===========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.

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2. Install & Import Libraries

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

In [107]:

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

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

In [54]:

```
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

In [55]:

```
# 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

In [56]:

```
train_df.head()
```

Out[56]:

	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

4.1.2. Data Shape - Train Data

In [57]:

```
train_df.shape
```

Out[57]:

```
(14999, 9)
```

4.1.3. Data Information - Train Data

In [58]:

```
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

In [59]:

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

Out[59]:

	vidid	adview	views	likes	dislikes	comment	published	duration	category
count	14999	1.499900e+04	14999	14999	14999	14999	14999	14999	14999
unique	14999	NaN	14588	4789	1546	2007	2386	3146	8
top	VID_12352	NaN	238	1	0	0	2016-08-26	PT31S	D
freq	1	NaN	4	174	1091	1290	42	147	7558
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

4.1.5. Data Type - Train Data

In [60]:

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

Out[60]:

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

4.1.6. Null Value - Train Data

In [61]:

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

Out[61]:

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

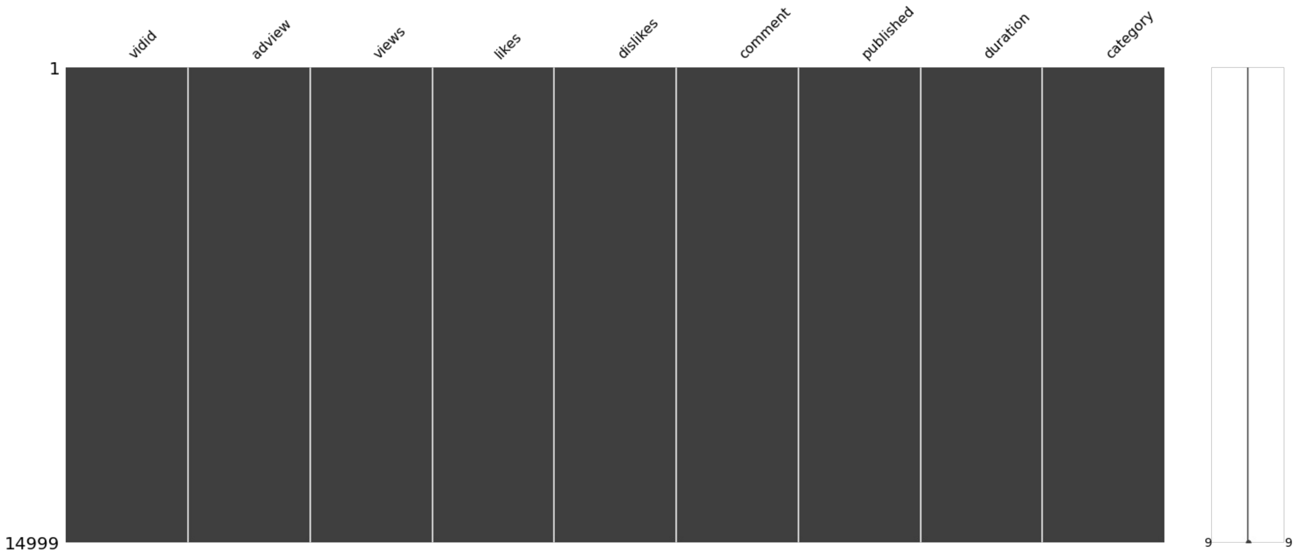
4.1.7. Visualize missing value using Misingno - Train Data

In [62]:

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

Out[62]:

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



4.2. Test Data Exploration

4.2.1. First 5 rows - Test Data

In [63]:

```
test_df.head()
```

Out[63]:

	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

In [64]:

```
test_df.shape
```

Out[64]:

(8764, 8)

4.2.3. Data Type - Test Data

In [65]:

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

Out[65]:

```
object    8
dtype: int64
```

4.2.4. Data Information - Test Data

In [66]:

```
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

In [67]:

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

Out[67]:

	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

In [68]:

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

Out[68]:

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

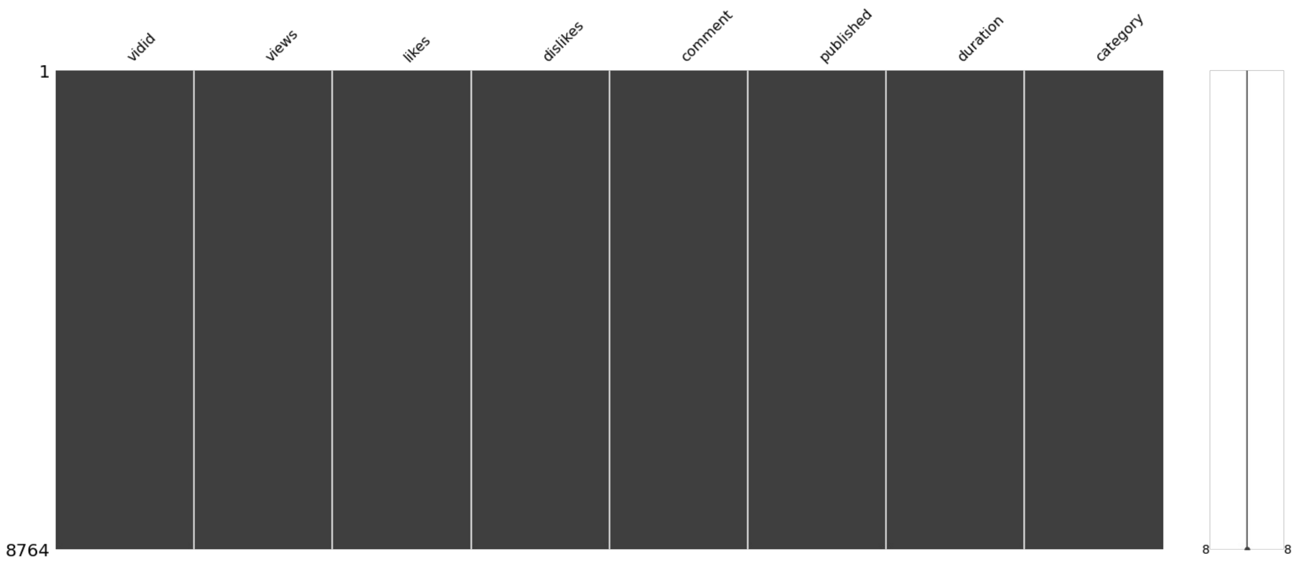
4.2.7. Visualize missing value using Misingno - Test Data

In [69]:

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

Out[69]:

```
<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

In [70]:

```
# 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)
```

Out[70]:

self	other

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

4.3.2. Null Value Comparison

In [71]:

```
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
```

Out[71]:

self	other

- 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

In [72]:

```
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

In [73]:

```
train_df.head()
```

Out[73]:

	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 [74]:

```
# 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

In [75]:

```
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')
```

In [76]:

```
train_df.head()
```

Out[76]:

	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 [77]:

```
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

In [78]:

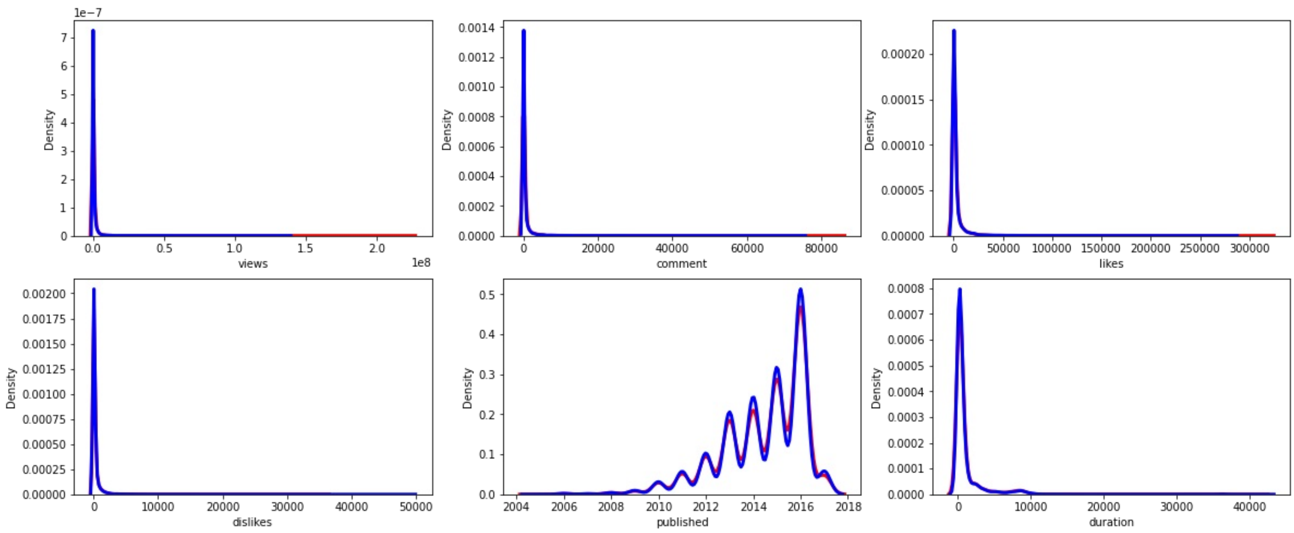
```
# combined train and test datasets
combined_df = pd.concat([train_df,test_df],axis=0)

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

4.3.4. Distribution Comparison - Continuous

In [79]:

```
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:

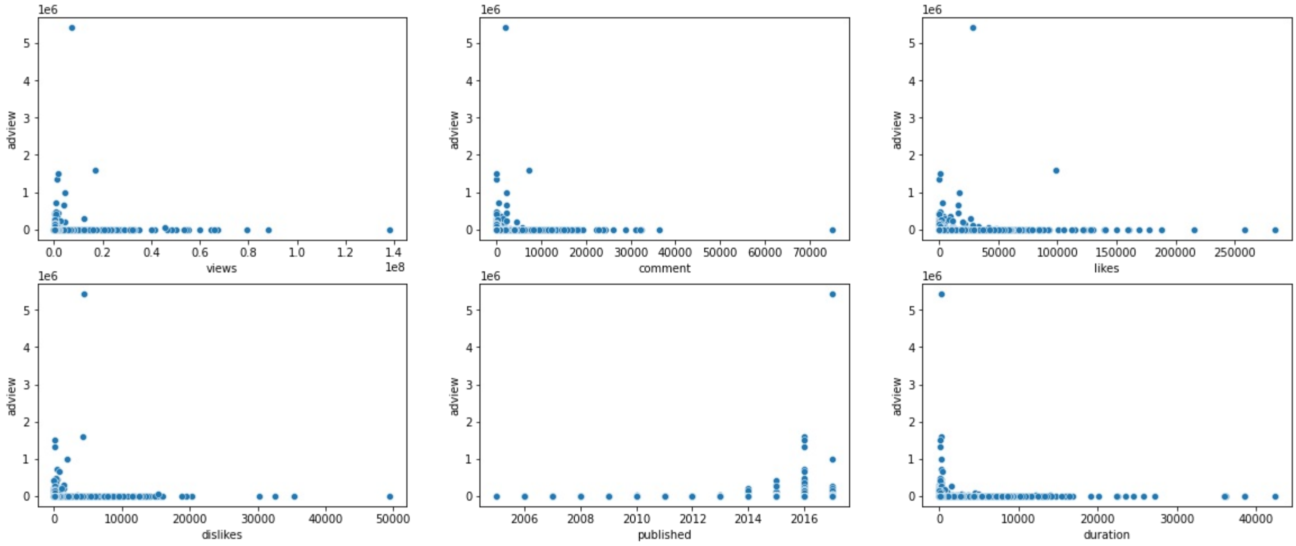
- The distribution of train and test data are similar for most continous features.
- All distributions are not **normally distributed**.

