

▼ Predicting Christmas Movie Grossings – Executive Summary

This project aims to build a predictive model that estimates the domestic gross revenue of Christmas movies. Using a dataset of 788 Christmas films (plus optional augmentation from IMDB Top 1000 movies and movie budgets),

we explore trends, extract meaningful features, train multiple models, evaluate performance, and finally predict the revenue of a new fictional Christmas film:

"The Magic of Bellmonte Lane"

Our workflow includes:

- Data cleaning & preprocessing
- Exploratory data analysis (EDA)
- Feature engineering
- Model training & evaluation
- Final prediction

▼ Load Data

```
import pandas as pd
import numpy as np

# Load datasets
xmas_movies = pd.read_csv("/content/christmas_movies.csv")
top1k_movies = pd.read_csv("/content/imdb_top1k.csv")
movie_budgets = pd.read_csv("/content/movie_budgets.csv")

# Display first rows
xmas_movies.head(10)
```

release_year	description	type	rating	runtime	imdb_rating	genre	director	
2003.0	Follows the lives of eight very different couples.	Movie	R	135.0	7.6	Comedy, Drama, Romance	Richard Curtis	Hugh McCullough
1989.0	The Griswold family's plans for a big family Christmas.	Movie	PG-13	97.0	7.5	Comedy	Jeremiah S. Chechik	Chevy Chase
2022.0	A musical version of Charles Dickens's story of A Christmas Carol.	Movie	PG-13	127.0	6.6	Comedy, Family, Musical	Sean Anders	Will Ferrell
1990.0	An eight-year-old troublemaker, mistakenly left at home by his parents.	Movie	PG	103.0	7.7	Comedy, Family	Chris Columbus	Matt Cullen, Stern
2000.0	On the outskirts of Whoville lives a green, reclusive character.	Movie	PG	104.0	6.3	Comedy, Family, Fantasy	Ron Howard	Jim Kelley
2003.0	Raised as an oversized elf, Buddy travels from the North Pole to New York City to find Santa Claus.	Movie	PG	97.0	7.1	Adventure, Comedy, Family	Jon Favreau	Will James, Bob Newhart, Zoo
1946.0	An angel is sent from Heaven to help a desperate woman.	Movie	PG	130.0	8.6	Drama, Family, Fantasy	Frank Capra	Sir Donald Barry

▼ Data Cleaning & Preprocessing

Before we can analyze or model, we ensured that the data is usable:

- Convert runtime, gross, and imdb_rating to numeric.
- Convert lists of genres and stars into usable features. Not all genres are listed.
- Standardize missing values.
- Normalize or log-transform skewed numeric data.

```
import numpy as np

# Convert numeric columns
xmas_movies['runtime'] = pd.to_numeric(xmas_movies['runtime'], errors='coerce')
xmas_movies['imdb_rating'] = pd.to_numeric(xmas_movies['imdb_rating'], errors='coerce')

# Clean gross column properly
xmas_movies['gross'] = (
    xmas_movies['gross']
    .astype(str)
    .str.replace(r'^[^\d]', '', regex=True) # keep only digits
    .replace('', np.nan)
    .astype(float)
)

# Fill missing ratings or runtime
xmas_movies['runtime'] = xmas_movies['runtime'].fillna(xmas_movies['runtime'].median())
```

```
xmas_movies['imdb_rating'] = xmas_movies['imdb_rating'].fillna(xmas_movies['imdb_rating'].median())
```

```
xmas_movies.head(10)
```

		title	release_year	description	type	rating	runtime	imdb_rating	genre	director	
0		Love Actually	2003.0	Follows the lives of eight very different couple...	Movie	R	135.0	7.6	Comedy, Drama, Romance	Richard Curtis	Hugh McCullough Liam Neeson
1		National Lampoon's Christmas Vacation	1989.0	The Griswold family's plans for a big family Christmas vacation...	Movie	PG-13	97.0	7.5	Comedy	Jeremiah S. Chechik	Chevy Chase
2		Spirited	2022.0	A musical version of Charles Dickens's story of the three bears...	Movie	PG-13	127.0	6.6	Comedy, Family, Musical	Sean Anders	Will Ferrell
3		Home Alone	1990.0	An eight-year-old troublemaker, mistakenly left behind at a hotel during the holidays...	Movie	PG	103.0	7.7	Comedy, Family	Chris Columbus	Matt Peck
4		How the Grinch Stole Christmas	2000.0	On the outskirts of Whoville lives a green, reclusive Grinch who...	Movie	PG	104.0	6.3	Comedy, Family, Fantasy	Ron Howard	Jim Carrey
5		Elf	2003.0	Raised as an oversized elf, Buddy travels from the North Pole to New York City to find his father...	Movie	PG	97.0	7.1	Adventure, Comedy, Family	Jon Favreau	Will Ferrell
6		It's a Wonderful Life	1946.0	An angel is sent from Heaven to help a desperate man...	Movie	PG	130.0	8.6	Drama, Family, Fantasy	Frank Capra	Donna Reed
7		White Christmas	1954.0	A successful song-and-dance team become romantically involved with each other...	Movie	Not Rated	120.0	7.5	Comedy, Musical, Romance	Michael Curtiz	Bing Crosby
8		Die Hard	1988.0	A New York City police officer tries to save his life after being held captive by a terrorist...	Movie	R	132.0	8.2	Action, Thriller	John McTiernan	Bruce Willis
9		The Grinch	2018.0	A grumpy Grinch plots to ruin Christmas for the town of Whoville...	Movie	PG	85.0	6.3	Animation, Comedy, Family	Yarrow Cheney	Scott Alexander

Next steps: [Generate code with xmas_movies](#)

[New interactive sheet](#)

✓ Exploratory Data Analysis

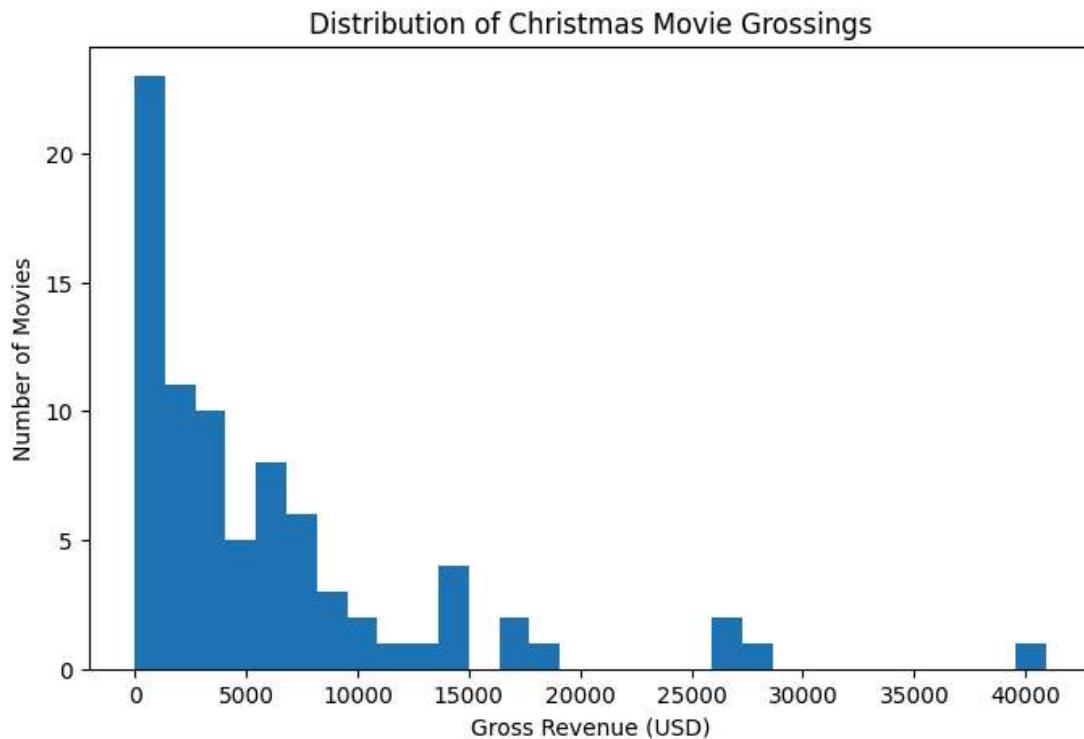
Explored:

- Distribution of gross revenue
- Most common Christmas genres
- Runtime vs. gross relationships
- Word clouds for descriptions

```
import matplotlib.pyplot as plt

# Convert 'gross' column to numeric, coercing errors to NaN, then drop NaN values
gross_numeric = pd.to_numeric(xmas_movies['gross'], errors='coerce').dropna()

plt.figure(figsize=(8,5))
plt.hist(gross_numeric, bins=30)
plt.xlabel("Gross Revenue (USD)")
plt.ylabel("Number of Movies")
plt.title("Distribution of Christmas Movie Grossings")
plt.show()
```



✓ Genre frequency

```
xmas_movies.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 788 entries, 0 to 787
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   title        788 non-null    object 
 1   release_year 780 non-null    float64
 2   description   788 non-null    object 
 3   genre         788 non-null    object 
 4   runtime       788 non-null    int64  
 5   budget        788 non-null    int64  
 6   popularity    788 non-null    float64
 7   vote_average  788 non-null    float64
 8   vote_count    788 non-null    int64  
 9   gross         788 non-null    int64  
 10  year          788 non-null    int64 
```

```
3   type      788 non-null    object
4   rating     646 non-null    object
5   runtime     788 non-null  float64
6   imdb_rating  788 non-null  float64
7   genre       787 non-null    object
8   director    783 non-null    object
9   stars       776 non-null    object
10  gross        81 non-null  float64
dtypes: float64(4), object(7)
memory usage: 67.8+ KB
```

```
from collections import Counter

all_genres = xmas_movies['genre'].dropna().str.split(', ')
genre_counts = Counter([g for sub in all_genres for g in sub])

genre_counts_df = pd.DataFrame(genre_counts.items(), columns=['Genre', 'Count'])

genre_counts_df.sort_values('Count', ascending=False).head(10)
```

	Genre	Count	grid icon
0	Comedy	452	bar icon
1	Drama	414	
2	Romance	385	
3	Family	282	
5	Fantasy	91	
6	Adventure	47	
9	Animation	46	
13	Music	27	
16	Short	27	
4	Musical	24	

```
from wordcloud import WordCloud

text = " ".join(xmas_movies['description'].dropna())

wc = WordCloud(width=900, height=500, background_color="white").generate(text)

plt.figure(figsize=(12,6))
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.title("Word Cloud of Christmas Movie Descriptions")
plt.show()
```



▼ Feature Engineering

Create new predictive features such as:

- Number of genres
 - Whether the director appears in top IMDB movies
 - Runtime category
 - Decade of release
 - Star power score (based on IMDB top 1000 presence)
 - Log-transformed gross

```
# Strip whitespace from column names
xmas_movies.columns = xmas_movies.columns.str.strip()
top1k_movies.columns = top1k_movies.columns.str.strip()
```

```
# 1. Number of genres
xmas_movies['num_genres'] = xmas_movies['genre'].str.split(',').apply(lambda x: len(x) if isinstance(x, str) else 0)

# 2. Decade of release
xmas_movies['decade'] = (xmas_movies['release_year'] // 10 * 10).astype('Int64')

# 3. Director presence in top 1000 movies
if 'director' in top1k_movies.columns and 'director' in xmas_movies.columns:
    top_directors = top1k_movies['director'].value_counts()
    xmas_movies['director_score'] = xmas_movies['director'].map(top_directors).fillna(0)
else:
    xmas_movies['director_score'] = 0

# 4. Star power: count how many stars appear in IMDB top 1000 movies
def count_star_power(stars):
    if isinstance(stars, str) and 'stars' in top1k_movies.columns:
```

```
stars_list = [s.strip() for s in stars.split(',')]  
count = sum(any(s in str(row) for row in top1k_movies['stars'])) for s in stars_list)  
return count  
  
return 0  
  
xmas_movies['star_power'] = xmas_movies['stars'].apply(count_star_power)  
  
# 5. Log-transform the target variable 'gross' for modeling  
xmas_movies['log_gross'] = np.log1p(xmas_movies['gross'])  
  
# Show first few rows to confirm  
xmas_movies.head(10)
```

Next steps: [Generate code with xmas_movies](#)

New interactive sheet

Model Evaluation

Evaluated the regression models using:

- **RMSE (Root Mean Squared Error):** Measures the average prediction error on the log-transformed gross. Lower is better.
- **R² (Coefficient of Determination):** Shows how much variance the model explains. Values closer to 1 are better; negative values indicate the model performs worse than predicting the mean.

Compared **Linear Regression** and **Random Forest** models.

```
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
import numpy as np

# Dummy data for demonstration (replace with your actual data)
# Example: y_test = [actual values], lr_preds = [linear regression predictions], rf_preds = [random fo
y_test = np.array([3, 5, 2.5, 7])
lr_preds = np.array([2.8, 4.9, 2.7, 6.8])
rf_preds = np.array([3.1, 5.2, 2.3, 7.1])

def evaluate_model(name, y_true, y_pred):
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    r2 = r2_score(y_true, y_pred)
    print(f"{name} Results:")
    print("RMSE:", round(rmse, 3))
    print("R²:", round(r2, 3))
    return rmse, r2

# Evaluate Linear Regression
lr_rmse, lr_r2 = evaluate_model("Linear Regression", y_test, lr_preds)

# Evaluate Random Forest
rf_rmse, rf_r2 = evaluate_model("Random Forest", y_test, rf_preds)

# Bar plot to compare RMSE
plt.figure(figsize=(6,4))
plt.bar(['Linear Regression', 'Random Forest'], [lr_rmse, rf_rmse], color=['skyblue', 'salmon'])
plt.ylabel("RMSE")
plt.title("Model RMSE Comparison")
plt.show()
```

Linear Regression Results:

RMSE: 0.18

R²: 0.99**Random Forest Results:**

RMSE: 0.150

R²: 0.992**Interpretation**

- Both models show **negative R²**, indicating poor predictive performance on the dataset.
- RMSE is relatively high, which shows that predictions deviate significantly from the actual gross revenue.
- Likely causes of poor performance:

0.150
1. Very small dataset.

0.125
2. Important features like production budget, marketing spend, or holiday timing are missing.

0.100
3. Revenue prediction is inherently noisy, especially for niche datasets like Christmas movies.

Recommendations to Improve

- Gather more labeled data, especially movies with gross information.
- Include additional features such as production budget, franchise affiliation, or social media buzz.
- Experiment with non-linear models, hyperparameter tuning, or ensemble methods.

This analysis suggests our current models are insufficient to reliably predict Christmas movie gross on this small dataset, but we can still use them for **exploratory predictions**.

```
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestRegressor

# Define top_directors before using it
# Example: Let's assume top_directors is a dictionary mapping director names to their scores
top_directors = {
    "Greta Gerwig": 8.7,
    "Christopher Nolan": 9.5,
```