Youtube Adview Prediction

Import Libraries and Dataset

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
```

Looking Into Basic Information of Data

In [2]:
```
data = pd.read_csv('train.csv')
```

In [3]:
```
data.head()
```

Out[3]:

	vidid	adview	views	likes	dislikes	comment	published	duration	category
0	VID_18655	40	1031602	8523	363	1095	2016-09-14	PT7M37S	F
1	VID_14135	2	1707	56	2	6	2016-10-01	PT9M30S	D
2	VID_2187	1	2023	25	0	2	2016-07-02	PT2M16S	C
3	VID_23096	6	620860	777	161	153	2016-07-27	PT4M22S	H
4	VID_10175	1	666	1	0	0	2016-06-29	PT31S	D

In [4]:
```
data.shape
```

Out[4]:
```
(14999, 9)
```

In [5]:
```
data.size
```

Out[5]:
```
134991
```

In [6]:
```
data.columns
```

Out[6]:
```
Index(['vidid', 'adview', 'views', 'likes', 'dislikes', 'comment', 'published',
       'duration', 'category'],
      dtype='object')
```

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 9 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   vidid      14999 non-null  object
 1   adview     14999 non-null  int64 
 2   views      14999 non-null  object
 3   likes      14999 non-null  object
 4   dislikes   14999 non-null  object
 5   comment    14999 non-null  object
 6   published  14999 non-null  object
 7   duration   14999 non-null  object
 8   category   14999 non-null  object
dtypes: int64(1), object(8)
memory usage: 1.0+ MB
```

In [8]:
```
data.describe(include = "all")
```

Out[8]:

	vidid	adview	views	likes	dislikes	comment	published	duration	category
count	14999	1.499900e+04	14999	14999	14999	14999	14999	14999	1499
unique	14999	NaN	14588	4789	1546	2007	2386	3146	8
top	VID_18655	NaN	885	1	0	0	2016-08-26	PT31S	D
freq	1	NaN	4	174	1091	1290	42	147	755
mean	NaN	2.107791e+03	NaN	NaN	NaN	NaN	NaN	NaN	NaN
std	NaN	5.237711e+04	NaN	NaN	NaN	NaN	NaN	NaN	NaN
min	NaN	1.000000e+00	NaN	NaN	NaN	NaN	NaN	NaN	NaN
25%	NaN	1.000000e+00	NaN	NaN	NaN	NaN	NaN	NaN	NaN
50%	NaN	2.000000e+00	NaN	NaN	NaN	NaN	NaN	NaN	NaN
75%	NaN	6.000000e+00	NaN	NaN	NaN	NaN	NaN	NaN	NaN
max	NaN	5.429665e+06	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Data Cleaning

Checking for missing values and removing if present.

In [9]:
```
data.isnull().any()
```

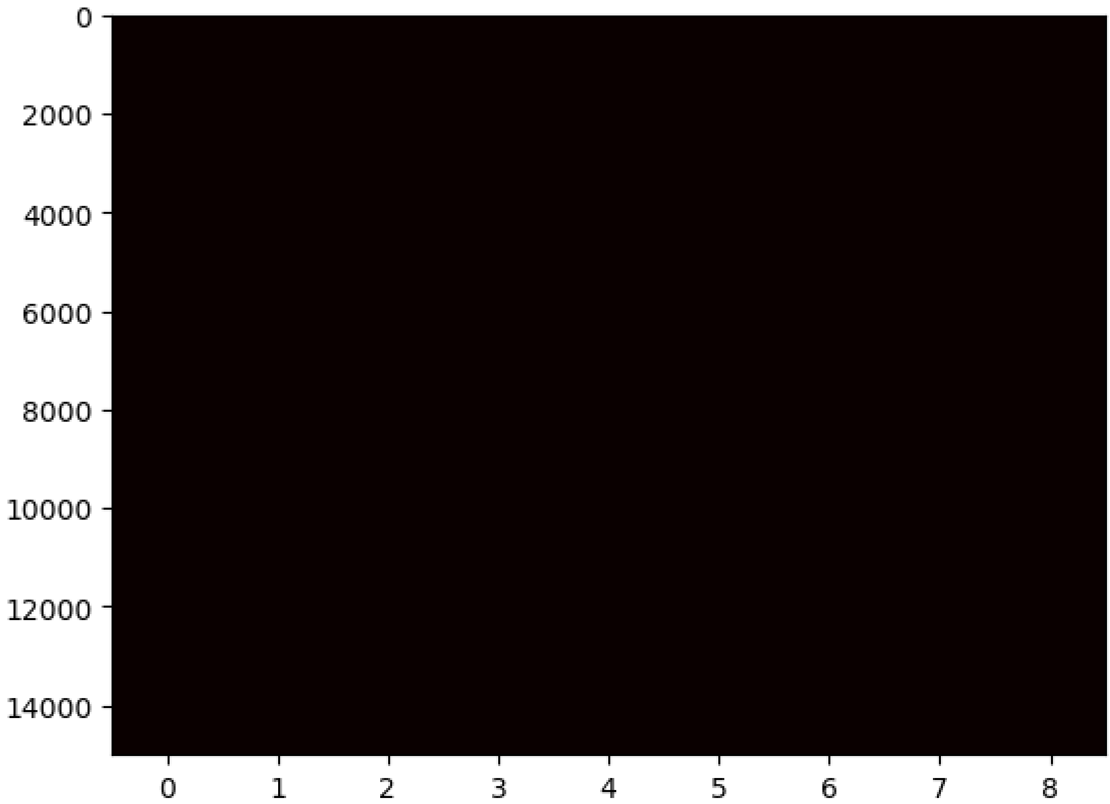
Out[9]:
```
vidid        False
adview       False
views        False
likes        False
dislikes     False
comment      False
published    False
duration     False
category     False
dtype: bool
```

In [10]:
```
data.isnull().sum()
```

Out[10]:
```
vidid        0
adview       0
views        0
likes        0
dislikes     0
comment      0
published    0
duration     0
category     0
dtype: int64
```

In [11]:
```
# Lets plot the missing values
```

In [12]:
```
plt.imshow(data.isnull(), cmap='hot', aspect='auto')
plt.show()
```



In [13]:
```
# So, there are no null values present in our data.
```

Convert Categorical Columns into Numerical Columns

In [14]:
```
# Removing the character F present in the data.
data = data[data['views'] != 'F' ]
data = data[data['likes'] != 'F' ]
data = data[data['dislikes'] != 'F' ]
data = data[data['comment'] != 'F' ]
```

In [15]:
```
# Converting features with object data type into numeric.
data['views'] = pd.to_numeric(data['views'])
data['likes'] = pd.to_numeric(data['likes'])
data['dislikes'] = pd.to_numeric(data['dislikes'])
data['comment'] = pd.to_numeric(data['comment'])
```

In [16]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 14637 entries, 0 to 14998
Data columns (total 9 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   vidid      14637 non-null  object
 1   adview     14637 non-null  int64 
 2   views      14637 non-null  int64 
 3   likes      14637 non-null  int64 
 4   dislikes   14637 non-null  int64 
 5   comment    14637 non-null  int64 
 6   published  14637 non-null  object
 7   duration   14637 non-null  object
 8   category   14637 non-null  object
dtypes: int64(5), object(4)
memory usage: 1.1+ MB
```

Checking for missing values and removing if present.

Converting Duration Column into Seconds

In [17]:

```
import datetime
import time
```

In [18]:

```
def checki(x):
    y = x[2:]
    h = ''
    m = ''
    s = ''
    mm = ''
    P = ['H','M','S']
    for i in y:
        if i not in P:
            mm+=i
        else:
            if(i=="H"):
                h = mm
                mm = ''
            elif(i == "M"):
                m = mm
                mm = ''
            else:
                s = mm
                mm = ''
    if(h==''):
        h = '00'
    if(m == ''):
        m = '00'
    if(s==''):
        s='00'
    bp = h+':'+m+':'+s
    return bp

train=pd.read_csv("train.csv")
mp = pd.read_csv("train.csv")["duration"]
time = mp.apply(checki)

def func_sec(time_string):
    h, m, s = time_string.split(':')
    return int(h) * 3600 + int(m) * 60 + int(s)

time1=time.apply(func_sec)
```

```
data["duration"]=time1
data.head()
```

Out[18]:

	vidid	adview	views	likes	dislikes	comment	published	duration	category
0	VID_18655	40	1031602	8523	363	1095	2016-09-14	457	F
1	VID_14135	2	1707	56	2	6	2016-10-01	570	D
2	VID_2187	1	2023	25	0	2	2016-07-02	136	C
3	VID_23096	6	620860	777	161	153	2016-07-27	262	H
4	VID_10175	1	666	1	0	0	2016-06-29	31	D

Converting date to year format in published column

In [19]:
```
data['published'] = pd.DatetimeIndex(data['published']).year

# Converting published column to numerical column
data['published'] = data['published'].astype('int')
```

In [20]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 14637 entries, 0 to 14998
Data columns (total 9 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   vidid      14637 non-null  object
 1   adview     14637 non-null  int64 
 2   views      14637 non-null  int64 
 3   likes      14637 non-null  int64 
 4   dislikes   14637 non-null  int64 
 5   comment    14637 non-null  int64 
 6   published  14637 non-null  int32 
 7   duration   14637 non-null  int64 
 8   category   14637 non-null  object
dtypes: int32(1), int64(6), object(2)
memory usage: 1.1+ MB
```

In [21]:
```
numerical_columns = data.select_dtypes(include=['number']).columns
categorical_columns = data.select_dtypes(exclude=['number']).columns

print('Number of numerical columns : ' + str(len(numerical_columns)))
print('Number of categorical columns: ' + str(len(categorical_columns)))
```

```
Number of numerical columns : 7
Number of categorical columns: 2
```

Visualizing the data

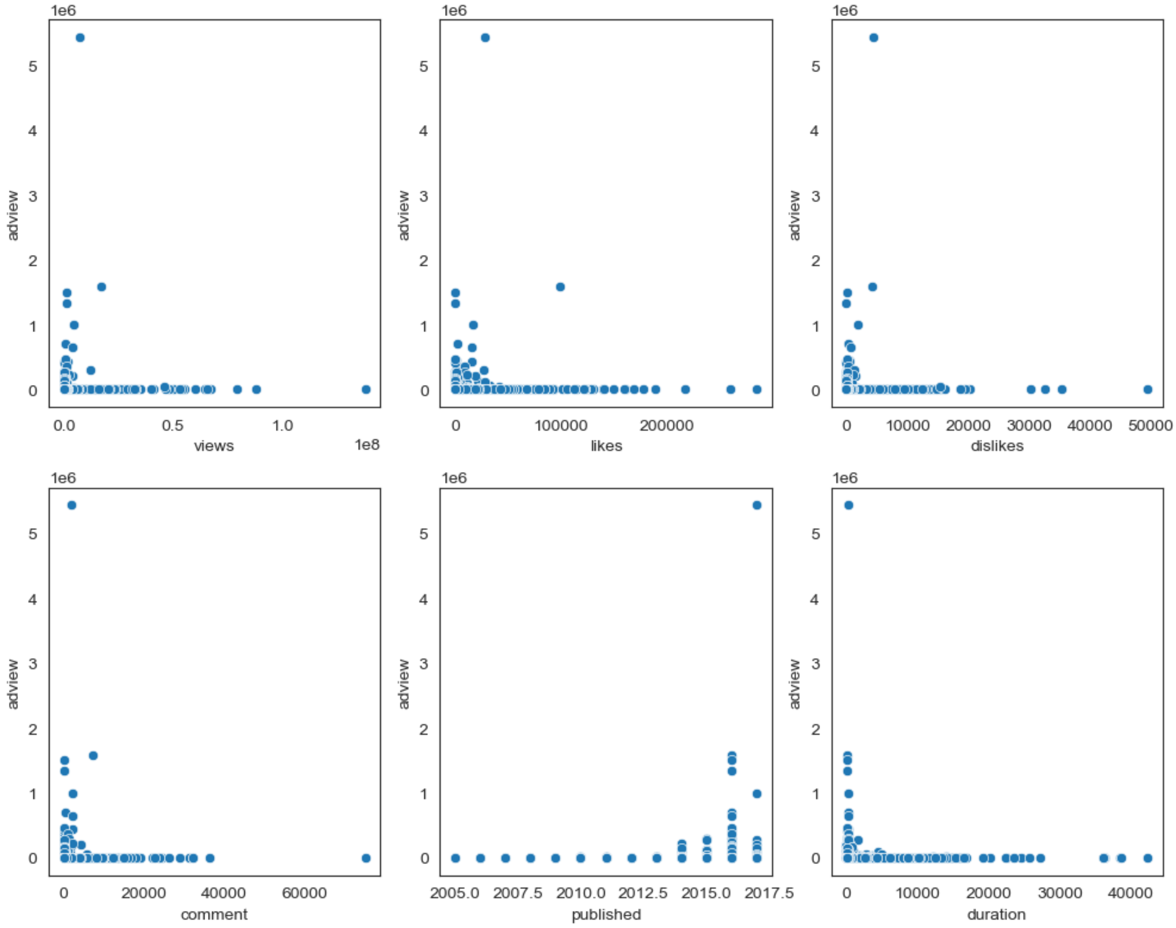
In [22]:
```
data.head()
```

Out[22]:

	vidid	adview	views	likes	dislikes	comment	published	duration	category
0	VID_18655	40	1031602	8523	363	1095	2016	457	F
1	VID_14135	2	1707	56	2	6	2016	570	D
2	VID_2187	1	2023	25	0	2	2016	136	C
3	VID_23096	6	620860	777	161	153	2016	262	H
4	VID_10175	1	666	1	0	0	2016	31	D

In [23]:

```
sns.set_style('white')
fig, axes = plt.subplots(2, 3 , figsize = (10,8))
sns.scatterplot(data=data, x='views', y='adview', ax=axes[0,0])
sns.scatterplot(data=data, x='likes', y='adview', ax=axes[0,1])
sns.scatterplot(data=data, x='dislikes', y='adview', ax=axes[0,2])
sns.scatterplot(data=data, x='comment', y='adview', ax=axes[1,0])
sns.scatterplot(data=data, x='published', y='adview', ax=axes[1,1])
sns.scatterplot(data=data, x='duration', y='adview', ax=axes[1,2])
plt.tight_layout()
```

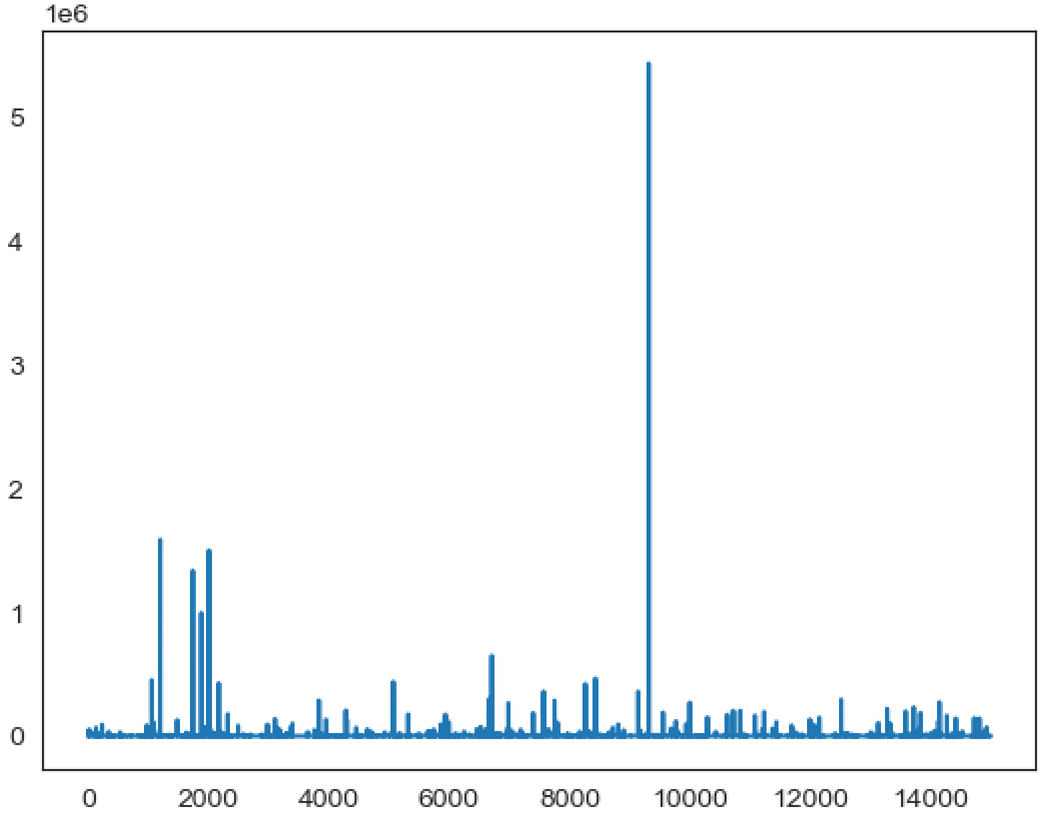


In [24]:

```
plt.plot(data['adview'])
```

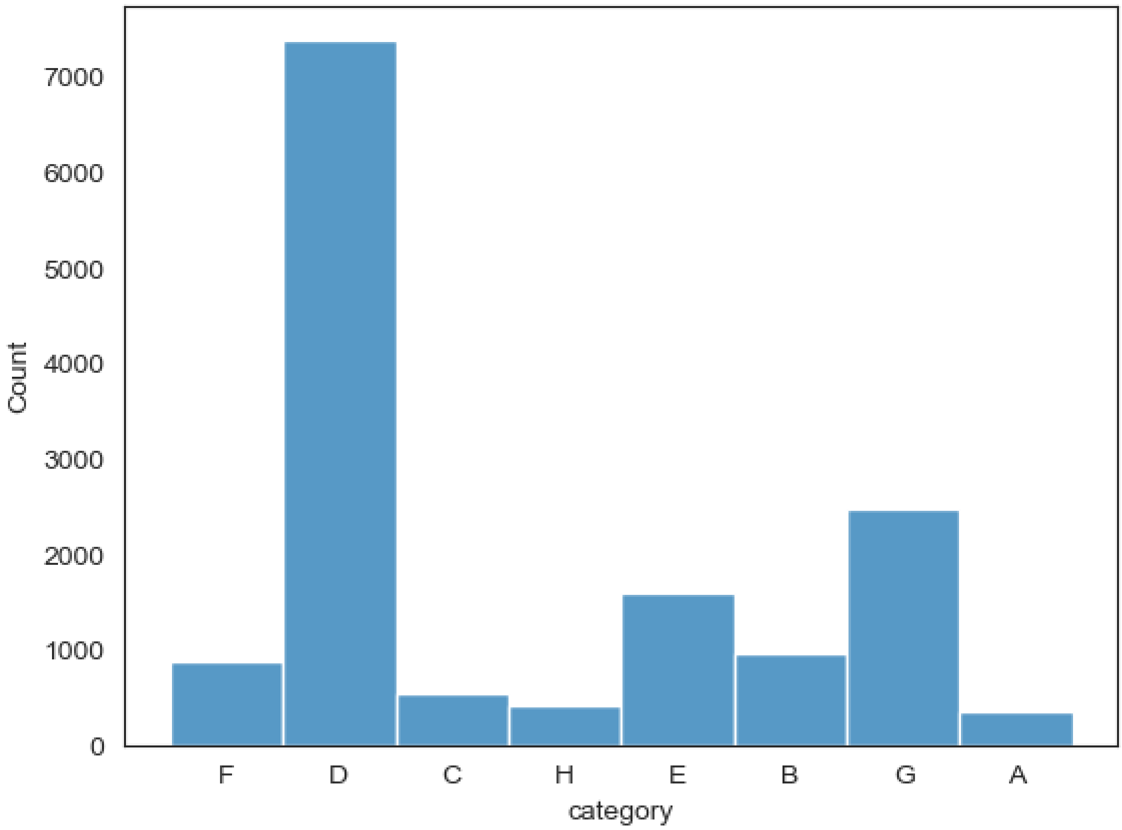
Out[24]:

```
[<matplotlib.lines.Line2D at 0x1da87117fd0>]
```



In [25]:
```
# Lets see distribution of category column:
sns.histplot(data['category'])
```

Out[25]: <Axes: xlabel='category', ylabel='Count'>



In [26]:
```
correlation_matrix = data.corr(numeric_only = True)

# Create a heatmap
plt.figure(figsize=(10, 8))  # Set the figure size
```

```
sns.heatmap(correlation_matrix, annot=True, cmap="BuPu", linewidths=.5)
plt.title('Data Correlation')
```

Out[26]: Text(0.5, 1.0, 'Data Correlation')

Feature Engineering

In [27]:
```
# Columns which are not neccessary can be removed
```

In [28]:
```
df = data.drop(['vidid', 'published', 'duration'], axis = 1)
```

In [29]:
```
df.head()
```

Out[29]:

	adview	views	likes	dislikes	comment	category
0	40	1031602	8523	363	1095	F
1	2	1707	56	2	6	D
2	1	2023	25	0	2	C
3	6	620860	777	161	153	H
4	1	666	1	0	0	D

In [1]:
```
# If there are any Non-numerical labels should be converted into numericals before
```

In [2]:
```
# This process can be done by using label encoder from data preprocessing.
# As we have labels in numerical form there is no need to use labelencoder
```

In [33]:
```
# Generate dummy columns:
# Here new columns are created for each category and old ones are deleted.
# get_dummies creates binary columns for each category.
# If a instance has category 'F' then category_F column value is 1 and remaining co
df = pd.get_dummies(df).reset_index(drop=True)
df
```

Out[33]:

	adview	views	likes	dislikes	comment	category_A	category_B	category_C	category_
0	40	1031602	8523	363	1095	0	0	0	
1	2	1707	56	2	6	0	0	0	
2	1	2023	25	0	2	0	0	1	
3	6	620860	777	161	153	0	0	0	
4	1	666	1	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	
14632	2	525949	1137	83	86	1	0	0	
14633	1	665673	3849	156	569	0	0	0	
14634	4	3479	16	1	1	0	1	0	
14635	1	963	0	0	0	0	0	0	
14636	1	15212	22	5	4	0	0	0	

14637 rows × 13 columns

In [3]:
```
# Now categorical column is transformed into numericals.
```

In [35]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14637 entries, 0 to 14636
Data columns (total 13 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   adview      14637 non-null  int64
 1   views       14637 non-null  int64
 2   likes       14637 non-null  int64
 3   dislikes    14637 non-null  int64
 4   comment     14637 non-null  int64
 5   category_A  14637 non-null  uint8
 6   category_B  14637 non-null  uint8
 7   category_C  14637 non-null  uint8
 8   category_D  14637 non-null  uint8
 9   category_E  14637 non-null  uint8
 10  category_F  14637 non-null  uint8
 11  category_G  14637 non-null  uint8
 12  category_H  14637 non-null  uint8
dtypes: int64(5), uint8(8)
memory usage: 686.2 KB
```

Splitting the dataset into Test and Train

In [45]:
```
from sklearn.model_selection import train_test_split

# input for the model will be views, likes, dislikes, and, category columns.
x = df.drop(['adview'] , axis = 1)

# The model should predict adview which is y
y = df['adview']
```

In [46]:
```
x.shape
```

Out[46]: (14637, 12)

In [47]:
```
y.shape
```

Out[47]: (14637,)

In [48]:
```
x_train , x_test , y_train , y_test = train_test_split(x , y , test_size = 0.3 , r
```

In [49]:
```
x_train.shape
```

Out[49]: (10245, 12)

In [50]:
```
x_test.shape
```

Out[50]: (4392, 12)

In [51]:
```
y_train.shape
```

Out[51]: (10245,)

In [52]:
```
y_test.shape
```

Out[52]: (4392,)

Scaling features

Scaling the features to a common range (usually between 0 and 1) ensures that all features have equal importance during model training. The MinMaxScaler specifically scales the features such that they all fall within the specified range (0 to 1 by default).

In [57]:
```
# Now we have to normalise the data.

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.fit_transform(x_test)
```

Model Development

Various machine learning models can be employed for training, and the selection can be based on the one that yields the optimal outcome. Here we will be using regression architecture to develop machine learning models.

Linear Regression

In [58]:
```
# Linear Regression:
from sklearn.linear_model import LinearRegression
linear_reg = LinearRegression()
linear_reg.fit(x_train , y_train)
prediction1 = linear_reg.predict(x_test)
```

Support Vector Regression

In [59]:
```
# Support vector regression:
from sklearn.svm import SVR
sv_reg = SVR()
sv_reg.fit(x_train , y_train)
prediction2 = sv_reg.predict(x_test)
```

Decision Tree Regressor

In [60]:
```
# Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor
Dt_reg = DecisionTreeRegressor()
Dt_reg.fit(x_train, y_train)
prediction3 = Dt_reg.predict(x_test)
```

Random Forest Regressor

In [63]:
```
# Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor
Rf_reg = RandomForestRegressor(n_estimators = 200  , random_state = 42 )
Rf_reg.fit(x_train , y_train)
prediction4 = Dt_reg.predict(x_test)
```

Accuracy Check

- Evaluation metrics for Regression problems are :
  - mean_absolute_error
  - mean_squared_error
  - root_mean_squared_error

In [64]:
```
# Best model is selected based on the accuracy of predictions.

from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error


def accuracy_check(y_test , prediction , model):
    print(model,':')
    print('Mean Absolute Error : ' ,  mean_absolute_error(y_test, prediction))
    print('Mean Squared Error : ' , mean_squared_error(y_test, prediction))
    print('Root Mean Squared Error : ' , np.sqrt(mean_squared_error(y_test, predic
    print()

accuracy_check(y_test , prediction1 , 'linear regression')
accuracy_check(y_test , prediction2 , 'support vector regression')
accuracy_check(y_test , prediction3 , 'decision tree regression')
accuracy_check(y_test , prediction4 , 'Random froest regression')
```

```
linear regression :
Mean Absolute Error :  3604.803887973459
Mean Squared Error :  659798344.3953929
Root Mean Squared Error :  25686.54014061436

support vector regression :
Mean Absolute Error :  1372.175694675267
Mean Squared Error :  640498095.7968979
Root Mean Squared Error :  25308.063849233862

decision tree regression :
Mean Absolute Error :  3696.215093854233
Mean Squared Error :  2285482093.169039
Root Mean Squared Error :  47806.71598393931

Random froest regression :
Mean Absolute Error :  3696.215093854233
Mean Squared Error :  2285482093.169039
Root Mean Squared Error :  47806.71598393931
```

Picking the best model based on error

In [65]:
```
# With the least mea absolute error we can choose support vector regression model
```

In [66]:
```
# After selecting the best model we can save the model by using joblib package
```

Save The Model Using Joblib

In [67]:
```
import joblib
joblib.dump(sv_reg, "supportvector_youtubeadview.pkl")
```

Out[67]:
```
['supportvector_youtubeadview.pkl']
```

We can load the model anytime to predict on any test data

In [74]:
```
# Model can be loaded as:
model = joblib.load('supportvector_youtubeadview.pkl')
```

In [69]:
```
model
```

Out[69]:
```
▾ SVR
SVR()
```