Figure size 640x480 with 0 Axes>

In [3]: `#Uploading dataset and checking its shape`
`data=pd.read_csv('dogs-ranking-dataset.csv')`
`data.shape`

Out [3]: (87, 19)

```
In [4]: #overview of dataset
data.head()
```

Out [4]:

	Breed	type	score	popularity ranking	size	intelligence	congenital ailments	score for kids	size.1	\$LIFETIME COST
0	Border Terrier	terrier	3.61	61	1	Above average	none	4.99	small	\$22,600
1	Cairn Terrier	terrier	3.53	48	1	Above average	'lion jaw', heart problems	4.91	small	\$21,900
2	Siberian Husky	working	3.22	16	2	Average	none	4.72	medium	\$22,000
3	Welsh Springer Spaniel	sporting	3.34	81	2	Above average	hip problems	4.71	medium	\$20,200
4	English Cocker Spaniel	sporting	3.33	51	2	Excellent	none	4.70	medium	\$18,900

```
In [5]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 87 entries, 0 to 86
Data columns (total 19 columns):
#   Column                                     Non-Null Count  Dtype
---  -
0   Breed                                     87 non-null     object
1   type                                     87 non-null     object
2   score                                    87 non-null     float64
3   popularity ranking                       87 non-null     int64
4   size                                     87 non-null     int64
5   intelligence                             87 non-null     object
6   congenital ailments                     87 non-null     object
7   score for kids                           87 non-null     float64
8   size.1                                   87 non-null     object
9   $LIFETIME COST                           87 non-null     object
10  INTELLIGENCE RANK                         87 non-null     int64
11  INTELLIGENCE %                           87 non-null     object
12  LONGEVITY(YEARS)                         87 non-null     float64
13  NUMBER OF GENETIC AILMENTS              87 non-null     int64
14  GENETIC AILMENTS                        87 non-null     object
15  PURCHASE PRICE                           87 non-null     object
16  FOOD COSTS PER YEAR                      87 non-null     object
17  GROOMING FREQUENCY                       87 non-null     object
18  SUITABILITY FOR CHILDREN                 87 non-null     int64
dtypes: float64(3), int64(5), object(11)
memory usage: 13.0+ KB
```

```
In [6]: #checking whether the dataset containg any null value or not
null_values = data.isnull().sum()
null_percentage = (data.isnull().sum() / len(data)) * 100

null_stats = pd.DataFrame({
    'Column': data.columns,
    'Null Values': null_values.values,
    'Percentage': null_percentage.values
})

print(null_stats)
```

	Column	Null Values	Percentage
0	Breed	0	0.0
1	type	0	0.0
2	score	0	0.0
3	popularity ranking	0	0.0
4	size	0	0.0
5	intelligence	0	0.0
6	congential ailments	0	0.0
7	score for kids	0	0.0
8	size.1	0	0.0
9	\$LIFETIME COST	0	0.0
10	INTELLIGENCE RANK	0	0.0
11	INTELLIGENCE %	0	0.0
12	LONGEVITY(YEARS)	0	0.0
13	NUMBER OF GENETIC AILMENTS	0	0.0
14	GENETIC AILMENTS	0	0.0
15	PURCHASE PRICE	0	0.0
16	FOOD COSTS PER YEAR	0	0.0
17	GROOMING FREQUENCY	0	0.0
18	SUITABILITY FOR CHILDREN	0	0.0

```
In [7]: #describing data to see its numerical parameters
data.describe()
```

Out [7]:

	score	popularity ranking	size	score for kids	INTELLIGENCE RANK	LONGEVITY(YEARS)	NUN GEN AILMI
count	87.000000	87.000000	87.000000	87.000000	87.000000	87.000000	87.00
mean	2.603678	44.000000	1.954023	3.681839	41.540230	11.117701	1.68
std	0.570288	25.258662	0.819927	0.655736	21.979803	1.938465	1.70
min	0.990000	1.000000	1.000000	1.860000	1.000000	6.290000	0.00
25%	2.185000	22.500000	1.000000	3.180000	27.000000	10.000000	0.50
50%	2.710000	44.000000	2.000000	3.810000	43.000000	11.560000	1.00
75%	3.035000	65.500000	3.000000	4.115000	59.000000	12.430000	2.00
max	3.640000	87.000000	3.000000	4.990000	80.000000	16.500000	9.00

```
In [8]: # Remove '$' and ',' and convert to float
data['$LIFETIME COST'] = data['$LIFETIME COST'].astype(str).str.replace('$', '')

# Remove '%' and convert to float
data['INTELLIGENCE %'] = data['INTELLIGENCE %'].str.rstrip('%').astype(float)

# Remove '$' and ',' and convert to float
data['PURCHASE PRICE'] = data['PURCHASE PRICE'].astype(str).str.replace('$', '')

data['FOOD COSTS PER YEAR'] = data['FOOD COSTS PER YEAR'].str.replace('$', '')
```

```
In [9]: #creating a new dataset containing object datatype
data_category = data.select_dtypes(include=['object'])
```

```
In [10]: #creating a new dataset containing int, float datatype
data_numeric = data.select_dtypes(include=['int64', 'float64'])
```

```
In [11]: data_category.head()
```

Out[11]:

	Breed	type	intelligence	congenital ailments	size.1	GENETIC AILMENTS	GROOMING FREQUENCY
0	Border Terrier	terrier	Above average	none	small	none	Once a week
1	Cairn Terrier	terrier	Above average	'lion jaw', heart problems	small	'lion jaw', heart problems	Once a week
2	Siberian Husky	working	Average	none	medium	none	Once in a few weeks
3	Welsh Springer Spaniel	sporting	Above average	hip problems	medium	hip problems	Once a week
4	English Cocker Spaniel	sporting	Excellent	none	medium	none	Once a week

```
In [12]: data_numeric.head()
```

Out[12]:

	score	popularity ranking	size	score for kids	\$LIFETIME COST	INTELLIGENCE RANK	INTELLIGENCE %	LONGEVITY(YEAR)
0	3.61	61	1	4.99	22638.0	30	70.0	14
1	3.53	48	1	4.91	21992.0	35	61.0	13
2	3.22	16	2	4.72	22049.0	45	45.0	12
3	3.34	81	2	4.71	20224.0	31	69.0	12
4	3.33	51	2	4.70	18993.0	18	82.0	11

```
#NO missing value found
#NO duplicate value found
#A separate dataframe has been created for categorical Variable
called as data_category
```

