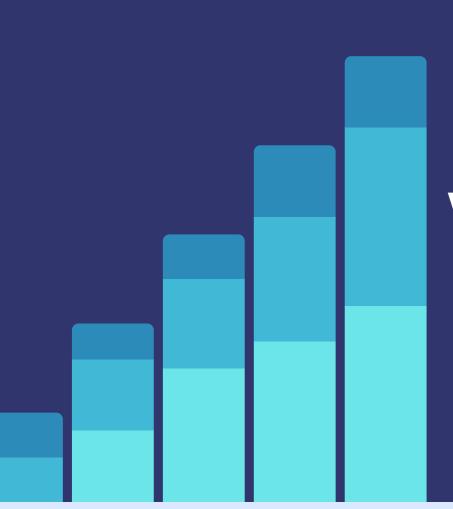
TOP 10,000 POPULAR MOVIES TMDB

VIDEO PRESENTATION



IMTRODUCTION

Why Did We Choose This Topic?

- rich in data, well-structured, and highly valuable in business
- a widely loved form of entertainment

Aims

"What factors contribute most to a movie's financial success, and how can these insights help filmmakers and producers make data-driven decisions?"

Our problem

Dataset : Kaggle (online platform for accessing datasets, collaborating on data science projects and taking part in machine learning competitions)

The analysis aims to identify the factors influencing the popularity of films by studying their budget, duration and number of votes. It explores the distribution of films according to various criteria and uses clustering to group films by profile (blockbusters, independent films, etc.). The aim is to optimise studio decisions, improve streaming platform recommendations and better understand trends in the film market.

DATASET

The dataset consists of 10,000 rows (each representing a movie) and multiple columns (attributes) that describe various aspects of each movie.

Note: because of a very large file with a huge amount of data, some information has been incorrectly transcribed and some analyses may therefore contain errors.

Attributes

Title Release date

Genre Original language

Average vote Vote count

Popularity Budget

Production company

Runtime

Revenu

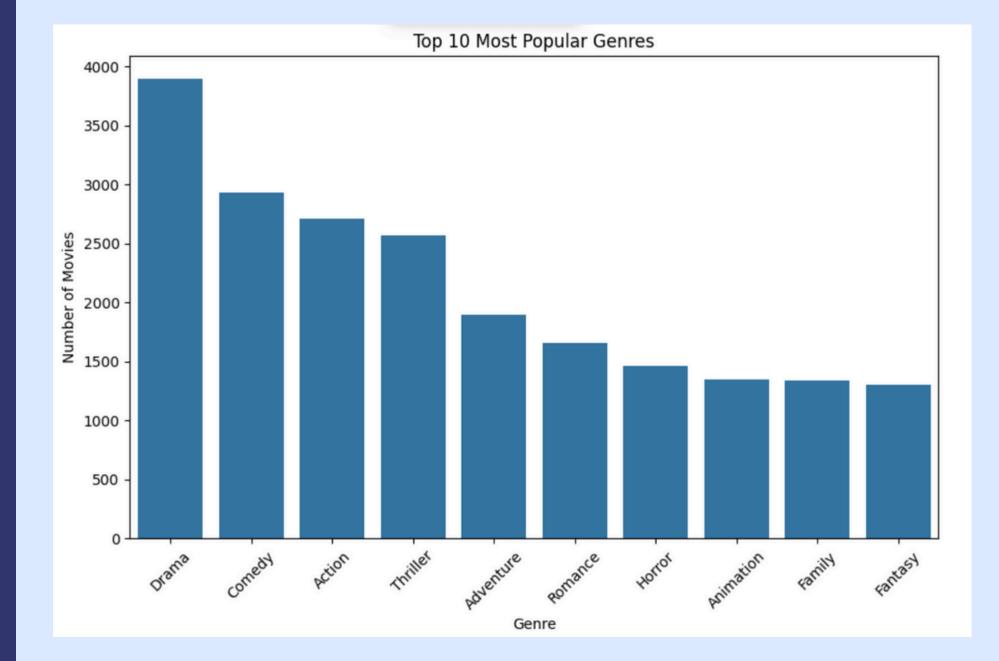
+ Profit (revenue-budget)

TOP 10 MOST POPULAR GENRES

In film and television, drama is a category or genre of narrative fiction (or semifiction) intended to be more serious than humorous in tone.

