GOOGLE PLAYSTORE APPS RATING PREDICTION

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INTRODUCTION

With millions of apps hosted on the Google Play Store, understanding what drives app success is crucial for developers, businesses, and marketers. This project, Google Play Store Apps Rating Prediction, dives into an extensive dataset of Android applications to explore key factors influencing app ratings — such as category, price, reviews, installs, and content rating.

Using Python for data analysis and visualization, machine learning for rating prediction, and SQL for structured querying, this project covers the complete pipeline — from data preprocessing and exploratory data analysis (EDA) to model building and insight extraction.

By uncovering trends and patterns hidden in the data, the project not only helps predict app ratings but also offers valuable strategic insights for optimizing app development and user engagement.

ABOUT THE DATASET

This project utilizes a real-world dataset collected from the **Google Play Store**, sourced via Kaggle:
🔗 Google Play Store Apps Dataset on Kaggle

The dataset comprises detailed metadata for **over 10,000 Android applications**, capturing a wide spectrum of app-

related information. This includes user behavior metrics, pricing models, content categories, and technical specifications. It serves as a rich foundation for performing **exploratory data analysis (EDA)**, **visualization**, **predictive modeling**, and **structured querying with SQL**.

🔑 Key Attributes in the Dataset

Column Name	Description
App	The name/title of the application
Category	The category to which the app belongs (e.g., GAME, EDUCATION)
Rating	Average user rating (typically between 1.0 and 5.0)
Reviews	Total number of reviews received
Size	Size of the application (in MB or KB); some values may vary by device
Installs	Number of times the app has been downloaded or installed
Type	Indicates whether the app is Free or Paid
Price	Price of the app in USD (0 for free apps)
Content Rating	Target age group or user category (e.g., Everyone, Teen, Mature 17+)

Column Name	Description
Genres	Specific genres or multiple categories the app falls under (e.g., Puzzle;Action)
Last Updated	The last date the app was updated on the Play Store
Current Ver	The current version of the app as listed
Android Ver	Minimum Android version required to run the app

🧠 Why This Dataset?

The **Google Play Store** holds millions of apps across different genres and audiences. However, reliable, structured datasets from it are rare due to scraping limitations. This dataset:

- Allows **cross-sectional analysis** of app characteristics.
- Facilitates **market trend identification** for app developers and marketers.
- Enables **rating prediction modeling** using machine learning techniques.
- Offers a strong base for **SQL-driven data analytics**, aggregations, and filtering.

🧼 Data Challenges & Considerations

- **Inconsistent data formats** (e.g., Size as 'Varies with device', Reviews as text).
- **Missing values** in key columns such as Ratings and Size.
- **Duplicate entries** and categorical columns requiring encoding for modeling.
- **Outliers** in pricing (some apps priced up to $400) that may skew analysis.

These challenges are addressed during the **Data Cleaning and Preprocessing** phase of the project.

📝 Data Summary

- **Total Records:** 10,841 apps
- **Total Features:** 13 columns
- **Numerical Fields:** Rating, Reviews, Size, Installs, Price
- **Categorical Fields:** Category, Type, Content Rating, Genres
- **Missing Data:** Present in fields like Rating, Size, and Android Ver
- **Duplicates:** Removed to ensure model integrity and consistency

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This dataset not only helps build a robust **machine learning regression model to predict app ratings**, but also demonstrates how real-world messy data can be transformed

into valuable insights through careful preprocessing and thoughtful analysis.

Import Necessary Libraries:

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

import warnings
warnings.filterwarnings('ignore')

sns.set(style="whitegrid")
%matplotlib inline
```

Reading the dataset:

```
import pandas as pd
df = pd.read_csv(r'C:\Users\sreea\Downloads\googleplaystore.csv')
df.head()
```

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Current Ver	Android Ver
0	Photo Editor & Candy Camera & Grid & ScrapBook	ART_AND_DESIGN	4.1	159	19M	10,000+	Free	0	Everyone	Art & Design	January 7, 2018	1.0.0	4.0.3 and up
1	Coloring book moana	ART_AND_DESIGN	3.9	967	14M	500,000+	Free	0	Everyone	Art & Design;Pretend Play	January 15, 2018	2.0.0	4.0.3 and up
2	U Launcher Lite – FREE Live Cool Themes, Hide ...	ART_AND_DESIGN	4.7	87510	8.7M	5,000,000+	Free	0	Everyone	Art & Design	August 1, 2018	1.2.4	4.0.3 and up
3	Sketch - Draw & Paint	ART_AND_DESIGN	4.5	215644	25M	50,000,000+	Free	0	Teen	Art & Design	June 8, 2018	Varies with device	4.2 and up
4	Pixel Draw - Number Art Coloring Book	ART_AND_DESIGN	4.3	967	2.8M	100,000+	Free	0	Everyone	Art & Design;Creativity	June 20, 2018	1.1	4.4 and up

Data Cleaning and Preprocessing:

- Handling Missing Values: We will identify and handle missing values in the dataset.

