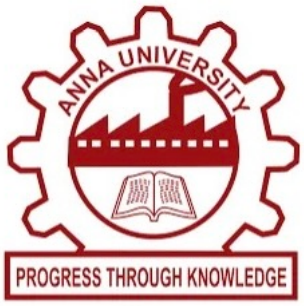
University College of Engineering Villupuram



Department of computer Science and Engineering

Experience Based Project Learning - IBM (E2324)
Conducted by IBM

Personalized content recommendation system
phase - 3 Document

Submitted by

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Personalized content recommendation system
Phase 3 : Exploratory data analysis and Data Visualization

Introduction :

Data visualization is the process of using visual elements like charts, graphs, or maps to represent data. It translates complex, high-volume, or numerical data into a visual representation that is easier to process. It benefits them to recognize new patterns and errors in the data.To build a movie recommender system ,EDA helps in understanding the distribution of ratings, genres, user demographics, etc. This knowledge is essential for designing effective recommendation algorithms.

Objectives of Exploratory data analysis :

It involves analyzing and visualizing data to understand its key characteristics, uncover patterns, and identify relationships between variables refers to the method of studying and exploring record sets to apprehend their predominant traits, discover patterns, locate outliers, and identify relationships between variables.

1.Understanding Data Structure :

- Identify and comprehend the structure and types of data available (e.g., movie details, user ratings, genres, metadata).
- Understand the relationships between different data entities (e.g., movies, users, ratings).

2.Data Cleaning :

- Detect and handle missing values, outliers, and inconsistencies in the dataset.
- Ensure data quality and reliability by addressing duplicate records and correcting erroneous entries.

3.Data Summarization :

- Generate summary statistics to get a sense of the data distribution (e.g., mean, median, mode, standard deviation).
- Create visualizations (e.g., histograms, box plots) to summarize the data and identify patterns or anomalies.

4.Feature Engineering :

- Identify important features and create new features that could enhance the recommendation system (e.g., combining genres, calculating average ratings, deriving user preferences).

Dataset Description :

The TMDb dataset used to build content based recommendation system .The TMDb (The Movie Database) is a comprehensive movie database that provides information about movies.The movie dataset csv file contains movie title, movie id ,release date, run time ,vote average , genres ,keywords , tagline ,overview of the movie etc . The credit dataset csv file contains cast and crew of movie . These datasets are used to build the content based movie recommendation system.

Data Visualization Techiniques :

Data visualization is the process of creating graphical representations of information. This process helps the presenter communicate data in a way that's easy for the viewer to interpret and draw conclusions. Univariate, Bivariate and Multivariate Analysis are used to understand the dataset . Data visualization is using visual elements like charts, graphs, and maps, data visualization tools provide an accessible way to see and understand trends, outliers, and patterns in data.

Import the libraries :

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Load the dataset :

```
movies = pd.read_csv("Movies.csv")
credit = pd.read_csv("Credit.csv")
```

Merge the dataset :

The dataset is merged to build the recommendation system .

```
df = movies.merge(credit , on = "title")
```

Preprocessing the dataset for Exploratory data analysis :

The preprocessing step is performed to convert the datatypes of each column into suitable form for exploratory data analysis using the data preprocessing techniques used in phase 2 of personalized content recommendation system.

Applying Data visualization techniques after the columns are preprocessed into suitable columns :

1.Univariate Analysis :

Univariate Analysis is a type of data visualization where we visualize only a single variable at a time. Univariate graphs are used to visualize the distribution and frequency of a single variable.

1. Bar Graph :

- A bar graph is typically used to display univariate data. Univariate data involves only one variable, and a bar graph is a simple and effective way to represent the frequency or distribution of that variable across different categories.
- A bar graph is the graphical representation of categorical data using rectangular bars where the length of each bar is proportional to the value they represent.
- Bar graph represents categorical data.
- Data can be arranged in any order in a bar graph .
- The x-axis can represent anything.
- Equal space between every two consecutive bars.

2. Histogram :

- Represents the frequency distribution of a continuous numerical variable by dividing the data into bins or intervals.
- A Histogram is the graphical representation of data where data is grouped into continuous number ranges and each range corresponds to a vertical bar.
- Data is arranged in the order of range.Histogram represents numerical data (discrete or continuous data).
- The x-axis should represent only continuous data that is in terms of numbers.No space between two consecutive bars. They should be attached to each other.

Example: A histogram showing the distribution of exam scores for a class.

3. Pie Chart :

Shows the relative proportions or percentages of different categories of a single variable as slices of a circle.
Example: A pie chart displaying the market share of different smartphone brands.

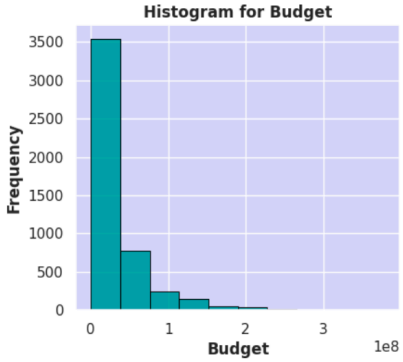
4. Box Plot :

Summarizes the distribution of a numerical variable by showing its median, quartiles, and potential outliers.
Example: A box plot illustrating the distribution of monthly salaries in a company.

Histogram for Budget :
code :

```
plt.figure(figsize = (4.5,4))
sns.set(rc={'axes.facecolor':'#d4d4f7', 'figure.facecolor':'white'})
sns.histplot(data = df , x = "budget" , bins = 10 , color = "darkcyan",
edgecolor = "black" ,linewidth = 0.65)
plt.xlabel("Budget",weight='bold')
plt.ylabel("Frequency",weight='bold')
plt.title("Histogram for Budget",weight='bold')
plt.show()
```

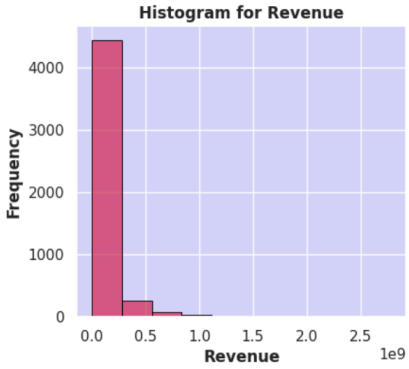
output :



Histogram for Revenue :
code :

```
plt.figure(figsize = (4.5,4))
sns.set(rc={'axes.facecolor':'#d4d4f7', 'figure.facecolor':'white'})
sns.histplot(data = df , x = "revenue" , bins = 10 ,color = "#c23d5e",
edgecolor = "black" ,linewidth = 0.65)
plt.xlabel("Revenue",weight='bold')
plt.ylabel("Frequency",weight='bold')
plt.title("Histogram for Revenue",weight='bold')
plt.show()
```

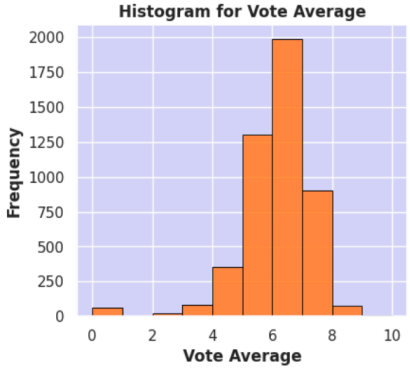
output :



Histogram for Vote Average :
code :

```
sns.set(rc={'axes.facecolor':'#d4d4f7', 'figure.facecolor':'white'})
sns.histplot(data = df , x = "vote_average" , bins = 10 , color = "#ff751a",
edgecolor = "black" ,linewidth = 0.65)
plt.xlabel("Vote Average",weight='bold')
plt.ylabel("Frequency",weight='bold')
plt.title("Histogram for Vote Average",weight='bold')
 plt.show()
```

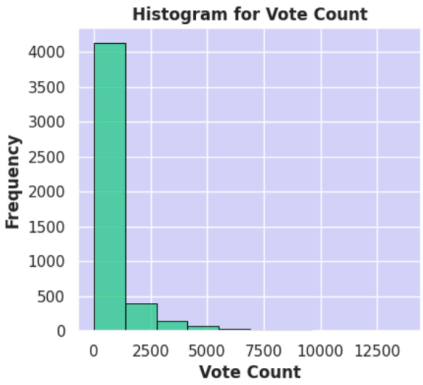
Output :



Histogram for Vote count :
code :

```
plt.figure(figsize = (4.5,4))
sns.set(rc={'axes.facecolor':'#d4d4f7', 'figure.facecolor':'white'})
sns.histplot(data = df , x = "vote_count" , bins = 10,
color ="#53c68c",edgecolor = "black" ,linewidth = 0.65 )
plt.xlabel("Vote Count",weight='bold')
plt.ylabel("Frequency",weight='bold')
plt.title("Histogram for Vote Count",weight='bold')
plt.show()
```

output :



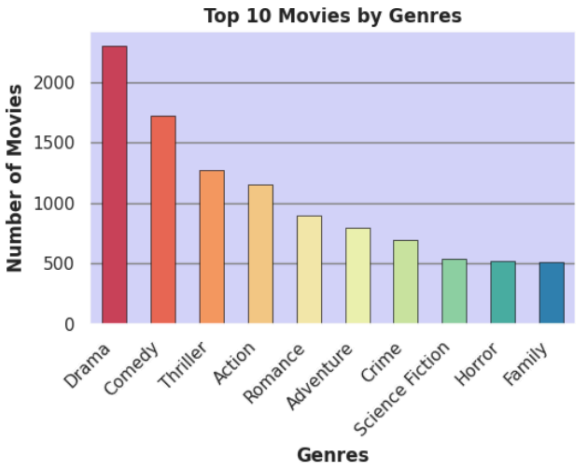
Bar graph :

Top 10 Movie Genres :
code :

```
genres_count = df["genres"].explode().value_counts()
genres_df = pd.DataFrame(genres_count).reset_index()
genres_count = df["genres"].explode().value_counts()
genres_df = pd.DataFrame(genres_count).reset_index()
plt.figure(figsize = (5.5,4.5))
sns.set(rc={'axes.facecolor':'#d4d4f7', 'figure.facecolor':'white' , "grid.color" : "grey"})
sns.barplot(x = genres_df["genres"].head(10),y = genres_df["count"].head(10),data = df ,
width = 0.5,edgecolor = "black" ,palette ="Spectral",linewidth = 0.45)
plt.xlabel("Genres",weight='bold')
plt.ylabel("Number of Movies",weight='bold')
plt.title("Top 10 Movies by Genres",weight='bold')
plt.xticks(rotation = 45 ,ha = "right")
```

```
plt.tight_layout()
plt.show()
```

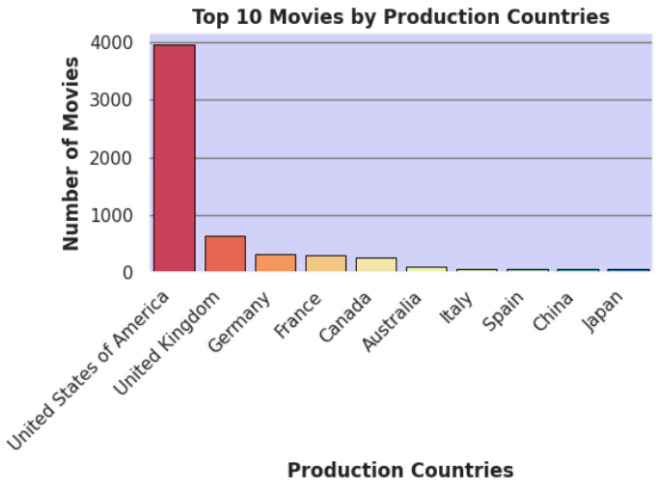
output :



Top 10 Production Countries :
code :

```
countries_count = df["production_countries"].explode().value_counts()
countries_count_df = pd.DataFrame(countries_count).reset_index()
plt.figure(figsize = (6,4.5))
sns.set(rc={'axes.facecolor':'#d4d4f7', 'figure.facecolor':'white' , "grid.color" : "grey"})
sns.barplot(x = countries_count_df["production_countries"].head(10),
y = countries_count_df["count"].head(10), data = df , linewidth = 0.65, palette="Spectral",
edgecolor = "black" )
plt.xlabel("Production Countries",weight='bold')
plt.ylabel("Number of Movies",weight='bold')
plt.title("Top 10 Movies by Production Countries",weight='bold')
plt.xticks(rotation = 45 ,ha = "right")
plt.tight_layout() # Adjust layout to prevent overlap plt.show()
```

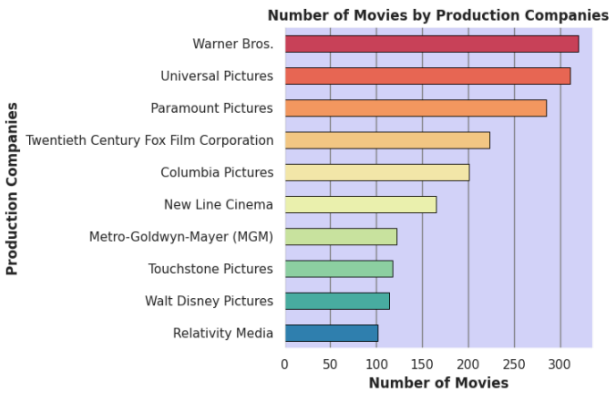
output :



Top 10 Production Companies :
code :

```
company_count = df["production_companies"].explode().value_counts()
company_count_df = pd.DataFrame(company_count).reset_index()
plt.figure(figsize = (7.5,5))
sns.set(rc={'axes.facecolor':'#d4d4f7', 'figure.facecolor':'white', "grid.color" : "grey"})
sns.barplot(x = company_count_df["count"].head(10),
data = df ,y=company_count_df["production_companies"].head(10),
palette="Spectral",edgecolor='black',width = 0.5,linewidth=0.65)
plt.ylabel("Production Companies",weight='bold')
plt.xlabel("Number of Movies",weight='bold')
plt.title("Number of Movies by Production Companies",weight='bold')
plt.tight_layout()
plt.show()
```

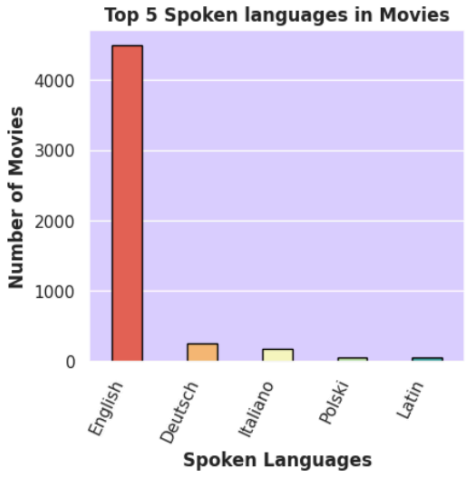
output :



Top 5 Spoken languages :
code :

```
language_count = df["spoken_languages"].explode().value_counts()
language_df = pd.DataFrame(language_count).reset_index()
language_df = language_df[language_df["spoken_languages"].str.match(r"[a-zA-Z]+$")]
plt.figure(figsize = (4.5,4))
sns.set(rc = {"axes.facecolor" : "#dacffc" , "figure.facecolor" : "white"})
sns.barplot(x = language_df["spoken_languages"].head(5) , y =language_df["count"].head(5) ,
palette= "Spectral",edgecolor ="black",width = 0.4)
plt.xlabel("Spoken Languages",weight='bold')
plt.ylabel("Number of Movies",weight='bold')
plt.title("Top 5 Spoken languages in Movies",weight='bold')
plt.xticks(rotation = 65 ,ha = "right")
plt.show()
```

output :

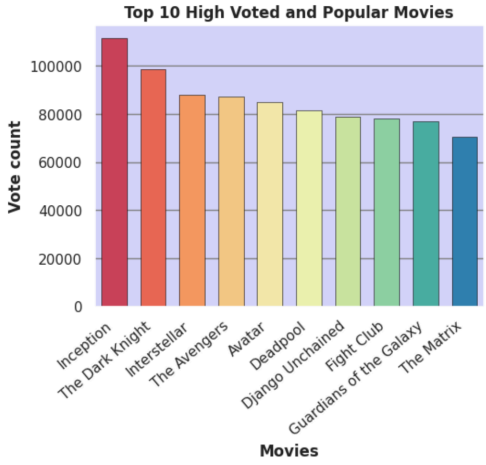


Top 10 Popular Movies :
code :

```
vote_df = pd.DataFrame(df[["title","vote_average","vote_count"]])
vote_df["vote"] = vote_df["vote_average"]*vote_df["vote_count"]
vote_df = vote_df.sort_values("vote",ascending = False)
plt.figure(figsize = (5.5,4))
sns.set(rc={'axes.facecolor':'#d4d4f7', 'figure.facecolor':'white' , "grid.color" : "grey"})
sns.barplot(x = vote_df["title"].head(10) , y = vote_df["vote"].head(10) , data = vote_df ,
edgecolor = "black", palette = "Spectral",width = 0.65,linewidth = 0.4)
plt.xlabel("Movies",weight='bold')
plt.ylabel("Vote count",weight='bold')
plt.title("Top 10 High Voted and Popular Movies",weight='bold')
```

```
plt.xticks(rotation =40 , ha = "right")
plt.show()
```

output :



2.Bivariate Analysis :

Bivariate analysis is the simultaneous analysis of two variables. It explores the concept of the relationship between two variable whether there exists an association and the strength of this association or whether there are differences between two variables and the significance of these differences**.**

common types of graphs used in bivariate analysis :

Scatter Plot:
Displays individual data points on a two-dimensional graph, with one variable on the x-axis and the other on the y-axis. It is useful for identifying patterns, correlations between the two variables.
Example: A scatter plot showing the relationship between hours studied and exam scores.

Line Graph:
Often used to display the relationship between two variables over time. Multiple lines can be used to compare different groups .
Example: A line graph showing the relationship between time spent exercising and weight loss over several weeks.

Bar Graph (Grouped or Clustered Bar Graph):
Displays two categorical variables where each group of bars represents one category of the first variable, and the bars within each group represent the categories of the second variable.
Example: A grouped bar graph showing the average test scores of students in different subjects, separated by gender.

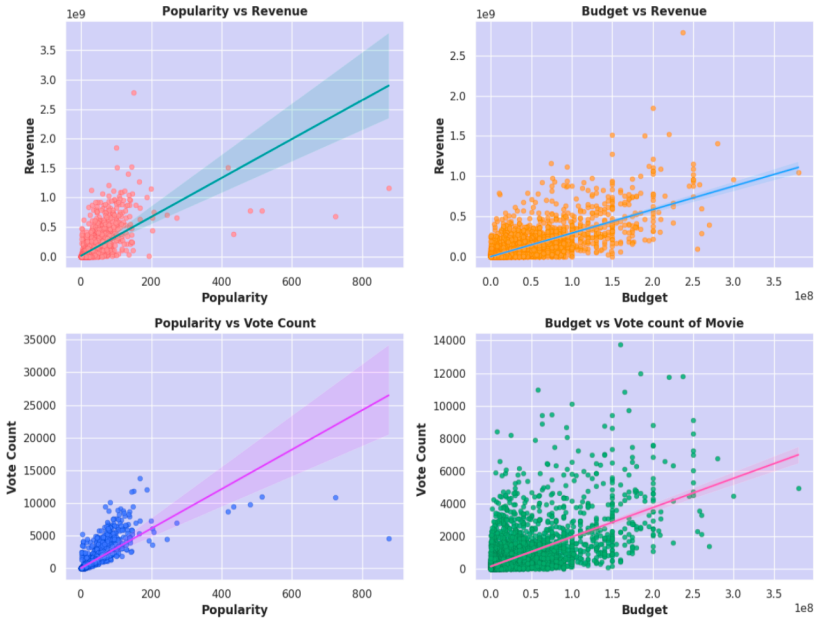
Box Plot (Grouped Box Plot):
Compares the distribution of a numerical variable across different categories of a second variable.
Example: Grouped box plots showing the distribution of salaries across different job titles.

Scatter plot for Bivariate analysis :

code :

```
# Subplot 1
# Scatter plot for Popularity and Revenue
sns.regplot(x="popularity", y="revenue", data=df ,color = "#ff9999" ,
        scatter_kws={'edgecolor': '#ff5050','linewidths': 0.3,'s' : 25},
        line_kws={'color': '#009999','linewidth':1.8}, ax=axes[0][0])
axes[0][0].set_xlabel("Popularity", fontweight='bold',fontsize = 12)
axes[0][0].set_ylabel("Revenue", fontweight='bold',fontsize = 12)
axes[0][0].set_title("Popularity vs Revenue", fontweight='bold',fontsize =12)

# Subplot 2
# Scatter plot for Budget vs Revenue
sns.regplot(x = "budget", y = "revenue" , data = df ,color = "#ffa64d" ,
        scatter_kws={'edgecolor': '#ff8000','linewidths': 0.3,'s' : 25},
        line_kws={'color': '#4da6ff','linewidth':1.8}, ax=axes[0][1])
axes[0][1].set_xlabel("Budget", fontweight='bold',fontsize = 12)
axes[0][1].set_ylabel("Revenue", fontweight='bold',fontsize = 12)
axes[0][1].set_title("Budget vs Revenue", fontweight='bold',fontsize =12)

# Subplot 3
# Scatter plot for Popularity vs Vote Count
sns.regplot(x = "popularity", y = "vote_count" , data = df ,color = "#4d79ff" ,
        scatter_kws={'edgecolor': '#002db3','linewidths': 0.3,'s' : 25},
        line_kws={'color': '#d24dff','linewidth':1.8}, ax=axes[1][0])
axes[1][0].set_xlabel("Popularity", fontweight='bold',fontsize = 12)
axes[1][0].set_ylabel("Vote Count", fontweight='bold',fontsize = 12)
axes[1][0].set_title("Popularity vs Vote Count", fontweight='bold',fontsize =12)

# Subplot 4
# Scatter plot for Budget vs Vote count of Movie
sns.regplot(x = "budget", y = "vote_count" ,data = df ,color = "#39ac73" ,
        scatter_kws={'edgecolor': '#26734d','linewidths': 0.3,'s' : 25},
        line_kws={'color': '#ff66b3','linewidth':1.8}, ax=axes[1][1])
axes[1][1].set_xlabel("Budget", fontweight='bold',fontsize = 12)
axes[1][1].set_ylabel("Vote Count ", fontweight='bold',fontsize = 12)
axes[1][1].set_title("Budget vs Vote count of Movie", fontweight='bold',fontsize = 12)

# Adjust layout for better display
plt.tight_layout()
plt.show()
```

output :



Multivariate data analysis :

Multivariate data refers to datasets where each observation or sample point consists of multiple variables or features. These variables can represent different aspects, characteristics, or measurements related to the observed phenomenon. When dealing with three or more variables, the data is specifically categorized as multivariate.

- It only summarize more than 2 variables.
- It does not deal with causes and relationships and analysis is done.
- It is similar to bivariate but it contains more than 2 variables.
- The main purpose is to study the relationship among them.

Scatter Plot Matrix (Pair Plot):

- A grid of scatter plots showing the relationship between each pair of variables.
- Diagonal elements often show a histogram or kernel density plot of individual variables.
- Useful for identifying patterns, correlations, and potential outliers.
- A pair plot, also known as a scatterplot matrix, is a matrix of graphs that enables the visualization of the relationship between each pair of variables in a dataset.
- It combines both histogram and scatter plots, providing a unique overview of the dataset's distributions and correlations.

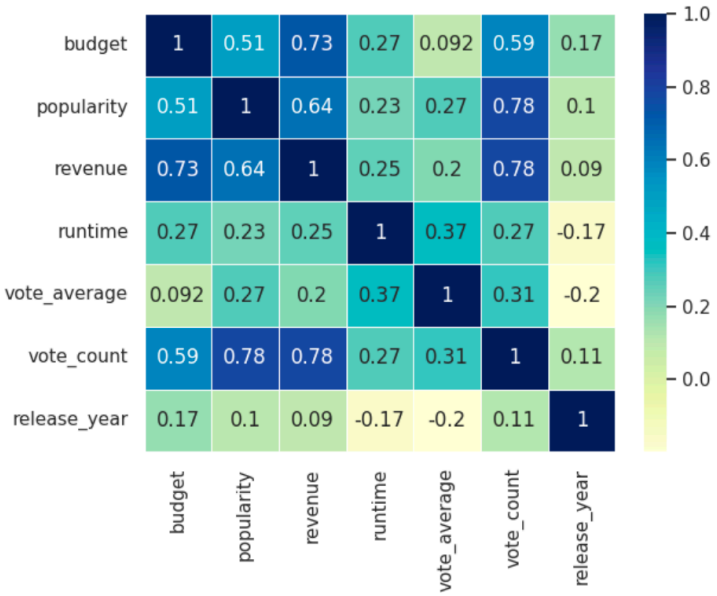
Heatmaps :

- A matrix where values are represented by colors.
- Useful for displaying the correlation matrix of variables or for visualizing data points across two categorical dimensions.
- A Heat map is a graphical representation of multivariate data that is structured as a matrix of columns and rows. Heat maps are very useful in describing correlation among several numerical variables, visualizing patterns and anomalies.

Heat Map for Multivariate Analysis :
code :

```
numerical_data = pd.DataFrame(df)
numerical_data.drop(columns =["genres","keywords","original_language",
                    "original_title","overview","production_companies","production_countries",
                    "release_date","spoken_languages","status","title",
                    "cast","crew","id"],inplace = True)
corr_matrix = numerical_data.corr()
sns.heatmap(corr_matrix ,annot = True,linewidths=.5 ,cmap="YlGnBu")
plt.show()
```

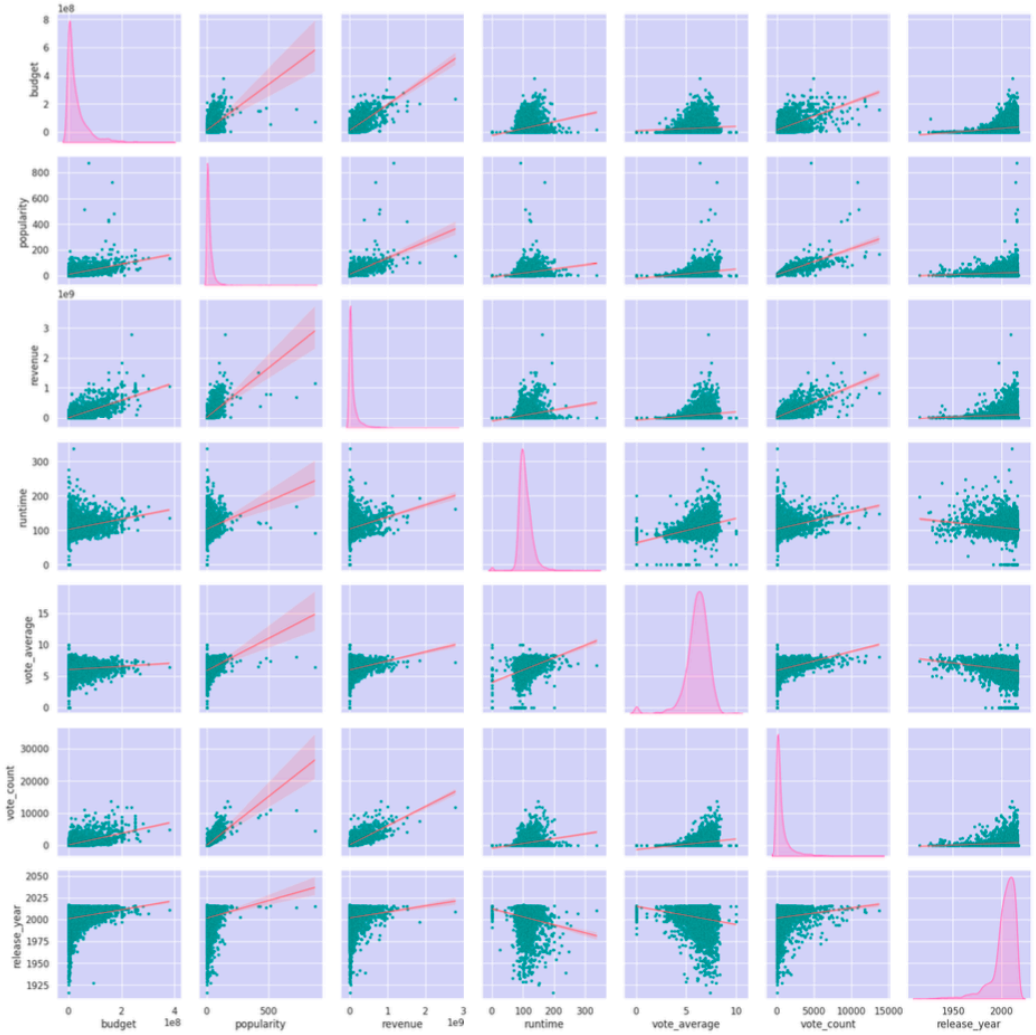
output :



Pair plot for Multivariate Analysis :
code :

```
plt.figure(figsize = (10,10))
sns.set(rc={'axes.facecolor':'#d4d4f7', 'figure.facecolor':'white' , "grid.color" : "white"})
sns.pairplot(data = numerical_data ,diag_kind="kde",diag_kws = {"color": "hotpink"},kind="reg",
        plot_kws={'color':'#00b3b3','scatter_kws': {'s': 6.5 ,'edgecolor': 'darkcyan' },
        'line_kws':{'color':'#ff4d4d', 'linewidth':0.95}} )
plt.show()
```

output :



Conclusion :

To build a content based personalized movie recommendation system ,the Exploratory Data Analysis (EDA) process is very important and necessary step in analysing the dataset . The process involves analyzing and summarizing the main characteristics of the dataset, often using visual methods.By examining the relationships between different variables, EDA helps in identifying which features are most relevant for the recommendation model. Thus by performing EDA on the dataset the appropriate algorithm for building the recommendation system is selected for developing enhanced recommendation system.