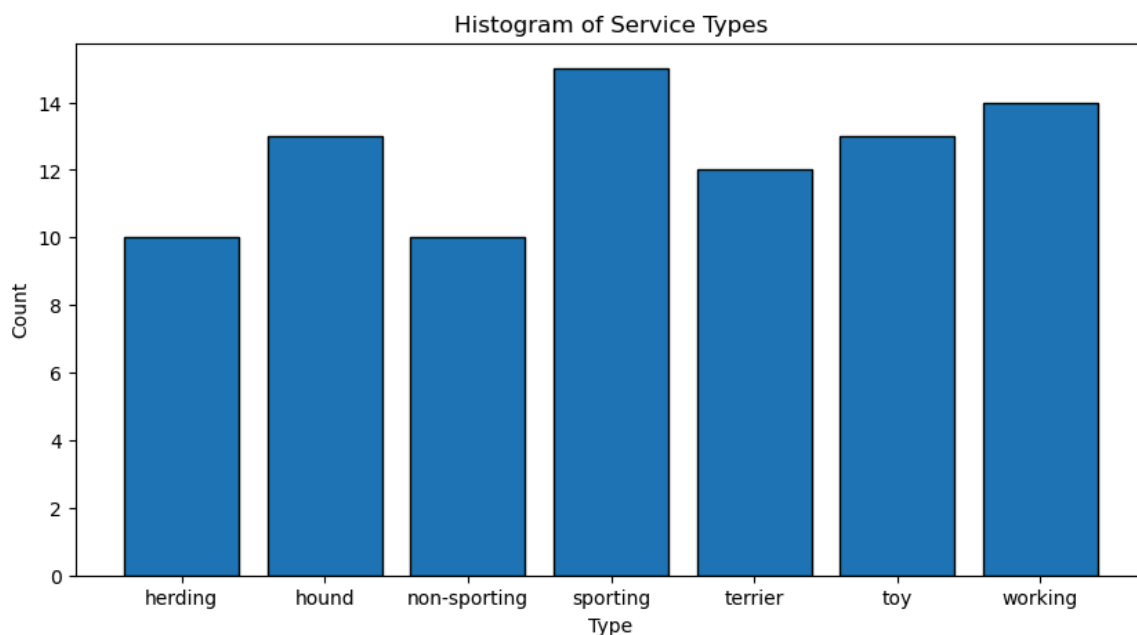
```
#A seperate dataframe has been created for numerical Variable called  
as data_numeric
```

Univariate analysis

```
In [13]: #looking for frequency of particular variable and its value count  
data['type'].value_counts()
```

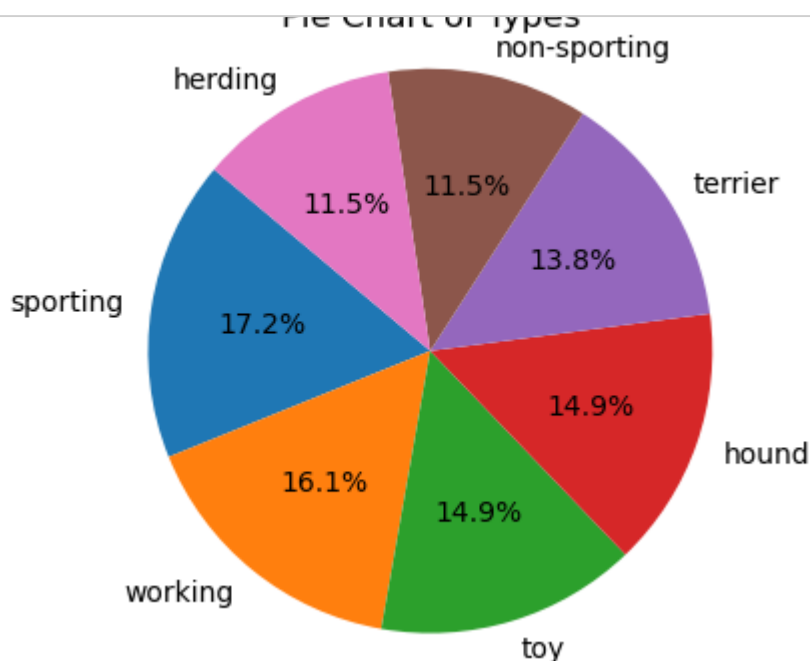
```
Out[13]: type  
sporting      15  
working       14  
toy           13  
hound         13  
terrier       12  
non-sporting  10  
herding       10  
Name: count, dtype: int64
```

```
In [14]: #Count of type of Dog  
Type_count= data['type'].value_counts().sort_index()  
plt.figure(figsize=(10, 5))  
plt.bar(Type_count.index, Type_count.values, edgecolor='black')  
plt.xlabel('Type')  
plt.ylabel('Count')  
plt.title('Histogram of Service Types')  
plt.show()
```



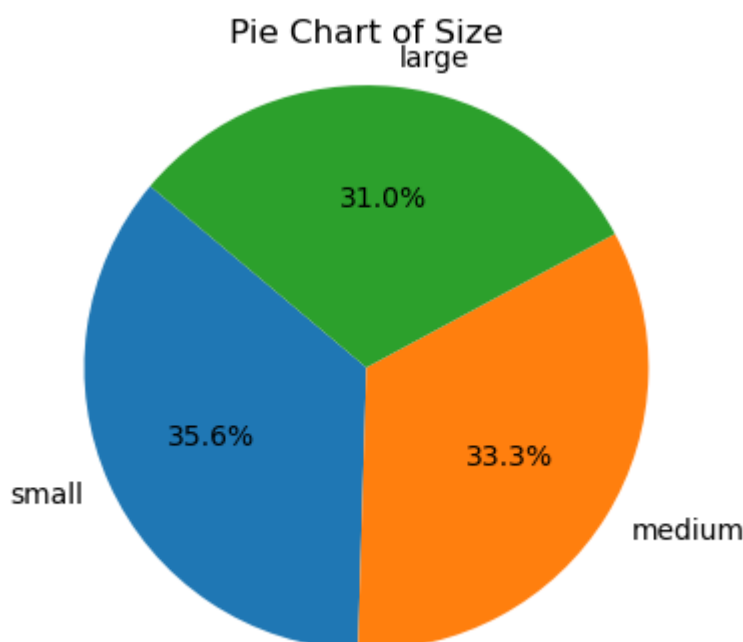
```
In [15]: type_counts = data['type'].value_counts()

# Create a pie chart
plt.figure(figsize=(4, 4))
plt.pie(type_counts, labels=type_counts.index, autopct='%1.1f%%', startangle=90)
plt.axis('equal') # Equal aspect ratio ensures that pie is drawn as a circle
plt.title("Pie Chart of Types")
plt.show()
```



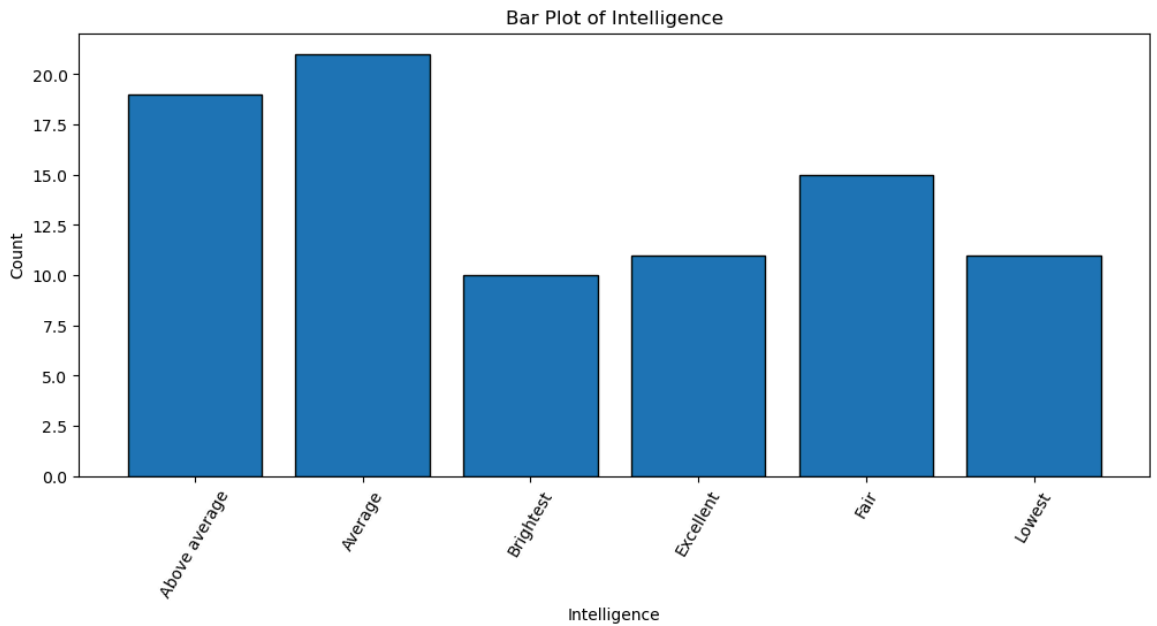
```
In [16]: size_counts = data['size.1'].value_counts()

# Create a pie chart
plt.figure(figsize=(4, 4))
plt.pie(size_counts, labels=size_counts.index, autopct='%1.1f%%', startangle=90)
plt.axis('equal') # Equal aspect ratio ensures that pie is drawn as a circle
plt.title("Pie Chart of Size")
plt.show()
```

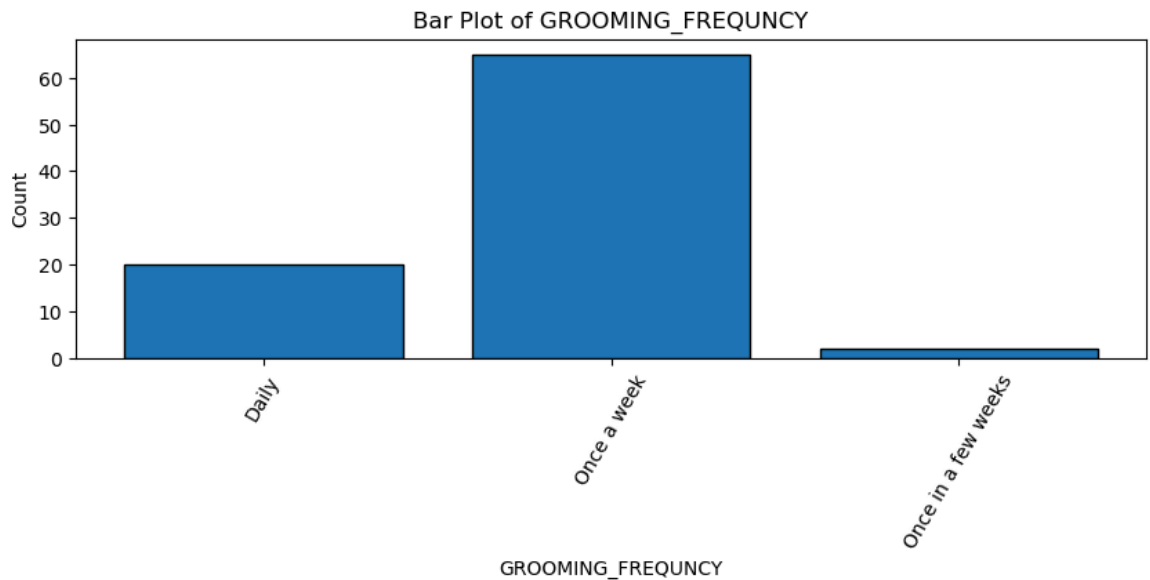


```
In [17]: #Dropping duplicate column as it has been presentt in the form of mune  
data = data.drop(columns=['size.1', 'congenital ailments'])
```

```
In [18]: #count of intelligence  
intelligence_counts = data['intelligence'].value_counts().sort_index()  
plt.figure(figsize=(12, 5))  
plt.bar(intelligence_counts.index, intelligence_counts.values, edgecolor='black')  
plt.xlabel('Intelligence')  
plt.xticks(rotation=60)  
plt.ylabel('Count')  
plt.title('Bar Plot of Intelligence')  
plt.show()
```

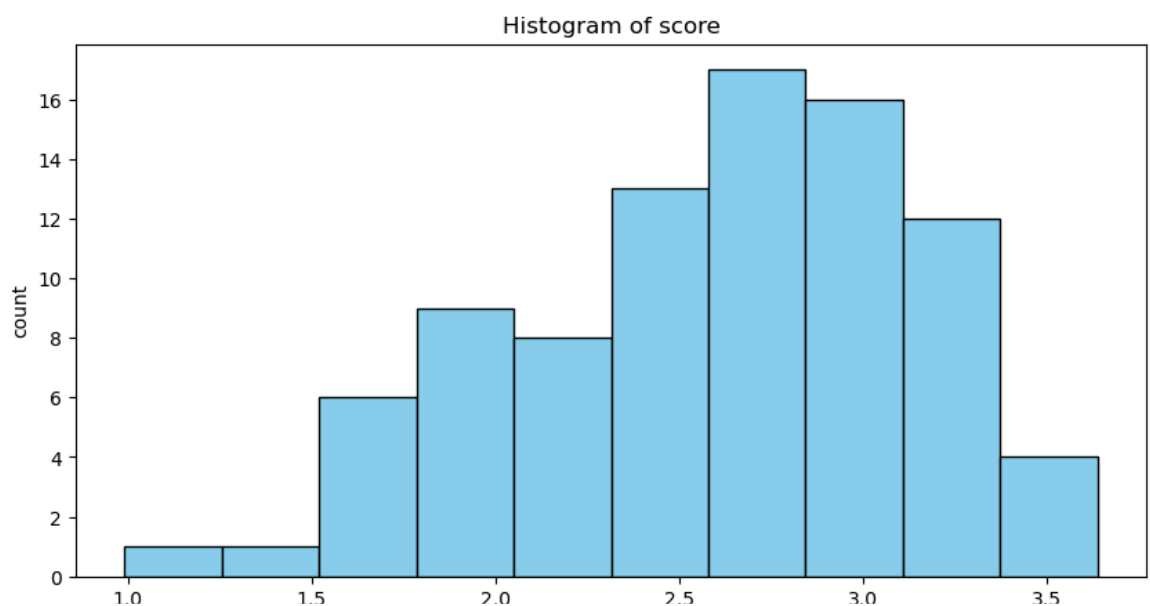


```
In [19]: # Count of Grooming Frequency
GROOMING_FREQUENCY=data['GROOMING FREQUENCY'].value_counts().sort_index()
plt.figure(figsize=(10,3))
plt.bar(GROOMING_FREQUENCY.index, GROOMING_FREQUENCY.values, edgecolor='black')
plt.xlabel('GROOMING_FREQUENCY')
plt.xticks(rotation=60)
plt.ylabel('Count')
plt.title('Bar Plot of GROOMING_FREQUENCY')
plt.show()
```



```
In [20]: plt.figure(figsize=(10,5))
plt.hist(data['score'],bins=10,color='skyblue', edgecolor='black')
plt.xlabel('Score')
plt.ylabel('count')
plt.title('Histogram of score')
plt.show
```

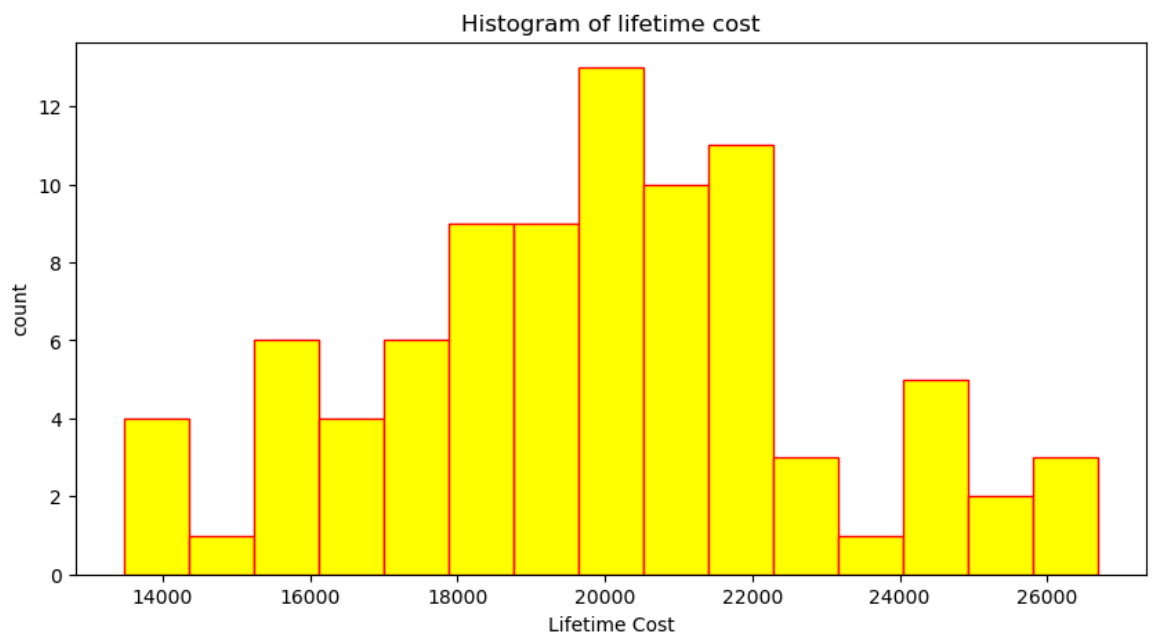
Out[20]: <function matplotlib.pyplot.show(close=None, block=None)>




```
In [21]: plt.figure(figsize=(10,5))
plt.hist(data['PURCHASE PRICE'], bins=15, color='red',edgecolor='green')
plt.xlabel('PURCHASE PRICE')
plt.ylabel('count')
plt.title('Histogram of purchase price')
plt.show()
```

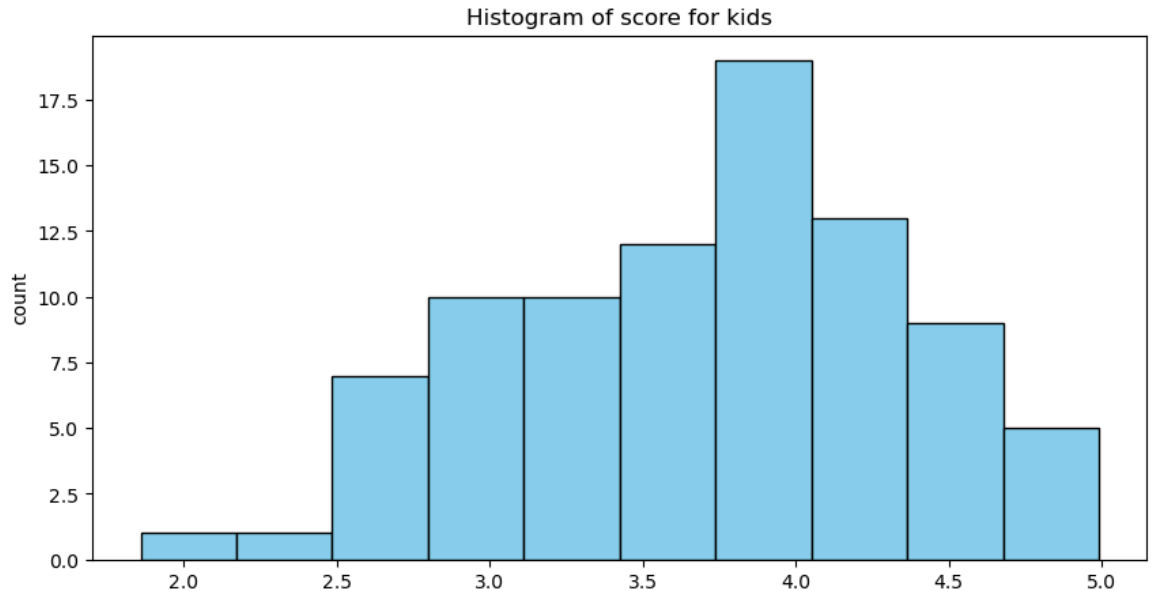


```
In [22]: plt.figure(figsize=(10,5))
plt.hist(data['$LIFETIME COST'], bins=15, color='yellow',edgecolor='red')
plt.xlabel('Lifetime Cost')
plt.ylabel('count')
plt.title('Histogram of lifetime cost')
plt.show()
```



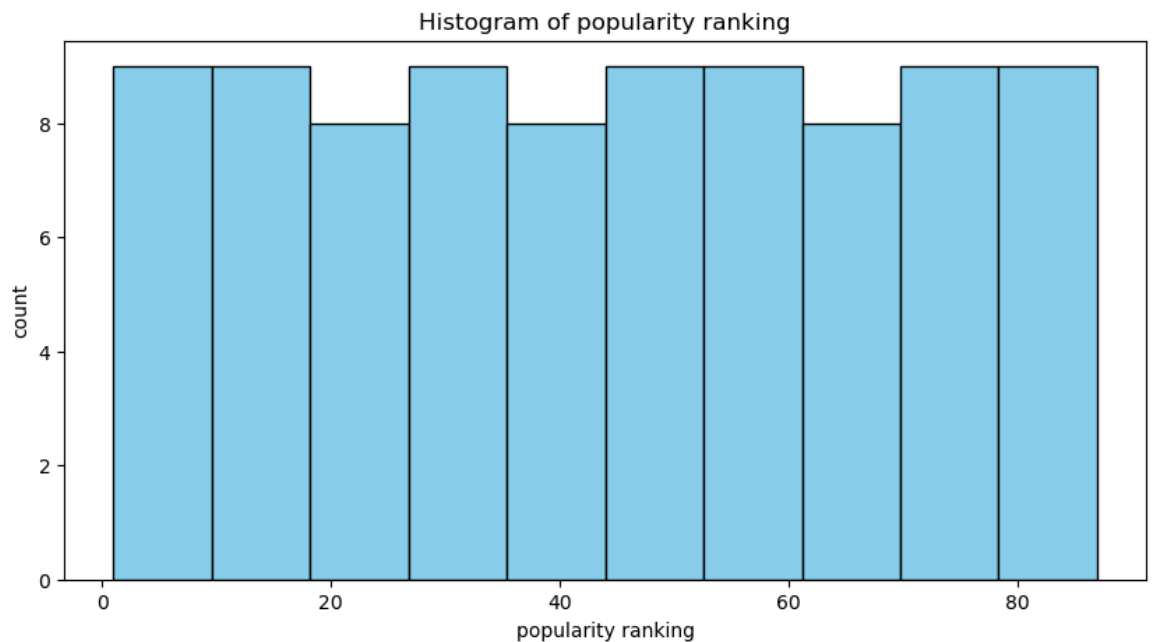
```
In [23]: plt.figure(figsize=(10,5))
plt.hist(data['score for kids'],bins=10,color='skyblue', edgecolor='b')
plt.xlabel('Score for kids')
plt.ylabel('count')
plt.title('Histogram of score for kids')
plt.show
```

Out[23]: <function matplotlib.pyplot.show(close=None, block=None)>



```
In [24]: plt.figure(figsize=(10,5))
plt.hist(data['popularity ranking'],bins=10,color='skyblue', edgecolor='b')
plt.xlabel('popularity ranking')
plt.ylabel('count')
plt.title('Histogram of popularity ranking')
plt.show
```

Out[24]: <function matplotlib.pyplot.show(close=None, block=None)>



Bivariate and Multivariate Analysis

```
In [25]: #function to examing whether the variables contain any outlier or not
def UVA_outlier(data, var_group, include_outlier=True):
    size = len(var_group)
    plt.figure(figsize=(20,10), dpi=100)

    for j, i in enumerate(var_group):
        # calculating descriptives of variable
        quant25 = data[i].quantile(0.25)
        quant75 = data[i].quantile(0.75)
        IQR = quant75 - quant25
        med = data[i].median()
        whis_low = med - (1.5 * IQR)
        whis_high = med + (1.5 * IQR)

        # Calculating Number of Outliers
        outlier_high = len(data[i][data[i] > whis_high])
        outlier_low = len(data[i][data[i] < whis_low])

        if include_outlier:
            # Plotting the variable with every information
            plt.subplot(1, size, j + 1)
            sns.boxplot(data[i], orient="v")
            plt.ylabel('{}'.format(i))
            plt.title('With Outliers\nIQR = {}; Median = {} \n 2nd,3rd
                        round(IQR, 2),
                        round(med, 2),
                        (round(quant25, 2), round(quant75, 2)),
                        (outlier_low, outlier_high)
                    ))
        else:
            # replacing outliers with max/min whisker
            data2 = data[var_group].copy()
            data2[i][data2[i] > whis_high] = whis_high + 1
            data2[i][data2[i] < whis_low] = whis_low - 1

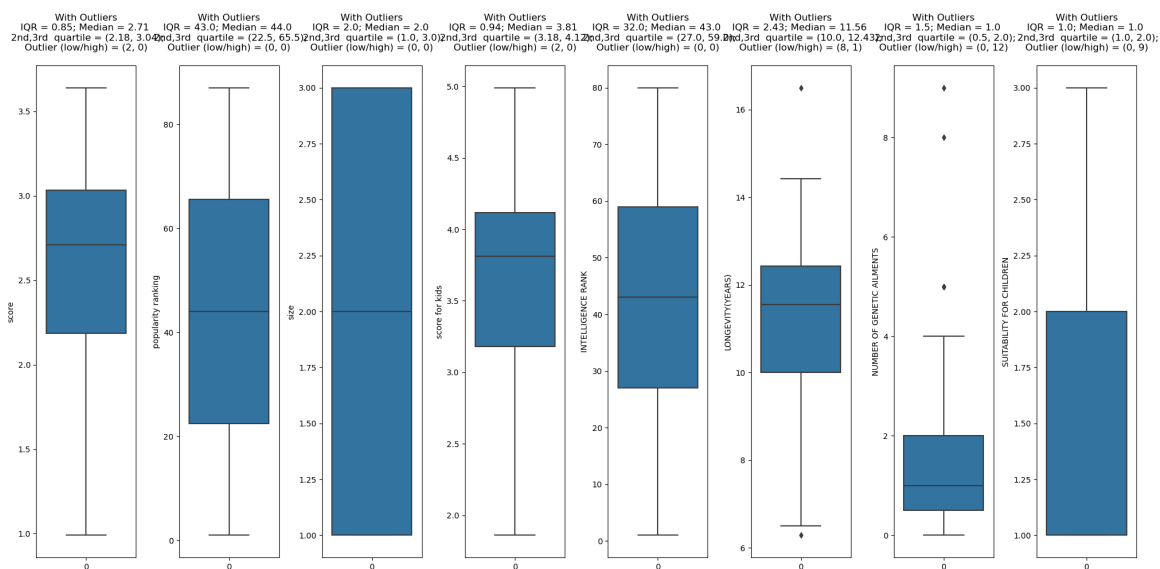
            # plotting without outliers
            plt.subplot(1, size, j + 1)
            sns.boxplot(data2[i], orient="v")
            plt.ylabel('{}'.format(i))
            plt.title('Without Outliers\nIQR = {}; Median = {} \n 2nd,3
                        round(IQR, 2),
                        round(med, 2),
                        (round(quant25, 2), round(quant75, 2)),
                        (outlier_low, outlier_high)
                    ))

    plt.tight_layout()
    plt.show()
```

```
In [26]: column_names_numeric = data_numeric.columns.tolist()
column_names_numeric
```

```
Out[26]: ['score',
'popularity ranking',
'size',
'score for kids',
'$LIFETIME COST',
'INTELLIGENCE RANK',
'INTELLIGENCE %',
'LONGEVITY(YEARS)',
'NUMBER OF GENETIC AILMENTS',
'PURCHASE PRICE',
'FOOD COSTS PER YEAR',
'SUITABILITY FOR CHILDREN']
```

```
In [27]: UVA_outlier(data_numeric,['score', 'popularity ranking', 'size', 'score for kids', 'INTELLIGENCE RANK', 'LONGEVITY(YEARS)', 'NUMBER OF GENETIC AILMENTS', 'PURCHASE PRICE', 'FOOD COSTS PER YEAR', 'SUITABILITY FOR CHILDREN'])
```



In [28]: data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 87 entries, 0 to 86
Data columns (total 17 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Breed                                87 non-null     object
1   type                                87 non-null     object
2   score                               87 non-null     float64
3   popularity ranking                   87 non-null     int64
4   size                                87 non-null     int64
5   intelligence                         87 non-null     object
6   score for kids                       87 non-null     float64
7   $LIFETIME COST                       87 non-null     float64
8   INTELLIGENCE RANK                   87 non-null     int64
9   INTELLIGENCE %                      87 non-null     float64
10  LONGEVITY(YEARS)                    87 non-null     float64
11  NUMBER OF GENETIC AILMENTS          87 non-null     int64
12  GENETIC AILMENTS                    87 non-null     object
13  PURCHASE PRICE                      87 non-null     float64
14  FOOD COSTS PER YEAR                 87 non-null     float64
15  GROOMING FREQUENCY                  87 non-null     object
16  SUITABILITY FOR CHILDREN            87 non-null     int64
dtypes: float64(7), int64(5), object(5)
memory usage: 11.7+ KB
```

Changing categorical variable into numerical

In [29]: *#imputing preprocessing libraries for converting the variable*
 from sklearn.preprocessing import LabelEncoder
 label_encoder = LabelEncoder()

In [30]: data['GROOMING FREQUENCY'].value_counts()

Out[30]: GROOMING FREQUENCY
 Once a week 65
 Daily 20
 Once in a few weeks 2
 Name: count, dtype: int64

In [31]: data['GROOMING FREQUENCY'] = data['GROOMING FREQUENCY'].map({'Once a week': 0,
 data['GROOMING FREQUENCY']

Out[31]: 0 0
 1 0
 2 2
 3 0
 4 0
 ..
 82 1
 83 0
 84 1
 85 0
 86 0
 Name: GROOMING FREQUENCY, Length: 87, dtype: int64

```
In [32]: data['type'].value_counts()
```

```
Out[32]: type
sporting      15
working       14
toy           13
hound         13
terrier       12
non-sporting  10
herding       10
Name: count, dtype: int64
```

```
In [33]: data['type']=data['type'].map({'sporting':0,'working':1,'toy':2,'hound':3,'terrier':4})
data['type']
```

```
Out[33]: 0      4
1      4
2      1
3      0
4      0
..
82     1
83     3
84     5
85     1
86     5
Name: type, Length: 87, dtype: int64
```

```
In [34]: data['intelligence'].value_counts()
```

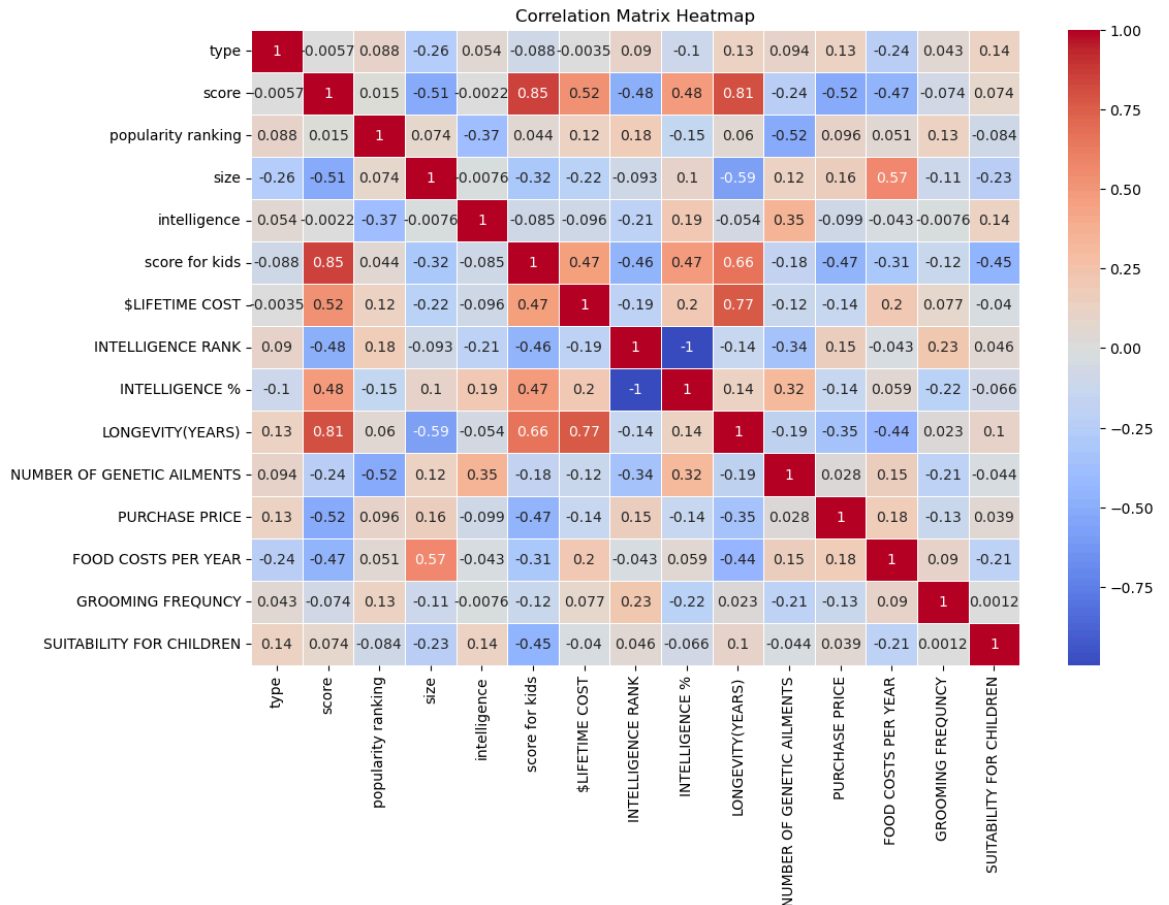
```
Out[34]: intelligence
Average      21
Above average 19
Fair         15
Excellent    11
Lowest       11
Brightest    10
Name: count, dtype: int64
```

```
In [35]: data['intelligence']=data['intelligence'].map({'Average':0,'Above average':1,'Fair':2,'Excellent':3,'Lowest':4,'Brightest':5})
data['intelligence']
```

```
Out[35]: 0      1
1      1
2      0
3      1
4      3
..
82     0
83     4
84     4
85     0
86     4
Name: intelligence, Length: 87, dtype: int64
```

```
In [36]: # Checking the correlation between the variables
data_corr = data.select_dtypes(include=['int', 'float'])
correlation_matrix = data_corr.corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
heatmap = sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
plt.title('Correlation Matrix Heatmap')
plt.show()
```



```
In [37]: data['GENETIC AILMENTS'].value_counts()
```

```
Out[37]: GENETIC AILMENTS
none
22
hip problems
12
heart problems
3
deafness, hip problems
2
knee problems
2
eye, hip problems
2
heart, spine, blood clotting disorders
1
hip problems, heart defects
1
kidney, eye problems, anaemia
1
mononucleosis, elbow, hip problems, complex immune disorder
```

```
In [38]: data = pd.get_dummies(data, columns=['Breed', 'GENETIC AILMENTS'])
data = data.astype(int)
```

```
In [39]: data
```

```
Out[39]:
```

	type	score	popularity ranking	size	intelligence	score for kids	\$LIFETIME COST	INTELLIGENCE RANK	INTELLIGENCE
0	4	3	61	1	1	4	22638	30	
1	4	3	48	1	1	4	21992	35	
2	1	3	16	2	0	4	22049	45	
3	0	3	81	2	1	4	20224	31	
4	0	3	51	2	3	4	18993	18	
...	
82	1	1	47	3	0	2	21986	50	
83	3	1	42	3	4	2	13824	75	
84	5	1	54	2	4	2	15808	77	

Splitting the Dataset

```
In [40]: #creating two dataset where x contain all variable except target variable
x=data.drop(['PURCHASE PRICE'],axis=1)
y=data['PURCHASE PRICE']
```

```
In [41]: #importing required libraries
from sklearn.model_selection import train_test_split
```

```
In [42]: #split dataset in two parts train and test with test size 20%
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=42)
print('x_train =',x_train.shape)
print('y_train =',y_train.shape)
print('x_test =',x_test.shape)
print('y_test =',y_test.shape)

x_train = (69, 151)
y_train = (69,)
x_test = (18, 151)
y_test = (18,)
```

Linear Regression

```
In [43]: from sklearn.linear_model import LinearRegression
# Instance the linear regression object
reg = LinearRegression().fit(x_train, y_train)
reg.score(x_train, y_train)
```

```
Out[43]: 1.0
```



```
In [44]: y_pred_train = reg.predict(x_train)
y_pred_test = reg.predict(x_test)
```

```
In [45]: from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
```

```
In [46]: from matplotlib import legend
# Function for evaluation metric for regression
def EvaluationMetric(Xt,yt,yp,disp="on"):
    ''' Take the different set of parameter and prints evaluation metric '''
    MSE=round(mean_squared_error(y_true=yt,y_pred=yp),4)
    RMSE=(np.sqrt(MSE))
    R2=(r2_score(y_true=yt,y_pred=yp))
    Adjusted_R2=(1-(1-r2_score(yt, yp))*((Xt.shape[0]-1)/(Xt.shape[0]-Xt
    if disp=="on":
        print("MSE :",MSE,"RMSE :", RMSE)
        print("R2 :",R2,"Adjusted R2 :",Adjusted_R2)

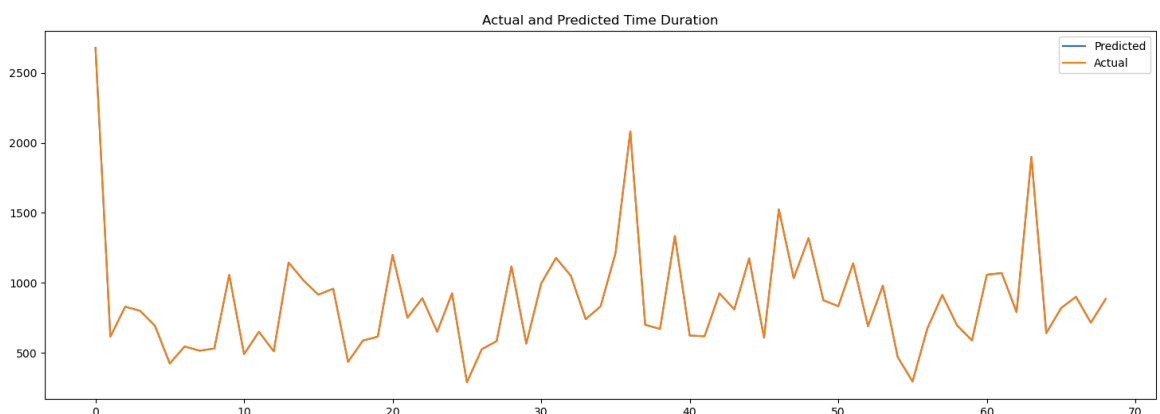
    #Plotting Actual and Predicted Values
    plt.figure(figsize=(18,6))
    plt.plot((yp)[:100])
    plt.plot((np.array(yt)[:100]))
    plt.legend(["Predicted","Actual"])
    plt.title('Actual and Predicted Time Duration')

    return (MSE,RMSE,R2,Adjusted_R2)
```

```
In [47]: #Evaluation metrics for Train set
EvaluationMetric(x_train,y_train,y_pred_train)
```

```
MSE : 0.0 RMSE : 0.0
R2 : 1.0 Adjusted R2 : 1.0
```

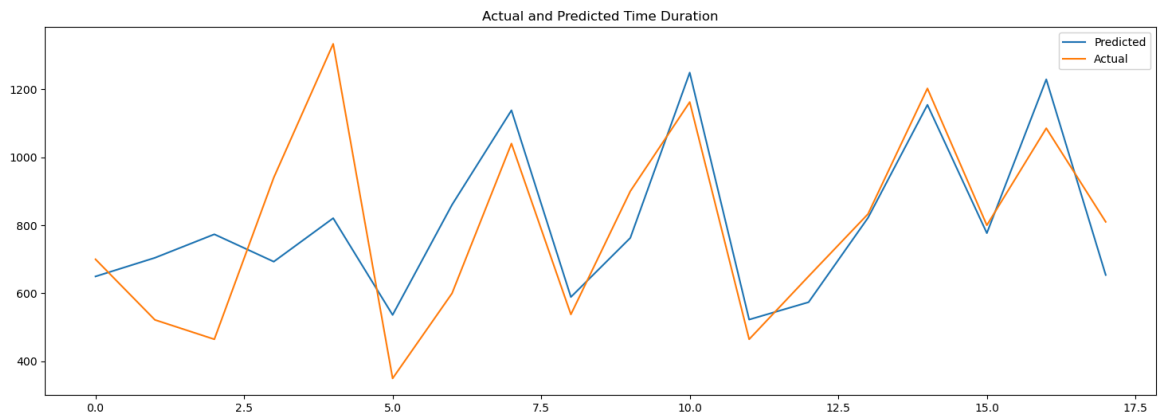
```
Out[47]: (0.0, 0.0, 1.0, 1.0)
```



```
In [48]: #Evaluation metrics for Test set
EvaluationMetric(x_test,y_test,y_pred_test)
```

MSE : 36242.6197 RMSE : 190.374945042671
 R2 : 0.531253709560429 Adjusted R2 : 1.0594678129662143

```
Out[48]: (36242.6197, 190.374945042671, 0.531253709560429, 1.0594678129662143)
```



Decision Tree

```
In [49]: from sklearn import tree
from sklearn.tree import DecisionTreeRegressor
```

```
In [50]: x.shape ,y.shape
```

```
Out[50]: ((87, 151), (87,))
```

```
In [51]: dt_model = tree.DecisionTreeRegressor()
dt_model = dt_model.fit(x, y)
```

```
In [52]: #checking the training score
dt_model.score(x_train, y_train)
```

```
Out[52]: 1.0
```

```
In [53]: #test score
dt_model.score(x_test, y_test)
```

```
Out[53]: 1.0
```

```
In [54]: # Maximum depth of trees
max_depth = [5,10]

# Minimum number of samples required to split a node
min_samples_split = [10,20]

# Minimum number of samples required at each leaf node
min_samples_leaf = [10,20]

# HYperparameter Grid
param_dt = {
    'max_depth' : max_depth,
    'min_samples_split' : min_samples_split,
    'min_samples_leaf' : min_samples_leaf}
```

```
In [55]: from sklearn.model_selection import GridSearchCV
```

```
In [56]: dt_model = DecisionTreeRegressor()

# Grid search
dt_grid = GridSearchCV(estimator=dt_model,
                        param_grid = param_dt,
                        cv = 5, verbose=2, scoring='r2')

