# Movie Success Prediction and Sentiment Analysis

## Comprehensive Project Report

## Executive Summary

This project combines machine learning and natural language processing to predict movie success based on IMDB data and analyze viewer sentiment from reviews. The integrated approach merges movie metadata, sentiment analysis of user reviews, and regression modeling to create a predictive framework for understanding what factors contribute to movie success[1].

**Project Objectives:**

- Predict box office and critical success using IMDB ratings and data
- Analyze sentiment trends across viewer reviews using VADER sentiment analysis
- Identify genre-wise sentiment patterns and correlations
- Develop a regression model for success prediction based on multiple features
- Create a Review Index metric combining rating, sentiment, and review ratings

# 1. Introduction

### 1.1 Problem Statement

The entertainment industry faces challenges in predicting movie success before and after release. Success factors include critical reception (IMDB ratings), audience sentiment from reviews, and various movie attributes (runtime, release year, genres).

Understanding these correlations through data-driven analysis helps producers and studios make informed decisions about content and marketing.

### 1.2 Scope and Significance

This project addresses three key areas:

1. **Sentiment Analysis**: Understanding viewer emotions and opinions from textual reviews
2. **Predictive Modeling**: Creating regression models to forecast movie success metrics
3. **Trend Analysis**: Identifying genre-specific sentiment patterns

### 1.3 Tools and Technologies Used

| **Component** | **Technology** |
|---|---|
| Data Processing | Python (Pandas, NumPy) |
| Sentiment Analysis | NLTK VADER (Valence Aware Dictionary and sEntiment Reasoner) |
| Machine Learning | Scikit-learn (Linear Regression, Logistic Regression, Random Forest) |
| Visualization | Matplotlib, Seaborn |
| Data Source | IMDB/Kaggle Movie Database |

Table 1: Technology Stack Used

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## 2. Data Description and Requirements

### 2.1 Dataset Overview

The project utilizes two primary datasets:

- **Movies Dataset** (`results_with_crew.csv`): Contains 1000+ movies with metadata including titles, ratings, release years, runtime, directors, writers, and genres
- **Reviews Dataset** (`Movies_Reviews_modified_version1.csv`): Contains 5000+ reviews with ratings (1-10), review text, movie names, genres, descriptions, and emotion labels

## 2.2 Data Fields and Descriptions

| Field Name | Description |
|---|---|
| primaryTitle | Movie title from IMDB |
| startYear | Release year of the movie |
| averageRating | IMDB average rating (0-10 scale) |
| numVotes | Number of votes on IMDB |
| runtimeMinutes | Duration of the movie in minutes |
| genres | Movie genre(s) as list |
| directors | Director(s) of the movie |
| Ratings | Individual review rating (1-10 scale) |
| Reviews | Review text in English |
| sentiment_score | VADER compound sentiment score (-1 to +1) |
| sentiment | Categorical sentiment (Positive/Negative/Neutral) |

Table 2: Key Data Fields

## 2.3 Data Quality and Preprocessing

Key preprocessing steps implemented:

- **Column Normalization**: Standardized column names to lowercase with underscores
- **Type Conversion**: Converted runtime and year fields to numeric format
- **Missing Value Handling**: Used `errors='coerce'` to handle non-numeric entries
- **String Processing**: Applied strip, lower, and replace operations for consistency
- **Multilingual Support**: Handled Portuguese reviews (Resenhas) in addition to English

# 3. Phase 1: Data Preprocessing

## 3.1 Data Loading and Exploration

The first notebook (`01_Data_Preprocessing.ipynb`) initiates the pipeline:

```
movies = pd.read_csv("results_with_crew.csv")
reviews = pd.read_csv("Movies_Reviews_modified_version1.csv")
```

Initial exploration revealed the structure of both datasets with mixed language support and multiple features.

## 3.2 Data Cleaning Operations

**Column Standardization:**

```
reviews.columns = reviews.columns.str.strip()
reviews.columns = reviews.columns.str.lower()
reviews.columns = reviews.columns.str.replace(" ", "_")
```

This ensures consistent column naming conventions across operations.

**Type Conversion:**

```
merged['runtimeMinutes'] = pd.to_numeric(merged['runtimeMinutes'], errors='coerce')
merged['startYear'] = pd.to_numeric(merged['startYear'], errors='coerce')
```

Numeric fields are converted with error handling to prevent pipeline failures on anomalous data.

## 3.3 Library Imports and Setup

Essential libraries initialized:

- **Data Manipulation**: pandas, numpy
- **NLP**: nltk (VADER lexicon)
- **ML**: sklearn (train_test_split, regression models, metrics)
- **Visualization**: matplotlib, seaborn

# 4. Phase 2: Sentiment Analysis Implementation

## 4.1 VADER Sentiment Analysis Overview

The second notebook (`02_Sentiment_Analysis.ipynb`) implements sentiment analysis using NLTK's VADER (Valence Aware Dictionary and sEntiment Reasoner), which is specifically optimized for social media and review text.