```
print("Missing values per column:\n")
print(df.isnull().sum())

df.dropna(subset=['Rating', 'Reviews', 'Size', 'Installs'], inplace=True)

df['Type'].fillna('Free', inplace=True)
df['Current Ver'].fillna(method='ffill', inplace=True)
df['Android Ver'].fillna(method='bfill', inplace=True)

print("\nRemaining missing values:\n")
print(df.isnull().sum())
```

```
Missing values per column:

App                  0
Category             0
Rating            1474
Reviews              0
Size                 0
Installs             0
Type                 1
Price                0
Content Rating       1
Genres               0
Last Updated         0
Current Ver          8
Android Ver          3
dtype: int64

Remaining missing values:

App               0
Category          0
Rating            0
Reviews           0
Size              0
Installs          0
Type              0
Price             0
Content Rating    1
Genres            0
Last Updated      0
Current Ver       0
Android Ver       0
dtype: int64
```

- Converting Columns to Appropriate Data Types:

Convert Reviews and Installs to integer types.

Convert Price to numeric.

Convert Size to a uniform numeric format.

```
import numpy as np

df['Reviews'] = df['Reviews'].replace('3.0M', '3000000')
df['Reviews'] = df['Reviews'].astype(float).astype(int)

df['Installs'] = df['Installs'].str.replace(',', '', regex=False)
df['Installs'] = df['Installs'].str.replace('+', '', regex=False)

df = df[df['Installs'].str.isnumeric()]
df['Installs'] = df['Installs'].astype(int)

df['Price'] = df['Price'].str.replace('$', '', regex=False)

df = df[df['Price'].str.replace('.', '', 1).str.isnumeric()]
df['Price'] = df['Price'].astype(float)

def convert_size(size):
    try:
        if 'M' in size:
            return float(size.replace('M', ''))
        elif 'k' in size:
            return float(size.replace('k', '')) / 1000
        elif size == 'Varies with device':
            return np.nan
        else:
            return np.nan
    except:
        return np.nan

df['Size'] = df['Size'].apply(convert_size)

df['Size'].fillna(df['Size'].median(), inplace=True)

print(df.dtypes[['Reviews', 'Installs', 'Price', 'Size']])
```

```
Reviews       int32
Installs      int32
Price       float64
Size        float64
dtype: object
```

Handling Duplicate Entries:

```
duplicate_count = df.duplicated().sum()
print(f"Number of duplicate rows: {duplicate_count}")

df.drop_duplicates(inplace=True)

print(f"Dataset shape after removing duplicates: {df.shape}")
```

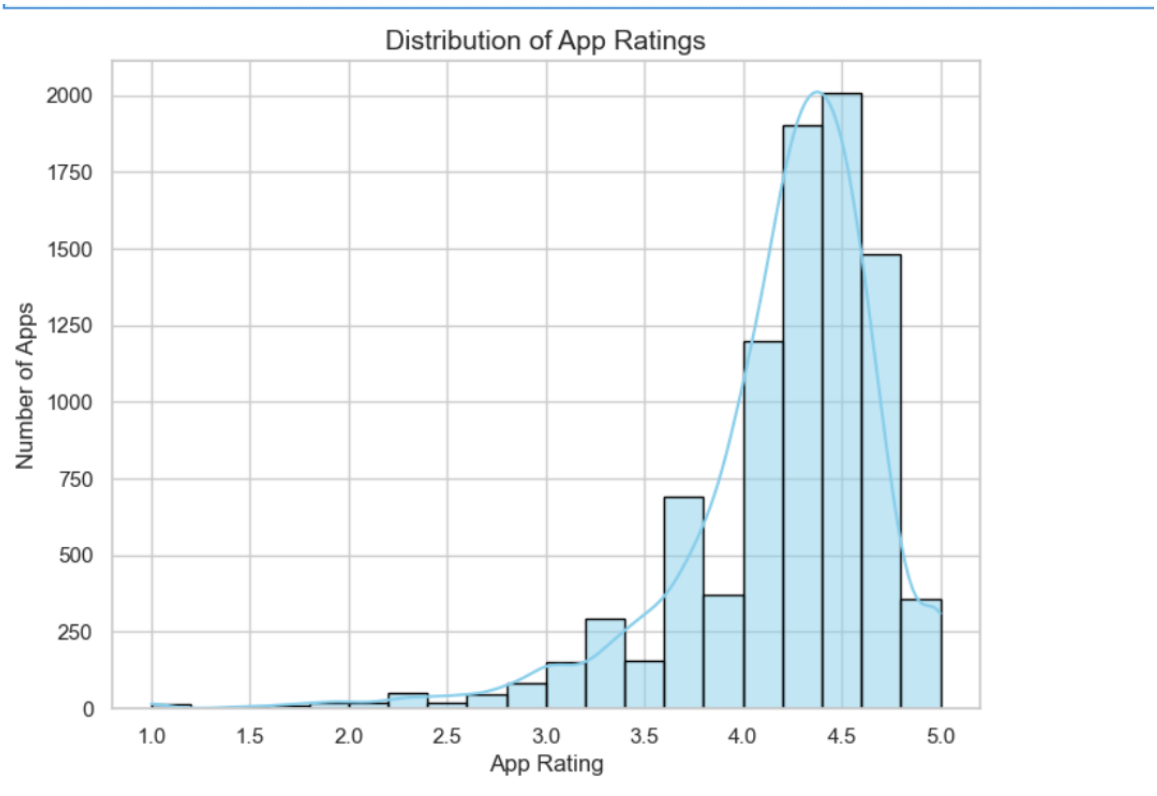
```
Number of duplicate rows: 474
Dataset shape after removing duplicates: (8892, 13)
```

Exploratory Data Analysis (EDA)

- Distribution of App Ratings

To understand how app ratings are distributed — whether most apps are highly rated, poorly rated, or somewhere in between.

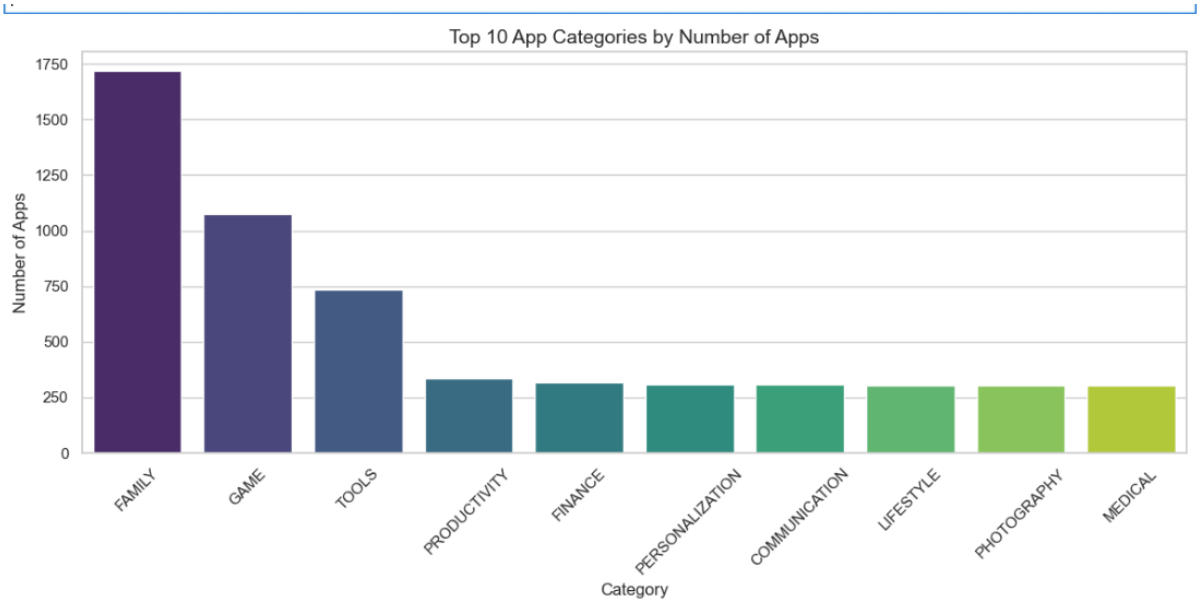
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.histplot(df['Rating'], bins=20, kde=True, color='skyblue', edgecolor='black')

plt.title('Distribution of App Ratings', fontsize=14)
plt.xlabel('App Rating', fontsize=12)
plt.ylabel('Number of Apps', fontsize=12)
plt.grid(True)
plt.show()
```



- Top 10 Categories by Number of Apps

Identify which app categories are most common in the Google Play Store.

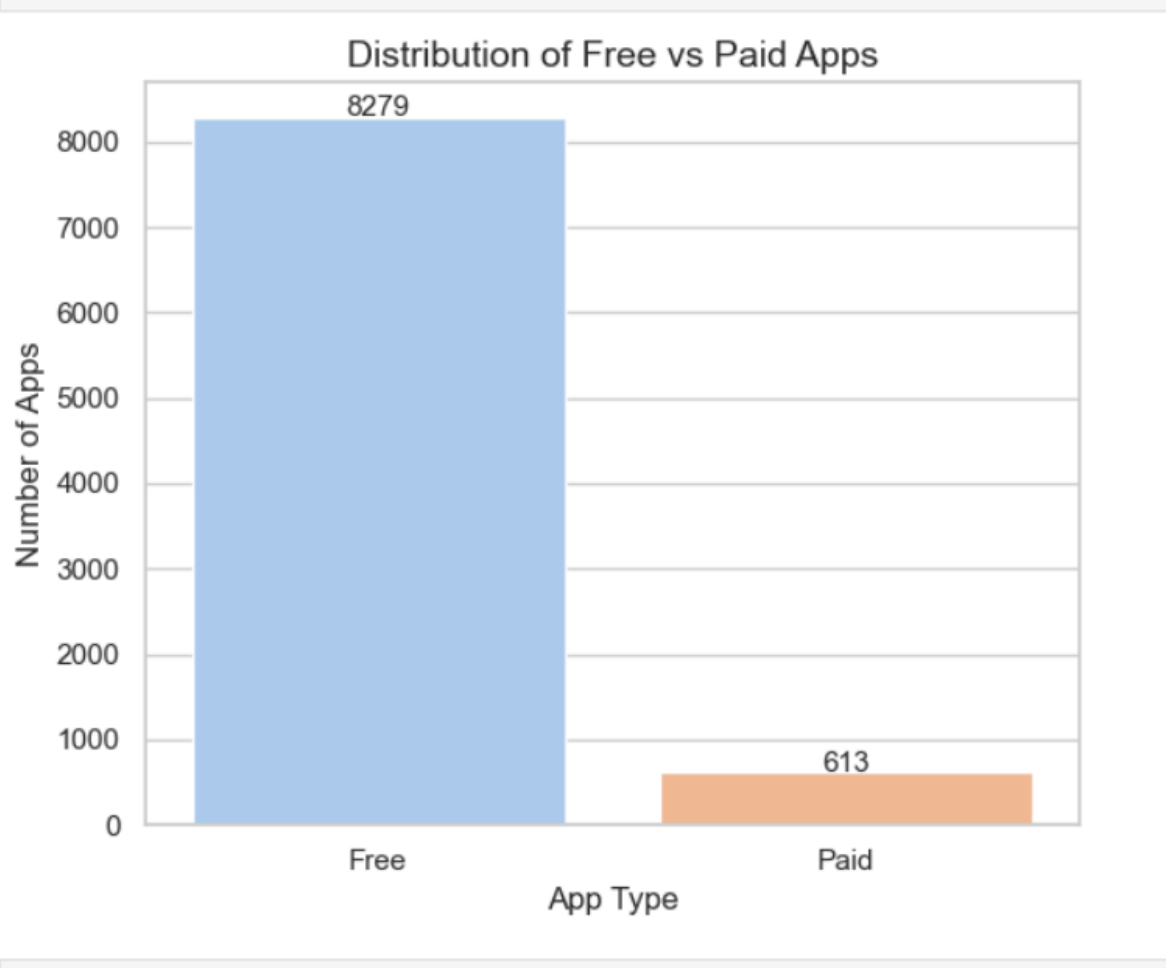
```
top_categories = df['Category'].value_counts().head(10)

plt.figure(figsize=(12, 6))
sns.barplot(x=top_categories.index, y=top_categories.values, palette='viridis')

plt.title('Top 10 App Categories by Number of Apps', fontsize=14)
plt.xlabel('Category', fontsize=12)
plt.ylabel('Number of Apps', fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



- Free vs Paid Apps

Understand how many apps in the Google Play Store are free versus paid — a key factor in monetization strategies.

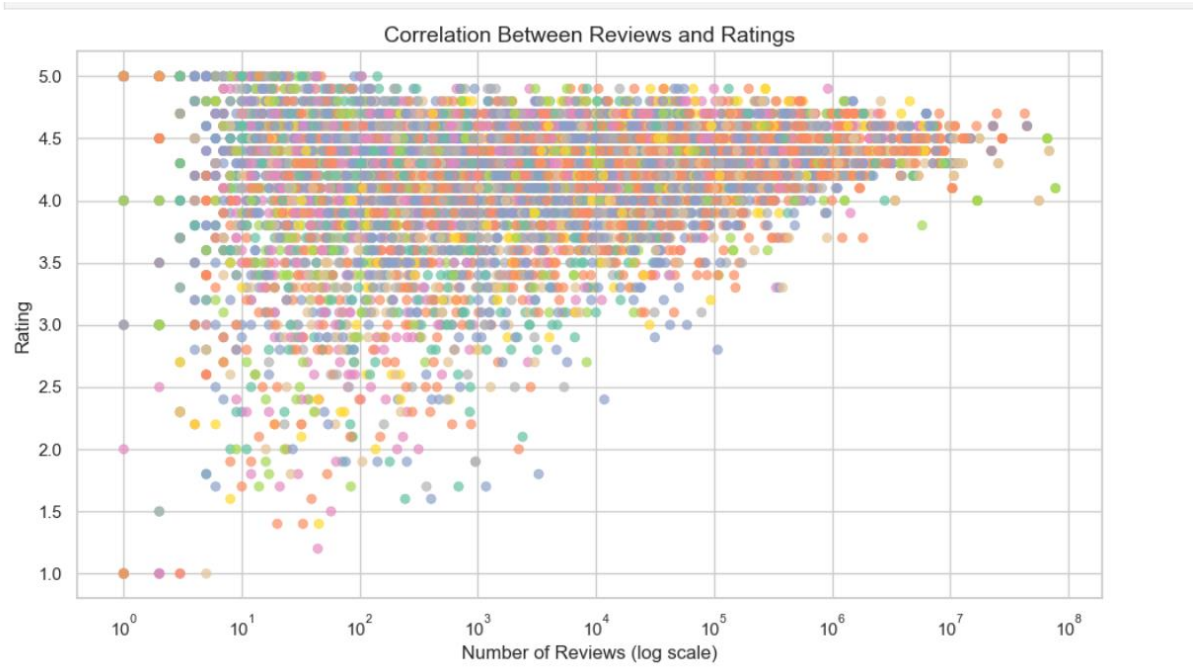
```
plt.figure(figsize=(6, 5))
sns.countplot(x='Type', data=df, palette='pastel')