4.3.5. Linearity Check

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

In [80]:

```
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

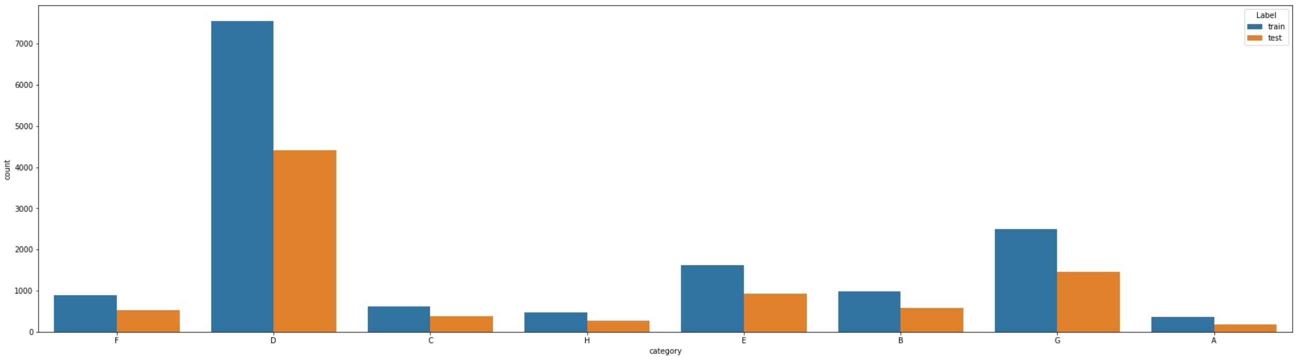
- There are two categorical features. These are **"category", "vidid"**.
- **"vidid"** is the id of video. So it has no impact to target variable.
- So we'll only check the distribution of **"category"** column.

In [81]:

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

Out[81]:

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



Above distribution shows that:

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

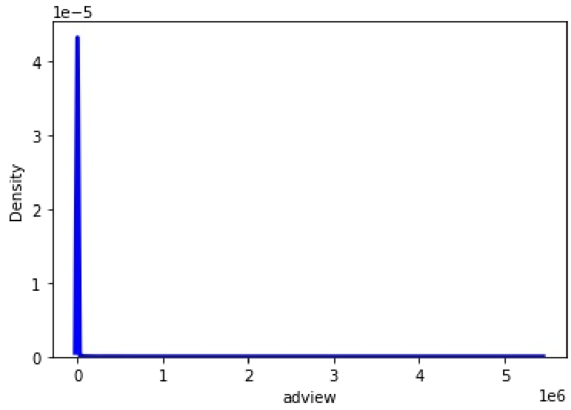
4.3.7. Distribution - Target Variable

In [82]:

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

Out[82]:

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



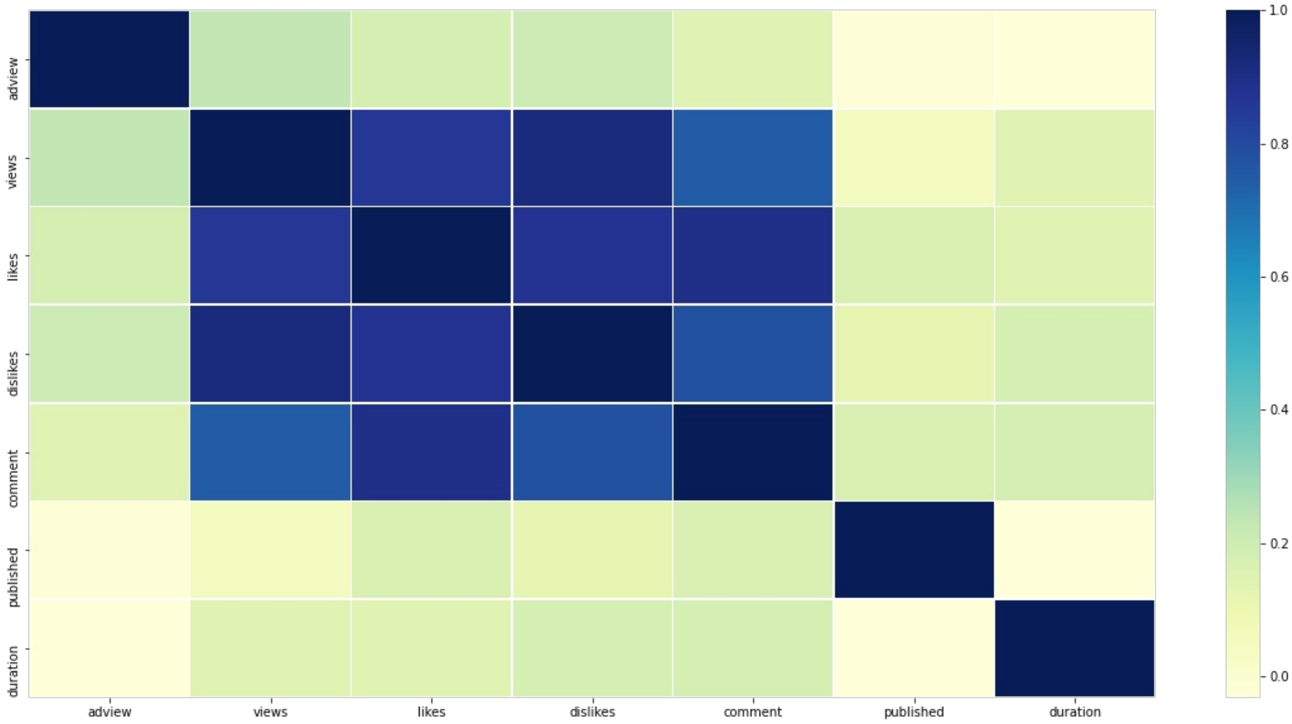
4.3.8. Data Correlation

In [83]:

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

Out[83]:

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



5. Feature Engineering

5.1. Drop Columns

Here we'll drop unnecessary columns

In [84]:

```
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

In [85]:

```
# 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
```

In [86]:

```
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

In [87]:

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

In [88]:

```
combined_df.head()
```

Out[88]:

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

In [89]:

```
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)
```

In [90]:

```
# 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

In [91]:

```
RANDOM_SEED = 23

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

In [92]:

```
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

In [93]:

```
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}
```

In [94]:

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

Out[94]:

```
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

In [95]:

```
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}
```

In [96]:

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

Out[96]:

```
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

In [97]:

```
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}
```

In [98]:

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

Out[98]:

```
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

In [99]:

```
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': 0.6375378736305
962, 'min_child_weight': 3.2347222003450633, 'subsample': 0.8792064649951686, 'reg_alpha': 8.764034303437914, 're
g_lambda': 7.475836220328881}
# Best score : -1.8258592810003325.
```

In [100]:

```
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.
```

Out[100]:

```
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

In [101]:

```
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}
```

In [102]:

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

Out[102]:

```
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

In [103]:

```
# 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.
```

Out[103]:

```
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

In [104]:

```
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.
```

Out[104]:

```
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

In [105]:

```
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
```

In [106]:

```
final_test_df.head()
```

Out[106]:

	vidid	views	likes	dislikes	comment	published	duration	category	AdView
0	VID_1054	440238	6153	218	1377	2017-02-18	PT7M29S	B	6
1	VID_18629	1040132	8171	340	1047	2016-06-28	PT6M29S	F	4
2	VID_13967	28534	31	11	1	2014-03-10	PT37M54S	D	3
3	VID_19442	1316715	2284	250	274	2010-06-05	PT9M55S	G	6
4	VID_770	1893173	2519	225	116	2016-09-03	PT3M8S	B	6

In [106]:

In [106]: