Shri Vile Parle Kelavani Mandal's
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)
NAAC Accredited with "A" Grade (CGPA : 3.18)

Department of Computer Science and Engineering (Data Science)

Subject: Machine Learning – I (DJ19DSC402)

Bhuvi Ghosh
60009210191

AY: 2022-23

Experiment 10

(Mini Project)

Aim: Design a classifier to solve a specific problem in the given domain.

Tasks to be completed by the students:
Select a specific problem from any of the given domain areas, such as: Banking, Education, Insurance, Government, Media, Entertainment, Retail, Supply chain, Transportation, Logistics, Energy and Utility.
Task 1: Select appropriate dataset, describe the problem and justify the suitability of your dataset.
Task 2: Perform exploratory data analysis and pre-processing (if required).
Task 3: Apply appropriate machine learning algorithm to build a classify. Perform appropriate testing of your model.
Task 4: Submit a report in the given format.

- Introduction
- Data Description
- Data Analysis
- Reason to select machine learning model
- Algorithm
- Result Analysis
- Conclusion and Future Scope.
- Python notebook

Task5: Presentation

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Report on Mini Project

Machine Learning -I (DJ19DSC402)

AY: 2022-23

Content monetisation & Revenue prediction on YouTube data.

NAME: Bhuvi Ghosh

Guided By: Dr Kriti Srivastava

CHAPTER 1: INTRODUCTION

Times New Roman, 12, Justified, 1.5 spacing, 1-inch space on all 4 sides.

CHAPTER 2: DATA DESCRIPTION

CHAPTER 3: DATA ANALYSIS

CHAPTER 4: DATA MODELLING

CHAPTER 4: CONCLUSION

CHAPTER 1: INTRODUCTION

Topic: Content monetisation & Revenue prediction on YouTube data.

YouTube is a highly popular platform for creators of video content, with more than 2 billion monthly active users. As a result, it has become a popular destination for content creators to showcase their abilities and reach a larger audience. Nonetheless, with such an immense amount of content available, it can be difficult to get noticed and obtain the necessary views and subscribers to monetise the content that they are posting. To overcome these challenges, YouTubers must optimize their videos to obtain the maximum amount of engagement, views, and subscribers. The dataset provided below takes into consideration various features that play a pivotal role in determining the revenue of Youtubers.

Area of research:

- Predicting the daily revenue of a certain youtuber with his/her channel's daily view, subscribers gained, average viewed duration, views, the number of subscribers, likes, dislikes, comments etc.
- Which factor is most related with increasing daily Revenue?
- If one has more videos posted on his/her channel, would she/he happen to earn more?

CHAPTER 2: DATA DESCRIPTION

Dataset attributes:

```
 #   Column                              Non-Null Count  Dtype
---  ------                              --------------  -----
 0   Date                                134 non-null    object
 1   Average views per viewer            134 non-null    float64
 2   Unique viewers                      134 non-null    int64
 3   Impressions click-through rate (%)  134 non-null    float64
 4   Impressions                         134 non-null    int64
 5   Comments added                      134 non-null    int64
 6   Shares                              134 non-null    int64
 7   Likes (vs. dislikes) (%)            99 non-null     float64
 8   Dislikes                            134 non-null    int64
 9   Subscribers lost                    134 non-null    int64
 10  Subscribers gained                  134 non-null    int64
 11  Likes                               134 non-null    int64
 12  Average percentage viewed (%)       134 non-null    float64
 13  Videos published                    9 non-null      float64
 14  Videos added                        9 non-null      float64
 15  Subscribers                         134 non-null    int64
 16  Views                               134 non-null    int64
 17  Watch time (hours)                  134 non-null    float64
 18  Average view duration               134 non-null    object
 19  Your estimated revenue (USD)        134 non-null    int64
```

CHAPTER 3: DATA ANALYSIS

```
[ ] import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    %matplotlib inline
    import plotly.express as px
    import seaborn as sns
```

```
[ ] sns.set_style('darkgrid')
```

```
[ ] df1=pd.read_csv('/content/Table data 2018.csv')
```

```
[ ] df2=pd.read_csv('/content/Table data 2019.csv')
```

```
[ ] df3=pd.read_csv('/content/Table data 2020.csv')
```

```
[ ] df1=df1[1:]
```

```
[ ] df2=df2[1:]
```

```
[ ] df3=df3[1:]
```

```
[ ] df=pd.concat([df1,df2,df3],axis=0)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1135 entries, 1 to 501
Data columns (total 20 columns):
 #   Column                              Non-Null Count  Dtype
---  ------                              --------------  -----
 0   Date                                1135 non-null   object
 1   Average views per viewer            1133 non-null   float64
 2   Unique viewers                      1133 non-null   float64
 3   Impressions click-through rate (%)  1133 non-null   float64
 4   Impressions                         1133 non-null   float64
 5   Comments added                      1133 non-null   float64
 6   Shares                              1133 non-null   float64
 7   Likes (vs. dislikes) (%)            1096 non-null   float64
 8   Dislikes                            1133 non-null   float64
 9   Subscribers lost                    1133 non-null   float64
 10  Subscribers gained                  1133 non-null   float64
 11  Likes                               1133 non-null   float64
 12  Average percentage viewed (%)       1133 non-null   float64
 13  Videos published                    991 non-null    float64
 14  Videos added                        991 non-null    float64
 15  Subscribers                         1133 non-null   float64
 16  Views                               1133 non-null   float64
 17  Watch time (hours)                  1133 non-null   float64
 18  Average view duration               1133 non-null   object
 19  Your estimated revenue (USD)        1133 non-null   float64
dtypes: float64(18), object(2)
memory usage: 186.2+ KB
```

```
df.columns
```

```
Index(['Date', 'Average views per viewer', 'Unique viewers',
       'Impressions click-through rate (%)', 'Impressions',
       'Comments added', 'Shares', 'Likes (vs. dislikes) (%)', 'Dislikes',
       'Subscribers lost', 'Subscribers gained', 'Likes',
       'Average percentage viewed (%)', 'Videos published',
```

```
columns=df.select_dtypes(include=['int','float']).columns
columns=columns.tolist()
```