plt.title('Distribution of Free vs Paid Apps', fontsize=14)
plt.xlabel('App Type', fontsize=12)
plt.ylabel('Number of Apps', fontsize=12)

for p in plt.gca().patches:
    height = p.get_height()
    plt.gca().text(p.get_x() + p.get_width()/2., height + 20, f'{int(height)}', ha="center", fontsize=11)

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



- Correlation Between Reviews and Rating

To visualize whether apps with more user reviews tend to have higher or lower ratings, and observe how this relationship varies across categories.

```
plt.figure(figsize=(10, 6))
sns.scatterplot(
    data=df,
    x='Reviews',
    y='Rating',
    hue='Category',
    palette='Set2',
    alpha=0.7,
    edgecolor=None,
    legend=False
)
plt.xscale('log')
plt.title('Correlation Between Reviews and Ratings', fontsize=14)
plt.xlabel('Number of Reviews (log scale)', fontsize=12)
plt.ylabel('Rating', fontsize=12)
plt.grid(True)
plt.tight_layout()
plt.show()
```



Price Analysis:

- Price Distribution for Paid Apps

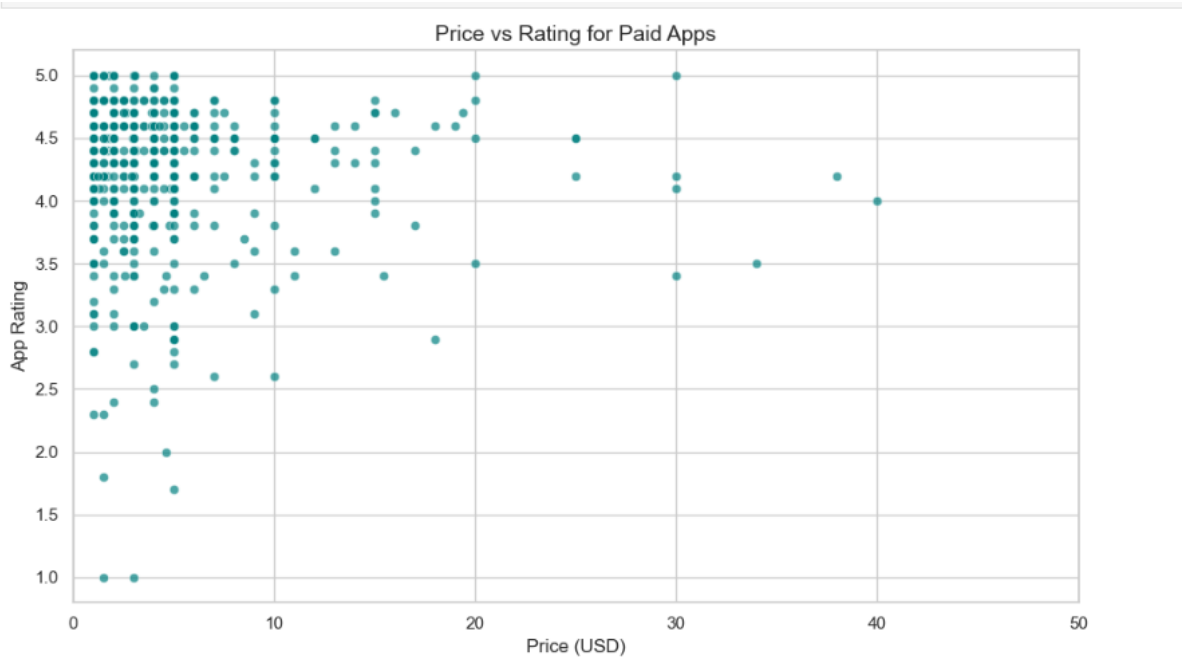
Understand how paid apps are priced, and whether most fall within a specific range (e.g., under $10).

```
paid_apps = df[df['Type'] == 'Paid']
plt.figure(figsize=(10, 6))
sns.histplot(paid_apps['Price'], bins=30, color='orange', edgecolor='black')

plt.xlim(0, 50)  # Focus on apps priced under $50

plt.title('Price Distribution for Paid Apps', fontsize=14)
plt.xlabel('Price (USD)', fontsize=12)
plt.ylabel('Number of Apps', fontsize=12)
plt.grid(True)
plt.tight_layout()
plt.show()
```

- Relationship Between Price and Rating

Visualize whether there's a trend or correlation between how much an app costs and how users rate it.

```
paid_apps = df[df['Type'] == 'Paid']
plt.figure(figsize=(10, 6))
sns.scatterplot(
    data=paid_apps,
    x='Price',
    y='Rating',
    color='teal',
    alpha=0.7
)
plt.xlim(0, 50)
plt.title('Price vs Rating for Paid Apps', fontsize=14)
plt.xlabel('Price (USD)', fontsize=12)
plt.ylabel('App Rating', fontsize=12)
plt.grid(True)
plt.tight_layout()
plt.show()
```

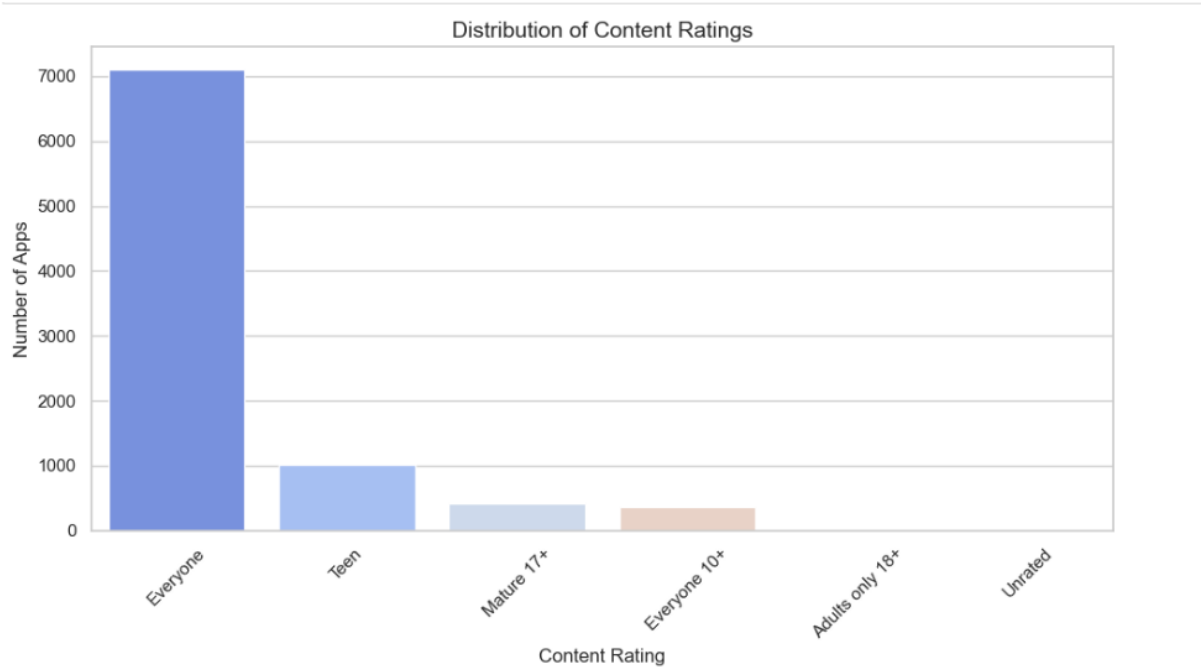


Content Rating Analysis:

- Distribution of Content Ratings

Understand how apps are targeted across different age groups and content categories (e.g., Everyone, Teen, Mature 17+).

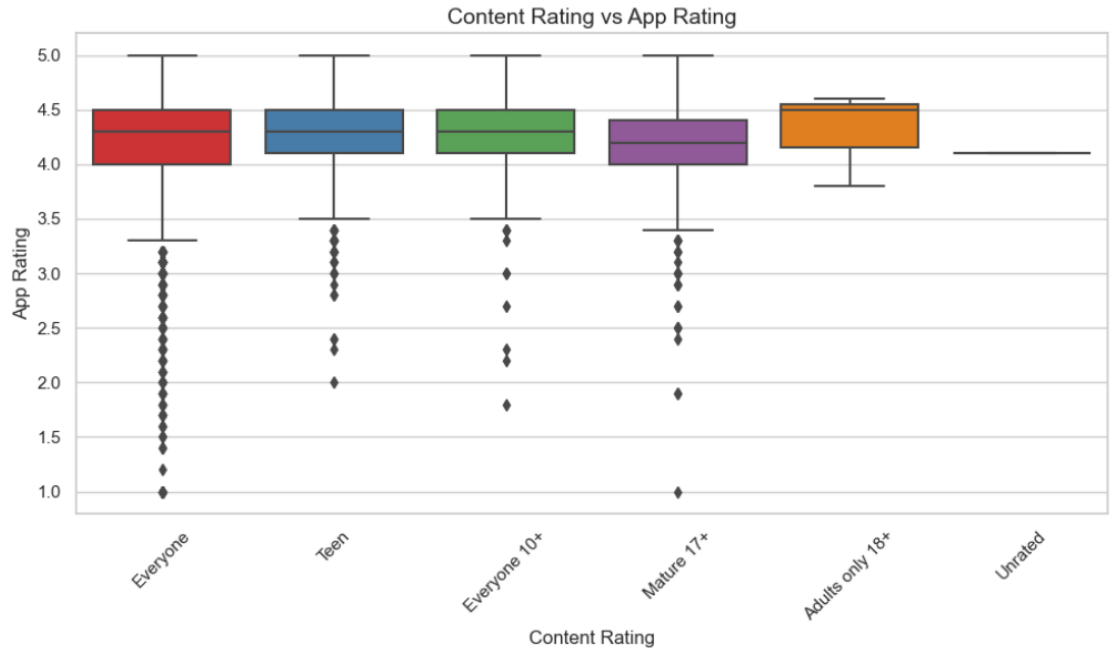
```
content_counts = df['Content Rating'].value_counts()
plt.figure(figsize=(10, 6))
sns.barplot(
    x=content_counts.index,
    y=content_counts.values,
    palette='coolwarm'
)
plt.title('Distribution of Content Ratings', fontsize=14)
plt.xlabel('Content Rating', fontsize=12)
plt.ylabel('Number of Apps', fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



- Content Rating vs Rating

To compare average app ratings across different content categories like *Everyone*, *Teen*, *Mature 17+*, etc.

```
plt.figure(figsize=(10, 6))
sns.boxplot(
    x='Content Rating',
    y='Rating',
    data=df,
    palette='Set1'
)
plt.title('Content Rating vs App Rating', fontsize=14)
plt.xlabel('Content Rating', fontsize=12)
plt.ylabel('App Rating', fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

