```
# 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	100.0000
1	2022-01-01	Indiranagar	CMH Road	30825	29.377125	1.500000	100.0000
2	2022-01-01	Whitefield	Marathahalli Bridge	7399	54.474398	1.039069	28.3479
3	2022-01-01	Koramangala	Sony World Junction	60874	43.817610	1.500000	100.0000
4	2022-01-01	Koramangala	Sarjapur Road	57292	41.116763	1.500000	100.0000

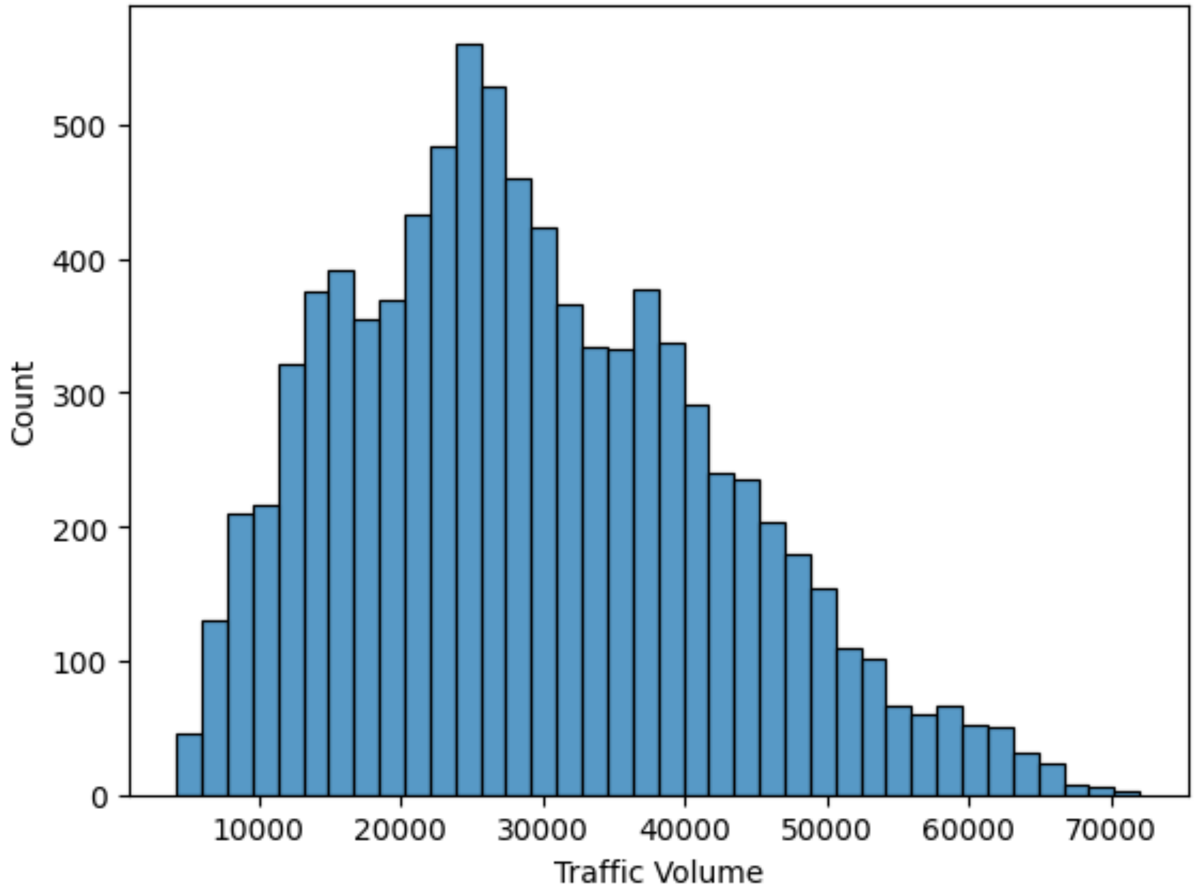
```
# lets find the individual column statistics
heading("Stats about non-numeric values")
print(dataSet.describe(include = "object"))

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]
```

```
# we normalize our dataset

# we use standadization for input variables, since they are of different scales
# standardization helps set the mean to 0 and std dev to 1.
intercept_column = X_shuffled[:, 0]
features = X_shuffled[:, 1:]

X_mean = np.mean(features, axis=0)
X_std = np.std(features, axis=0)

# Normalize features
X_norm_temp = (features - X_mean) / X_std
X_norm = np.column_stack((intercept_column, X_norm_temp))

# we use min max normaliztion for the output variable, since it is in fixed rar
# also, standardization may yeild negative values which may not be as intuitive
Y_mean = np.mean(Y, axis=0)
Y_std = np.std(Y, axis=0)

# Normalize features
Y_norm = (Y - Y_mean) / Y_std
```

```
# split the dataset into 80:20
split_ratio = 0.8
split_index = int(len(X_shuffled) * split_ratio)

X_train = X_norm[:split_index]
Y_train = Y_norm[:split_index]

X_test = X_norm[split_index:]
Y_test = Y_norm[split_index:]

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

print("Training set samples: ", X_train[:5])
print("Testing set samples: ", Y_train[:5])
```

```
Training set samples size:  7148
Testing set samples size:  1788
Training set samples:  [[ 1.          0.04836864 -0.26557885 -0.24502419  0
   0.48067702 -1.10593338  0.98437596 -0.39481515]
 [ 1.          0.51563584  0.42430854  0.61332466 -0.82137174 -2.20155768
  -3.06246808 -1.10593338 -1.58425655  2.21313545]
 [ 1.          0.04836864 -0.26557885  0.38672395 -2.10567337  0.17118203
   0.48067702 -1.10593338 -0.3993551   0.23000635]
 [ 1.         -1.35343297 -1.41539116 -1.81638862  0.75280715  0.81514828
   0.48067702  0.30254958  0.48295613 -0.17748593]
 [ 1.          0.04836864 -0.26557885  1.95049546  0.13711301 -1.99925888
  -1.5518211  -1.10593338 -1.28358925  1.85997547]]
Testing set samples:  [ 1.64247507  0.1222169  -1.67963323  2.4334862   2.1
```

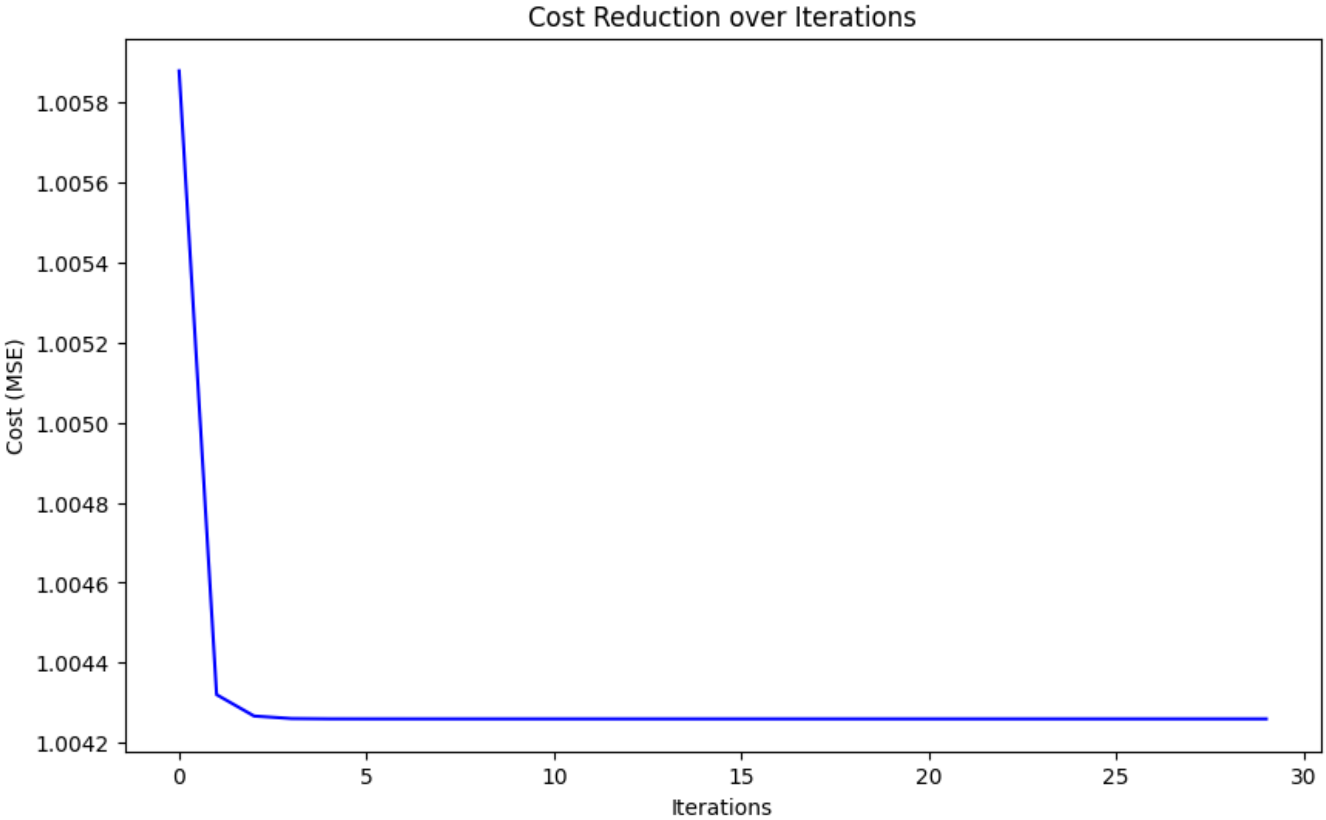
```
# for computing gradient descent, we use the the firmula new_weights = old_weig
# dJ/dW = -2X^T Y + 2X^T XW = 2X^T(XW-Y)

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 % 100 == 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,0.1,3000)
heading("Training on linear regression with given dataset for 10 iterations")
print(weights[:5])
```

```
Iteration 1: Cost 1.0058789972297144
Iteration 101: Cost 1.0043202614022586
Iteration 201: Cost 1.0042667705344606
Iteration 301: Cost 1.0042605008369565
Iteration 401: Cost 1.0042597657038155
Iteration 501: Cost 1.0042596795076422
Iteration 601: Cost 1.004259669400927
Iteration 701: Cost 1.0042596682158895
Iteration 801: Cost 1.0042596680769411
Iteration 901: Cost 1.0042596680606488
Iteration 1001: Cost 1.0042596680587388
Iteration 1101: Cost 1.0042596680585145
Iteration 1201: Cost 1.0042596680584883
Iteration 1301: Cost 1.0042596680584854
Iteration 1401: Cost 1.0042596680584848
Iteration 1501: Cost 1.004259668058485
Iteration 1601: Cost 1.0042596680584848
Iteration 1701: Cost 1.0042596680584848
Iteration 1801: Cost 1.0042596680584848
Iteration 1901: Cost 1.0042596680584848
Iteration 2001: Cost 1.0042596680584848
Iteration 2101: Cost 1.0042596680584848
Iteration 2201: Cost 1.004259668058485
Iteration 2301: Cost 1.0042596680584848
Iteration 2401: Cost 1.0042596680584848
Iteration 2501: Cost 1.0042596680584848
Iteration 2601: Cost 1.0042596680584848
Iteration 2701: Cost 1.0042596680584848
Iteration 2801: Cost 1.0042596680584848
Iteration 2901: Cost 1.0042596680584848


##### Training on linear regression with given dataset for 10 iterations ##
[-0.00058856 -0.01247141  0.00304069 -0.00042342  0.00373874]
```

```
# 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 denormalize the predictions and actual testing data
Y_pred_original = (Y_pred * Y_std) + Y_mean
Y_test_denorm = (Y_test * Y_std) + Y_mean

# we will use mean absolute percentage error to calculate the error percentage
MAPE = np.mean(np.abs((Y_test_denorm - Y_pred_original) / Y_test_denorm)) * 10(

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_original|
```

```
##### Printing the MAPE and first 10 predictions with actual values #####
MAPE: 51.3920872695371 %

Predicted value: 29112.69893525145      Actual value: 51665.0

Predicted value: 28845.33853487075      Actual value: 36384.0

Predicted value: 29363.322605982026     Actual value: 41692.0

Predicted value: 29185.897419801313     Actual value: 29831.0

Predicted value: 29258.280767655135     Actual value: 10915.0

Predicted value: 29134.03138423169      Actual value: 25909.0

Predicted value: 29060.315434471842     Actual value: 37720.0

Predicted value: 29040.760707823174     Actual value: 26712.0

Predicted value: 28838.098747263044     Actual value: 33467.0

Predicted value: 29915.88538897134      Actual value: 27426.0
```