# YOUTUBE ADVIEW PREDICTION

**A Term Paper Report**

**Submitted in partial fulfilment of the requirements for the award of degree of**

**Bachelor of Technology**

**(Computer Science Engineering)**

**Submitted to**

**LOVELY PROFESSIONAL UNIVERSITY PHAGWARA, PUNJAB**

**From 1st Feb 2024 to 23st April 2024**

**SUBMITTED BY**

**Name of student: Aravind Kontham**

**Registration Number: 12112090**

**Faculty: Ved Prakash Chaubey**

## Annexure-II: Student Declaration

## To whom so ever it may concern

I, **Aravind Kontham, 12112090**, hereby declare that the work done by me on **"YOUTUBE ADVIEW PREDICTION USING REGRESSION MODEL "** from Feb 2024 to April 2024, is a record of original work for the partial fulfilment of the requirements for the award of the degree, Bachelor of Technology.

**Name of the student:** Aravind Kontham

**Registration Number:** 12112090

**Dated: 23$^{TH}$ APRIL 2023**


## ACKNOWLEDGEMENT

Primarily I would like to thank God for being able to learn a new technology. Then I would like to express my special thanks of gratitude to the teacher and instructor of the course Machine Learning who provided me the golden opportunity to learn a new technology.

I would like to also thank my own college Lovely Professional University for offering such a course which not only improve my programming skill but also taught me other new technology.

Then I would like to thank my parents and friends who have helped me with their valuable suggestions and guidance for choosing this course.

Finally, I would like to thank everyone who have helped me a lot.

**Dated: 22$^{TH}$ APRIL 2024**

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# ABSTRACT

The main goal is to create a machine learning regression that can estimate the number of YouTube adviews based on other parameters. Advertisers on YouTube pay content creators based on how many times their ads are viewed and clicked. They want to estimate the adview based on other metrics like vidid, adviews, published, duration, views, comments, likes etc. CSV files are utilised for training and fitting, and then they are tested to get the best outcomes. As a result, the goal of the project is to train multiple regression models and select the best one for predicting the number of adviews. We validate datasets and packages like Numpy, Pandas, and Sklearn for their form and data type. Also, we visualise and clean the dataset followed by transforming attributes into numerical values. Using different regression algorithms, normalise the data and separate it into training and test sets. The model is saved and used to predict on the test set. To acquire better outcomes, data or information must be improved, filtered, and cleansed before being fed in based on numerous criteria.


# OBJECTIVE

Understanding the popularity dynamics of YouTube videos poses a significant challenge due to the diverse range of users, sponsorships, and content creators involved. Researchers tackle this challenge by analyzing meta-level features to define video popularity. Various parametric models are employed for this purpose, often using time series data of view counts to estimate model parameters. For instance, ARMA time series models, a type of multivariate linear regression, are commonly used to forecast future view counts based on historical data. One notable finding suggests that videos falling within a specific range of view counts tend to be more popular than others. To enhance predictive accuracy, researchers continually refine regression models to approximate and forecast view counts more effectively.

# INTRODUCTION

YouTube, launched in May 2005, has become a global platform for billions of users to explore, watch, and share a vast array of original videos. It serves as a hub for individuals worldwide to engage, educate, and inspire each other, while also functioning as a pivotal distribution channel for content creators and advertisers of all scales. The number of views a video accumulates is a crucial metric indicating its popularity or "user engagement" and serves as the basis for compensating content creators on YouTube. This research endeavors to predict the number of views, particularly ad views, a specific video will garner to promote a particular deal or brand. Leveraging a dataset for model training, the file "train.csv" contains data on approximately 15,000 YouTube videos, encompassing metrics such as views, ad views, likes, dislikes, and comments, along with publication date, duration, and category. The target variable for prediction, ad views, is also included in the CSV file. Various data visualization techniques are employed to forecast the desired value, with thorough data refinement and cleaning performed to enhance algorithmic accuracy. YouTube stands out as a platform fostering high user engagement compared to other social media platforms, making it an effective space for marketing and promotion in today's tech-driven world. Thus, a Machine Learning project is devised to predict ad views for videos marketed in specific publication years, utilizing previous data collected from two CSV files: "train" and "test." The train dataset, comprising around 15,000 records, is partitioned into an 80-20 split for further analysis in subsequent stages of the project.

# LITERATURE SURVEY

Analyzing the popularity of YouTube videos based on meta-level features presents a complex challenge due to the diverse array of users, sponsorships, and content providers. Various parametric models are employed to gauge the popularity of these videos, leveraging time series data of view counts to estimate model parameters accurately.

Among these models, ARMA time series models stand out as effective tools, utilizing multivariate linear regression to forecast future view counts based on historical data. These models provide insights into the evolving popularity trends of YouTube videos over time.

One notable finding from this analysis is the observation that YouTube videos falling within specific view count ranges tend to garner more popularity compared to others. This insight highlights the significance of understanding the dynamics of view counts in determining a video's overall appeal to audiences.

In pursuit of optimizing predictive accuracy, researchers endeavor to identify the most effective regression models for forecasting view counts. By doing so, they aim to provide creators and advertisers with more accurate estimations of the expected popularity of their content on the platform.

# EXISTING SYSTEM

Regression models are powerful tools for estimating the number of ad views content will receive. These models, including linear regression, decision trees, and support vector machines, analyze various metrics associated with the content, such as likes, dislikes, comments, and even video length or category. By learning the relationships between these factors and historical ad view data, the models can predict the expected ad views for new content.

**Key Point**: While these models can't pinpoint the exact number of ad views (due to inherent randomness
in user behavior), they can generate highly accurate estimations. This provides significant advantages:

**Campaign Optimization**: Advertisers can leverage these predictions to optimize their campaigns. By targeting content with a higher predicted ad view count, they can maximize their reach and return on investment.

Content Strategy: Creators can use these insights to tailor their content strategy. Understanding which elements (like video length or specific thumbnail designs) are associated with higher predicted ad views allows creators to focus on what resonates with the audience.

# PROPOSED SYSTEM

I have developed a system that utilizes a single regression model, specifically the support vector regression. Through extensive testing, I've found that the support vector regression offers superior prediction accuracy compared to other regression models. It consistently yields fewer errors when predicting adviews based on actual data. This system serves the purpose of predicting the adviews of a particular video, which is invaluable for marketing strategies aimed at promoting a sale or a brand.

During the development process, I trained the regression models using available data and then rigorously tested them using separate test data sets. By comparing the performance of various regression models, I identified the support vector regression as the optimal choice due to its ability to minimize prediction errors.

Advantages:

This system provides a reliable method for predicting adviews for individual videos, thereby facilitating targeted marketing efforts for specific products or brands.

## IMPLEMENTATION

(1) Importing datasets and libraries is the initial step. It involves checking their shape and datatype for thorough analysis.

- Start by importing necessary libraries and datasets.
- Verify the shape and datatype of the imported data.

(2) Preprocessing involves converting characteristics into numerical values for better analysis.

- As the data is initially in object format, it needs conversion into float for further processing.
- Manipulate time into seconds and date into numeric format.
- Split the date into year, month, and day for detailed analysis.
- Convert views, likes, dislikes, and comment data into numeric using pandas.to_numeric() with errors="coerce" to handle non-numeric values.
- Convert the published date into numeric and split it into year, month, and day.

(3) Cleaning the dataset involves removing missing values and unnecessary data.

- Eliminate null characters and other miscellaneous data to prevent interference with further processing.
- Drop or remove null entries and any irrelevant data.
- Rearrange the columns for ease of data splitting during training.

(4) Visualizing the dataset through plots and heatmaps provides insights into data distributions and relationships between variables. Here are the visualizations for further analysis:

- *Year vs Total Ad views*: This heatmap illustrates the total number of ad views each year, revealing an increasing trend over time.
- *Year vs Views:* Utilizing a scatter plot, this visualization displays ad views across different years from 2005 to 2017. It identifies outliers, such as a single video with views exceeding 2,000,000, which may need exclusion before training the data to prevent skewing results.
- *Category vs Number of Videos*: This plot showcases the distribution of videos across different categories. Category 3 appears to have a higher number of videos compared to other categories.

(5) Normalizing the data and splitting it into appropriate training and test sets are essential steps in model preparation:

- Divide the data into training and test sets, ensuring the right ratio for each.
- Develop a function to compute mean absolute error, mean square error, and mean square root error for evaluating model performance.

(6) Training the data involves employing various regression models and assessing their performance:Use linear regression, Support Vector Regressor, and Decision Tree algorithms to train the data.

Record and compare errors for each model to determine their effectiveness in predicting ad views accurate

===========YouTube AdView Prediction============

# 1. Introduction

### Objective:

To build a machine learning model which will predict youtube adview count based on other youtube metrics.

### Data Description:

- train.csv - the training set
- test.csv - the test set
- The file train.csv contains metrics and other details of about 15000 youtube videos. The metrics include number of views, likes, dislikes, comments and apart from that published date, duration and category are also included. The train.csv file also contains the metric number of adviews which is our target variable for prediction.

### Table of Content:



# 2. Install & Import Libraries

- Run the below cell, if you've not install these libraries before.

```
# # use to visualize missing value
# !pip install missingno

# # use for hyper parameter tuning
# !pip install optuna

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
## Display all the columns of the dataframe
pd.pandas.set_option('display.max_columns',None)
from scipy import stats
from scipy.stats import norm, skew # for some statistics
import warnings # to ignore warning
from sklearn.preprocessing import RobustScaler, PowerTransformer, LabelEncoder
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import train_test_split

import optuna
from sklearn.model_selection import KFold, cross_val_score
from sklearn.linear_model import Ridge, Lasso
from sklearn.ensemble import StackingRegressor, RandomForestRegressor,
GradientBoostingRegressor
from sklearn.svm import SVR
import xgboost as xgb
import lightgbm as lgb
import joblib
import warnings
```

```
warnings.filterwarnings('ignore')
print("Library Imported!!")
```

```
Library Imported!!
```

## 3. Load Datasets

```
# load train and test dataset
train_df = pd.read_csv("/content/train.csv")
test_df = pd.read_csv("/content/test.csv")
```

## 4. Exploratory Data Analysis

### 4.1. Train Data Exploration

For both train and test dataset, We'll explore following things

- First 5 rows
- Data shape
- Data information
- Data types
- Null value

#### 4.1.1. First 5 records

```
train_df.head()
```

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

  category
0        F
1        D
2        C
3        H
4        D
```

#### 4.1.2. Data Shape - Train Data

```
train_df.shape
```

```
(14999, 9)
```

#### 4.1.3. Data Information - Train Data

```
train_df.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
```

### 4.1.4. Statistical analysis - Train Data

```
train_df.describe(include='all')
```

```
            vidid        adview  views  likes dislikes comment   published  \
count       14999  1.499900e+04  14999  14999    14999   14999       14999
unique      14999           NaN  14588   4789     1546    2007        2386
top     VID_12352           NaN    238      1        0       0  2016-08-26
freq            1           NaN      4    174     1091    1290          42
mean          NaN  2.107791e+03    NaN    NaN      NaN     NaN         NaN
std           NaN  5.237711e+04    NaN    NaN      NaN     NaN         NaN
min           NaN  1.000000e+00    NaN    NaN      NaN     NaN         NaN
25%           NaN  1.000000e+00    NaN    NaN      NaN     NaN         NaN
50%           NaN  2.000000e+00    NaN    NaN      NaN     NaN         NaN
75%           NaN  6.000000e+00    NaN    NaN      NaN     NaN         NaN
max           NaN  5.429665e+06    NaN    NaN      NaN     NaN         NaN

       duration category
count     14999    14999
unique     3146        8
top       PT31S        D
freq        147     7558
mean        NaN      NaN
std         NaN      NaN
min         NaN      NaN
25%         NaN      NaN
50%         NaN      NaN
75%         NaN      NaN
max         NaN      NaN
```

### 4.1.5. Data Type - Train Data

```
train_dtype = train_df.dtypes
train_dtype.value_counts()
```

```
object    8
int64     1
dtype: int64
```

### 4.1.6. Null Value - Train Data

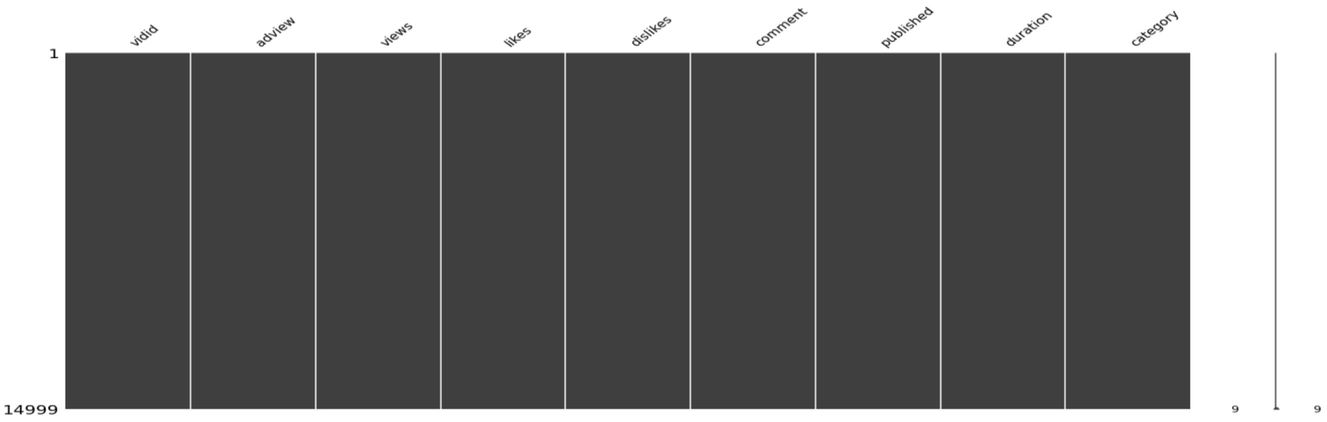
```
train_df.isnull().sum().sort_values(ascending = False).head(10)
```

```
category     0
duration     0
published    0
comment      0
dislikes     0
likes        0
views        0
adview       0
vidid        0
dtype: int64
```

### 4.1.7. Visualize missing value using Misingno - Train Data

```
msno.matrix(train_df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb96dc11950>
```




## 4.2. Test Data Exploration

### 4.2.1. First 5 rows - Test Data

```
test_df.head()
```

| | vidid | views | likes | dislikes | comment | published | duration | category |
|---|---|---|---|---|---|---|---|---|
| 0 | VID_1054 | 440238 | 6153 | 218 | 1377 | 2017-02-18 | PT7M29S | B |
| 1 | VID_18629 | 1040132 | 8171 | 340 | 1047 | 2016-06-28 | PT6M29S | F |
| 2 | VID_13967 | 28534 | 31 | 11 | 1 | 2014-03-10 | PT37M54S | D |
| 3 | VID_19442 | 1316715 | 2284 | 250 | 274 | 2010-06-05 | PT9M55S | G |
| 4 | VID_770 | 1893173 | 2519 | 225 | 116 | 2016-09-03 | PT3M8S | B |

### 4.2.2. Data Shape - Test Data

```
test_df.shape
```

```
(8764, 8)
```

### 4.2.3. Data Type - Test Data

```
test_dtype = test_df.dtypes
test_dtype.value_counts()
```

```
object    8
dtype: int64
```

### 4.2.4. Data Information - Test Data

```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8764 entries, 0 to 8763
Data columns (total 8 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   vidid      8764 non-null   object
 1   views      8764 non-null   object
 2   likes      8764 non-null   object
 3   dislikes   8764 non-null   object
 4   comment    8764 non-null   object
 5   published  8764 non-null   object
 6   duration   8764 non-null   object
 7   category   8764 non-null   object
dtypes: object(8)
memory usage: 547.9+ KB
```

### 4.2.5. Statistical analysis - Test Data

```
test_df.describe(include='all')
```

| | vidid | views | likes | dislikes | comment | published | duration | category |
|---|---|---|---|---|---|---|---|---|
| count | 8764 | 8764 | 8764 | 8764 | 8764 | 8764 | 8764 | 8764 |
| unique | 8764 | 8605 | 3434 | 1215 | 1556 | 2109 | 2330 | 8 |
| top | VID_14440 | 36679 | 2 | 0 | 0 | 2016-08-26 | PT31S | D |
| freq | 1 | 3 | 89 | 662 | 727 | 32 | 120 | 4419 |

### 4.2.6. Null Data - Test Data

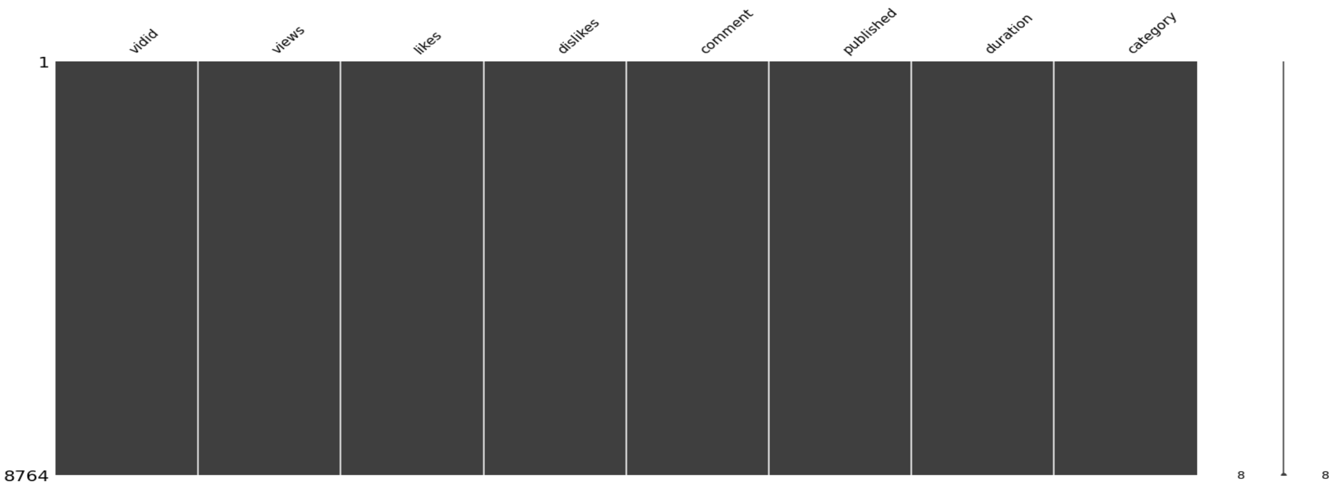
```
test_df.isnull().sum().sort_values(ascending = False).head(10)
```

```
category     0
duration     0
published    0
comment      0
dislikes     0
likes        0
views        0
vidid        0
dtype: int64
```

### 4.2.7. Visualize missing value using Misingno - Test Data

```
msno.matrix(test_df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb96db0c610>
```




### 4.2.8. Report - Data Exploration

- The shape of train and test datasets are (14999, 9) & (8764, 8)
- There is no null value present in both dataset.
- Some categorical columns should convert to numerical.
- e.g 'views', 'likes', 'dislikes', 'comment'.

### 4.3. Train & Test Data Comparison

Here we'll compare below things between train and test dataset.

- Data Type
- Null values
- Data Distribution

#### 4.3.1. Data Type Comparison

```
# as 'SalePrice' Column is not available in test dataset. So we'll delete it.
trn_dtype = train_dtype.drop('adview')
trn_dtype.compare(test_dtype)
```

```
Empty DataFrame
Columns: [self, other]
Index: []
```

- The data type of each columns is same in both train and test dataframe

#### 4.3.2. Null Value Comparison

```
null_train = train_df.isnull().sum()
null_test = test_df.isnull().sum()
null_train = null_train.drop('adview')
null_comp_df = null_train.compare(null_test).sort_values(['self'],ascending =
[False])
null_comp_df
```

```
Empty DataFrame
Columns: [self, other]
Index: []
```

- Here we can see that there is no null value present in test and train dataset.

#### 4.3.3. Distribution Comparison

Before going for distribution comparison,let's do some data preprocessing which will help in data analysis.

#### 4.3.3.1 Convert Categorical column to numerical

```
convert_col = ['views', 'likes', 'dislikes', 'comment']
# these columns contain 'F' letter. So replace it by '0'. As we are converting
columns to numerical.
for col in convert_col:
  train_df[col].replace({"F": 0}, inplace=True)
  test_df[col].replace({"F": 0}, inplace=True)

# Convert "categorical" feature to "numerical"
for col in convert_col:
  train_df[col] = train_df[col].astype('int')
  test_df[col] = test_df[col].astype('int')
```

#### 4.3.3.2. Temporal variable analysis

```
train_df.head()
```

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

  category
0        F
1        D
2        C
3        H
4        D
```

```python
# convert "duration" column format into "second" format
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_mp = train_df["duration"]
test_mp = test_df["duration"]

train_time = train_mp.apply(checki)
test_time = test_mp.apply(checki)

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

train_time=train_time.apply(func_sec)
test_time=test_time.apply(func_sec)

train_df["duration"]=train_time
test_df["duration"]=test_time
# train_df.head()
```

#### 4.3.3.3. Convert 'date' to 'year' format in 'published' column

```python
train_df['published'] = pd.DatetimeIndex(train_df['published']).year
test_df['published'] = pd.DatetimeIndex(test_df['published']).year

# convert to numerical feature
train_df['published'] = train_df['published'].astype('int')
test_df['published'] = test_df['published'].astype('int')

train_df.head()
```

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

  category
0        F
1        D
2        C
3        H
4        D
```

```
numerical_features = [col for col in train_df.columns if train_df[col].dtypes != 
'O']
discrete_features = [col for col in numerical_features if 
len(train_df[col].unique()) < 10 and col not in ['vidid']]
continuous_features = [feature for feature in numerical_features if feature not in 
discrete_features+['vidid']]
categorical_features = [col for col in train_df.columns if train_df[col].dtype == 
'O']

print("Total Number of Numerical Columns : ",len(numerical_features))
print("Number of discrete features : ",len(discrete_features))
print("No of continuous features are : ", len(continuous_features))
print("Number of categorical features : ",len(categorical_features))
```

```
Total Number of Numerical Columns :  7
Number of discrete features :  0
No of continuous features are :  7
Number of categorical features :  2
```

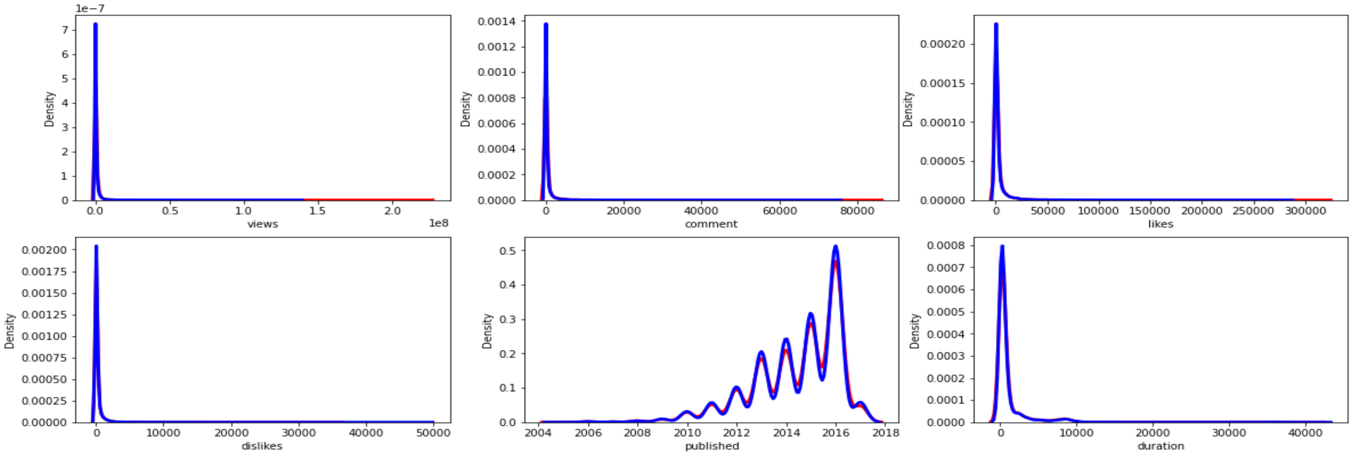
#### 4.3.3.4. Concat Train and Test datasets

```
# combined train and test datasets
combined_df = pd.concat([train_df,test_df],axis=0)

combined_df["Label"] = "test"
combined_df["Label"][:14999] = "train"
```

#### 4.3.4. Distribution Comparison - Continuous

```
plt.figure(figsize=(20, 8))
continuous_features = ['views', 'comment', 'likes', 'dislikes','published', 
'duration']
pos = 1
for i, feature in enumerate(continuous_features):
  plt.subplot(2 , 3 , pos)
  sns.distplot(test_df[feature], hist = False, kde = True, kde_kws = {'linewidth': 
3},color='r' )
  sns.distplot(train_df[feature], hist = False, kde = True, kde_kws = {'linewidth': 
3} ,color='b')
  pos = pos + 1
```



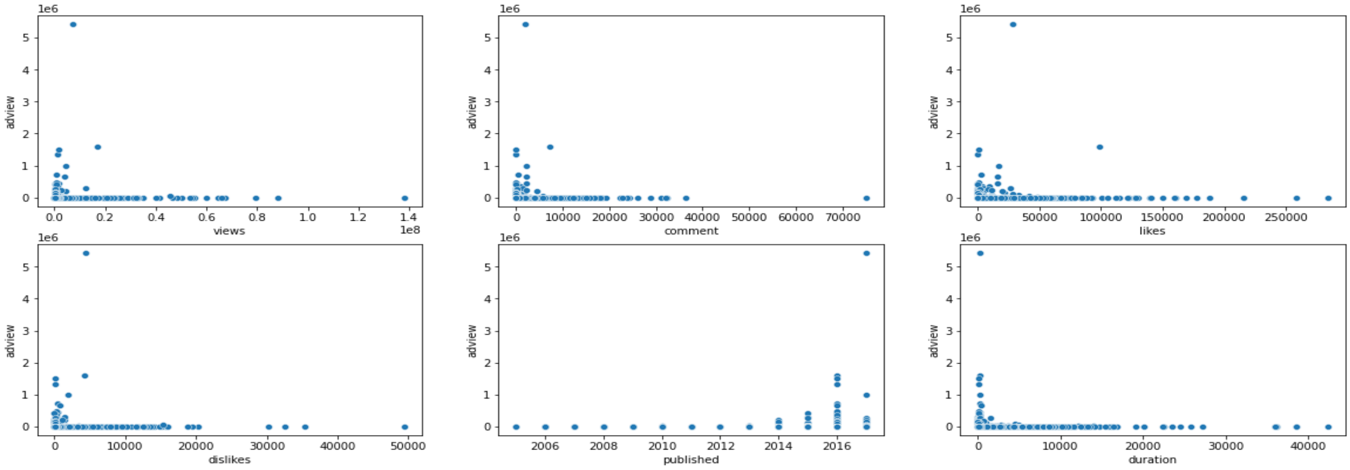

Above distribution shows that:

- The distribution of train and test data are similar for most continous features.
- All distributions are not **normally distributed**.

### 4.3.5. Linearity Check

Here we'll see the linearity between all features and the target variable.

```
plt.figure(figsize=(20, 8))
pos = 1
for i, feature in enumerate(continuous_features):
  plt.subplot(2 , 3 , pos)
  sns.scatterplot(data=combined_df, x = feature, y= "adview")
  pos = pos + 1
```

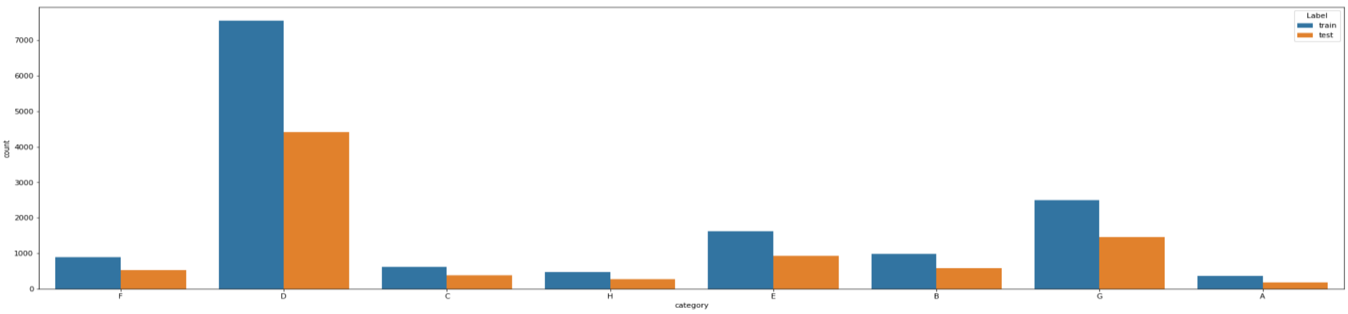



### 4.3.6. Distribution Comparison - Categorical

- There are two categorical features. These are **"category", "vidid"**.
- **"vidid"** is the id of video. So it has no impact to target variable.
- So we'll only check the distribution of **"category"** column.

```
plt.figure(figsize=(30, 8))
sns.countplot(data = combined_df, x = 'category', hue="Label")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb972109910>
```



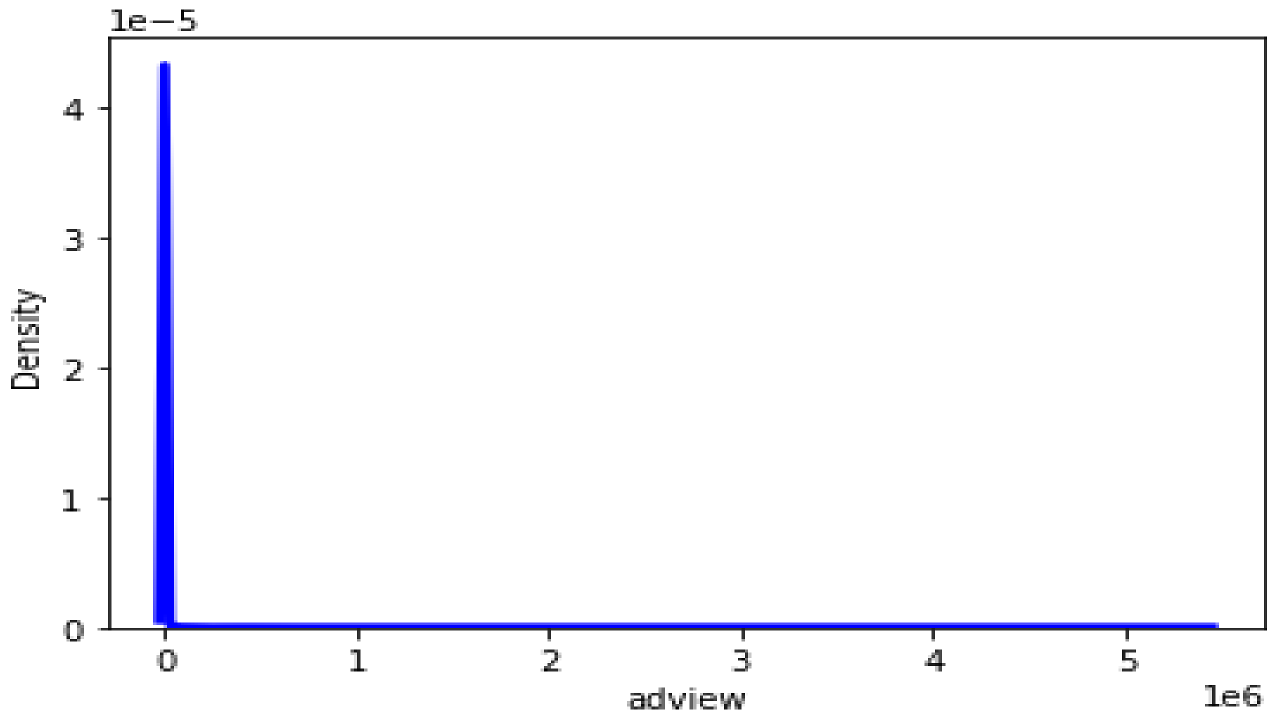

Above distribution shows that:

- The distribution of train and test data are similar for most categorical features.

### 4.3.7. Distribution - Target Variable

```
sns.distplot(train_df["adview"], hist = False, kde = True, kde_kws = {'linewidth':
3} ,color='b')
```

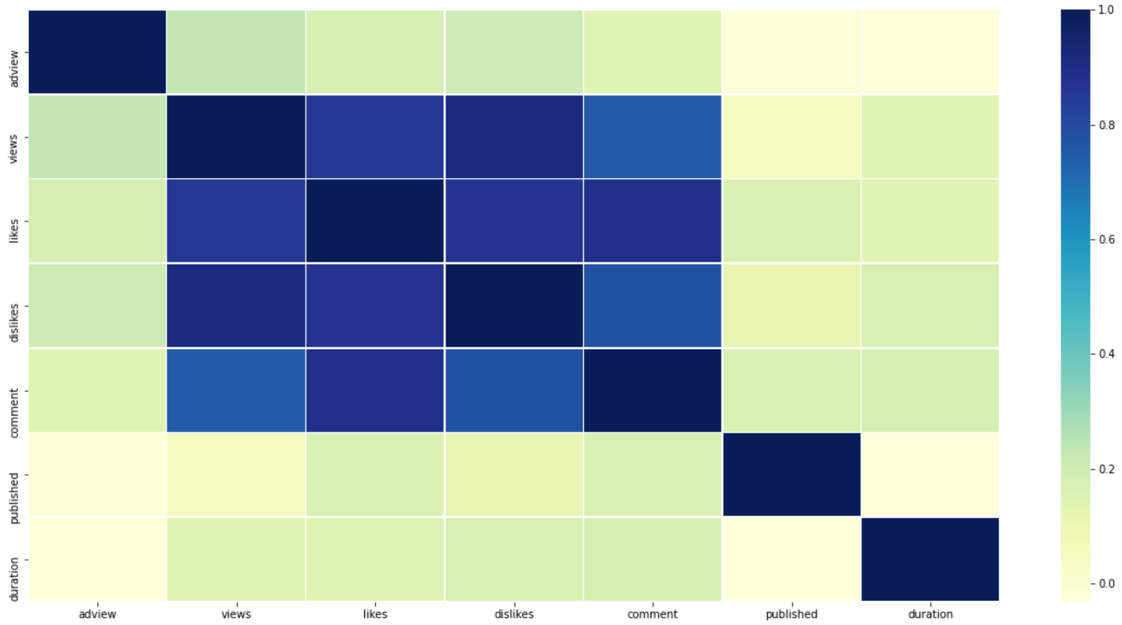
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb97219eed0>
```




### 4.3.8. Data Correlation

```
training_corr = train_df.corr(method='spearman')
plt.figure(figsize=(20,10))
sns.heatmap(training_corr,cmap="YlGnBu", linewidths=.5)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb96e46ae50>
```




# #5. Feature Engineering

## 5.1. Drop Columns

Here we'll drop unnecessary columns

```
drop_columns = ["vidid",'Label','published','duration']

#  Drop columns
print("Number of columns before dropping : ",len(combined_df.columns))
print("Number of dropping columns : ",len(drop_columns))
combined_df.drop(columns=drop_columns, inplace=True, errors='ignore')
print("Number of columns after dropping : ",len(combined_df.columns))
```

```
Number of columns before dropping :  10
Number of dropping columns :  4
Number of columns after dropping :  6
```

## 5.2. Apply PowerTransformer to columns

- We saw in distribution of continuous features that some features are not linear towards target feature. So we need to transform this.
- Lets check the skewness of these distributions

```
# check the skew of all numerical features
skew_check_col = ['views','likes','dislikes','comment']
skewed_feats = combined_df[skew_check_col].apply(lambda x :
skew(x.dropna())).sort_values(ascending = False)
print('\n Skew in numberical features: \n')
skewness_df = pd.DataFrame({'Skew' : skewed_feats})
print(skewness_df.head(7))
```

```
 Skew in numberical features:

               Skew
views     29.926939
comment   18.761969
dislikes  18.269315
likes     11.914098
```

```
for col in skew_check_col:
  power = PowerTransformer(method='yeo-johnson', standardize=True)
  combined_df[[col]] = power.fit_transform(combined_df[[col]]) # fit with combined_data to avoid overfitting with training data

print('Number of skewed numerical features got transform : ', len(skew_check_col))
```

```
Number of skewed numerical features got transform :  4
```

### 5.7. Encoding Categorical Features

### Get-Dummies

```
# Generate one-hot dummy columns
combined_df = pd.get_dummies(combined_df).reset_index(drop=True)

combined_df.head()
```

```
   adview     views     likes  dislikes   comment  category_A  category_B  \
0    40.0  1.000244  1.441680  1.103359  1.398827           0           0
1     2.0 -1.693941 -0.819659 -1.200594 -0.781064           0           0
2     1.0 -1.641413 -1.119185 -1.747128 -1.168045           0           0
3     6.0  0.722749  0.280058  0.723964  0.577704           0           0
4     1.0 -1.970231 -2.009511 -1.747128 -1.679421           0           0

   category_C  category_D  category_E  category_F  category_G  category_H
0           0           0           0           1           0           0
1           0           1           0           0           0           0
2           1           0           0           0           0           0
3           0           0           0           0           0           1
4           0           1           0           0           0           0
```

```
new_train_data = combined_df.iloc[:len(train_df), :]
new_test_data = combined_df.iloc[len(train_df):, :]
X_train = new_train_data.drop('adview', axis=1)
y_train = np.log1p(new_train_data['adview'].values.ravel())
X_test = new_test_data.drop('adview', axis=1)

# Make Pipeline
pre_precessing_pipeline = make_pipeline(RobustScaler())

X_train = pre_precessing_pipeline.fit_transform(X_train)
X_test = pre_precessing_pipeline.transform(X_test)

print(X_train.shape)
print(X_test.shape)
```

```
(14999, 12)
(8764, 12)
```

# 6. Model Development

### 6.2. Hyperparameter Tuning using Optuna

```
RANDOM_SEED = 23

# 10-fold CV
kfolds = KFold(n_splits=10, shuffle=True, random_state=RANDOM_SEED)
```

```python
def tune(objective):
    study = optuna.create_study(direction="maximize")
    study.optimize(objective, n_trials=100)

    params = study.best_params
    best_score = study.best_value
    print(f"Best score: {best_score} \nOptimized parameters: {params}")
    return params
```

### 6.3. Ridge Regression

```python
def ridge_objective(trial):

    _alpha = trial.suggest_float("alpha", 0.1, 20)

    ridge = Ridge(alpha=_alpha, random_state=RANDOM_SEED)

    score = cross_val_score(
        ridge,X_train,y_train, cv=kfolds, scoring="neg_root_mean_squared_error"
    ).mean()
    return score

# ridge_params = tune(ridge_objective)


# Best score: -1.898690687982798
ridge_params = {'alpha': 19.99855836300504}

ridge = Ridge(**ridge_params, random_state=RANDOM_SEED)
ridge.fit(X_train,y_train)
```

```
Ridge(alpha=19.99855836300504, copy_X=True, fit_intercept=True, max_iter=None,
      normalize=False, random_state=23, solver='auto', tol=0.001)
```

### 6.4. Lasso Regression

```python
def lasso_objective(trial):

    _alpha = trial.suggest_float("alpha", 0.0001, 1)

    lasso = Lasso(alpha=_alpha, random_state=RANDOM_SEED)

    score = cross_val_score(
        lasso,X_train,y_train, cv=kfolds, scoring="neg_root_mean_squared_error"
    ).mean()
    return score


# lasso_params = tune(lasso_objective)

# Best score: -1.8987548559962844
lasso_params =  {'alpha': 0.0009661425571276957}

lasso = Lasso(**lasso_params, random_state=RANDOM_SEED)
lasso.fit(X_train,y_train)
```

```
Lasso(alpha=0.0009661425571276957, copy_X=True, fit_intercept=True,
      max_iter=1000, normalize=False, positive=False, precompute=False,
      random_state=23, selection='cyclic', tol=0.0001, warm_start=False)
```

### 6.5. Gradient Boosting Regressor

```
def gbr_objective(trial):
    _n_estimators = trial.suggest_int("n_estimators", 50, 2000)
    _learning_rate = trial.suggest_float("learning_rate", 0.01, 1)
    _max_depth = trial.suggest_int("max_depth", 1, 20)
    _min_samp_split = trial.suggest_int("min_samples_split", 2, 20)
    _min_samples_leaf = trial.suggest_int("min_samples_leaf", 2, 20)
    _max_features = trial.suggest_int("max_features", 10, 50)

    gbr = GradientBoostingRegressor(
        n_estimators=_n_estimators,
        learning_rate=_learning_rate,
        max_depth=_max_depth,
        max_features=_max_features,
        min_samples_leaf=_min_samples_leaf,
        min_samples_split=_min_samp_split,

        random_state=RANDOM_SEED,
    )

    score = cross_val_score(
        gbr, X_train,y_train, cv=kfolds, scoring="neg_root_mean_squared_error"
    ).mean()
    return score

# gbr_params = tune(gbr_objective)

# Best score: -1.8222372332051289
gbr_params = {'n_estimators': 1396, 'learning_rate': 0.014373145732630006,
'max_depth': 6, 'min_samples_split': 6, 'min_samples_leaf': 7, 'max_features': 10}

gbr = GradientBoostingRegressor(random_state=RANDOM_SEED, **gbr_params)
gbr.fit(X_train,y_train)

GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedman_mse',
                          init=None, learning_rate=0.014373145732630006,
                          loss='ls', max_depth=6, max_features=10,
                          max_leaf_nodes=None, min_impurity_decrease=0.0,
                          min_impurity_split=None, min_samples_leaf=7,
                          min_samples_split=6, min_weight_fraction_leaf=0.0,
                          n_estimators=1396, n_iter_no_change=None,
                          presort='deprecated', random_state=23, subsample=1.0,
                          tol=0.0001, validation_fraction=0.1, verbose=0,
                          warm_start=False)
```

### 6.6. XGBRegressor

```
def xgb_objective(trial):
    _n_estimators = trial.suggest_int("n_estimators", 50, 2000)
    _max_depth = trial.suggest_int("max_depth", 1, 20)
    _learning_rate = trial.suggest_float("learning_rate", 0.01, 1)
    _gamma = trial.suggest_float("gamma", 0.01, 1)
    _min_child_weight = trial.suggest_float("min_child_weight", 0.1, 10)
    _subsample = trial.suggest_float('subsample', 0.01, 1)
    _reg_alpha = trial.suggest_float('reg_alpha', 0.01, 10)
    _reg_lambda = trial.suggest_float('reg_lambda', 0.01, 10)
```

```
    xgbr = xgb.XGBRegressor(
        n_estimators=_n_estimators,
        max_depth=_max_depth,
        learning_rate=_learning_rate,
        gamma=_gamma,
        min_child_weight=_min_child_weight,
        subsample=_subsample,
        reg_alpha=_reg_alpha,
        reg_lambda=_reg_lambda,
        random_state=RANDOM_SEED,
    )


    score = cross_val_score(
        xgbr, X_train,y_train, cv=kfolds, scoring="neg_root_mean_squared_error"
    ).mean()
    return score


# xgb_params = tune(xgb_objective)

xgb_params =  {'n_estimators': 75, 'max_depth': 4, 'learning_rate': 
0.27059503805300894, 'gamma': 0.6375378736305962, 'min_child_weight': 
3.2347222003450633, 'subsample': 0.8792064649951686, 'reg_alpha': 8.764034303437914, 
'reg_lambda': 7.475836220328881}
# Best score : -1.8258592810003325.

xgbr = xgb.XGBRegressor(random_state=RANDOM_SEED, **xgb_params)
xgbr.fit(X_train,y_train)
```

```
[16:30:54] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is 
now deprecated in favor of reg:squarederror.

XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0.6375378736305962,
             importance_type='gain', learning_rate=0.27059503805300894,
             max_delta_step=0, max_depth=4, min_child_weight=3.2347222003450633,
             missing=None, n_estimators=75, n_jobs=1, nthread=None,
             objective='reg:linear', random_state=23,
             reg_alpha=8.764034303437914, reg_lambda=7.475836220328881,
             scale_pos_weight=1, seed=None, silent=None,
             subsample=0.8792064649951686, verbosity=1)
```

### 6.7. LGBMRegressor

```
import lightgbm as lgb

def lgb_objective(trial):
    _num_leaves = trial.suggest_int("num_leaves", 50, 100)
    _max_depth = trial.suggest_int("max_depth", 1, 20)
    _learning_rate = trial.suggest_float("learning_rate", 0.01, 1)
    _n_estimators = trial.suggest_int("n_estimators", 50, 2000)
    _min_child_weight = trial.suggest_float("min_child_weight", 0.1, 10)
    _reg_alpha = trial.suggest_float('reg_alpha', 0.01, 10)
    _reg_lambda = trial.suggest_float('reg_lambda', 0.01, 10)
    _subsample = trial.suggest_float('subsample', 0.01, 1)
```

```
    lgbr = lgb.LGBMRegressor(objective='regression',
                             num_leaves=_num_leaves,
                             max_depth=_max_depth,
                             learning_rate=_learning_rate,
                             n_estimators=_n_estimators,
                             min_child_weight=_min_child_weight,
                             subsample=_subsample,
                             reg_alpha=_reg_alpha,
                             reg_lambda=_reg_lambda,
                             random_state=RANDOM_SEED,
    )


    score = cross_val_score(
        lgbr, X_train,y_train, cv=kfolds, scoring="neg_root_mean_squared_error"
    ).mean()
    return score


# lgb_params = tune(lgb_objective)

# Best score: -1.824529794158143
lgb_params =  {'num_leaves': 84, 'max_depth': 10, 'learning_rate':
0.011076909667786489, 'n_estimators': 727, 'min_child_weight': 4.921109754366219,
'reg_alpha': 4.370797996109474, 'reg_lambda': 8.552921079737136, 'subsample':
0.4411906869457217}

lgbr = lgb.LGBMRegressor(objective='regression', random_state=RANDOM_SEED,
**lgb_params)
lgbr.fit(X_train,y_train)

LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              importance_type='split', learning_rate=0.011076909667786489,
              max_depth=10, min_child_samples=20,
              min_child_weight=4.921109754366219, min_split_gain=0.0,
              n_estimators=727, n_jobs=-1, num_leaves=84,
              objective='regression', random_state=23,
              reg_alpha=4.370797996109474, reg_lambda=8.552921079737136,
              silent=True, subsample=0.4411906869457217,
              subsample_for_bin=200000, subsample_freq=0)
```

### 6.8. StackingRegressor

```
# stack models
stack = StackingRegressor(
    estimators=[
        ('ridge', ridge),
        ('lasso', lasso),
        ('gradientboostingregressor', gbr),
        ('xgb', xgbr),
        ('lgb', lgbr),
        # ('svr', svr), # Not using this for now as its score is significantly worse
than the others
    ],
    cv=kfolds)
stack.fit(X_train,y_train)
```

```
[16:31:41] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[16:38:25] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[16:38:26] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[16:38:26] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[16:38:27] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[16:38:28] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[16:38:29] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[16:38:29] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[16:38:30] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[16:38:31] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[16:38:32] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.

StackingRegressor(cv=KFold(n_splits=10, random_state=23, shuffle=True),
                  estimators=[('ridge',
                               Ridge(alpha=19.99855836300504, copy_X=True,
                                     fit_intercept=True, max_iter=None,
                                     normalize=False, random_state=23,
                                     solver='auto', tol=0.001)),
                              ('lasso',
                               Lasso(alpha=0.0009661425571276957, copy_X=True,
                                     fit_intercept=True, max_iter=1000,
                                     normalize=False, positive=False,
                                     precompu...
                                             max_depth=10, min_child_samples=20,
                                             min_child_weight=4.921109754366219,
                                             min_split_gain=0.0,
                                             n_estimators=727, n_jobs=-1,
                                             num_leaves=84,
                                             objective='regression',
                                             random_state=23,
                                             reg_alpha=4.370797996109474,
                                             reg_lambda=8.552921079737136,
                                             silent=True,
                                             subsample=0.4411906869457217,
                                             subsample_for_bin=200000,
                                             subsample_freq=0))],
                  final_estimator=None, n_jobs=None, passthrough=False,
                  verbose=0)
```

### 6.9. Save the Model

```
joblib.dump(stack, "prediction_model.pkl")
model=joblib.load("prediction_model.pkl")
model
```

```
[16:38:53] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[16:38:53] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
```

```
StackingRegressor(cv=KFold(n_splits=10, random_state=23, shuffle=True),
                  estimators=[('ridge',
                               Ridge(alpha=19.99855836300504, copy_X=True,
                                     fit_intercept=True, max_iter=None,
                                     normalize=False, random_state=23,
                                     solver='auto', tol=0.001)),
                              ('lasso',
                               Lasso(alpha=0.0009661425571276957, copy_X=True,
                                     fit_intercept=True, max_iter=1000,
                                     normalize=False, positive=False,
                                     precompu...
                                             max_depth=10, min_child_samples=20,
                                             min_child_weight=4.921109754366219,
                                             min_split_gain=0.0,
                                             n_estimators=727, n_jobs=-1,
                                             num_leaves=84,
                                             objective='regression',
                                             random_state=23,
                                             reg_alpha=4.370797996109474,
                                             reg_lambda=8.552921079737136,
                                             silent=True,
                                             subsample=0.4411906869457217,
                                             subsample_for_bin=200000,
                                             subsample_freq=0))],
                  final_estimator=None, n_jobs=None, passthrough=False,
                  verbose=0)
```

## 7. Find Prediction

```
print('Predict submission')
final_test_df = pd.read_csv("/content/test.csv")

final_test_df['AdView'] = np.round(np.expm1(model.predict(X_test))).astype(int)

final_test_df.to_csv('submission_test.csv', index=False)

Predict submission

final_test_df.head()

       vidid    views likes dislikes comment   published  duration category  \
0   VID_1054   440238  6153      218    1377  2017-02-18   PT7M29S        B
1  VID_18629  1040132  8171      340    1047  2016-06-28   PT6M29S        F
2  VID_13967    28534    31       11       1  2014-03-10  PT37M54S        D
3  VID_19442  1316715  2284      250     274  2010-06-05   PT9M55S        G
4    VID_770  1893173  2519      225     116  2016-09-03    PT3M8S        B

   AdView
0       6
1       4
2       3
3       6
4       6
```

# CONCLUSION

This project has delved into the utilization of various Python libraries such as NumPy, scikit-learn (sklearn), pandas, and Matplotlib to analyze and predict average sales for a hypothetical company, XYZ, leveraging YouTube as a marketing platform. By employing regression models and data preprocessing techniques, we've successfully forecasted the potential sales outcomes.

The automation of these predictive processes presents a significant advantage, as it streamlines operations for the sales and marketing teams. By implementing automated tools, the effort required to predict customer scope at the end of each day is substantially reduced. This not only enhances efficiency but also empowers the team to make informed decisions promptly, maximizing the effectiveness of marketing strategies.

Furthermore, the integration of automation fosters adaptability in response to dynamic market conditions. Continuous monitoring and adjustment of sales predictions based on real-time data ensure that the company remains agile and responsive to changing consumer behaviors and market trends.

In conclusion, by leveraging Python libraries and automation techniques, this project not only facilitates accurate sales predictions but also empowers the sales and marketing teams to navigate the complexities of the market landscape with confidence and efficiency.

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