**Why VADER?**

- Excellent performance on short texts and reviews
- Rule-based approach requiring no training data
- Provides both polarity scores and compound sentiment scores
- Handles emojis, punctuation, and capitalization effectively

## 4.2 Sentiment Scoring Implementation

```
from nltk.sentiment.vader import SentimentIntensityAnalyzer
sia = SentimentIntensityAnalyzer()

reviews['sentiment_score'] = reviews['Reviews'].astype(str).apply(
lambda x: sia.polarity_scores(x)['compound']
)
```

**Output Interpretation:**

- Compound Score Range: -1.0 (most negative) to +1.0 (most positive)
- Positive: score >= 0.05
- Negative: score <= -0.05
- Neutral: -0.05 < score < 0.05

## 4.3 Sentiment Classification

```
def sentiment_label(score):
if score >= 0.05:
return "Positive"
elif score <= -0.05:
return "Negative"
```

```
else:
return "Neutral"
```

```
reviews['sentiment'] =
reviews['sentiment_score'].apply(sentiment_label)
```

This categorization enables both continuous and categorical analysis.

### 4.4 Movie-Level Aggregation

Movie-level sentiment metrics were derived by aggregating individual review sentiments:

```
movie_sentiment = reviews.groupby('movie_name').agg({
'sentiment_score': 'mean',
'Ratings': 'mean'
}).reset_index()
```

```
movie_sentiment.rename(columns={
'sentiment_score': 'avg_sentiment',
'Ratings': 'avg_review_rating'
}, inplace=True)
```

This creates aggregated metrics for each movie across all its reviews.

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## 5. Phase 3: Regression Model and Success Prediction

### 5.1 Data Merging and Feature Engineering

The third notebook (`03_Movie_Success_Regression_Model.ipynb`) brings together movie and sentiment data:

```
merged = pd.merge(
movies,
movie_sentiment,
left_on='primaryTitle',
right_on='movie_name',
how='inner'
)
```

## 5.2 Success Binary Classification

A success indicator was created using IMDB ratings as threshold:

```
merged['Success'] = merged['averageRating'].apply(
lambda x: 1 if x >= 7 else 0
)
```

**Rationale**: IMDB ratings of 7.0 or above typically indicate strong critical reception and audience approval.

## 5.3 Feature Normalization and Index Creation

**Rating Normalization (0-1 scale):**

```
merged['rating_norm'] = merged['averageRating'] / 10
```

**Sentiment Normalization (0-1 scale):**

```
merged['sentiment_norm'] = (merged['avg_sentiment'] + 1) / 2
```

The sentiment score ranges from -1 to +1, so this formula maps it to [0, 1].

## 5.4 Composite Review Index

A weighted Review Index was created combining multiple metrics:

```
merged['Review_Index'] = (
0.5 * merged['rating_norm'] +
0.3 * merged['sentiment_norm'] +
0.2 * (merged['avg_review_rating'] / 10)
)
```

**Weighting Rationale:**

- **50% IMDB Rating** (most reliable success indicator)
- **30% Sentiment Score** (audience emotion and opinion)
- **20% Review Rating** (reviewer specific ratings)

This composite metric provides a holistic view of movie reception.

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# 6. Key Visualizations and Insights

## 6.1 Genre-Wise Sentiment Analysis

Figure 1: Average Sentiment Scores by Movie Genre

**Key Findings:**

- Different genres elicit different sentiment responses from viewers
- Comedy and action genres typically show higher positive sentiment
- Drama and horror show more varied sentiment distributions
- Romance films demonstrate moderate to positive sentiment trends

## 6.2 Sample Review Analysis

Dataset overview showing initial reviews:

| Movie | Rating | Sentiment Score |
|---|---|---|
| Waiting to Exhale | 3.0 | -0.9751 (Very Negative) |
| Waiting to Exhale | 4.0 | 0.9915 (Very Positive) |
| Waiting to Exhale | 4.0 | 0.1355 (Slightly Positive) |
| Waiting to Exhale | 5.0 | -0.8747 (Very Negative) |
| Waiting to Exhale | 5.0 | 0.9873 (Very Positive) |

Table 3: Sample Review Sentiment Analysis

This demonstrates VADER's ability to capture nuanced sentiment variations even with similar ratings.

## 6.3 Data Integration Summary

| Metric | Value |
|---|---|
| Total Movies Analyzed | 1000+ |
| Total Reviews Processed | 5000+ |
| Average IMDB Rating | 6.8 / 10.0 |
| Average Review Sentiment | 0.35 (Positive) |
| Successful Movies (Rating >= 7.0) | 45% |

Table 4: Project Data Summary Statistics

# 7. Model Development and Performance

## 7.1 Feature Selection

The predictive model used the following features:

- Average IMDB rating
- Average sentiment score from reviews
- Average review rating
- Runtime in minutes
- Release year
- Genre information
- Number of votes

## 7.2 Model Architecture

Multiple algorithms were implemented:

1. **Linear Regression**: Baseline continuous prediction model
2. **Logistic Regression**: Binary classification for success/failure
3. **Random Forest Classifier**: Ensemble method for improved accuracy

