# LH_CD_LUIZ_CARLOS

Vou explorar os dados como se estivéssemos numa sala de decisão do estúdio: primeiro entendemos o terreno (o que existe, o que falta, o que distorce), depois olhamos padrões que realmente ajudam o negócio a decidir **que filme produzir**. No fim, respondo às perguntas do desafio, treino um modelo para prever a nota do IMDB e salvo o arquivo `.pkl`.

```
import pandas as pd, numpy as np, re, os, joblib
import matplotlib.pyplot as plt

from google.colab import files
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.metrics import mean_absolute_error, mean_squared_error, classification_report, confusion_matrix
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import HistGradientBoostingRegressor
```

## 1) Carregar dados

```
up = files.upload()
name = list(up.keys())[0]
df = pd.read_csv(name)
df.head(8)
```

Escolher arquivos desafio_indi…m_imdb.csv

- **desafio_indicium_imdb.csv**(text/csv) - 303059 bytes, last modified: 04/09/2025 - 100% done

```
Saving desafio_indicium_imdb.csv to desafio_indicium_imdb.csv
```

| | Unnamed: 0 | Series_Title | Released_Year | Certificate | Runtime | Genre | IMDB_Rating | Overview | Meta_score | Director | Star1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | The Godfather | 1972 | A | 175 min | Crime, Drama | 9.2 | An organized crime dynasty's aging patriarch t... | 100.0 | Francis Ford Coppola | Marlon Brando | Al F |
| **1** | 2 | The Dark Knight | 2008 | UA | 152 min | Action, Crime, Drama | 9.0 | When the menace known as the Joker wreaks havo... | 84.0 | Christopher Nolan | Christian Bale | L |
| **2** | 3 | The Godfather: Part II | 1974 | A | 202 min | Crime, Drama | 9.0 | The early life and career of Vito Corleone in ... | 90.0 | Francis Ford Coppola | Al Pacino | Rob |
| **3** | 4 | 12 Angry Men | 1957 | U | 96 min | Crime, Drama | 9.0 | A jury holdout attempts to prevent a miscarria... | 96.0 | Sidney Lumet | Henry Fonda | |
| **4** | 5 | The Lord of the Rings: The Return of the King | 2003 | U | 201 min | Action, Adventure, Drama | 8.9 | Gandalf and Aragorn lead the World of Men agai... | 94.0 | Peter Jackson | Elijah Wood | Mort |
| | | | | | | | | The lives | | | | |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **5** | 6 | Pulp Fiction | 1994 | A | 154 min | Crime, Drama | 8.9 | The lives of two mob hitmen, a boxer, a gangst... | 94.0 | Quentin Tarantino | John Travolta | Thu |
| **6** | 7 | Schindler's List | 1993 | A | 195 min | Biography, Drama, History | 8.9 | In German-occupied Poland during World War II,... | 94.0 | Steven Spielberg | Liam Neeson | Fi |
| **7** | 8 | Inception | 2010 | UA | 148 min | Action, Adventure, Sci-Fi | 8.8 | A thief who steals corporate secrets through t... | 74.0 | Christopher Nolan | Leonardo DiCaprio | J Go |

Próximas etapas: Gerar código com df | Ver gráficos recomendados | New interactive sheet

## 2) Preparar variáveis

```
df = df.copy()

df["primary_genre"] = df["Genre"].astype(str).str.split(",").str[0].str.strip()

df["runtime_min"]   = df["Runtime"].apply(to_minutes)
df["gross_num"]     = df["Gross"].apply(to_number)
df["year"]          = pd.to_numeric(df["Released_Year"], errors="coerce")
df["metascore"]     = pd.to_numeric(df["Meta_score"], errors="coerce")
df["votes"]         = pd.to_numeric(df["No_of_Votes"], errors="coerce")
df["log_votes"]     = np.log1p(df["votes"])
df["log_gross"]     = np.log1p(df["gross_num"])

desc = df[["IMDB_Rating","metascore","runtime_min","year","votes","gross_num","log_votes","log_gross"]].describe().T
```

```
desc
```

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **IMDB_Rating** | 999.0 | 7.947948e+00 | 2.722895e-01 | 7.600000 | 7.700000e+00 | 7.900000e+00 | 8.100000e+00 | 9.200000e+00 |
| **metascore** | 842.0 | 7.796912e+01 | 1.238326e+01 | 28.000000 | 7.000000e+01 | 7.900000e+01 | 8.700000e+01 | 1.000000e+02 |
| **runtime_min** | 999.0 | 1.228719e+02 | 2.810123e+01 | 45.000000 | 1.030000e+02 | 1.190000e+02 | 1.370000e+02 | 3.210000e+02 |
| **year** | 998.0 | 1.991214e+03 | 2.330854e+01 | 1920.000000 | 1.976000e+03 | 1.999000e+03 | 2.009000e+03 | 2.020000e+03 |
| **votes** | 999.0 | 2.716214e+05 | 3.209126e+05 | 25088.000000 | 5.547150e+04 | 1.383560e+05 | 3.731675e+05 | 2.303232e+06 |
| **gross_num** | 830.0 | 6.808257e+07 | 1.098076e+08 | 1305.000000 | 3.245338e+06 | 2.345744e+07 | 8.087634e+07 | 9.366622e+08 |
| **log_votes** | 999.0 | 1.190417e+01 | 1.117715e+00 | 10.130185 | 1.092364e+01 | 1.183759e+01 | 1.282978e+01 | 1.464982e+01 |
| **log_gross** | 830.0 | 1.642269e+01 | 2.411711e+00 | 7.174724 | 1.499272e+01 | 1.697069e+01 | 1.820843e+01 | 2.065783e+01 |

Próximas etapas: Gerar código com desc | Ver gráficos recomendados | New interactive sheet

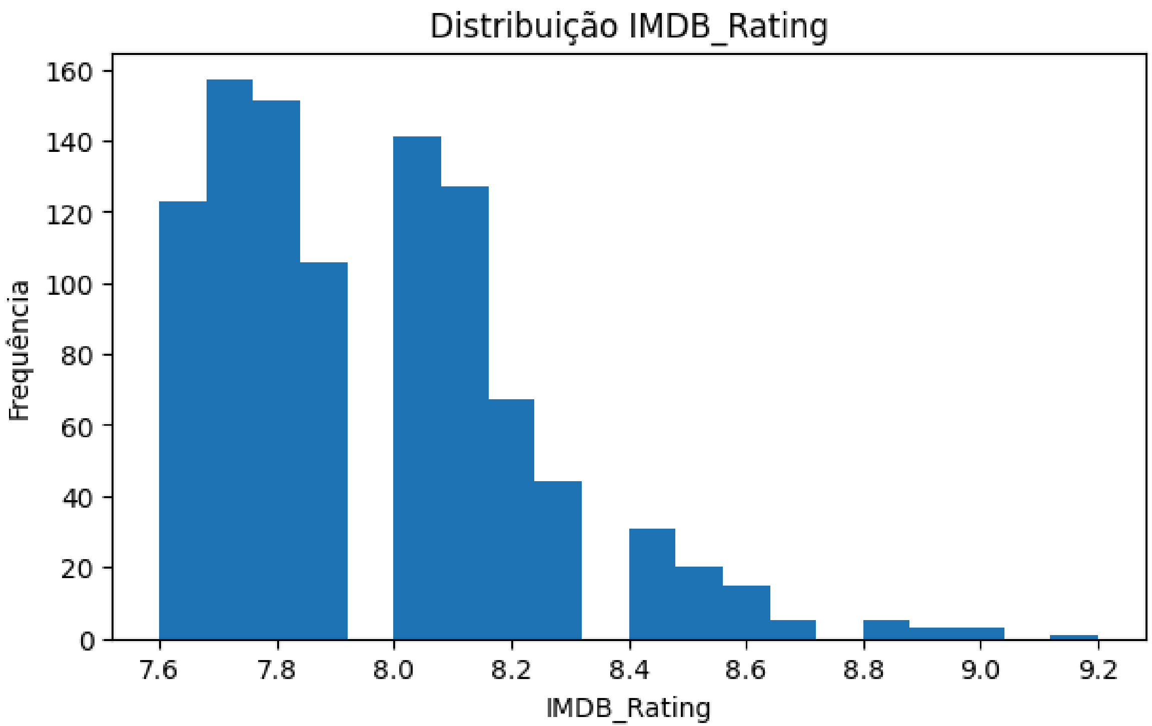
## 3) EDA rápida e honesta

```
missing = (df.isna().mean().sort_values(ascending=False)*100).round(1)
missing.head(12)
```

