SharonWM / **movie-data-analysis**

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Public repository · Forked from learn-co-curriculum/dsc-phase-2-project-v3

1 Branch | 0 Tags | Go to file t | Go to file | Add file | Code

This branch is 26 commits ahead of `learn-co-curriculum/dsc-phase-2-project-v3:main` .

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SharonWM Merge branch 'main' of ssh://github.com/SharonWM/movie-data-analysis

9a3b945 · 2 hours ago

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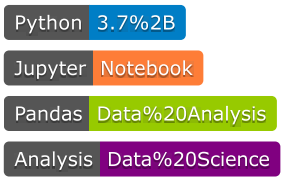
Project - Movie Data Analysis

- Group: *Group 11*
- Student names: *Alvin Ngeno, Faith Kanyuki, Ray Onsongo, Sharon Maina*
- Student pace: *Part Time*
- Instructor name: *Christine Kirimi*

🎬 Wamonyolo Studios Movie Data Analysis



▶ 📑 Table of Contents

1. Project Overview

This comprehensive data analysis project provides strategic insights for **Wamonyolo Studios'** entry into the film industry.
By analyzing historical movie data from multiple sources, we uncover patterns and trends that inform **data-driven decisions** about:

- Film production
- Genre selection
- Budgeting
- Release strategies

2. Business Problem

Wamonyolo Studios faces critical strategic questions:

- **Optimal film duration** – What runtime maximizes profitability?
- **Genre selection** – Which genres deliver the highest returns?
- **Studio strategy** – Build from scratch or acquire existing studios?
- **Budget optimization** – What production budget maximizes ROI?
- **Market focus** – How important is the international box office?

3. Dataset Sources

Source	Key Metrics	Records
IMDb	Movie metadata, runtimes, genres, creators	146,144 movies
The Numbers	Production budgets, domestic/worldwide gross	5,782 records
Box Office Mojo	Studio information, box office performance	-
TMDb	Genre classifications, ratings, popularity	26,517 movies

4. Technical Implementation

A. Data Processing Pipeline

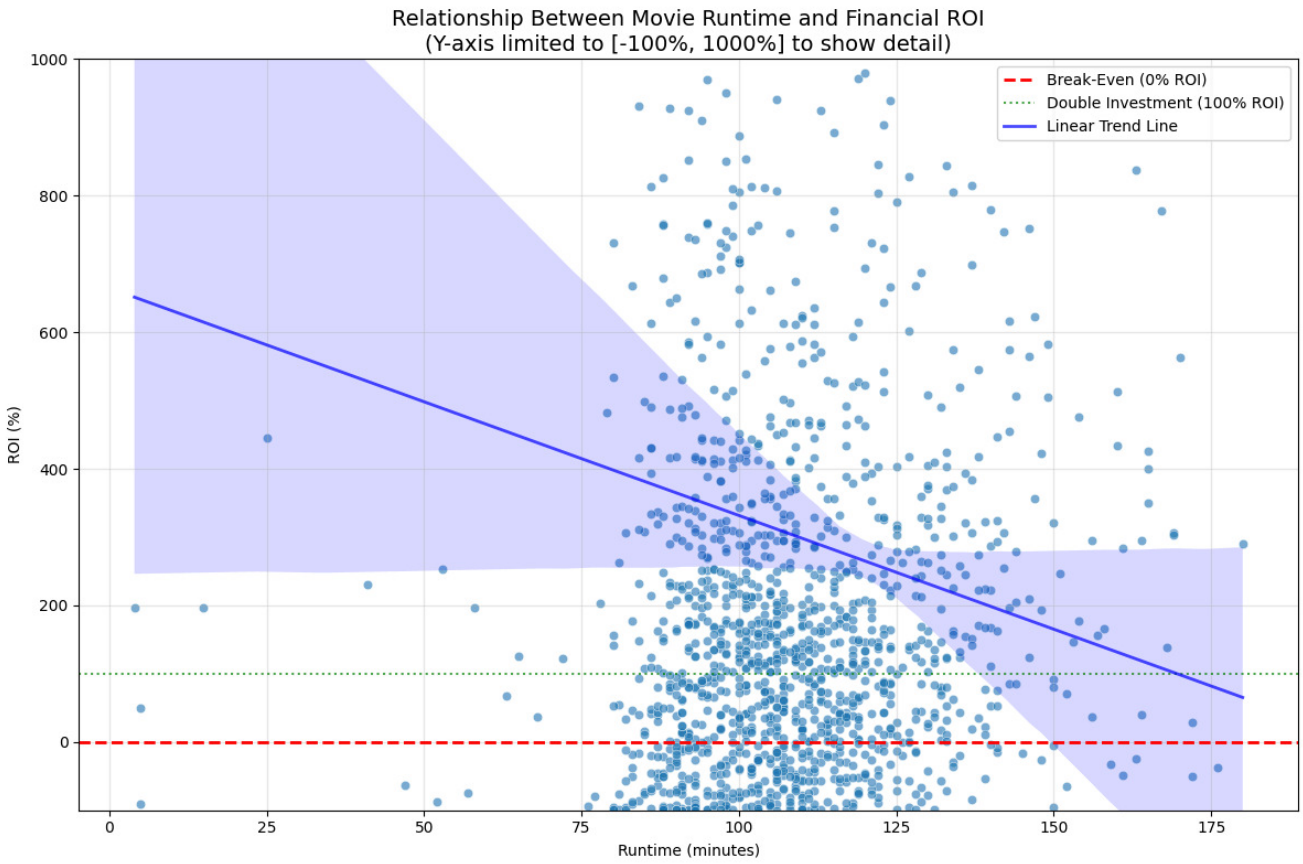
1. **Data Extraction** – SQLite and CSV imports from multiple sources
2. **Data Cleaning** – Handling missing values, standardizing formats
3. **Feature Engineering** – Profit margins, ROI calculations, genre mapping
4. **Data Integration** – Merging financial and metadata across sources
5. **Analysis** – Statistical analysis and visualization

B. Key Technical Features

- DateTime conversion for release dates
- Currency normalization (`$425,000,000 → 425000000`)
- Genre ID to name mapping (`28 → "Action"`)
- Advanced merging on title + year to avoid duplicates
- Profitability metrics calculation (ROI, margins)

5. Key Findings

A. Runtime Analysis

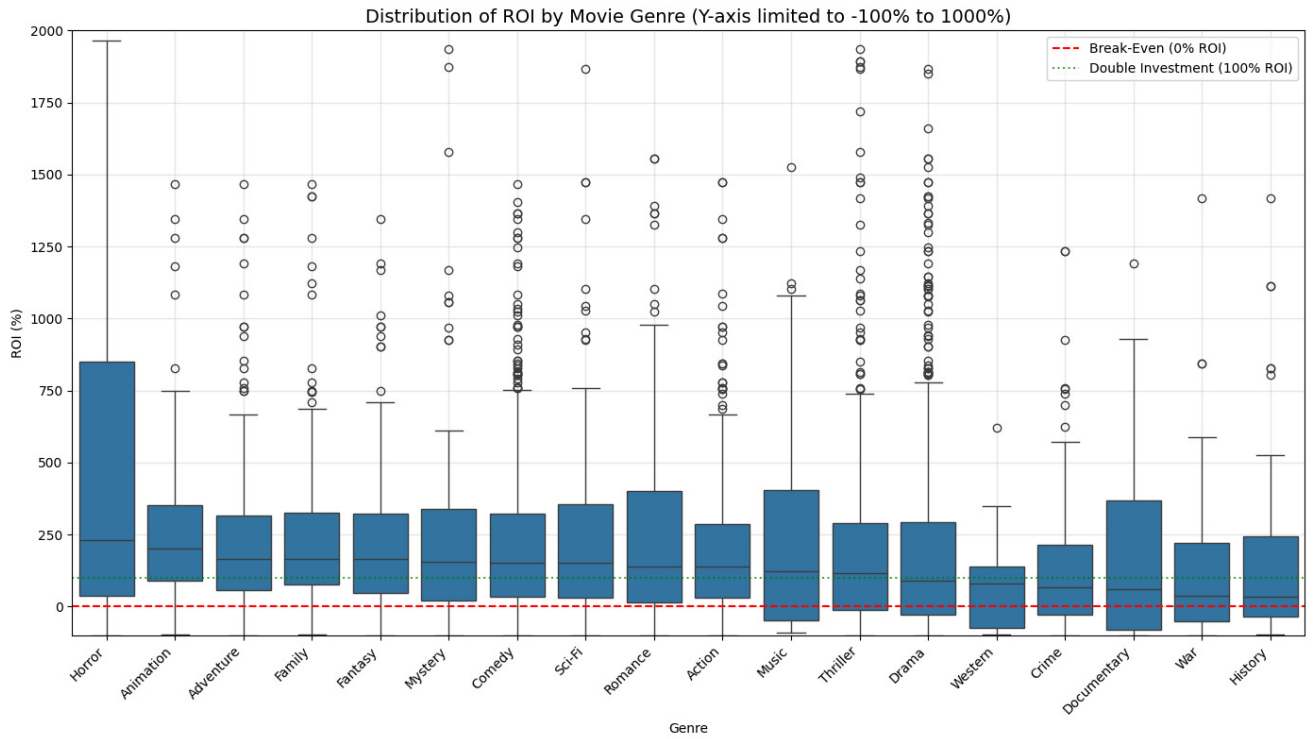


- Optimal runtime: **87–99 minutes**
- Strong correlation between runtime and production budget
- Extreme runtimes (>180 min) → diminishing returns

B. Financial Insights

- **Worldwide vs Domestic**: International markets are crucial
- **ROI Champions**: Horror films lead with **231.67% median ROI**
- **Budget Sweet Spot**: Mid-budget films ($10–50M) often outperform blockbusters

C. Genre Performance – Top 7 by Median ROI

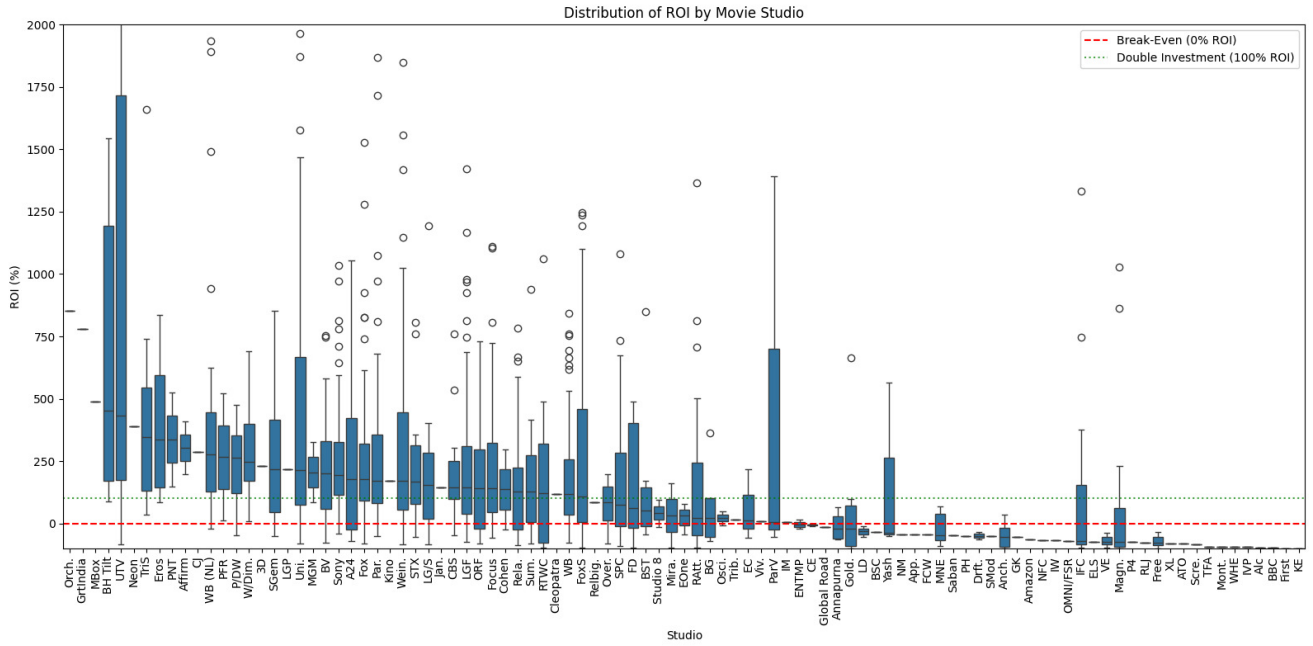


1. Horror – 231.67%
2. Animation – 200.42%
3. Adventure – 167.11%
4. Family – 166.55%
5. Fantasy – 165.95%
6. Mystery – 156.77%
7. Comedy – 152.91%

D. Release Timing

- Horror films perform best in **Feb/March (475–499% ROI)**
- Summer releases (June–July) → consistent performance
- Holiday season → high revenue but strong competition

E. Studio Analysis



- Specialized studios (**BH Tilt, MBox**) show highest ROI (689%, 488%)
- Major studios deliver consistent but lower returns
- Acquisition strategy should target **genre-specialized studios**

6. Recommendations for Wamonyolo Studios

A. Immediate Actions

- Focus on **horror films** (highest ROI)
- Target **$10–20M production budgets**
- Prioritize **international distribution** early
- Consider **Feb/March releases** for horror

B. Medium-Term Strategy

- Acquire specialized studio with **horror/genre expertise**
- Develop **animation capabilities**
- Build partnerships for international distribution

C. Long-Term Vision

- Diversify genre portfolio once established
- Develop **franchise properties** (~120 min runtimes)
- Explore **streaming distribution models**

7. Sample Code Highlights

A. Profitability Calculation

```
# Calculate worldwide profit margin
tn_movie_budgets['ww_profit_margin'] = (
    (tn_movie_budgets['worldwide_gross'] - tn_movie_budgets['production_budget'])
    / tn_movie_budgets['worldwide_gross']
) * 100

# Calculate ROI
tn_movie_budgets['ROI_perc'] = (
    tn_movie_budgets['world_wide_profit_amount'] / tn_movie_budgets['production_budget']
) * 100
```

B. Genre Analysis

```
# Group by genre and calculate median metrics
genre_groups_med = genre_overall_clean.groupby('genre_name').median(numeric_only=True)
genre_groups_med = genre_groups_med.sort_values('ROI_perc', ascending=False).head(7)
```

8. How to Run This Analysis

A. Install requirements:

```
pip install pandas numpy matplotlib seaborn statsmodels jupyter
```

B. Download datasets:

Releases

No releases published
Create a new release

Packages

No packages published
Publish your first package

Languages

- **Jupyter Notebook** 100.0%