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

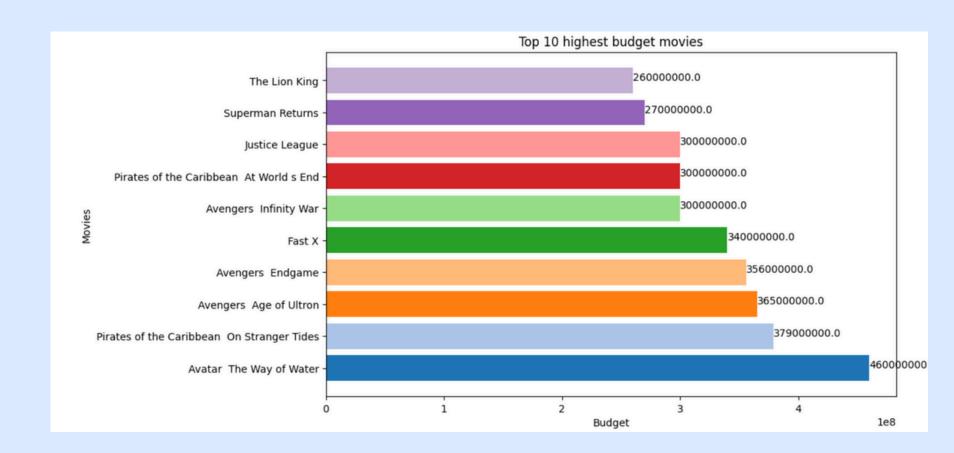
# Plot the top 10 most popular genres
plt.figure(figsize=(10, 6))
sns.barplot(x=genre_counts.head(10).index, y=genre_counts.head(10).values)
plt.title('Top 10 Most Popular Genres')
plt.xlabel('Genre')
plt.ylabel('Number of Movies')
plt.xticks(rotation=45)
plt.show()
```

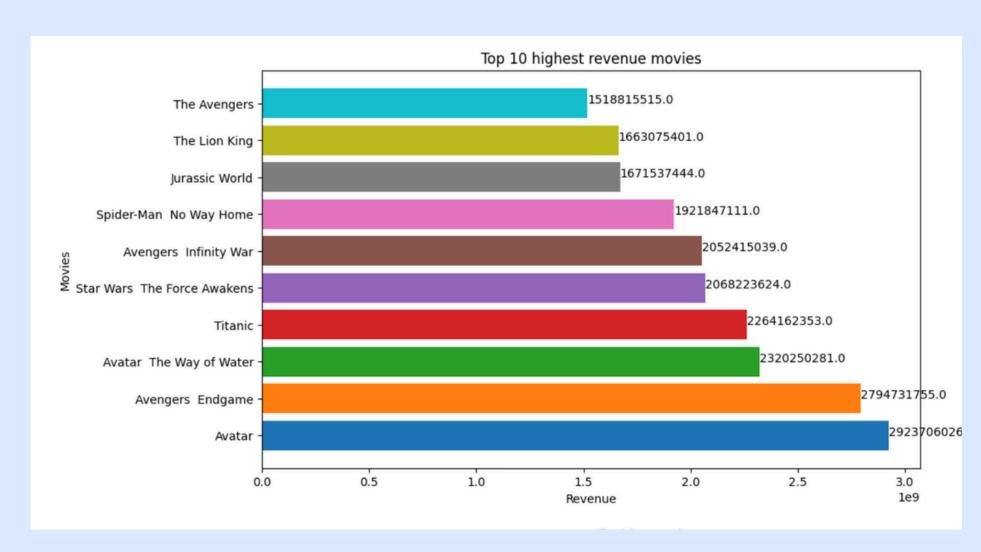


TOP 10 HIGHEST BUDGET & REVENUE

We will analyze the relationship between a movie's budget and its revenue. Do higher budgets always lead to higher revenues? Are there any outliers where low-budget movies have performed exceptionally well?

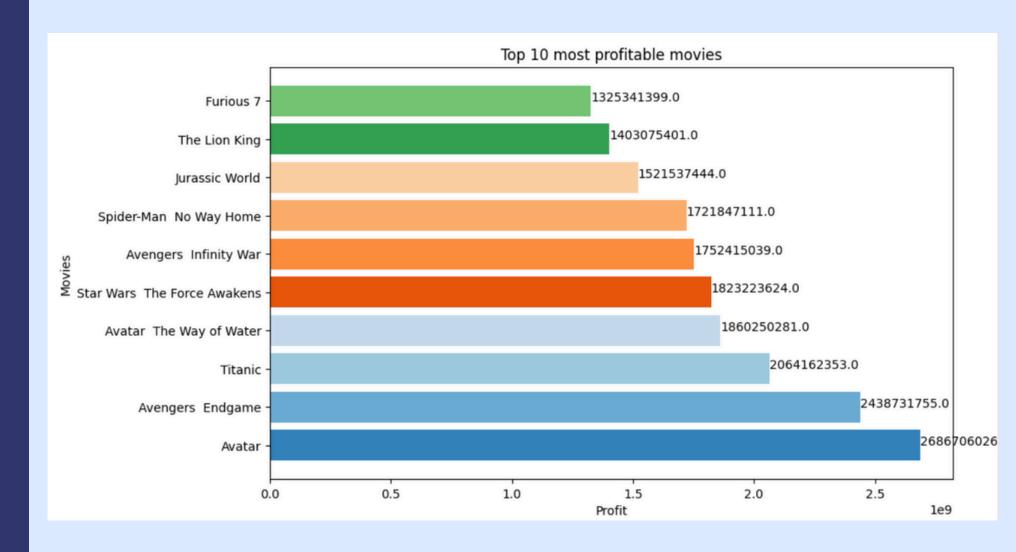
- Most of these movies belong to a popular production company → importance of the brand and characters, familiar world
- Massive marketing campaign contributing to success
- Leader in technological innovations such as special effects and 3D (avengers, avatar)
- Word of mouth and positive reviews have amplified the success





TOP 10 MOSTE PROFITABLE MOUIES

Worldwide distribution: Success on international markets (Jurassic World, The Lion King) is decisive, based on universal stories and appropriate marketing. Cultural phenomena: Films such as Avatar or Avengers Endgame are going beyond the cinema to become cultural references, expanding their audience and revenues.



TOP 5 MOST PROFITABLE MOUIES BY GENRE

- 1. <u>Comedy</u>: often lower budgets, which can lead to high profits even with moderate box office. Comedies that capture elements of popular culture or are based on franchises can attract large audiences.
- 2. Action: high budgets due to special effects and stunts. But generate huge revenues, especially if they distributed internationally. Franchises such as 'Fast & Furious' or 'James Bond' are classic examples.
- 3. <u>Drama</u>: varying budgets, but their success often depends on the quality of the script and the performances of the actors. Films that win awards or receive critical acclaim can see their profits rise thanks to increased visibility.

```
Top 5 films les plus rentables pour le genre 'Comedy ':

title profit revenue budget

The Super Mario Bros. Movie 1.208767e+09 1.308767e+09 100000000.0

Minions 1.082731e+09 1.156731e+09 74000000.0

Zootopia 8.737842e+08 1.023784e+09 150000000.0

Toy Story 3 8.669697e+08 1.066970e+09 20000000.0

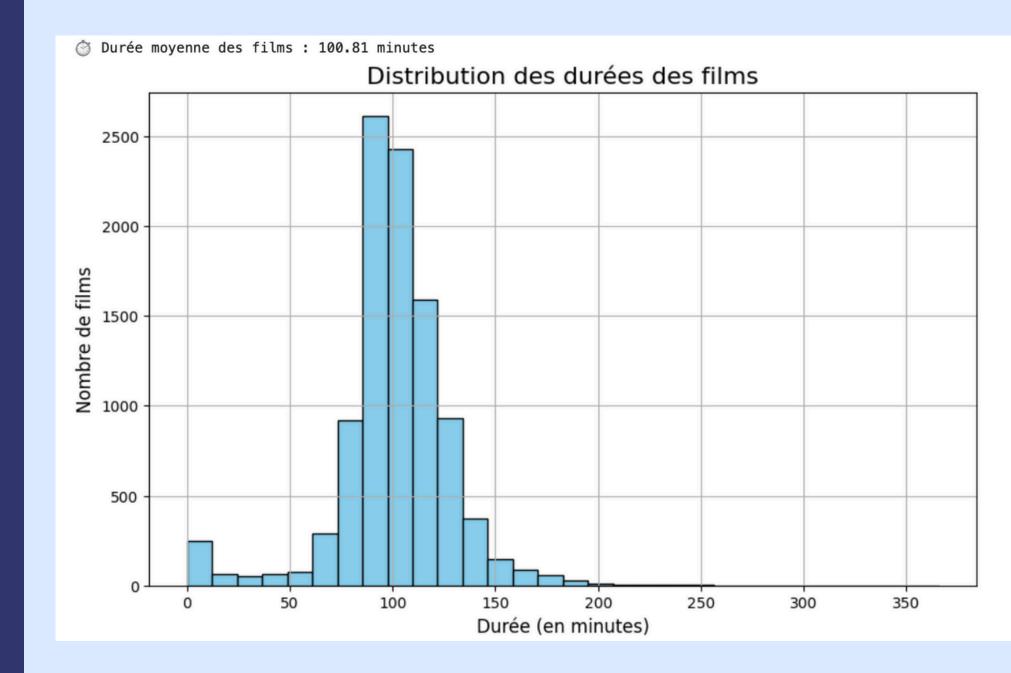
Deadpool 7.251000e+08 7.831000e+08 58000000.0
```

```
Top 5 films les plus rentables pour le genre 'Action':
                            title
                                         profit
                                                                   budget
                                                      revenue
82
                           Avatar 2.686706e+09 2.923706e+09
                                                              237000000.0
1009
     Star Wars The Force Awakens 1.823224e+09 2.068224e+09
                                                              245000000.0
129
            Avengers Infinity War 1.752415e+09
                                                2.052415e+09
46
           Spider-Man No Way Home 1.721847e+09 1.921847e+09
                                                              200000000.0
545
                   Jurassic World 1.521537e+09 1.671537e+09
                                                              150000000.0
```

```
Top 5 films les plus rentables pour le genre '
                                               Drama':
                                   profit
                      title
                                                 revenue
                                                               budget
254
                    Titanic 2.064162e+09
                                           2.264162e+09
                                                          200000000.0
401
                                           1.663075e+09
              The Lion King
                             1.403075e+09
                                                          260000000.0
1324
                                           9.039929e+08
          Bohemian Rhapsody
                             8.519929e+08
                                                           52000000.0
771
      The Dark Knight Rises
                             8.310413e+08
                                           1.081041e+09
                                                          250000000.0
430
                                           1.004558e+09
            The Dark Knight
                            8.195584e+08
                                                          185000000.0
```

LENGTH OF MOVIES

- Average running time: Most films run between 90 and 120 minutes (average: ~100 minutes). This is the industry standard, as it corresponds to the audience's attention span.
- Peak of popularity: Films between 1h30 and 2h dominate. Too short (<90 min) or too long (>2h30) are rare (risk of boredom or frustration).



TOP 5 PRODUCTION COMPANIES WITH THE MOST FILMS

- Universal Pictures leads with 23.5%
- → Probably thanks to very profitable recent films (e.g. Jurassic World, Fast & Furious).
- Warner Bros just behind (22.4%)
- → Strong with blockbusters like Harry Potter or DC Comics.
- Columbia, Paramount and 20th Century Fox are grouped together (17-18%)
- → Intense competition, need for regular hits to stay in the race.

What this means

- Universal & Warner Bros have more clout to fund big films and massive ads.
- The other companies have to innovate or build on existing franchises (*ex.: Paramount with Mission: Impossible).

Possible developments

- If Universal keeps its place, it could influence trends (e.g. more sequels, family films).
- If we compare with 10 years ago, perhaps Disney (absent here?) dominated before (Marvel, Star Wars).

Impact on viewers

- The dominant studios decide to some extent what genres are fashionable (e.g. superheroes, family films).
- More budgets = more spectacular films, but perhaps fewer creative risks.

```
companies_column = df['production_companies']

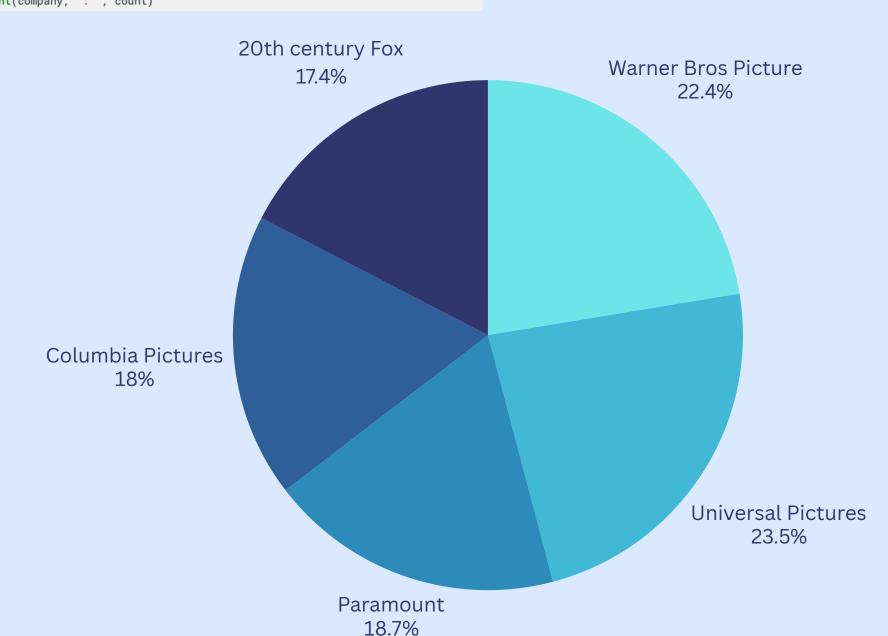
# Create an empty dictionary to store company names and their movie counts
company_counts = {}

# Iterate over each row in the companies column
for companies_list in companies_column:
        companies = eval(companies_list) # Convert the string representation of list
to a list
    for company in companies:
        if company in company_counts:
            company_counts[company] += 1 # Increment the movie count
        else:
            company_counts[company] = 1 # Add the company with initial movie count

sorted_companies = sorted(company_counts.items(), key=lambda x: x[1], reverse=Tr
ue)

top_5_companies = sorted_companies[:5]

for company, count in top_5_companies:
    print(company, ": ", count)
```



5 CLUSTERS

Clusters	Length	Popularity	Interpretations
0	around 120 mins	average/high between 920 - 1170	quite popular but a specific public
1	90-100 mins	quite high	more horror, action thriller genre. Niche public
2	92-170 mins	box office - global success	blockbusters : actions, adventure, animation
3	117-192 mins	quite high	often sequel to a successful film. Target large audience
4	could be short and long	quite low	either little known or still in preparation

Cluster 0:			
title runtime popularity			
2 My Fault 117.0 1170.670			
•			
16 The Pope s Exorcist 103.0 1037.514 20 Project Wolf Hunting 122.0 937.849			
21 To Catch a Killer 119.0 920.656			
22 Guy Ritchie s The Covenant 123.0 917.907			
22 day kitchie s The Covenant 125.0 917.907			
Cluster 1:			
title runtime popularity			
The Black Demon 100.0 1777.200			
15 Accident Man Hitman s Holiday 96.0 1117.559			
Cluster 2:			
title runtime popularity			
0 Fast X 142.0 8363.473			
1 John Wick Chapter 4 170.0 4210.313			
2 The Super Mario Bros. Movie 92.0 3394.458			
4 Hypnotic 94.0 2654.854			
Cluster 3:			
title runtime popularity			
7 The Little Mermaid 135.0 1448.640			
Avatar The Way of Water 192.0 1344.884			
192.0 1344.004 11 Guardians of the Galaxy Vol. 3 150.0 1262.366			
13 Ant-Man and the Wasp Quantumania 125.0 1167.790			
24 Spider-Man Into the Spider-Verse 117.0 914.969			
24 Spider Hall Tito the Spider Verse 117:0 914:909			
Cluster 4:			
title runtime popularity			
84 Spider-Man Beyond the Spider-Verse 0.0 245.865			
109 Extraction 2 123.0 202.753			
122 Tayuan 0.0 187.835			
133 Lego Friends The Next Chapter New Beginnings 45.0 177.548			
174 Meg 2 The Trench 116.0 146.569			
174 neg 2 me menen 110.0 140.509			

TOOLS USED IN THIS ANALYSIS

PROGRAMMING LANGUAGE ANALYTICAL METHODS

DATA SCIENCE LIBRARIES

PROGRAMMING LANGUAGE

Python: used for data processing and analysis

DATA SCIENCE LIBRARIES

- Pandas: data manipulation and cleaning
- NumPy: management of numerical tables and calculations
- <u>Matplotlib & Seaborn</u>: data visualisation in the form of graphs
- <u>Scikit-learn</u>: application of clustering algorithms and statistical analysis

ANALYTICAL METHODS

- Exploratory analysis to understand the distribution of variables (budget, duration, popularity, etc.).
- Correlation and regression to identify relationships between film characteristics and their success.
- Clustering (e.g. K-Means) to group films according to their similarities.

1. Collect the dataset on kaggle

- 2. Importing data
 - Load dataset containing
 information on films (budget,
 duration, popularity, rating, etc.).
 - Data cleansing (management of missing values, format conversion).

```
import pandas as pd

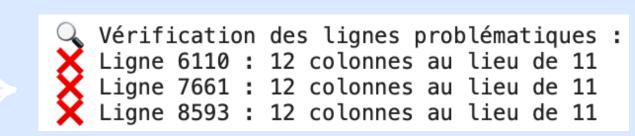
file_path = "/content/test N°X 2.0.csv"

try:
    df = pd.read_csv(file_path, sep=";", encoding="utf-8-sig")
    print("\n Fichier chargé avec succès !")
    print(df.head()) # Afficher les 5 premières lignes

except pd.errors.ParserError as e:
    print("\n Fireur lors du chargement du fichier :", e)
    print("\n Tentative de lecture en ignorant les erreurs...")
    df = pd.read_csv(file_path, sep=";", encoding="utf-8-sig", on_bad_lines="skip")
    print("\n Fichier chargé en sautant les lignes problématiques !")
    print(df.head())
```

```
# Étape 2 : Vérifier si certaines lignes ont un nombre anormal de colonnes
expected_cols = lines[0].count(";") + 1 # Nombre de colonnes attendu d'après l'en-tête

print("\n Vérification des lignes problématiques :")
for i, line in enumerate(lines[1:], start=2): # On commence à la ligne 2 (1 en-tête)
    cols = line.count(";") + 1
    if cols != expected_cols:
        print(f" Ligne {i} : {cols} colonnes au lieu de {expected_cols}")
```



```
Recherche de ligne manquant de l'information "genre" pour les supprimer

In [66]: df[df['genres'].str.len() == 2]

Out[66]: title release_date genres original_language vote_average vote_count popularity budget production_companies revenue

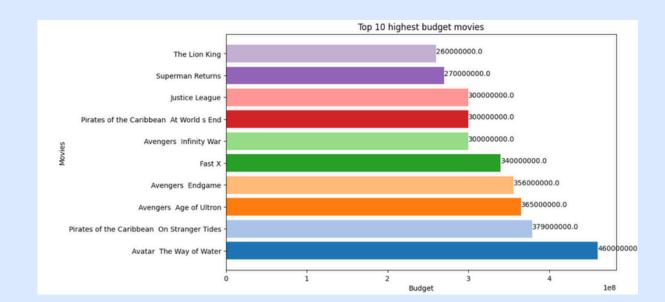
**Recherche de ligne mon compte avec l'information "compagnie de production" pour les supprimer **

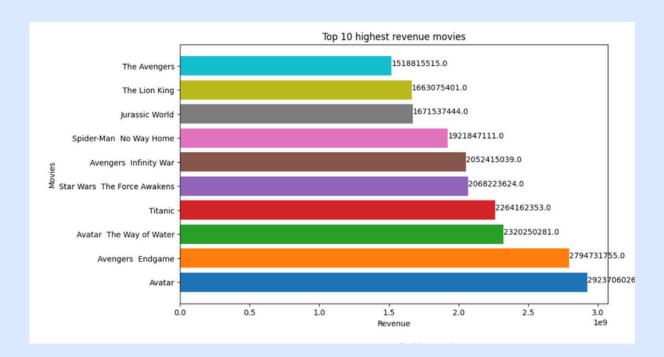
In [67]: df[df['production_companies'].str.len() == 2]

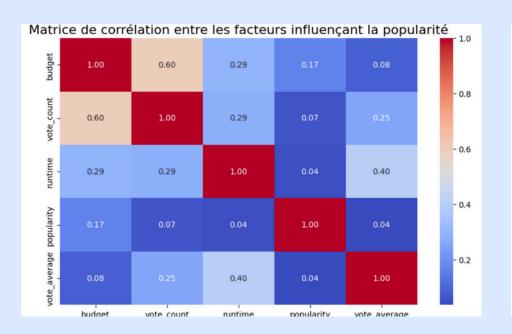
Out[67]: title release_date genres original_language vote_average vote_count popularity budget production_companies

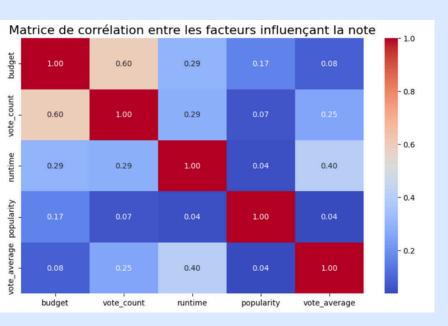
The 3821 Weekend 03/03/2022 Thriller, Mystery English 6.0 572 21.723 0.0 42
```

- 3. Exploratory Data Analysis (EDA)
 - Visualisation of distributions:
 histograms to show the distribution
 of budget, duration, popularity, etc.
 - Correlations between variables:
 study of the relationships between
 budget, number of votes and
 popularity using heatmaps and
 scatter plots.

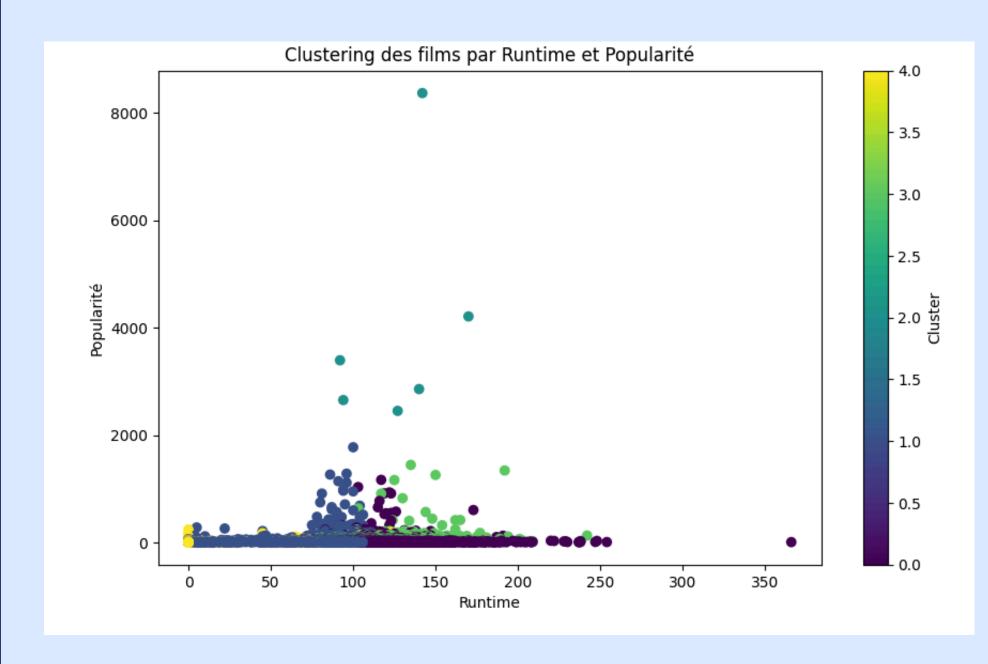




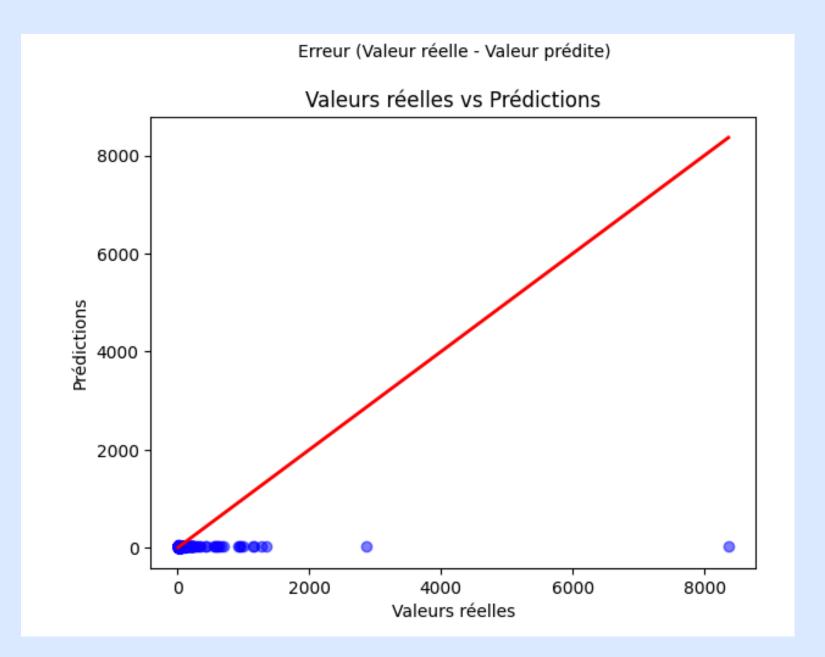




- 4. Clustering films
 - Application of a clustering
 algorithm (e.g. K-Means) to group
 films according to similar
 characteristics.
 - Interpretation of the groups:
 blockbusters, independent films,
 critically acclaimed films, etc.



- 5. Modelling and trends
 - Identification of factors influencing film popularity.
 - Comparison of film performance by budget and length.



Conclusion : Le modèle de régression linéaire utilisé avec ces paramètres n'explique pas bien la popularité des films. L'erreur quadratique moyenne est relativement élevée, et le R² est très faible. Cela suggère que la popularité des films pourrait être influencée par d'autres facteurs non pris en compte dans ce modèle (comme la distribution géographique, les campagnes marketing, la distribution des films, etc.). Il serait peut-être utile d'explorer d'autres modèles (comme des modèles non linéaires) ou d'ajouter davantage de variables explicatives pour améliorer les prédictions.

CONCLUSION "What factors contribute most to a movie's financial success, and how can these insights help filmmakers and producers make data-driven decisions?"

What makes a film successful?

- High budget → More resources for special effects, stars and ads (e.g. Avengers)
 - Optimum running time \rightarrow 90-120 minutes to keep attention
 - Audience ratings and votes \rightarrow A film with good ratings attracts more people
- Media visibility \rightarrow The more people talk about it (social networks, media), the bigger the hit

Key strategies for studios

- Invest wisely: Focus on what pays off (special effects, targeted marketing)
- Target the audience: Adapt films to the tastes of viewers (e.g. action films for young people, dramas for adults)
 - Predicting hits: Using AI to predict a film's potential before it is released

The power of data

- Film groups: Classify films by style (e.g. 'blockbusters', 'arthouse films') to sell them better.
- Personalised recommendations: Platforms (Netflix, Disney+) use these groups to suggest similar films

The future

- Less risk: Data helps avoid flops by spotting trends
- Tailor-made films: Understanding the audience helps create work that really appeals
 - Competition: Studios that ignore data risk disappearing

In short: Cinema is becoming a science! Budget, length, target audience... Everything is calculated to maximise the chances of success.

##