Dropping duplicate values:

```
df.drop_duplicates(inplace=True)
```

Checking is null values exist & dropping them in case they are in a minor percentage:

```
df.isnull().sum()/len(df)
```

```
Date                                  0.000000
Average views per viewer              0.000882
Unique viewers                        0.000882
Impressions click-through rate (%)    0.000882
Impressions                           0.000882
Comments added                        0.000882
Shares                                0.000882
Likes (vs. dislikes) (%)              0.033510
Dislikes                              0.000882
Subscribers lost                      0.000882
Subscribers gained                    0.000882
Likes                                 0.000882
Average percentage viewed (%)         0.000882
Videos published                      0.126102
Videos added                          0.126102
Subscribers                           0.000882
Views                                 0.000882
Watch time (hours)                    0.000882
Average view duration                 0.000882
Your estimated revenue (USD)          0.000882
dtype: float64
```

```
df.dropna(inplace=True)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 988 entries, 1 to 500
Data columns (total 20 columns):
 #   Column                              Non-Null Count  Dtype
---  ------                              --------------  -----
 0   Date                                988 non-null    object
 1   Average views per viewer            988 non-null    float64
 2   Unique viewers                      988 non-null    float64
 3   Impressions click-through rate (%)  988 non-null    float64
 4   Impressions                         988 non-null    float64
 5   Comments added                      988 non-null    float64
 6   Shares                              988 non-null    float64
 7   Likes (vs. dislikes) (%)            988 non-null    float64
 8   Dislikes                            988 non-null    float64
 9   Subscribers lost                    988 non-null    float64
 10  Subscribers gained                  988 non-null    float64
 11  Likes                               988 non-null    float64
 12  Average percentage viewed (%)       988 non-null    float64
 13  Videos published                    988 non-null    float64
 14  Videos added                        988 non-null    float64
 15  Subscribers                         988 non-null    float64
 16  Views                               988 non-null    float64
 17  Watch time (hours)                  988 non-null    float64
 18  Average view duration               988 non-null    object
 19  Your estimated revenue (USD)        988 non-null    float64
dtypes: float64(18), object(2)
```

```
[ ] df.head()
```

	Date	Average views per viewer	Unique viewers	Impressions click-through rate (%)	Im-pres-sions	Com-ments added	Shares	Likes (vs. dis-likes) (%)	Dis-likes	Sub-scribers lost	Sub-scribers gained	Likes	Average percent-age viewed (%)	Videos pub-lished	Videos added	Sub-scribers	Views	Watch time (hours)	Average view duration	Your es-timated revenue (USD)
1	2018-08-21	1.1538	13.0	7.38	122.0	2.0	1.0	100.0	0.0	0.0	5.0	5.0	53.59	1.0	1.0	5.0	15.0	0.4666	0:01:51	0.0
13	2018-09-02	1.1681	119.0	13.24	846.0	0.0	2.0	100.0	0.0	0.0	1.0	9.0	43.36	1.0	1.0	1.0	139.0	3.8101	0:01:38	0.0
18	2018-09-07	1.5297	202.0	10.92	2171.0	4.0	2.0	100.0	0.0	2.0	14.0	16.0	43.47	1.0	2.0	12.0	309.0	10.6117	0:02:03	0.0
19	2018-09-08	1.5778	225.0	10.37	2489.0	3.0	2.0	100.0	0.0	1.0	8.0	24.0	35.78	1.0	1.0	7.0	355.0	9.0243	0:01:31	0.0
84	2018-11-12	1.0968	31.0	10.66	272.0	3.0	1.0	100.0	0.0	0.0	0.0	1.0	30.21	0.0	4.0	0.0	34.0	1.4151	0:02:29	0.0

Function to remove outliers:

```
def remove_outliers(df, col_list, z_thresh=4.3):
    for col in col_list:
        z_scores = np.abs((df[col] - df[col].mean()) / df[col].std())
        df = df[z_scores < z_thresh]
    return df
remove_outliers(df,columns,4.3)
```

Converting date column from object to Datetime type:

```
[ ] df['Date'] = pd.to_datetime(df['Date'])
    df['month'] = df['Date'].dt.month
    df['day'] = df['Date'].dt.day
    df['year'] = df['Date'].dt.year
```

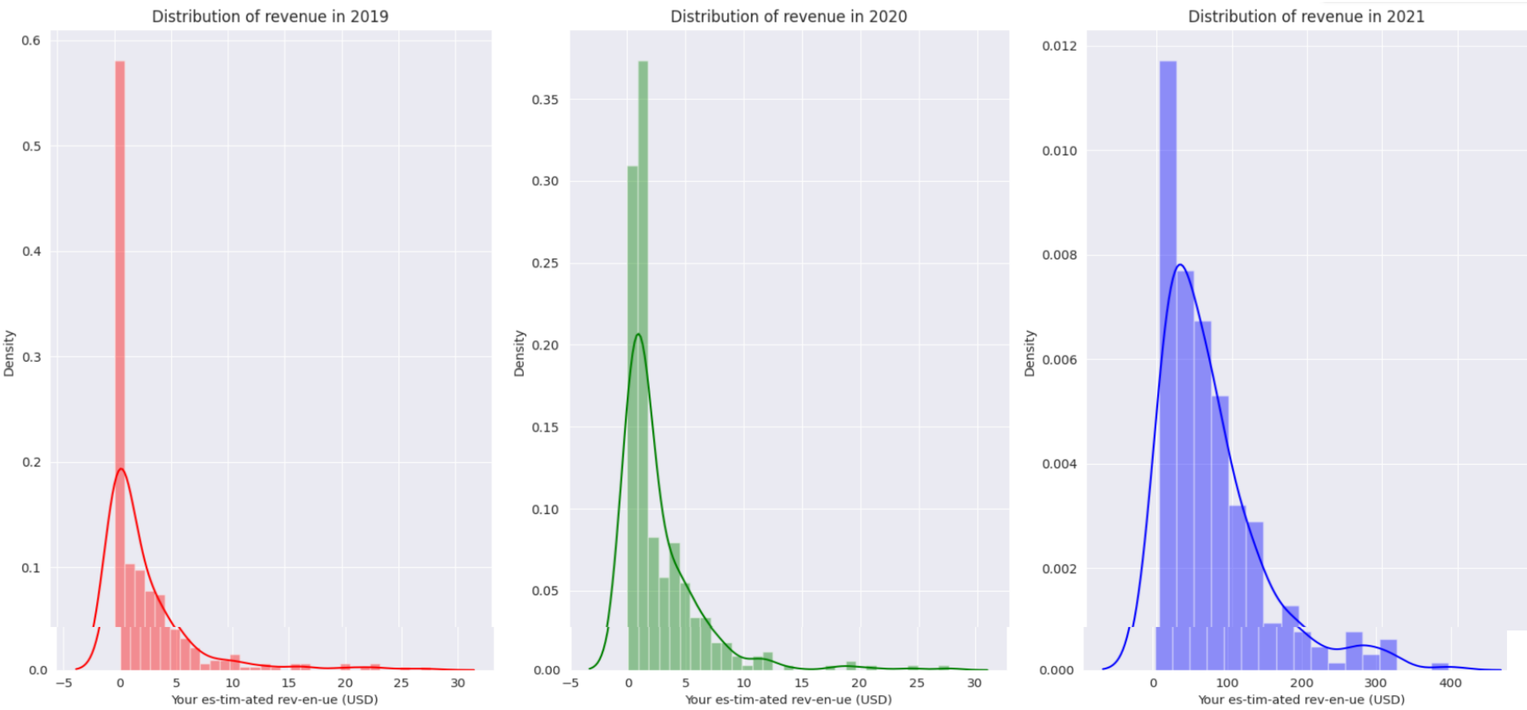
```
[ ] df['year'].unique()

    array([2018, 2019, 2020, 2021])
```

```
df.head()
```