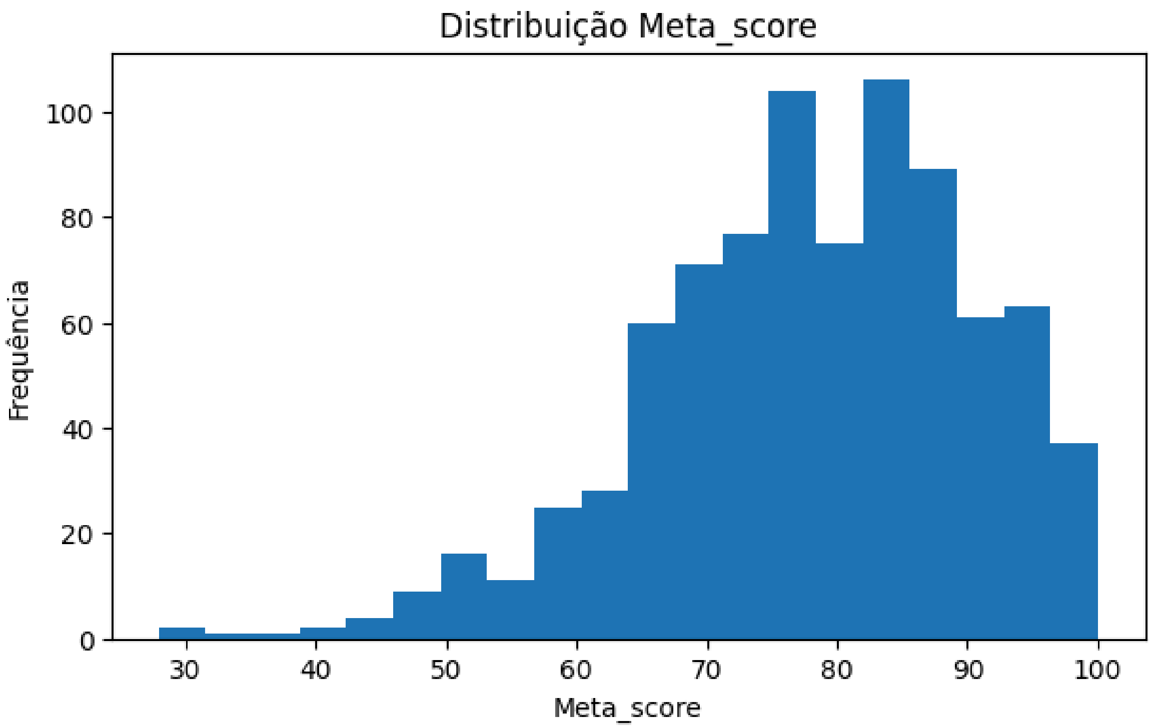
| | 0 |
|---|---|
| **gross_num** | 16.9 |
| **log_gross** | 16.9 |
| **Gross** | 16.9 |
| **Meta_score** | 15.7 |
| **metascore** | 15.7 |
| **Certificate** | 10.1 |
| **year** | 0.1 |
| **Unnamed: 0** | 0.0 |
| **Overview** | 0.0 |
| **IMDB_Rating** | 0.0 |
| **Genre** | 0.0 |
| **Runtime** | 0.0 |

**dtype:** float64

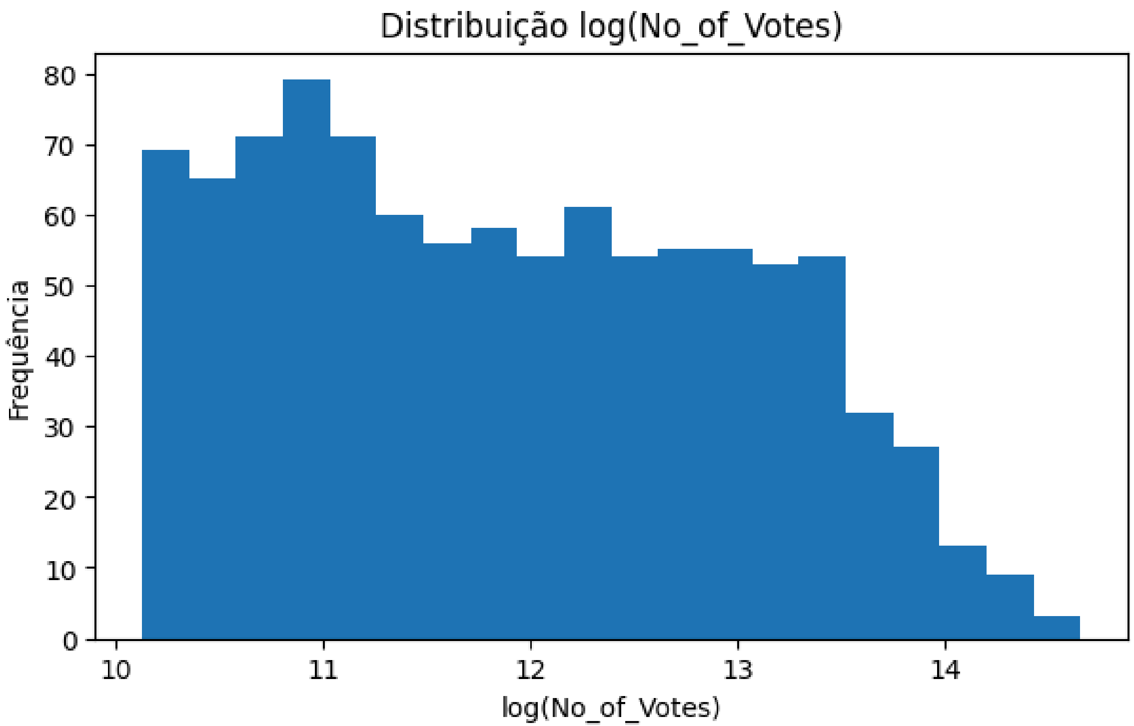
```
plt.figure(figsize=(7,4))
plt.hist(df["IMDB_Rating"].dropna(), bins=20)
plt.title("Distribuição IMDB_Rating")
plt.xlabel("IMDB_Rating"); plt.ylabel("Frequência")
plt.show()
```



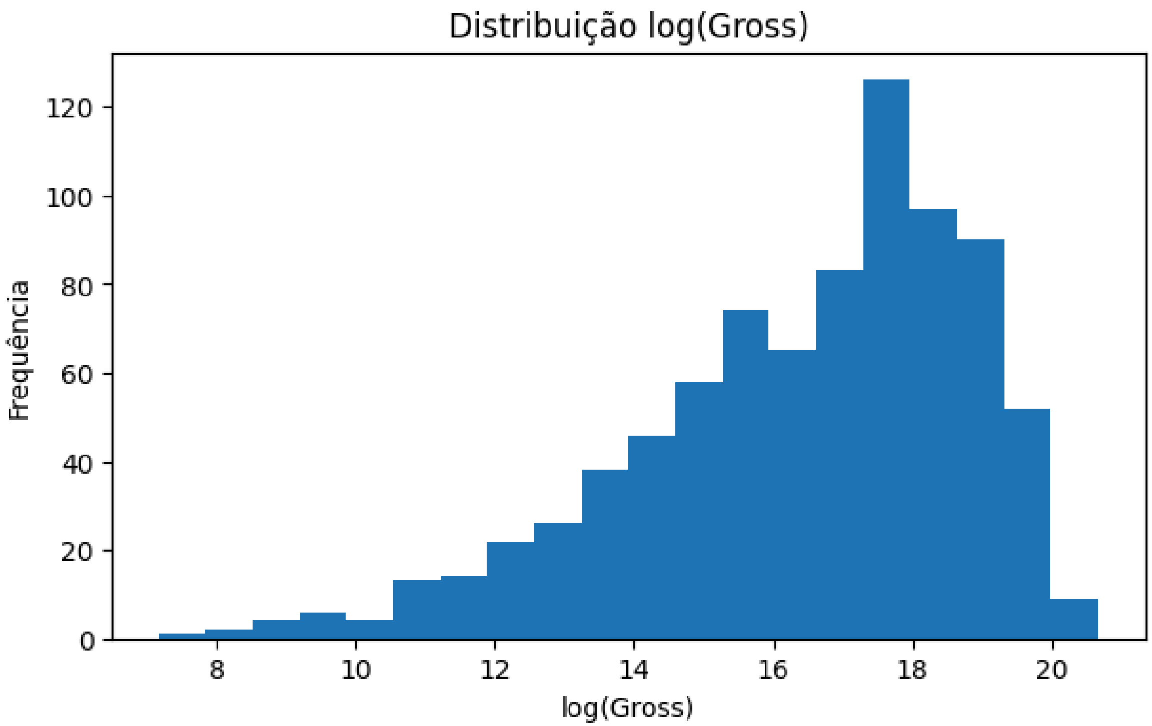

```
plt.figure(figsize=(7,4))
plt.hist(df["metascore"].dropna(), bins=20)
plt.title("Distribuição Meta_score")
plt.xlabel("Meta_score"); plt.ylabel("Frequência")
plt.show()
```




```
plt.figure(figsize=(7,4))
plt.hist(df["log_votes"].dropna(), bins=20)
plt.title("Distribuição log(No_of_Votes)")
plt.xlabel("log(No_of_Votes)"); plt.ylabel("Frequência")
plt.show()
```

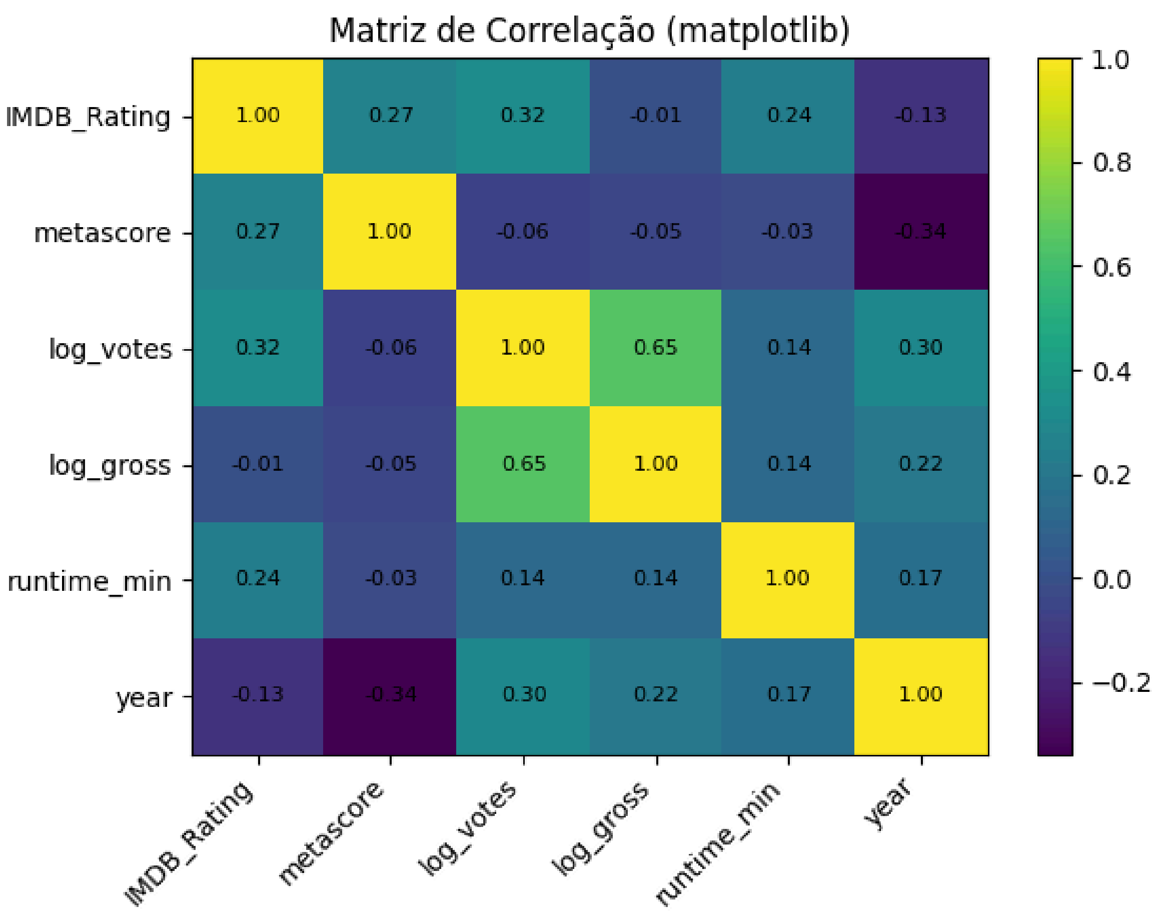



```
plt.figure(figsize=(7,4))
plt.hist(df["log_gross"].dropna(), bins=20)
plt.title("Distribuição log(Gross)")
plt.xlabel("log(Gross)"); plt.ylabel("Frequência")
plt.show()
```



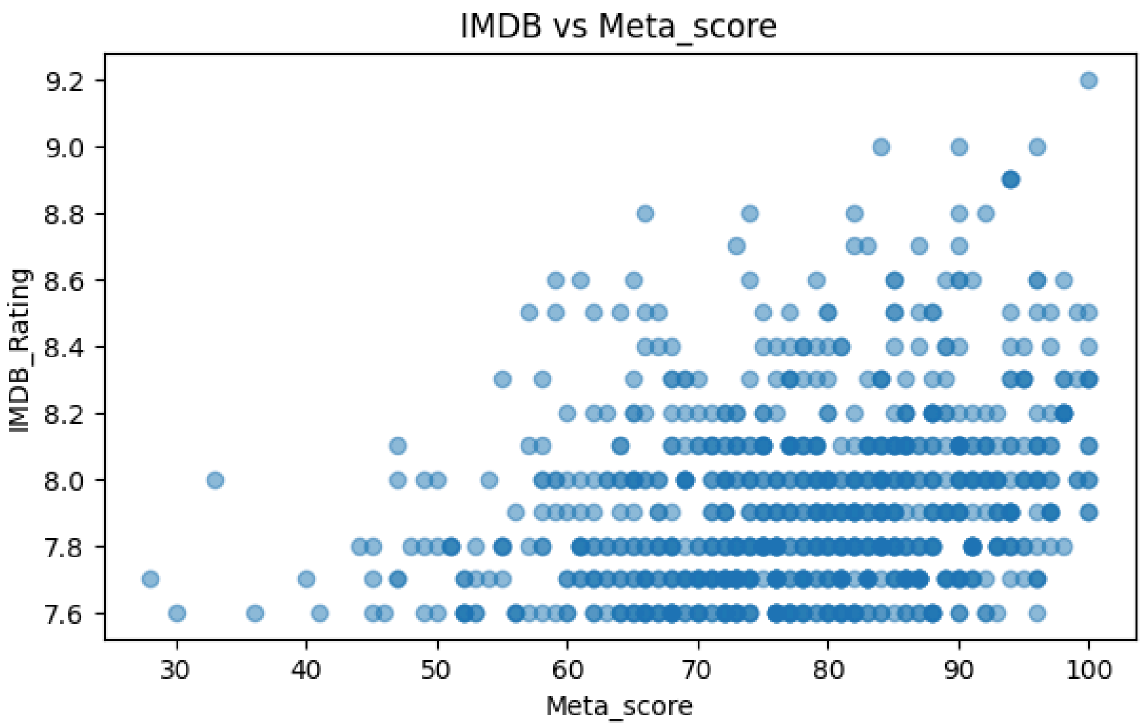

## Padrões de associação (correlações numéricas)

```
num = ["IMDB_Rating","metascore","log_votes","log_gross","runtime_min","year"]
C = df[num].corr(numeric_only=True)
fig, ax = plt.subplots(figsize=(6.5,5))
im = ax.imshow(C.values, aspect="auto")
ax.set_xticks(range(len(num))); ax.set_xticklabels(num, rotation=45, ha="right")
ax.set_yticks(range(len(num))); ax.set_yticklabels(num)
for i in range(len(num)):
    for j in range(len(num)):
        ax.text(j, i, f"{C.values[i,j]:.2f}", ha="center", va="center", fontsize=8)
plt.title("Matriz de Correlação (matplotlib)")
plt.colorbar(im); plt.tight_layout(); plt.show()
```

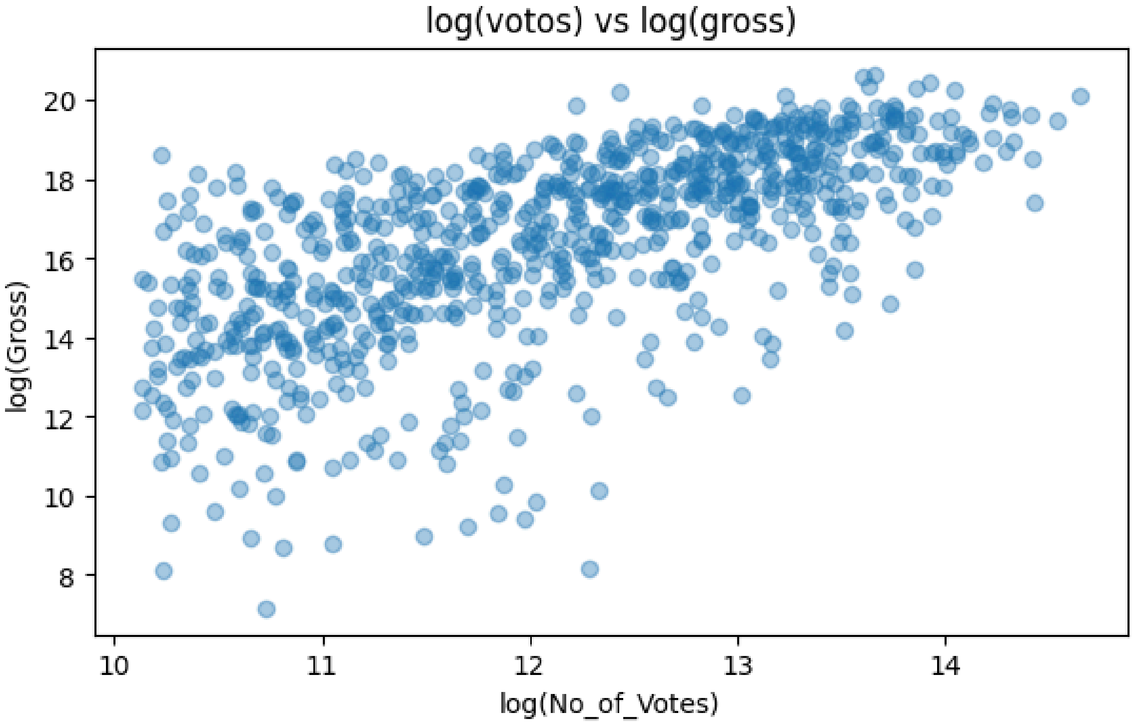



## Relações que interessam ao negócio

```
plt.figure(figsize=(7,4))
plt.scatter(df["metascore"], df["IMDB_Rating"], alpha=0.5)
plt.title("IMDB vs Meta_score")
plt.xlabel("Meta_score"); plt.ylabel("IMDB_Rating")
plt.show()
```



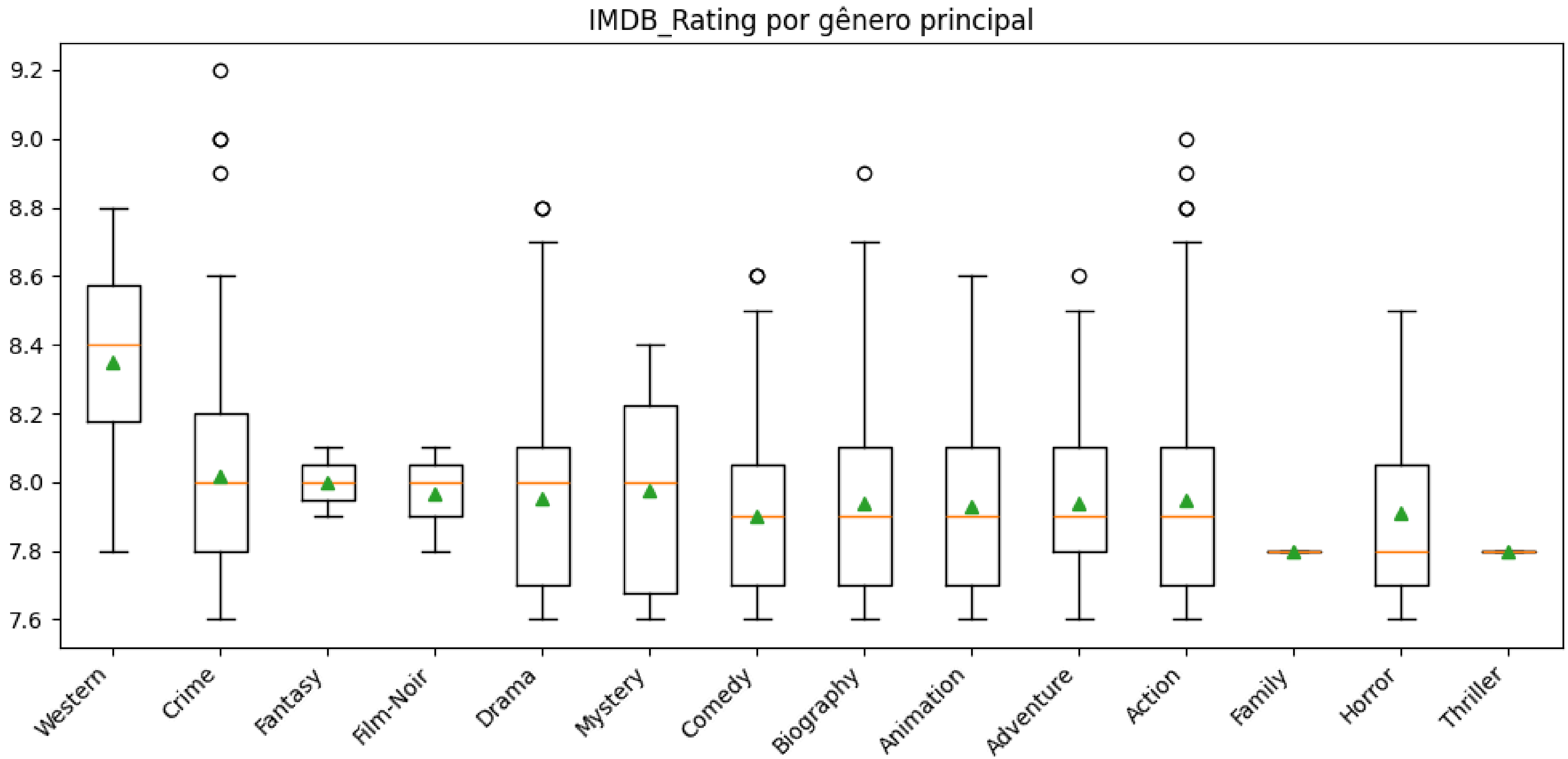

```
plt.figure(figsize=(7,4))
plt.scatter(df["log_votes"], df["log_gross"], alpha=0.4)
plt.title("log(votos) vs log(gross)")
plt.xlabel("log(No_of_Votes)"); plt.ylabel("log(Gross)")
x = df["log_votes"].replace([np.inf,-np.inf], np.nan).dropna()
y = df.loc[x.index, "log_gross"].dropna()
if len(x)==len(y) and len(x)>2:
    c = np.polyfit(x, y, 1)
    xp = np.linspace(x.min(), x.max(), 100)
    yp = c[0]*xp + c[1]
    plt.plot(xp, yp)
plt.show()
```



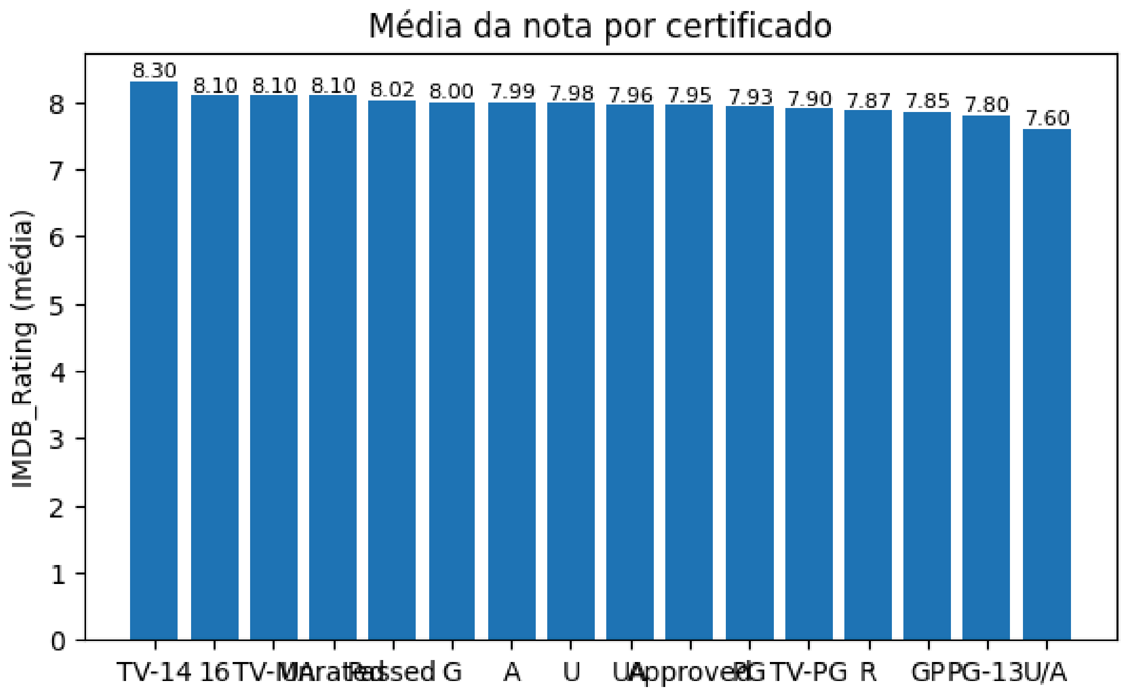

## Notas por gênero e por certificado

```
g_order = df.groupby("primary_genre")["IMDB_Rating"].median().dropna().sort_values(ascending=False)
labels = g_order.index.tolist()
data = [df.loc[df["primary_genre"]==g, "IMDB_Rating"].dropna().values for g in labels]
plt.figure(figsize=(10,5))
plt.boxplot(data, labels=labels, showmeans=True)
plt.xticks(rotation=45, ha="right")
plt.title("IMDB_Rating por gênero principal")
plt.tight_layout(); plt.show()
```

```
/tmp/ipython-input-874748225.py:5: MatplotlibDeprecationWarning: The 'labels' parameter of boxplot() has been renamed 'tick_labels' sir
  plt.boxplot(data, labels=labels, showmeans=True)
```



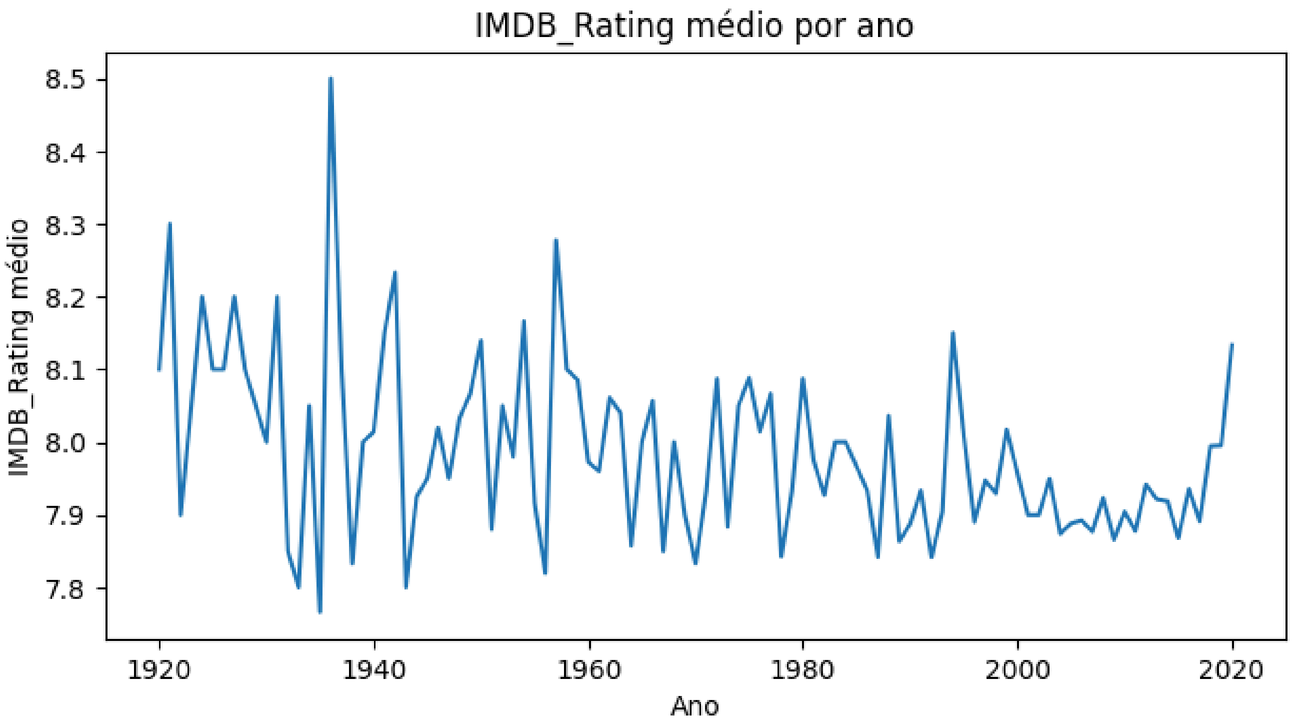
```
grp = df.groupby("Certificate")["IMDB_Rating"].describe()[["mean","count"]].sort_values("mean", ascending=False)
fig, ax = plt.subplots(figsize=(7,4))
ax.bar(grp.index.astype(str), grp["mean"].values)
ax.set_title("Média da nota por certificado"); ax.set_ylabel("IMDB_Rating (média)")
for i,v in enumerate(grp["mean"].values):
    ax.text(i, v, f"{v:.2f}", ha="center", va="bottom", fontsize=8)
plt.show()
```




## Tendência temporal da nota

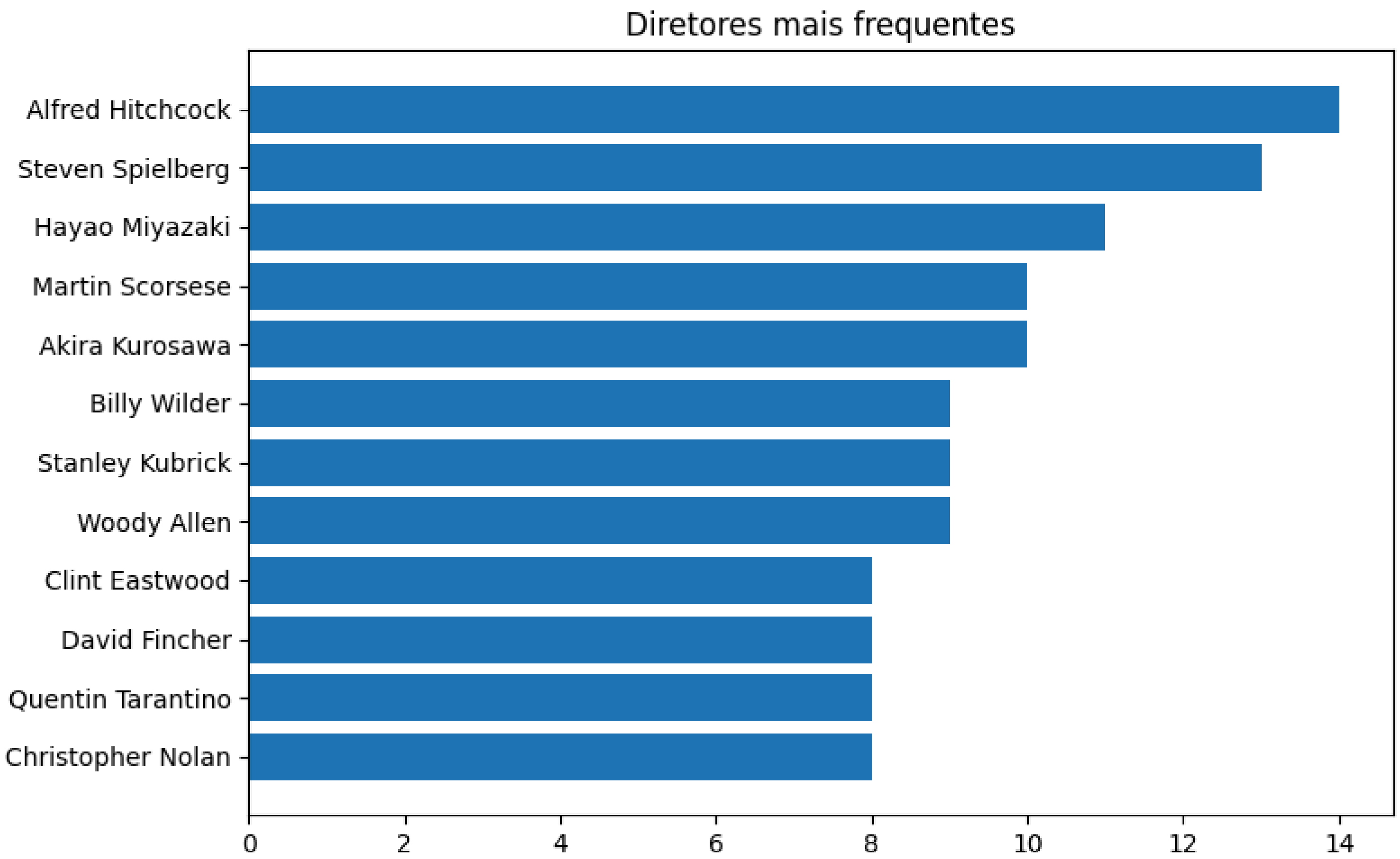
```
year_mean = df.dropna(subset=["year"]).groupby("year")["IMDB_Rating"].mean()
plt.figure(figsize=(8,4))
plt.plot(year_mean.index, year_mean.values)
plt.title("IMDB_Rating médio por ano")
```

```
plt.xlabel("Ano"); plt.ylabel("IMDB_Rating médio")
plt.show()
```

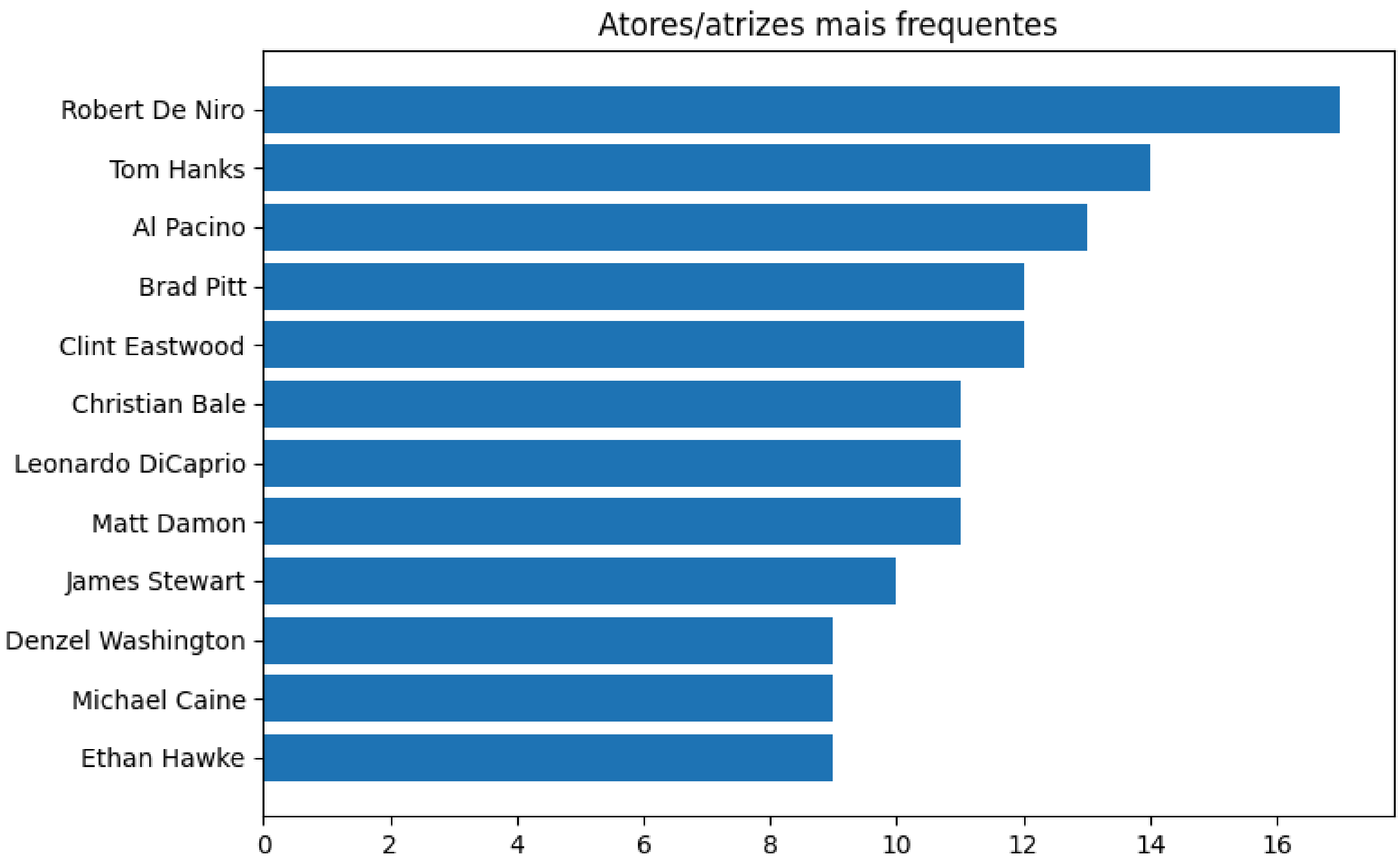



## Quem domina o dataset?

```
top_dir = df["Director"].value_counts().head(12)
fig, ax = plt.subplots(figsize=(8,5))
ax.barh(top_dir.index[::-1], top_dir.values[::-1])
ax.set_title("Diretores mais frequentes"); plt.tight_layout(); plt.show()
```




```
stars = pd.concat([df["Star1"],df["Star2"],df["Star3"],df["Star4"]])
top_star = stars.value_counts().head(12)
fig, ax = plt.subplots(figsize=(8,5))
ax.barh(top_star.index[::-1], top_star.values[::-1])
ax.set_title("Atores/atrizes mais frequentes"); plt.tight_layout(); plt.show()
```




## Hipóteses iniciais

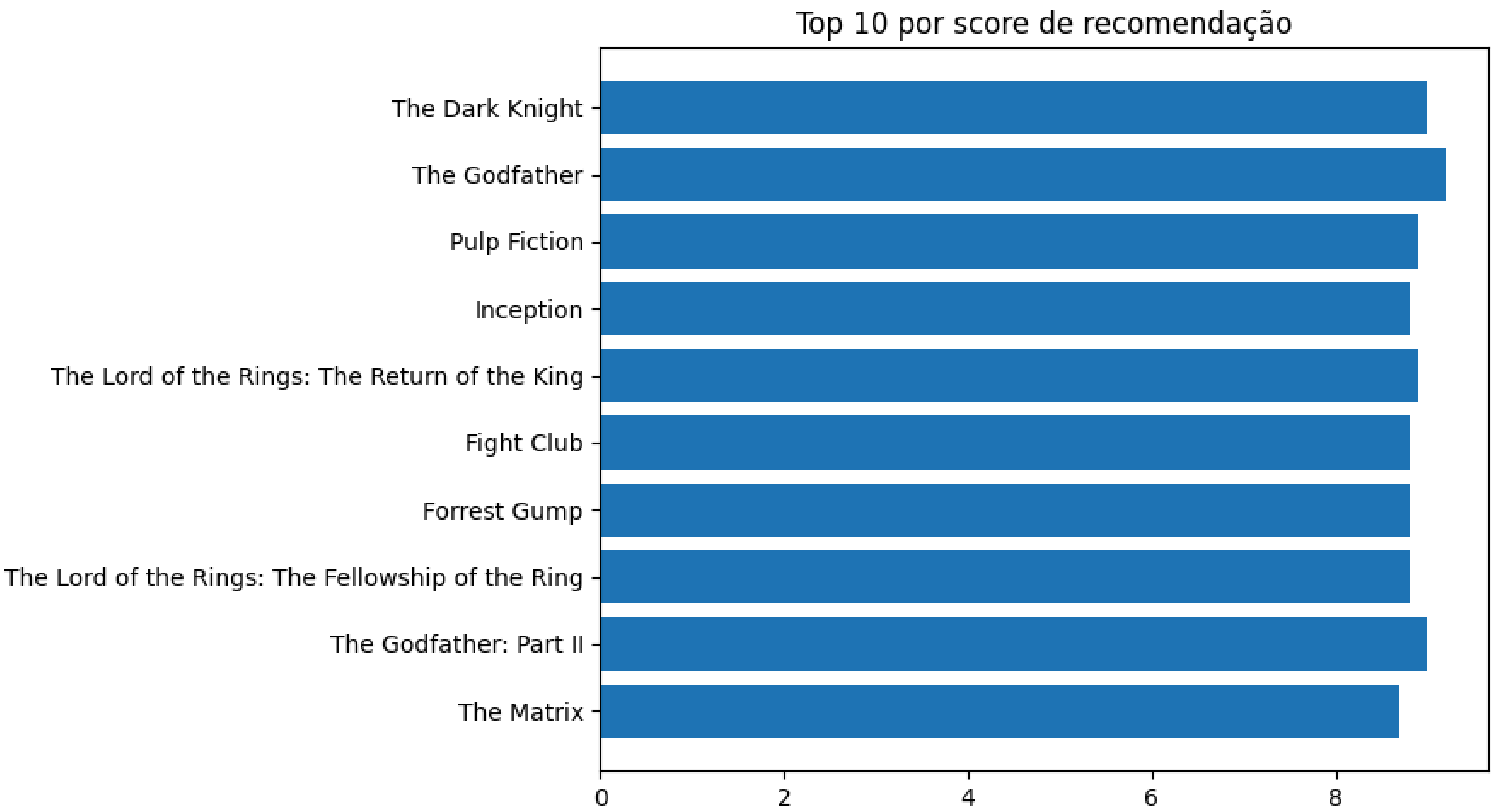
Minha impressão é que popularidade puxa faturamento; que a crítica e o público andam juntos na média; que tempo demais pode cansar; e que o texto do `Overview` entrega pistas fortes do gênero.

## Perguntas do desafio

# 1) O que eu recomendo para alguém que eu não conheço?

Gosto de equilibrar qualidade e alcance. Crio um score que multiplica a nota pelo peso relativo de votos. A lista abaixo é a minha “carta na manga”.

```
t = df.copy()
t["score"] = t["IMDB_Rating"] * (t["log_votes"]/t["log_votes"].max())
rec = t.sort_values(["score","IMDB_Rating","votes"], ascending=False)[["Series_Title","IMDB_Rating","votes","Genre"]].head(10)
rec_plot = rec.iloc[::-1]
fig, ax = plt.subplots(figsize=(9,5))
ax.barh(rec_plot["Series_Title"], rec_plot["IMDB_Rating"].values)
ax.set_title("Top 10 por score de recomendação")
plt.tight_layout(); plt.show()
rec
```




| | Series_Title | IMDB_Rating | votes | Genre |
|---|---|---|---|---|
| **1** | The Dark Knight | 9.0 | 2303232 | Action, Crime, Drama |
| **0** | The Godfather | 9.2 | 1620367 | Crime, Drama |
| **5** | Pulp Fiction | 8.9 | 1826188 | Crime, Drama |
| **7** | Inception | 8.8 | 2067042 | Action, Adventure, Sci-Fi |
| **4** | The Lord of the Rings: The Return of the King | 8.9 | 1642758 | Action, Adventure, Drama |
| **8** | Fight Club | 8.8 | 1854740 | Drama |
| **10** | Forrest Gump | 8.8 | 1809221 | Drama, Romance |

| | | | | |
|---|---|---|---|---|
| **9** | The Lord of the Rings: The Fellowship of the Ring | 8.8 | 1661481 | Action, Adventure, Drama |
| **2** | The Godfather: Part II | 9.0 | 1129952 | Crime, Drama |
| **13** | The Matrix | 8.7 | 1676426 | Action, Sci-Fi |

Próximas etapas: Gerar código com rec | Ver gráficos recomendados | New interactive sheet

## 2) O que se relaciona com alta expectativa de faturamento?

Uso `log_gross` como variável de interesse e vejo associações simples com itens que controlam popularidade e apelo de mercado.

```
cand = ["metascore","runtime_min","year","votes","IMDB_Rating","log_gross"]
df[cand].corr(numeric_only=True)["log_gross"].sort_values(ascending=False)
```

| | log_gross |
|---|---|
| **log_gross** | 1.000000 |
| **votes** | 0.545438 |
| **year** | 0.218014 |
| **runtime_min** | 0.141440 |
| **IMDB_Rating** | -0.005405 |
| **metascore** | -0.046170 |

**dtype:** float64

## 3) O que dá para tirar do `Overview`? Dá para inferir gênero?

Faço um teste rápido com TF-IDF + Regressão Logística. Se houver classes raras, reduzo. Mostro o relatório e, se couber, uma matriz de confusão enxuta.

```
ok = df.dropna(subset=["Overview","primary_genre"]).copy()
freq = ok["primary_genre"].value_counts()
ok = ok[ok["primary_genre"].isin(freq[freq>=2].index)]
X_text = ok["Overview"].astype(str)
y_gen = ok["primary_genre"].astype(str)

if y_gen.nunique() >= 2 and y_gen.value_counts().min() >= 2:
    vec = TfidfVectorizer(max_features=4000, ngram_range=(1,2), min_df=3)
    Xv = vec.fit_transform(X_text)
    Xtr, Xte, ytr, yte = train_test_split(Xv, y_gen, test_size=0.2, random_state=42, stratify=y_gen)
    clf = LogisticRegression(max_iter=300)
    clf.fit(Xtr, ytr)
    yp = clf.predict(Xte)
    print(classification_report(yte, yp))
    labs = sorted(yte.unique())
    if len(labs) <= 10:
        cm = confusion_matrix(yte, yp, labels=labs)
        fig, ax = plt.subplots(figsize=(0.6*len(labs)+3, 0.6*len(labs)+3))
        im = ax.imshow(cm, aspect="auto")
        ax.set_xticks(range(len(labs))); ax.set_xticklabels(labs, rotation=45, ha="right")
        ax.set_yticks(range(len(labs))); ax.set_yticklabels(labs)
        for i in range(len(labs)):
            for j in range(len(labs)):
                ax.text(j, i, str(cm[i,j]), ha="center", va="center", fontsize=8)
        plt.title("Matriz de confusão (gênero via Overview)"); plt.colorbar(im); plt.tight_layout(); plt.show()
else:
    print("Classes insuficientes para estratificar. Separamos as mais raras para manter o teste honesto.")
```

```
              precision    recall  f1-score   support

      Action       0.50      0.37      0.43        35
   Adventure       0.00      0.00      0.00        14
   Animation       1.00      0.06      0.12        16
   Biography       0.50      0.06      0.10        18
      Comedy       0.40      0.06      0.11        31
       Crime       0.00      0.00      0.00        22
       Drama       0.33      0.93      0.48        58
```

```
   Film-Noir       0.00      0.00      0.00         1
      Horror       0.00      0.00      0.00         2
     Mystery       0.00      0.00      0.00         2
     Western       0.00      0.00      0.00         1

    accuracy                           0.35       200
   macro avg       0.25      0.14      0.11       200
weighted avg       0.37      0.35      0.25       200

/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and b
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and b
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and b
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

## 4) Como eu prevejo a nota do IMDB?

Trato como **regressão**. Entro com numéricas (metascore, duração, ano, log de votos e de receita), categóricas (certificado, gênero, diretor e elenco) e texto (Overview via TF-IDF). Avalio com **RMSE** e **MAE** — erro médio é fácil de explicar, RMSE pesa deslizes maiores.

```python
y = df["IMDB_Rating"].astype(float)
X = df[["Overview","Certificate","primary_genre","Director","Star1","Star2","Star3","Star4",
        "metascore","runtime_min","year","log_votes","log_gross"]]

num = ["metascore","runtime_min","year","log_votes","log_gross"]
cat = ["Certificate","primary_genre","Director","Star1","Star2","Star3","Star4"]
txt = "Overview"

num_pipe = Pipeline([("imp", SimpleImputer(strategy="median")), ("sc", StandardScaler())])
cat_pipe = Pipeline([("imp", SimpleImputer(strategy="most_frequent")), ("oh", OneHotEncoder(handle_unknown="ignore"))])
tfidf = TfidfVectorizer(max_features=3500, ngram_range=(1,2), min_df=3)

pre = ColumnTransformer([("num", num_pipe, num),
                         ("cat", cat_pipe, cat),
                         ("txt", tfidf, txt)], sparse_threshold=0.0)
```

```
pipe = Pipeline([("pre", pre), ("model", HistGradientBoostingRegressor(random_state=42))])

Xtr, Xte, ytr, yte = train_test_split(X, y, test_size=0.2, random_state=42)
pipe.fit(Xtr, ytr)
pred = pipe.predict(Xte)
rmse = float(np.sqrt(mean_squared_error(yte, pred)))
mae  = float(mean_absolute_error(yte, pred))
{"RMSE": rmse, "MAE": mae}
```

```
{'RMSE': 0.20057878113830588, 'MAE': 0.15817527045027865}
```

```
plt.figure()
plt.scatter(yte, pred, alpha=0.6)
m = min(yte.min(), pred.min()); M = max(yte.max(), pred.max())
plt.plot([m,M],[m,M])
plt.xlabel("Real"); plt.ylabel("Predito"); plt.title("IMDB: Real vs Predito")
plt.show()
```