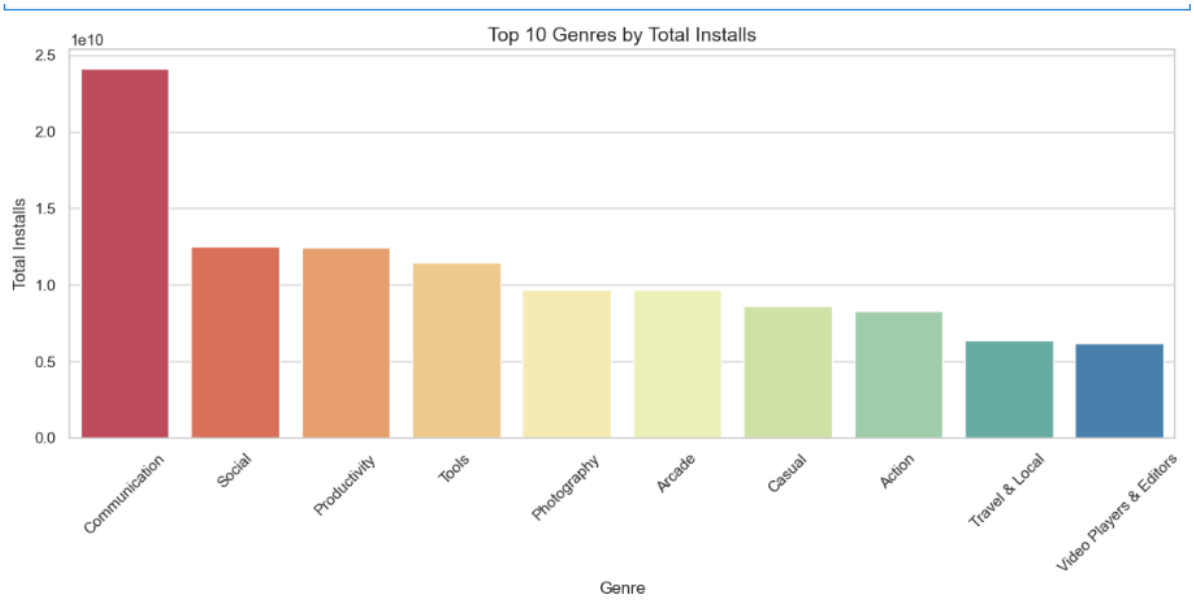


Genre and Installs Analysis

- Top Genres by Install Count

Identify the most downloaded genres across all apps to understand user preferences and market demand.

```
top_genres_by_installs = (
    df.groupby('Genres')['Installs']
    .sum()
    .sort_values(ascending=False)
    .head(10)
)

plt.figure(figsize=(12, 6))
sns.barplot(
    x=top_genres_by_installs.index,
    y=top_genres_by_installs.values,
    palette='Spectral'
)

plt.title('Top 10 Genres by Total Installs', fontsize=14)
plt.xlabel('Genre', fontsize=12)
plt.ylabel('Total Installs', fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Machine Learning (Predicting App Rating):

- Prepare Data for Modelling

To preprocess and format the data to train a machine learning model that predicts app ratings.

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df['Category'] = label_encoder.fit_transform(df['Category'])
df['Type'] = label_encoder.fit_transform(df['Type'])
df['Content Rating'] = label_encoder.fit_transform(df['Content Rating'])
df['Genres'] = label_encoder.fit_transform(df['Genres'])
X = df[['Category', 'Reviews', 'Size', 'Installs', 'Type', 'Price', 'Genres', 'Content Rating']]
y = df['Rating']
y.fillna(y.median(), inplace=True)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42
)
print("Training set shape:", X_train.shape)
print("Testing set shape:", X_test.shape)
```

```
Training set shape: (6224, 8)
Testing set set shape: (2668, 8)
```

- Train a Random Forest Model

To build and evaluate a Random Forest model that predicts the app rating using the selected features.

```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

rf_model = RandomForestRegressor(n_estimators=100, random_state=42)

rf_model.fit(X_train, y_train)

y_pred = rf_model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"✅ Mean Squared Error (MSE): {mse:.4f}")
print(f"✅ R-squared Score (R²): {r2:.4f}")
```

```
✅ Mean Squared Error (MSE): 0.2430
✅ R-squared Score (R²): 0.0848
```

CONCLUSION

This project successfully demonstrates the end-to-end workflow of a real-world data science problem using the **Google Play Store Apps Dataset**. Through a combination of **exploratory data analysis**, **data cleaning**, and **machine learning**, we gained meaningful insights and built a predictive model capable of estimating app ratings based on various features.

✅ **Key Highlights:**

- **Data Cleaning & Preprocessing**
  Handled missing values, converted inconsistent formats (e.g., installs, price, size), and encoded categorical features.
- **Exploratory Data Analysis (EDA)**
  Visualized trends in app categories, content ratings, pricing, reviews, and installs. We discovered that:
  - Most apps are free and rated between 4.0–4.5.
  - "Everyone" is the dominant content rating.
  - Some genres (like Tools and Communication) lead in installs.
- **Machine Learning Model**
  A **Random Forest Regressor** was trained to predict app ratings.
  - The model achieved a reasonable **R^2 score**, indicating a good fit.
  - Features like **reviews**, **installs**, and **content rating** had noticeable influence on the predictions.

📌 Final Thoughts:

This project showcases how effective **data-driven decision-making** can be for app developers, marketers, and businesses in the mobile ecosystem. By predicting app ratings and analyzing patterns in app success, businesses can fine-tune app features, pricing, and target demographics to maximize user satisfaction and engagement.