	Date	Average views per viewer	Unique viewers	Impressions click-through rate (%)	Im-pres-sions	Com-ments added	Shares	Likes (vs. dis-likes) (%)	Dis-likes	Sub-scribers lost	...	Videos pub-lished	Videos added	Sub-scribers	Views	Watch time (hours)	Average view duration	Your es-timated revenue (USD)	month	day	year
1	2018-08-21	1.1538	13.0	7.38	122.0	2.0	1.0	100.0	0.0	0.0	...	1.0	1.0	5.0	15.0	0.4666	0:01:51	0.0	8	21	2018
13	2018-09-02	1.1681	119.0	13.24	846.0	0.0	2.0	100.0	0.0	0.0	...	1.0	1.0	1.0	139.0	3.8101	0:01:38	0.0	9	2	2018
18	2018-09-07	1.5297	202.0	10.92	2171.0	4.0	2.0	100.0	0.0	2.0	...	1.0	2.0	12.0	309.0	10.6117	0:02:03	0.0	9	7	2018

Checking the distribution of the output variable:

```
# set the style to darkgrid
sns.set_style('darkgrid')

# create a grid of subplots with 1 row and 3 columns
fig, axes = plt.subplots(ncols=3, figsize=(17,8))

# plot the distribution of revenue in 2019 on the first subplot
sns.distplot(df[df['year']==2019]['Your estimated revenue (USD)'], color='red', ax=axes[0])
axes[0].set_title('Distribution of revenue in 2019')

# plot the distribution of revenue in 2020 on the second subplot
sns.distplot(df[df['year']==2020]['Your estimated revenue (USD)'], color='green', ax=axes[1])
axes[1].set_title('Distribution of revenue in 2020')

# plot the distribution of revenue in 2021 on the third subplot
sns.distplot(df[df['year']==2021]['Your estimated revenue (USD)'], color='blue', ax=axes[2])
axes[2].set_title('Distribution of revenue in 2021')

# adjust the spacing between subplots
plt.tight_layout()

# display the plot
plt.show()
```

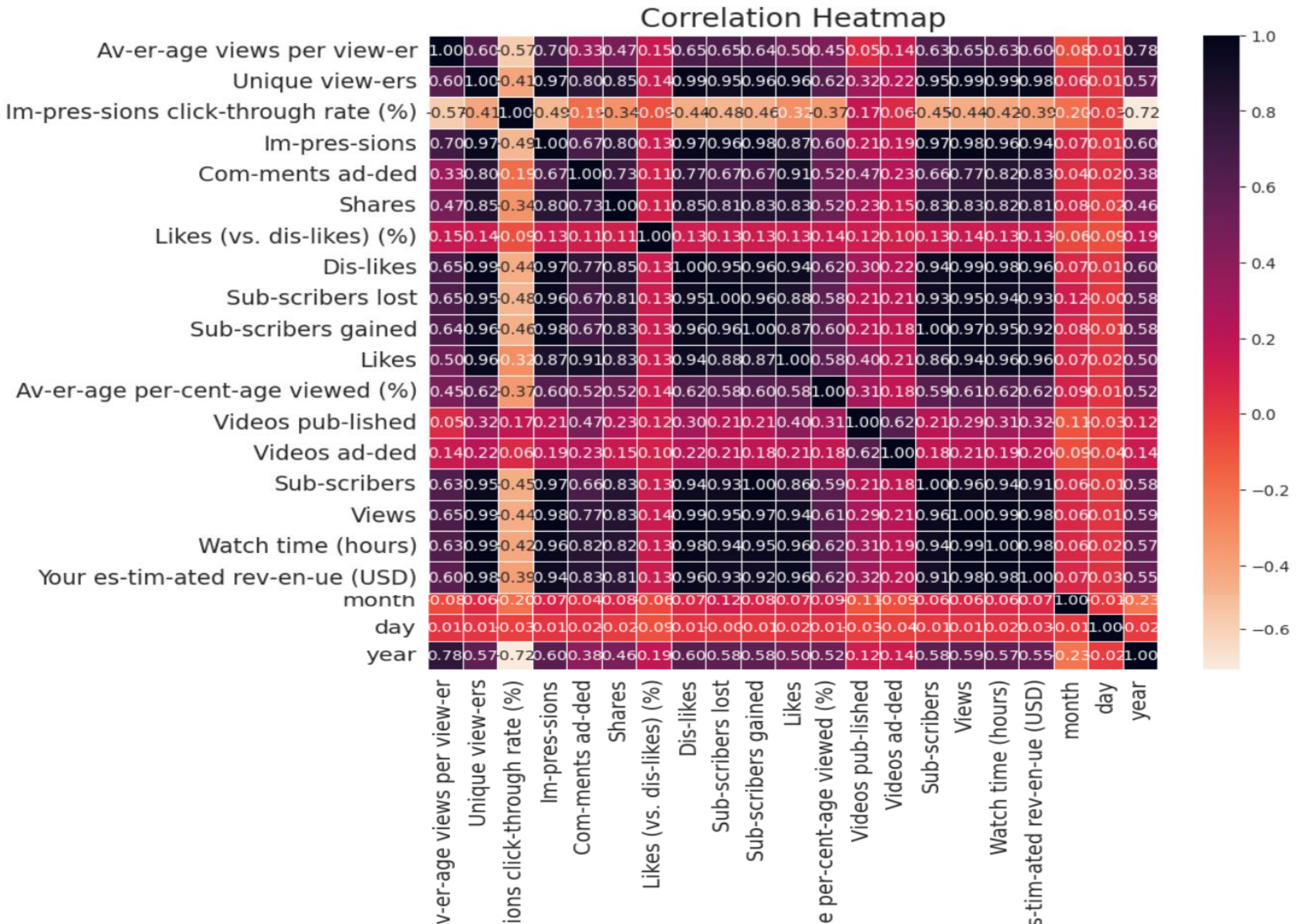


It is right skewed for the three given years.

Finding correlation between the variables:

```
[ ] fig, ax = plt.subplots(figsize=(10, 8))
    sns.heatmap(df.corr(), cmap="rocket_r", annot=True, linewidths=0.5, fmt=".2f", ax=ax)
    ax.set_title("Correlation Heatmap", fontsize=18)
    ax.tick_params(labelsize=14)
    sns.despine(ax=ax, top=True, bottom=True)
    plt.show()
```

```
<ipython-input-669-e50ef237404e>:2: FutureWarning:

The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence
```