dt_grid.fit(x_train,y_train)
```

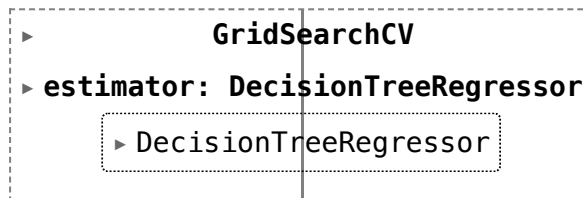
```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
[CV] END max_depth=5, min_samples_leaf=10, min_samples_split=10; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=10, min_samples_split=10; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=10, min_samples_split=10; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=10, min_samples_split=10; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=10, min_samples_split=10; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=10, min_samples_split=20; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=10, min_samples_split=20; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=10, min_samples_split=20; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=10, min_samples_split=20; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=10, min_samples_split=20; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=20, min_samples_split=10; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=20, min_samples_split=10; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=20, min_samples_split=10; tot
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[CV] END max_depth=5, min_samples_leaf=20, min_samples_split=10; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=20, min_samples_split=10; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=20, min_samples_split=20; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=20, min_samples_split=20; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=20, min_samples_split=20; tot
al time= 0.0s
[CV] END max_depth=5, min_samples_leaf=20, min_samples_split=20; tot
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[CV] END max_depth=5, min_samples_leaf=20, min_samples_split=20; tot
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[CV] END max_depth=5, min_samples_leaf=20, min_samples_split=20; tot
al time= 0.0s
[CV] END max_depth=10, min_samples_leaf=10, min_samples_split=10; to
tal time= 0.0s
[CV] END max_depth=10, min_samples_leaf=10, min_samples_split=10; to
tal time= 0.0s
[CV] END max_depth=10, min_samples_leaf=10, min_samples_split=10; to
tal time= 0.0s
[CV] END max_depth=10, min_samples_leaf=10, min_samples_split=10; to
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[CV] END max_depth=10, min_samples_leaf=10, min_samples_split=10; to
tal time= 0.0s
[CV] END max_depth=10, min_samples_leaf=10, min_samples_split=20; to
tal time= 0.0s
[CV] END max_depth=10, min_samples_leaf=10, min_samples_split=20; to
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[CV] END max_depth=10, min_samples_leaf=10, min_samples_split=20; to
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[CV] END max_depth=10, min_samples_leaf=10, min_samples_split=20; to
tal time= 0.0s
[CV] END max_depth=10, min_samples_leaf=10, min_samples_split=20; to
tal time= 0.0s
[CV] END max_depth=10, min_samples_leaf=10, min_samples_split=20; to
tal time= 0.0s
```

```

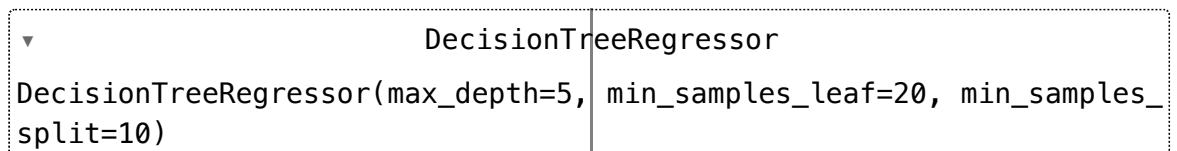
[CV] END max_depth=10, min_samples_leaf=20, min_samples_split=10; to
tal time= 0.0s
[CV] END max_depth=10, min_samples_leaf=20, min_samples_split=10; to
tal time= 0.0s
[CV] END max_depth=10, min_samples_leaf=20, min_samples_split=10; to
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[CV] END max_depth=10, min_samples_leaf=20, min_samples_split=10; to
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[CV] END max_depth=10, min_samples_leaf=20, min_samples_split=10; to
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[CV] END max_depth=10, min_samples_leaf=20, min_samples_split=20; to
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[CV] END max_depth=10, min_samples_leaf=20, min_samples_split=20; to
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[CV] END max_depth=10, min_samples_leaf=20, min_samples_split=20; to
tal time= 0.0s
[CV] END max_depth=10, min_samples_leaf=20, min_samples_split=20; to
tal time= 0.0s
[CV] END max_depth=10, min_samples_leaf=20, min_samples_split=20; to
tal time= 0.0s

```

Out [56]:

In [57]: `dt_grid.best_score_`Out [57]: `-0.0317273131918893`In [58]: `dt_grid.best_estimator_`

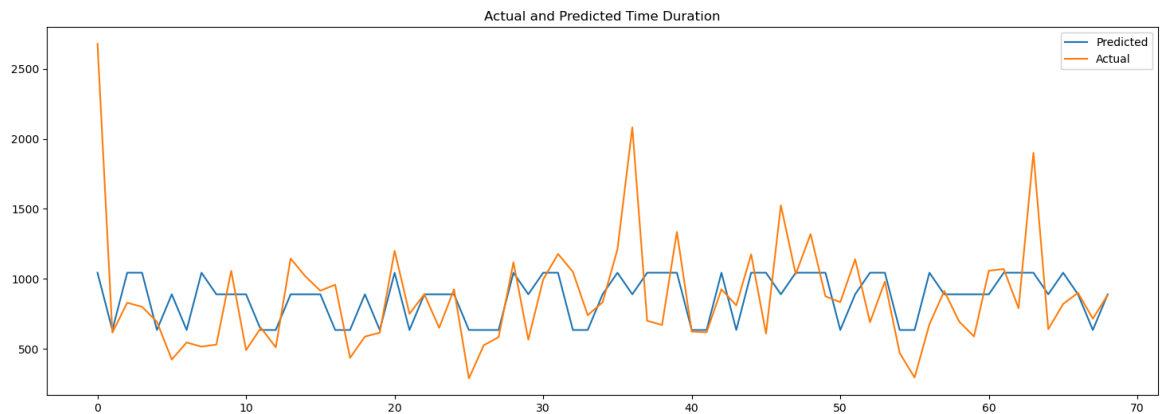
Out [58]:

In [59]: `dt_optimal_model = dt_grid.best_estimator_`
In [60]: `y_pred_dt_test=dt_optimal_model.predict(x_test)`
`y_pred_dt_train=dt_optimal_model.predict(x_train)`

```
In [61]: #Evaluation metrics for Train set  
EvaluationMetric(x_train,y_train,y_pred_dt_train)
```

MSE : 125128.0001 RMSE : 353.7343637533679
R2 : 0.18263361267317557 Adjusted R2 : 1.669649570340049

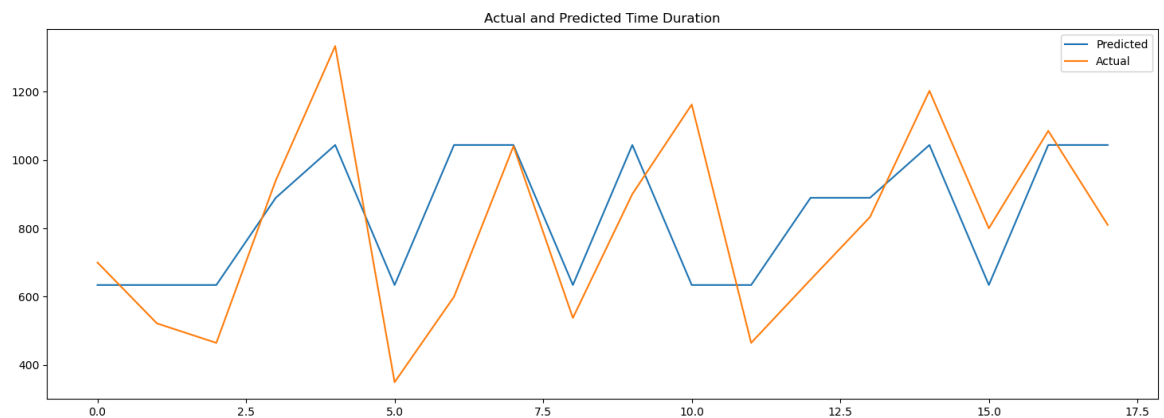
Out[61]: (125128.0001, 353.7343637533679, 0.18263361267317557, 1.669649570340049)



```
In [62]: #Evaluation metrics for Test set  
EvaluationMetric(x_test,y_test,y_pred_dt_test)
```

MSE : 50878.9357 RMSE : 225.56359568866606
R2 : 0.3419539604998376 Adjusted R2 : 1.0834834527724087

Out[62]: (50878.9357, 225.56359568866606, 0.3419539604998376, 1.0834834527724087)



In []: