```
# importing required packages

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings(action = 'ignore')


def heading(info):
    print("\n\n##### {} #####".format(info))


# read the dataset
dataSet = pd.read_csv('Banglore_traffic_Dataset.csv', encoding = 'unicode_escape
```

```
# print info about the data
dataSet.info()
heading("Sample data points from the dataset")
dataSet.head(5)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8936 entries, 0 to 8935
Data columns (total 16 columns):
 #   Column                              Non-Null Count  Dtype  
---  ------                              --------------  -----  
 0   Date                                8936 non-null   object 
 1   Area Name                           8936 non-null   object 
 2   Road/Intersection Name              8936 non-null   object 
 3   Traffic Volume                      8936 non-null   int64  
 4   Average Speed                       8936 non-null   float64
 5   Travel Time Index                   8936 non-null   float64
 6   Congestion Level                    8936 non-null   float64
 7   Road Capacity Utilization           8936 non-null   float64
 8   Incident Reports                    8936 non-null   int64  
 9   Environmental Impact                8936 non-null   float64
 10  Public Transport Usage              8936 non-null   float64
 11  Traffic Signal Compliance           8936 non-null   float64
 12  Parking Usage                       8936 non-null   float64
 13  Pedestrian and Cyclist Count        8936 non-null   int64  
 14  Weather Conditions                  8936 non-null   object 
 15  Roadwork and Construction Activity  8936 non-null   object 
dtypes: float64(8), int64(3), object(5)
memory usage: 1.1+ MB

##### Sample data points from the dataset #####
```

	Date	Area Name	Road/Intersection Name	Traffic Volume	Average Speed	Travel Time Index	Congestio Leve
0	2022-01-01	Indiranagar	100 Feet Road	50590	50.230299	1.500000	100.00000
1	2022-01-01	Indiranagar	CMH Road	30825	29.377125	1.500000	100.00000
2	2022-01-01	Whitefield	Marathahalli Bridge	7399	54.474398	1.039069	28.34799
3	2022-01-01	Koramangala	Sony World Junction	60874	43.817610	1.500000	100.00000
4	2022-01-01	Koramangala	Sarjapur Road	57292	41.116763	1.500000	100.00000

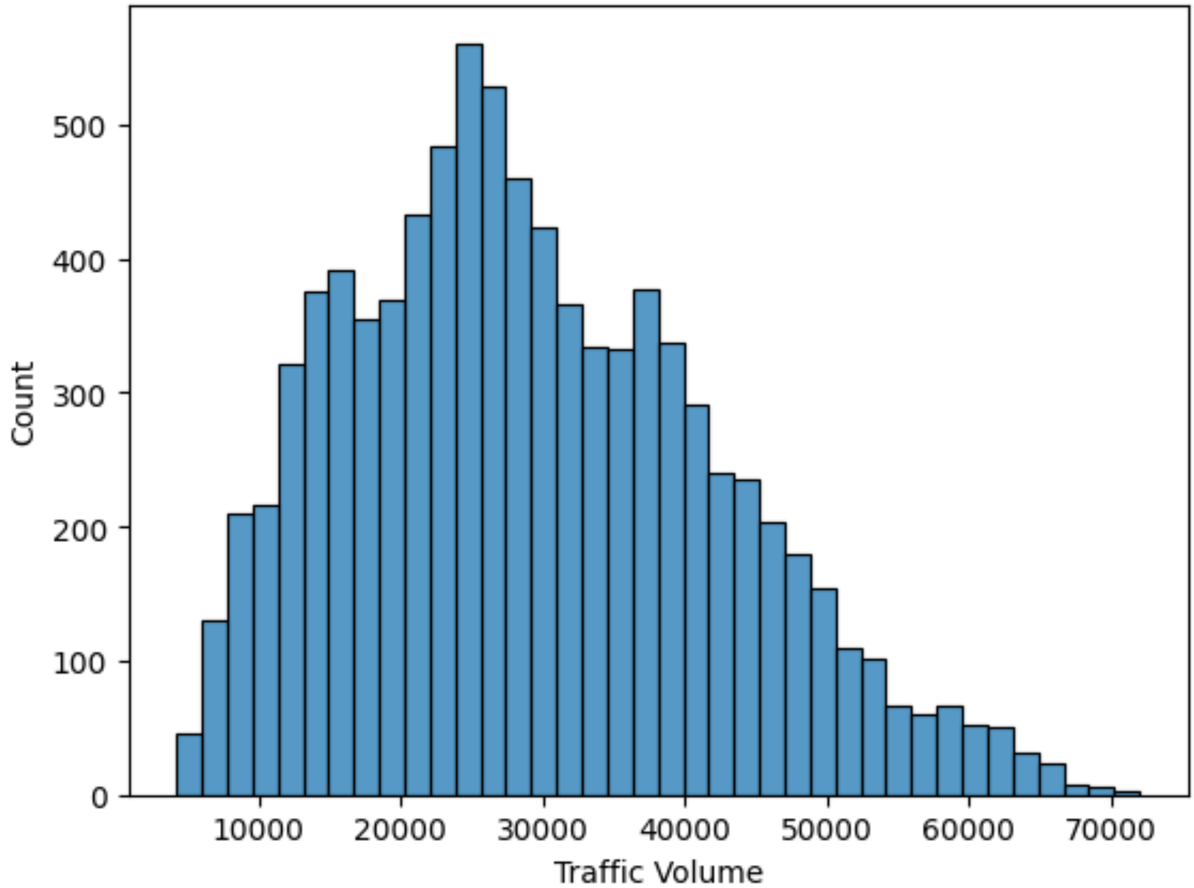
```
# lets find the individual column statistics
heading("Stats about non-numeric values")
print(dataSet.describe(include = "object"))

heading("Stats about numeric values")
print(dataSet.describe(include = "number"))
```

```
##### Stats about non-numeric values #####
              Date    Area Name Road/Intersection Name Weather Conditions
count         8936         8936                   8936               8936
unique         952            8                     16                  5
top     2023-01-24  Indiranagar         100 Feet Road              Clear
freq            15         1720                    860               5426

       Roadwork and Construction Activity
count                                8936
unique                                  2
top                                    No
freq                                 8054


##### Stats about numeric values #####
       Traffic Volume  Average Speed  Travel Time Index  Congestion Level
count     8936.000000    8936.000000        8936.000000       8936.000000
mean     29236.048120      39.447427           1.375554         80.818041
std      13001.808801      10.707244           0.165319         23.533182
min       4233.000000      20.000000           1.000039          5.160279
25%      19413.000000      31.775825           1.242459         64.292905
50%      27600.000000      39.199368           1.500000         92.389018
75%      38058.500000      46.644517           1.500000        100.000000
max      72039.000000      89.790843           1.500000        100.000000

       Road Capacity Utilization  Incident Reports  Environmental Impact  \
count                8936.000000       8936.000000           8936.000000
mean                   92.029215          1.570389            108.472096
std                    16.583341          1.420047             26.003618
min                    18.739771          0.000000             58.466000
25%                    97.354990          0.000000             88.826000
50%                   100.000000          1.000000            105.200000
75%                   100.000000          2.000000            126.117000
max                   100.000000         10.000000            194.078000

       Public Transport Usage  Traffic Signal Compliance  Parking Usage  \
count             8936.000000                8936.000000    8936.000000
mean                45.086651                  79.950243      75.155597
std                 20.208460                  11.585006      14.409394
min                 10.006853                  60.003933      50.020411
25%                 27.341191                  69.828270      62.545895
50%                 45.170684                  79.992773      75.317610
75%                 62.426485                  89.957358      87.518589
```

```
max                    79.979744                    99.993652       99.995049

       Pedestrian and Cyclist Count
count                   8936.000000
mean                     114.533348
std                       36.812573
min                       66.000000
25%                       94.000000
50%                      102.000000
75%                      111.000000
max                      243.000000
```

```
# lets first verify how to target variable is distributed
heading("Target variable \"Traffic volume\" distribution")
sns.histplot(data = dataSet, x = "Traffic Volume")
```

```
##### Target variable "Traffic volume" distribution #####
<Axes: xlabel='Traffic Volume', ylabel='Count'>
```



```
# lets convert the categorical values to numeric
def convert_categorical_to_numeric(dataframe, categorical_cols):

    for col in categorical_cols:
        if col in dataframe.columns:
            # create a mapping for the unique values in the column
            unique_values = dataframe[col].unique()
            value_mapping = {label: idx for idx, label in enumerate(unique_valu

            # apply the mapping to convert to numeric
            dataframe[col] = [value_mapping[val] for val in dataframe[col]]

    return dataframe

# leaving date column as of now and converting other columns

# we will backup the original dataset
originalDataset = dataSet.copy()

# select the relevant columns and convert them
columnsToConvert = ["Roadwork and Construction Activity","Weather Conditions",'
dataSet = convert_categorical_to_numeric(dataSet, columnsToConvert)

heading("After conversion to numeric values")
print(dataSet[columnsToConvert].head())
```

```
##### After conversion to numeric values #####
   Roadwork and Construction Activity  Weather Conditions  Area Name  \
0                                   0                   0          0
1                                   0                   0          0
2                                   0                   0          1
3                                   0                   0          2
4                                   0                   0          2

   Road/Intersection Name
0                       0
1                       1
2                       2
3                       3
4                       4
```

```
# drop unrequired columns based on corelation matrix
dropThem = ["Public Transport Usage", "Traffic Signal Compliance", "Parking Usa
dataSet = dataSet.drop(columns=dropThem)

heading("Final dataset columns")
print(dataSet.head())
```

```
##### Final dataset columns #####
   Area Name  Road/Intersection Name  Traffic Volume  Average Speed  \
0          0                       0           50590      50.230299
1          0                       1           30825      29.377125
2          1                       2            7399      54.474398
3          2                       3           60874      43.817610
4          2                       4           57292      41.116763

   Travel Time Index  Congestion Level  Road Capacity Utilization  \
0           1.500000        100.000000                 100.000000
1           1.500000        100.000000                 100.000000
2           1.039069         28.347994                  36.396525
3           1.500000        100.000000                 100.000000
4           1.500000        100.000000                 100.000000

   Incident Reports  Environmental Impact  Pedestrian and Cyclist Count
0                 0               151.180                           111
1                 1               111.650                           100
2                 0                64.798                           189
3                 1               171.748                           111
4                 3               164.584                           104
```

```
# seperate the input and target columns into numpy arrays
if isinstance(dataSet, pd.DataFrame):
    dataSet = dataSet.to_numpy()
# print(dataset)
X = dataSet[:, [0, 1, 3, 4,5,6,7,8,9]]
Y = dataSet[:, 2]

# adding extra column for intercepts
X = np.hstack((np.ones((X.shape[0], 1)), X))
heading("Printing X and Y variables for the model")
print(X[:5])
print(Y[:5])
```

```
##### Printing X and Y variables for the model #####
[[  1.           0.           0.          50.23029856   1.5
  100.         100.           0.         151.18       111.        ]
 [  1.           0.           1.          29.37712471   1.5
  100.         100.           1.         111.65       100.        ]
 [  1.           1.           2.          54.47439821   1.03906885
   28.34799386  36.39652494   0.          64.798      189.        ]
 [  1.           2.           3.          43.81761039   1.5
  100.         100.           1.         171.748      111.        ]
 [  1.           2.           4.          41.11676289   1.5
  100.         100.           3.         164.584      104.        ]]
[50590. 30825.  7399. 60874. 57292.]
```

```
# shuffle the datasets
indices = np.arange(X.shape[0])
np.random.shuffle(indices)
#
X_shuffled = X[indices]
Y_shuffled = Y[indices]

# split the dataset into 80:20
split_ratio = 0.2
split_index = int(len(X_shuffled) * split_ratio)

X_train = X_shuffled[:split_index]
Y_train = Y_shuffled[:split_index]

X_test = X_shuffled[split_index:]
Y_test = Y_shuffled[split_index:]

print("Training set samples: ", X_train.shape[0])
print("Testing set samples: ", X_test.shape[0])
```

```
Training set samples:  1787
Testing set samples:  7149
```

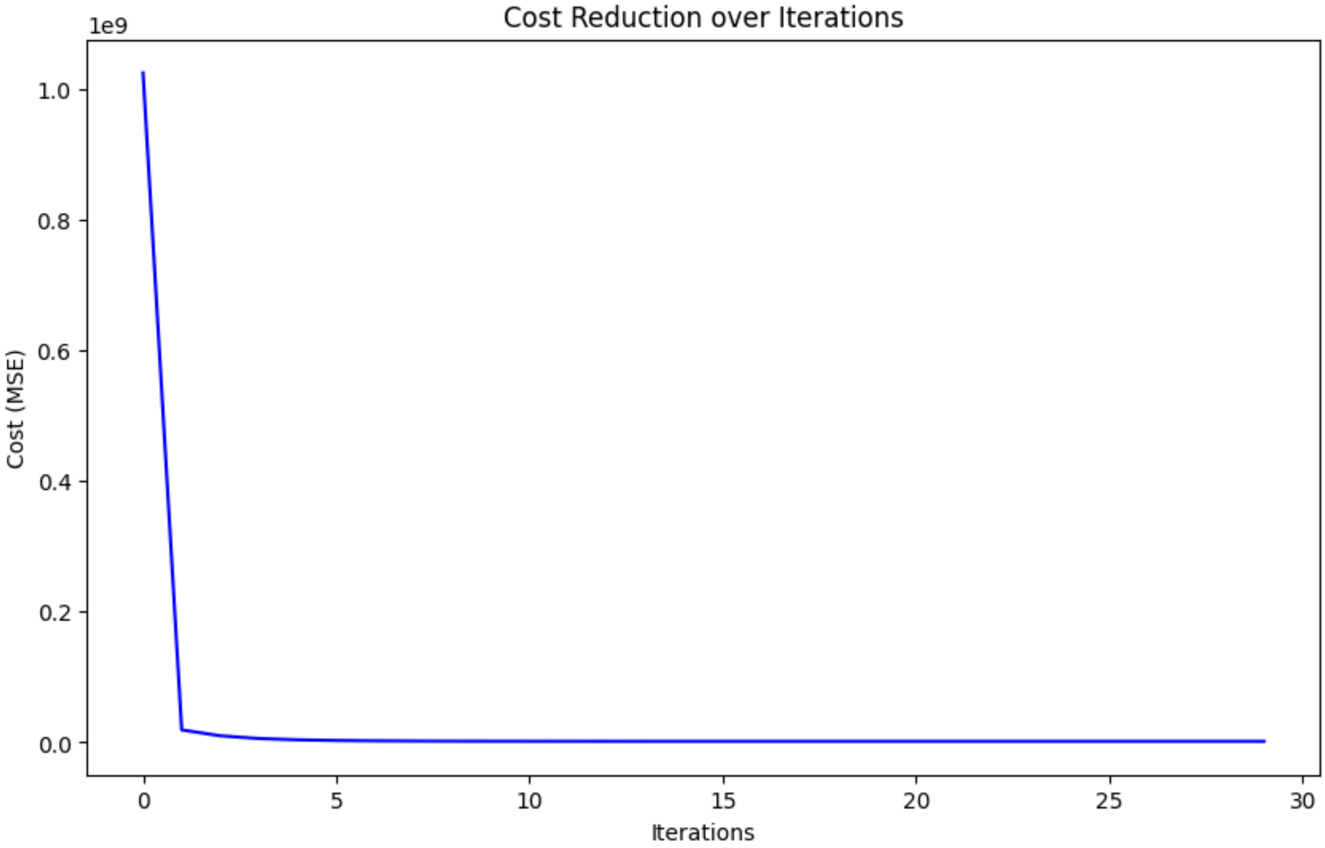
```
# for computing gradient descent, we use the the firmula new_weights = old_weig
# dJ/dW = -2X^T Y + 2X^T XW = 2X^T(XW-Y)

def gradient_descent(X, Y, learning_rate=0.01, iterations=1000):
    n_samples, n_features = X.shape

    # initialize weights to 0
    weights = np.zeros(n_features)
    # List to store cost at each iteration for plotting convergence
    cost_history = []

    for i in range(iterations):
        # Y_pred ->  XW
        Y_pred = X @ weights

        # compute the error -> XW-Y
        error = Y_pred - Y

        # compute gradient -> dJ/dW
        gradient = (2 / n_samples) * (X.T @ error)

        # Update weights
        weights -= learning_rate * gradient

        # Compute Mean Squared Error (Cost Function)
        cost = (1 / n_samples) * np.sum(error ** 2)

        # (Optional) Print cost at intervals
        if i % 50 == 0:
            print(f"Iteration {i+1}: Cost {cost}")
            cost_history.append(cost)

    return weights, cost_history
```

```
# we solve the least squares problem using the gradient descent algorithm
weights, cost_history = gradient_descent(X_train,Y_train,0.00002,1500)
heading("Training on linear regression with given dataset for 10 iterations")
print(weights[:5])
```

```
Iteration 1: Cost 1024440498.4297707
Iteration 51: Cost 19257093.994292814
Iteration 101: Cost 10232535.491425855
Iteration 151: Cost 6051920.219076406
Iteration 201: Cost 4053860.8857249906
Iteration 251: Cost 3060828.882377268
Iteration 301: Cost 2543862.3888015794
Iteration 351: Cost 2260861.998928928
Iteration 401: Cost 2098092.154895537
Iteration 451: Cost 2000241.9044550362
Iteration 501: Cost 1939238.3680511315
Iteration 551: Cost 1900124.1144997755
Iteration 601: Cost 1874519.4331545122
Iteration 651: Cost 1857503.5425434855
Iteration 701: Cost 1846068.2464918403
Iteration 751: Cost 1838315.207653634
Iteration 801: Cost 1833017.9106328539
Iteration 851: Cost 1829370.567145155
Iteration 901: Cost 1826837.6907410177
Iteration 951: Cost 1825060.655838286
Iteration 1001: Cost 1823798.0246972395
Iteration 1051: Cost 1822886.668808727
Iteration 1101: Cost 1822216.0840303628
Iteration 1151: Cost 1821711.262183427
Iteration 1201: Cost 1821321.1974394964
Iteration 1251: Cost 1821011.142274124
Iteration 1301: Cost 1820757.3758214433
Iteration 1351: Cost 1820543.6633198147
Iteration 1401: Cost 1820358.8571920535
Iteration 1451: Cost 1820195.2703071258


##### Training on linear regression with given dataset for 10 iterations ##
[ -5.4905183  -21.597431   -56.54143836 -35.13642342  -5.22527202]
```

```
# Plotting the cost history using seaborn
print(len(cost_history))
plt.figure(figsize=(10,6))
sns.lineplot(x=range(len(cost_history)), y=cost_history, color='blue')
plt.xlabel('Iterations')
plt.ylabel('Cost (MSE)')
plt.title('Cost Reduction over Iterations')
plt.show()
```

```
30
```



```
# lets predict values
Y_pred = X_test @ weights

# we will use mean absolute percentage error to calculate the error percentage
MAPE = np.mean(np.abs((Y_test - Y_pred) / Y_test)) * 100

heading("Printing the MAPE and first 10 predictions with actual values")
print("MAPE: {} %".format(MAPE))
for i in range(10):
    print("\nPredicted value: {0} \t Actual value: {1}".format(Y_pred[i], Y_tes
```

```
##### Printing the MAPE and first 10 predictions with actual values #####
MAPE: 5.557551943610017 %

Predicted value: 34426.65982240805      Actual value: 35269.0

Predicted value: 27926.53382259589      Actual value: 28038.0

Predicted value: 27379.23702980667      Actual value: 27049.0

Predicted value: 23692.006650849784     Actual value: 24265.0

Predicted value: 40315.83882924316      Actual value: 41557.0

Predicted value: 10393.53185509519      Actual value: 8059.0

Predicted value: 9942.332775055342      Actual value: 8077.0

Predicted value: 11039.920832360887     Actual value: 14725.0

Predicted value: 11215.776744104967     Actual value: 12832.0

Predicted value: 35995.83136993581      Actual value: 36190.0
```