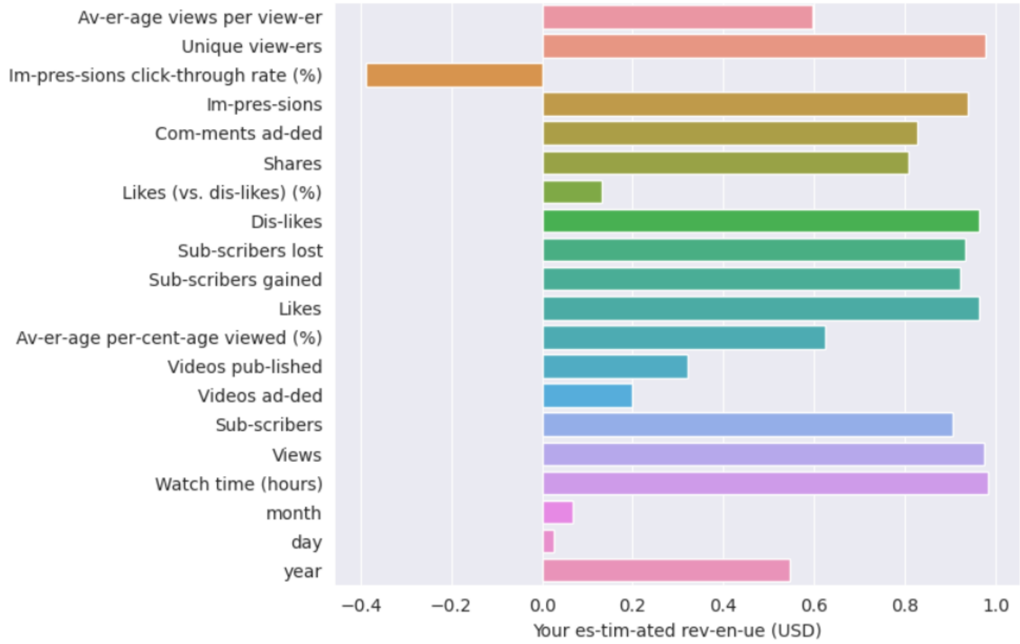


```
[ ] corr_matrix = df.corr()
    corr_values = corr_matrix['Your estimated revenue (USD)'].drop('Your estimated revenue (USD)')
```

```
<ipython-input-670-57ea96d97aac>:1: FutureWarning:

The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to si
```

Finding the correlation between the target attribute & the other attributes:

```
plt.figure(figsize=(7,6))
sns.barplot(y=corr_values.index,x=corr_values)
plt.show()
```




```
[ ] def get_correlated_attributes(df, target_var, threshold):
        # get the correlation matrix
        corr_matrix = df.corr()
        # get the correlation values for the target variable
        corr_values = corr_matrix[target_var].drop(target_var)
        # filter the attributes by the correlation threshold
        correlated_attrs = corr_values[corr_values >= threshold].index
        # return the list of correlated attributes
        return correlated_attrs
```

```
[ ] z_pos=get_correlated_attributes(df,'Your estimated revenue (USD)',0.6)
```

```
<ipython-input-672-054fbbdc8730>:3: FutureWarning:

The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify t
```

```
[ ] print(z_pos)
```

```
Index(['Unique viewers', 'Impressions', 'Comments added', 'Shares',
       'Dislikes', 'Subscribers lost', 'Subscribers gained', 'Likes',
       'Average percentage viewed (%)', 'Subscribers', 'Views',
       'Watch time (hours)'],
      dtype='object')
```

```
def get_correlated_attributes(df, target_var, threshold):
    # get the correlation matrix
    corr_matrix = df.corr()
    # get the correlation values for the target variable
    corr_values = corr_matrix[target_var].drop(target_var)
```

```
[ ]     # filter the attributes by the correlation threshold
        correlated_attrs = corr_values[corr_values <= threshold].index
        # return the list of correlated attributes
        return correlated_attrs
```

```
[ ] z_neg=get_correlated_attributes(df,'Your estimated revenue (USD)',-0.6)
```

```
<ipython-input-675-659e8b10d090>:3: FutureWarning:

The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of
```

```
[ ] z_neg
```

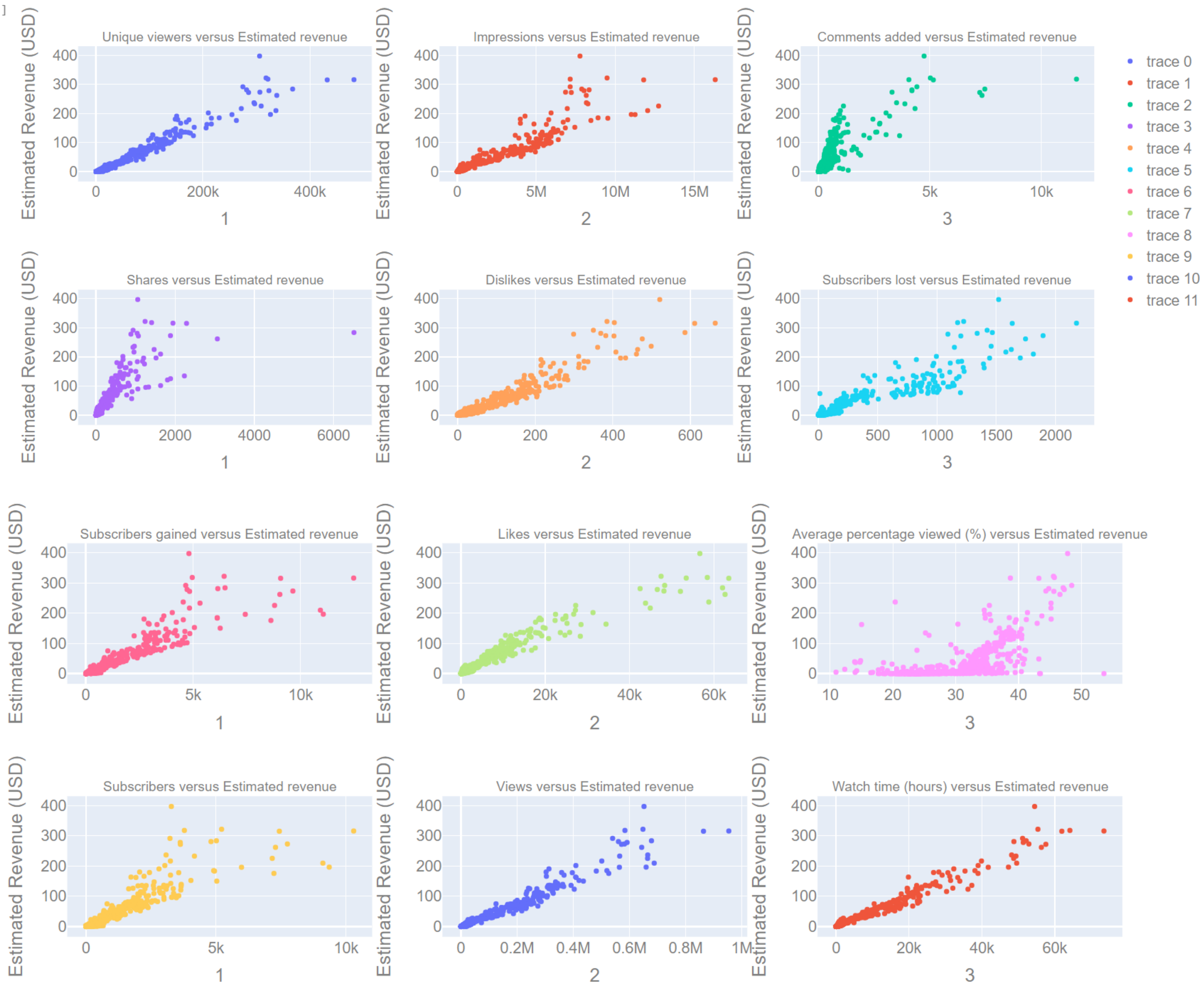
```
Index([], dtype='object')
```

```
[ ] import plotly.graph_objects as go
    from plotly.subplots import make_subplots
    fig = go.Figure(data=go.Scatter(x=df['Shares'], y=df['Your estimated revenue (USD)'], mode='markers'))
```

Is the target variable linearly dependent on the most important features? Let's check out how these features affect the target variable.

```
def plot_in_grid(z, df):
    fig = make_subplots(rows=4, cols=3, subplot_titles=z + ' versus Estimated revenue')
    trace = go.Scatter(x=df[col], y=df['Your estimated revenue (USD)'], mode='markers')
    row = (i // 3) + 1
    col = (i % 3) + 1
    fig.add_trace(trace, row=row, col=col)
    fig.update_xaxes(title_text=col, row=row, col=col)
    fig.update_yaxes(title_text='Estimated Revenue (USD)', row=row, col=col)

  fig.update_layout(
    height=1200,
    font=dict(
        family='Arial',
        size=18,
        color='#7f7f7f'
    ),
    margin=dict(
        l=50,
        r=50,
        b=50,
        t=80,
        pad=0
    )
  )

  fig.show()
plot_in_grid(z_pos,df)
```

[ ]

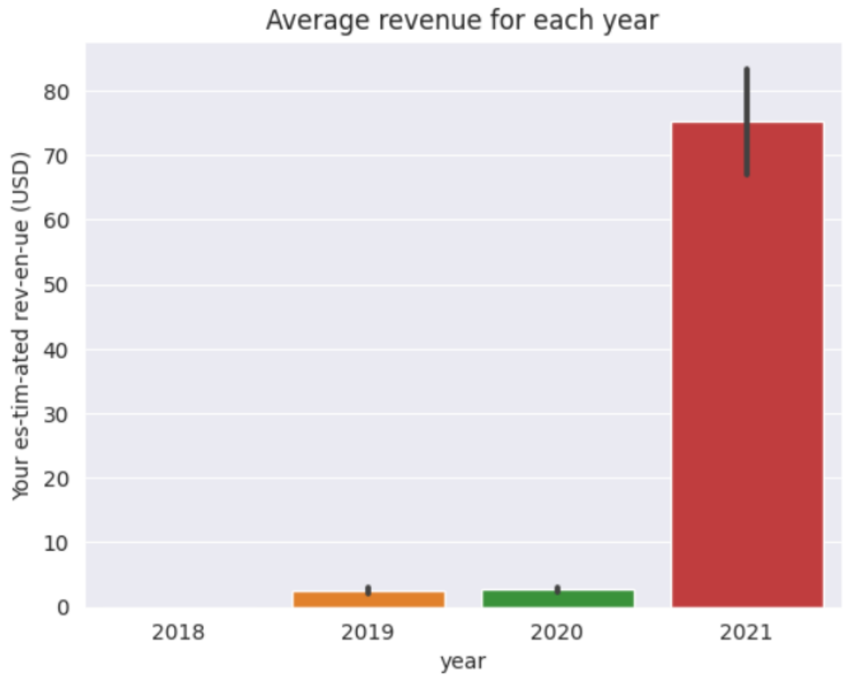


The revenue linearly increases with an increase in unique viewers, subscribers, subscribers gained, likes,dislikees, views, shares & impressions. However there is a non-linear change in the estimated revenue with respected to the percentage viewed going upto 400 illion dollars.

Average revenue per year:

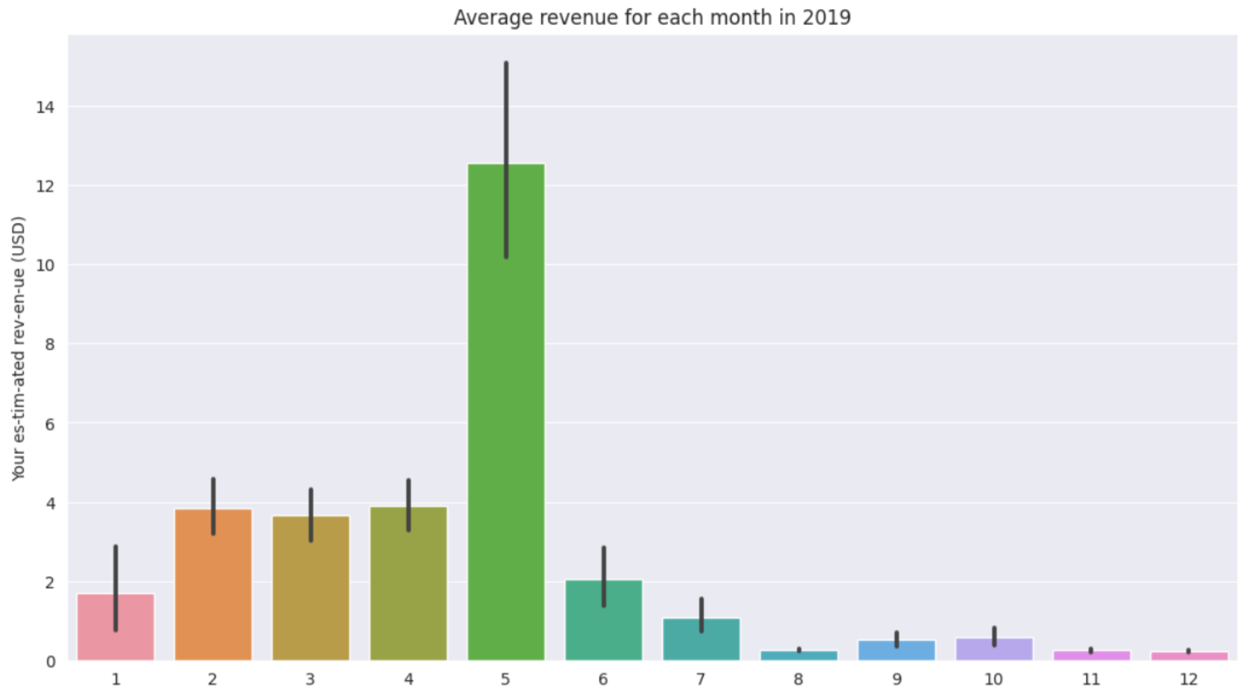
[ ]

```
sns.barplot(x='year',y='Your estimated revenue (USD)',data=df)
plt.title('Average revenue for each year')
plt.show()
```




```
[ ] df1=df[df['year']==2021]
    df2=df[df['year']==2020]
    df3=df[df['year']==2018]
    df4=df[df['year']==2019]
```

```
[ ] plt.figure(figsize=(13,7))
    sns.barplot(x='month',y='Your estimated revenue (USD)',data=df4)
    plt.title('Average revenue for each month in 2019')
    plt.show()
```

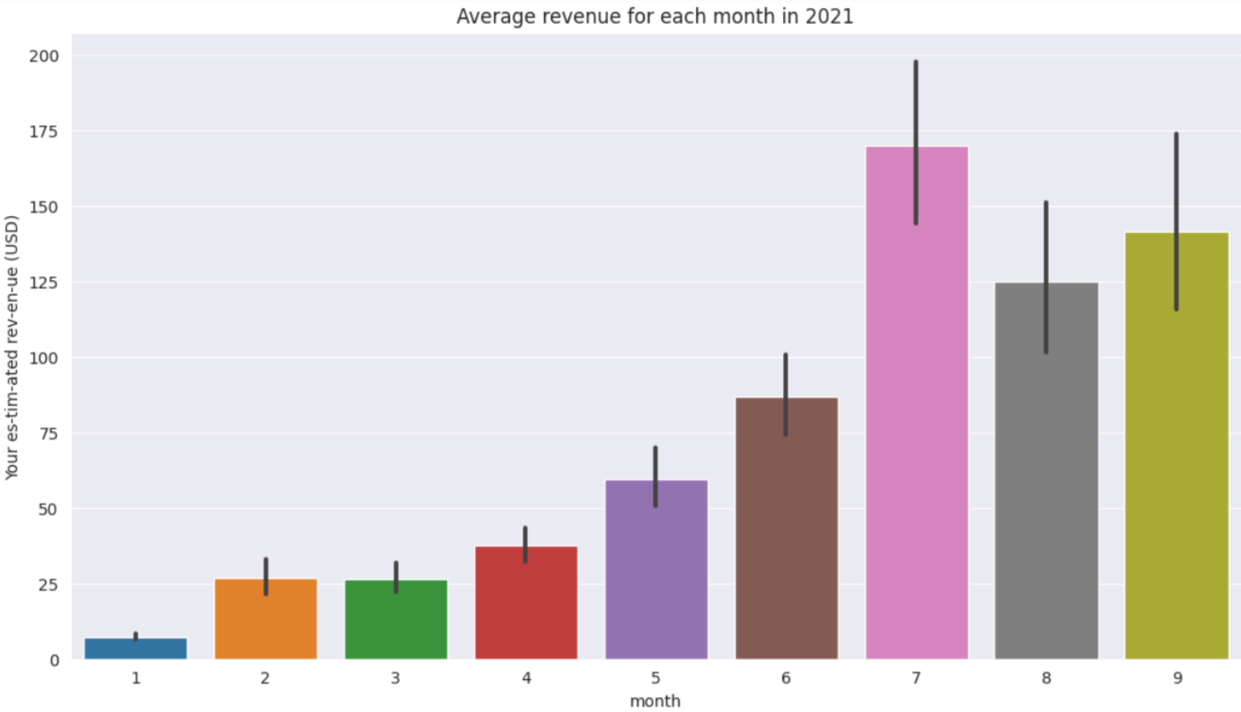


December had the maximum revenue earning during the year 2020 & March saw the least amount of earning.

```
plt.figure(figsize=(13,7))
sns.barplot(x='month',y='Your estimated revenue (USD)',data=df1)
plt.title('Average revenue for each month in 2021')
plt.show()
```

May had the maximum revenue earning during the year 2019 & December saw the least amount of earning.

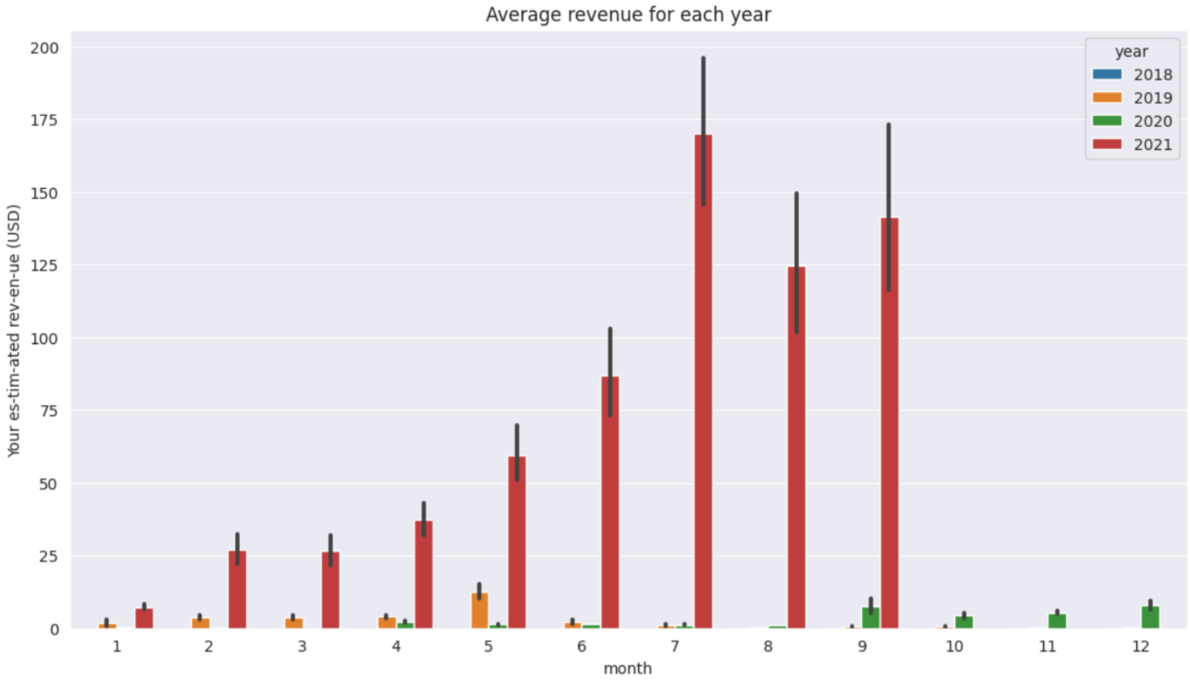
```
[ ] plt.figure(figsize=(13,7))
    sns.barplot(x='month',y='Your estimated revenue (USD)',data=df2)
    plt.title('Average revenue for each month in 2020')
    plt.show()
```



July had the maximum revenue earning during the year 2021 & January saw the least amount of earning.

Monthly comparison of average revenue of the years:

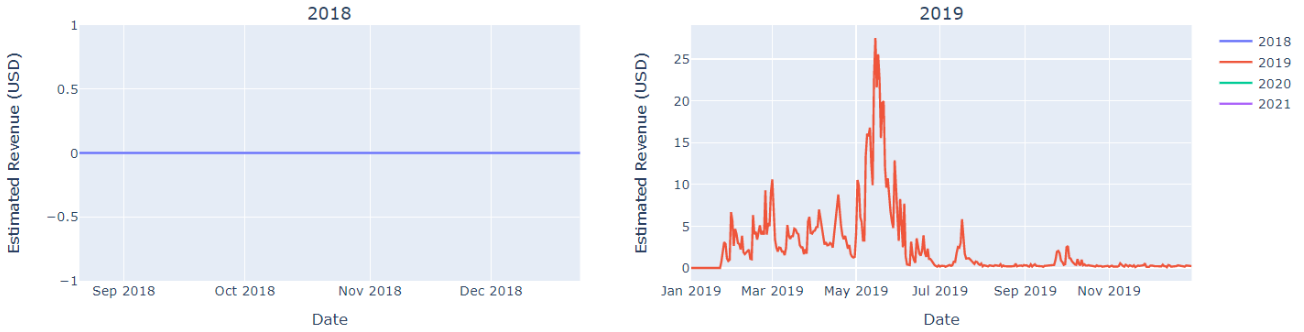
```
[ ] plt.figure(figsize=(13,7))
    sns.barplot(x='month',y='Your estimated revenue (USD)',hue='year',data=df)
    plt.title('Average revenue for each year')
    plt.show()
```

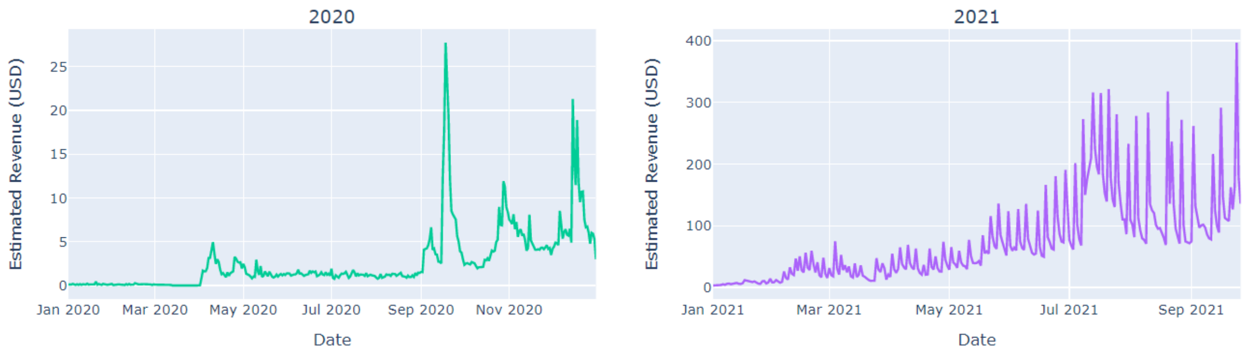


Revenue trends over the years:

```
[ ] def plot_in_grid(df1, df2, df3, df4):
        fig = make_subplots(rows=2, cols=2,
                            subplot_titles=('2018','2019','2020','2021'))

        fig.add_trace(go.Scatter(x=df3['Date'], y=df3['Your estimated revenue (USD)'],
                                 mode='lines', name='2018'), row=1, col=1)

        fig.add_trace(go.Scatter(x=df4['Date'], y=df4['Your estimated revenue (USD)'],
                                 mode='lines', name='2019'), row=1, col=2)

        fig.add_trace(go.Scatter(x=df2['Date'], y=df2['Your estimated revenue (USD)'],
                                 mode='lines', name='2020'), row=2, col=1)

        fig.add_trace(go.Scatter(x=df1['Date'], y=df1['Your estimated revenue (USD)'],
                                 mode='lines', name='2021'), row=2, col=2)

        fig.update_xaxes(title_text='Date', row=1, col=1)
        fig.update_xaxes(title_text='Date', row=1, col=2)
        fig.update_xaxes(title_text='Date', row=2, col=1)
        fig.update_xaxes(title_text='Date', row=2, col=2)

        fig.update_yaxes(title_text='Estimated Revenue (USD)', row=1, col=1)
        fig.update_yaxes(title_text='Estimated Revenue (USD)', row=1, col=2)
        fig.update_yaxes(title_text='Estimated Revenue (USD)', row=2, col=1)
        fig.update_yaxes(title_text='Estimated Revenue (USD)', row=2, col=2)

        fig.update_layout(height=800, width=1200, showlegend=True)

        fig.show()
```

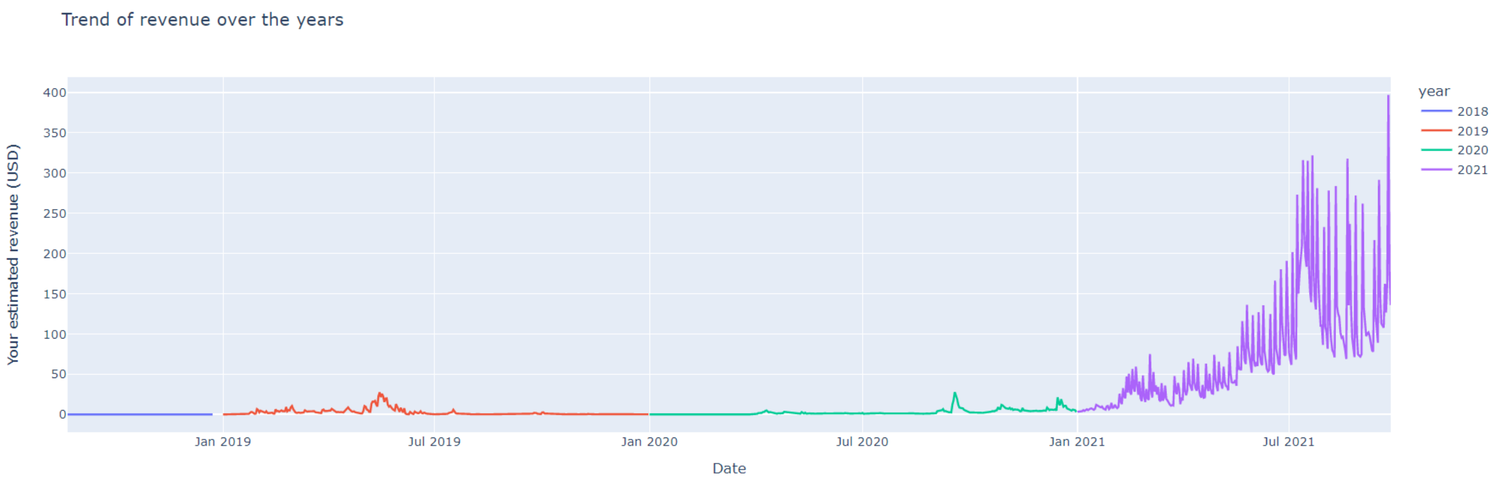
```
plot_in_grid(df1,df2,df3,df4)
```





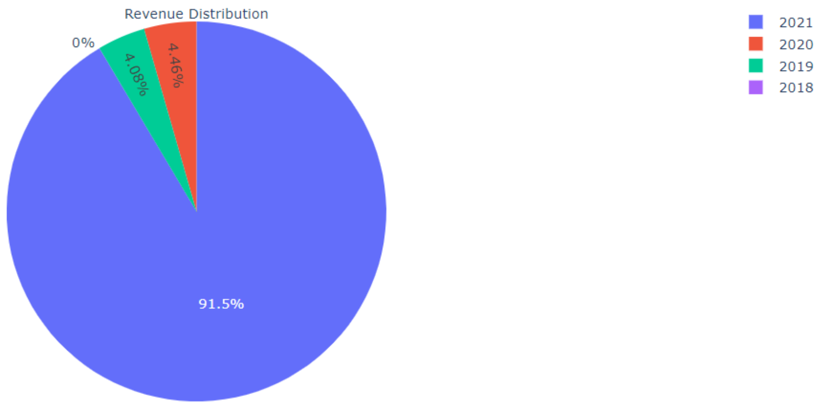
The above plots show the trend of revenue over the years. There is a spike in the mid 2019.In 2020, the revenue saw a considerable increase from September to December. In 2021 there is a constant increase in revenue with time.

```
[ ] px.line(df, x='Date', y='Your estimated revenue (USD)',title='Trend of revenue over the years',color='year')
```



Revenue distribution over the years:

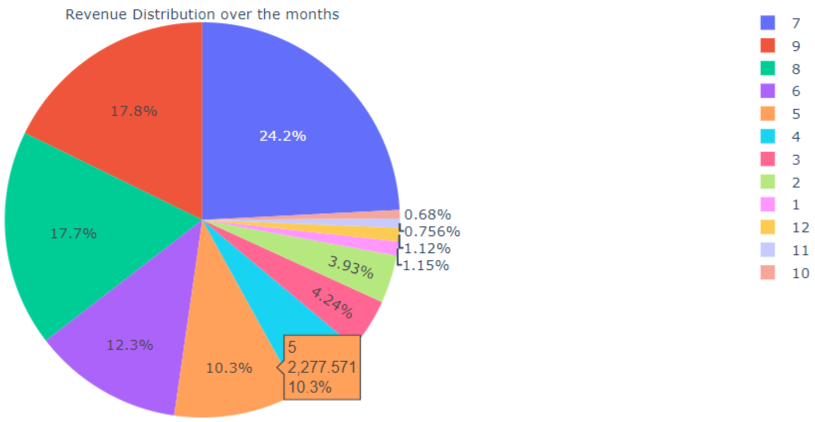
```
fig = go.Figure(data=[go.Pie(labels=df['year'], values=df['Your estimated revenue (USD)'],title='Revenue Distribution')])
fig.show()
```



Maximum revenue generation has occured in 2021 & it contributes to 91.5% of the total revenue generated.

Distribution of revenue over the months:

```
fig = go.Figure(data=[go.Pie(labels=df['month'], values=df['Your estimated revenue (USD)'],title='Revenue Distribution over the months')])
fig.show()
```



From the pie chart, it can be inferred that maximum amount of revenue has been generated in July & September over the years.November & December have the least revenue generation.

Insights from EDA:

1)The revenue linearly increases with an increase in unique viewers, subscribers, subscribers gained, likes, dislikes, views, shares & impressions.

However,there is a nonlinear change in the estimated revenue with respected to the percentag e viewed going up to 400 million dollars.

2)May had the maximum revenue earning during the year 2019 & December saw the least amount of earning.

3)December had the maximum revenue earning during the year 2020 & March saw the least amount of earning.

4)July had the maximum revenue earning during the year 2021 & January saw the least amount of earning.

5)The above plots show the trend of revenue over the years. There is a spike in the mid 2019. In 2020, the revenue saw a considerable increase from September to December. In 2021 there is a constant increase in revenue with time.

6)Maximum revenue generation has occured in 2021 & it contributes to 91.5% of the total revenue generated.

7)From the pie chart, it can be inferred that maximum amount of revenue has been generated in July & September over the years.November & December have the least revenue generation.

CHAPTER 3: DATA MODELLING

Algorithm:

I. Random forest:
Reason for selecting random forest:
1) Random forest is used over any other linear model since all the features were not linearly dependent on the target variable. Hence, using a linear model would not have been a suitable choice in this case.
2) Since the data is imbalanced using Random Forest is preferred over any other technique.

II) XG Boost Regressor:

Reason for selecting XG Boost Regressor:

1)XG Boost Regressor is selected since it combines all weak learners & sequentially learns from the errors made by the weak learners to build a robust model.

2)XG Boost Regressor performs the task of feature selection on its own which further makes it an appropriate model of choice in the regression problem given in this case.

3)XG Boost Regressor can handle both linear and non-linear relationships between the input features and the output variable. It uses a combination of decision trees and gradient boosting to capture complex relationships between the input features and the output variable.

III) SVM:

Reasons for choosing SVM:

1) SVMs can effectively handle non-linear data by mapping input features to a high-dimensional space and finding a hyperplane that separates data points with the largest margin.SVMs can be effective on small to medium-sized datasets, as they are less prone to overfitting and can generalize well to new data points.

2) SVMs are suitable for regression tasks that require good generalization to new data, as they have good generalization capabilities.

3) 3)SVMs are relatively robust to outliers in the data, which helps to improve the accuracy and robustness of the model.

Result Analysis:

I. Random Forest:
   1) R2 Score: -0.5931
      Negative R2 Score signifies that the model does not capture a significant amount of varience. Hence, choosing another model will be an appropriate choice in this case.

   2) Mean Squared Error: 1840.6971
   3) Mean Absolute Error: 34.6073

II. XG Boost:
   1) R2 Score: 0.7570
      This is a good r2 score & the model captures a significant amount of varience. Hence, it will generalise well even on unseen data to give significant results.

   2) Mean Squared Error: 1052.8185
   3) Mean Absolute Error: 24.1028

III. SVM:
   1) R2 Score: -2.4453
      Negative R2 Score signifies that the model does not capture a significant amou nt of varience. Hence, choosing another model will be an appropriate choice in this case.

   2) Mean Squared Error: 2276.7919
   3) Mean Absolute Error: 33.2934

Comparison of MSE & MAE of all 3 models:

Model chosen: XG Boost Regressor
R2 score of regressor: 0.7570
MSE of regressor:1052.8185
MAE of regressor: 24.1028

CHAPTER 4: CONCLUSION

1)The above plot compares the mean squared error & mean absolute error of the models. XG Boost has the least mean squared error & mean absolute error which indicates that it is a better regressor & is better suited for predictive analysis.

2)The XG Boost model has achieved a high R2 score, indicating that it is able to capture a significant amount of variance in the data, enabling it to effectively generalize to unseen data.

3)Conducting hyperparameter tuning in XG Boost helped to identify the optimal set of parameters for maximising the R2 score, thereby improving the model's ability to generalise to unseen data and providing superior results.

Future scope:

1) The future direction of this project involves fine-tuning the model on various categories of YouTube content to provide tailored insights based on the type of content produced by Youtubers.

2) The objective is to develop a recommendation system that enables Youtubers to form lucrative collaborations and further monetise their content.

3) The aim is to assist Youtubers in determining the optimal time to release a video based on its content to maximise monetisation.

4) The goal is to predict the type of content that holds the most promise for a particular age group within a given audience.

Colab link:
https://colab.research.google.com/drive/1XK2f3vBINhJI9nW5d2VMgrIy4TygpHRK