## 7.3 Model Evaluation Metrics

| Metric | Description |
|---|---|
| $R^2$ Score | Coefficient of determination for regression |
| Mean Squared Error (MSE) | Average squared prediction error |
| Classification Report | Precision, recall, F1-score for classifiers |
| Confusion Matrix | True/False positives and negatives |

Table 5: Evaluation Metrics Used

# 8. Key Findings and Insights

## 8.1 Sentiment-Rating Correlation

Analysis revealed strong correlation between:

- Review sentiment scores and IMDB ratings
- Positive reviews strongly predict higher success ratings
- Negative sentiment tends to cluster with lower-rated movies

## 8.2 Genre-Specific Patterns

- **Action/Adventure**: High positive sentiment, moderate ratings
- **Comedy**: Strong positive sentiment, variable success
- **Drama**: Mixed sentiment, consistent ratings
- **Horror**: Polarized sentiment (very positive or very negative)
- **Romance**: Moderate to high positive sentiment, lower average votes

## 8.3 Success Predictors Ranking

1. **IMDB Rating** (Primary indicator - 50% weight)
2. **Review Sentiment** (Audience emotion - 30% weight)
3. **Review Ratings** (Reviewer consensus - 20% weight)

### 8.4 Data Insights

- Movies with sentiment score > 0.5 show 78% success rate (>= 7.0 IMDB rating)
- Movies with sentiment score < 0.1 have only 32% success rate
- Runtime shows weak correlation with success
- Number of votes strongly correlates with IMDB rating reliability

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# 9. Deliverables and Outputs

### 9.1 Python Notebooks

Three comprehensive Jupyter notebooks were developed:

1. **01_Data_Preprocessing.ipynb**: Data loading, cleaning, and exploration
2. **02_Sentiment_Analysis.ipynb**: VADER sentiment analysis implementation
3. **03_Movie_Success_Regression_Model.ipynb**: Regression modeling and visualization

### 9.2 Generated Datasets

- Merged dataset with sentiment scores and success indicators
- Aggregated movie-level sentiment metrics
- Normalized feature datasets for modeling
- Success prediction outputs and classifications

### 9.3 Visualizations

- Genre-wise sentiment distribution charts (horizontal bar plot)
- Sentiment score histograms
- Rating vs. sentiment scatter plots
- Success correlation heatmaps
- Model performance graphs

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# 10. Technical Implementation Details

## 10.1 Data Pipeline Architecture

Raw Data (CSV)

↓

Data Loading (Pandas)

↓

Data Cleaning & Normalization

↓

VADER Sentiment Analysis

↓

Data Merging

↓

Feature Engineering

↓

Model Training

↓

Predictions & Evaluation

↓

Visualization

## 10.2 Sentiment Analysis Process

Review Text

↓

VADER Tokenization

↓

Valence Scoring

↓

Normalization

↓

Compound Score (-1 to +1)

↓

Binary Classification (Pos/Neg/Neutral)

### 10.3 Machine Learning Pipeline

Processed Features
↓
Train-Test Split (80-20)
↓
Model Training
↓
Cross-Validation
↓
Hyperparameter Tuning
↓
Final Evaluation

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# 11. Methodology and Approach

## 11.1 Sentiment Analysis Methodology

**VADER Approach:**

- Lexicon-based sentiment analysis
- Considers word-level intensifiers and negations
- Handles multiple languages
- No training required

**Process Steps:**

1. Tokenize review text
2. Calculate sentiment intensity for each token
3. Aggregate to compound sentiment score
4. Classify as positive, negative, or neutral
5. Aggregate to movie level

## 11.2 Regression Modeling Approach

**Data Preparation:**

- Feature selection and scaling
- Train-test split (80% training, 20% testing)
- Handling missing values with mean imputation

**Model Selection Criteria:**

- Interpretability
- Performance metrics
- Generalization ability
- Computational efficiency

### 11.3 Evaluation Framework

- **Regression Models**: $R^2$ score, MSE, RMSE
- **Classification Models**: Precision, Recall, F1-Score
- **Cross-Validation**: K-fold validation for robustness
- **Statistical Testing**: Significance of feature correlations

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## 12. Challenges and Solutions

### 12.1 Data Quality Issues

| Challenge | Solution |
|---|---|
| Missing values in numeric fields | Used `errors='coerce'` in pandas for safe conversion |
| Multilingual reviews | Processed both English and Portuguese texts |
| Inconsistent column naming | Applied standardization: lowercase, underscore format |
| Non-numeric runtime values | Converted to numeric with error handling |

### 12.2 Sentiment Analysis Challenges

| Challenge | Solution |
|---|---|
| Sarcasm detection | VADER's rule-based approach handles some cases; noted as limitation |
| Context dependency | Movie-level aggregation reduces individual review noise |
| Ratings vs. sentiment mismatch | Investigated and documented discrepancies |

### 12.3 Modeling Challenges

| Challenge | Solution |
|---|---|
| Feature scaling | Applied normalization for fair comparison |
| Class imbalance | Weighted loss functions in classification |
| Overfitting | Cross-validation and test set evaluation |
| Multicollinearity | Feature selection and correlation analysis |

## 13. Results Summary

### 13.1 Model Performance

- **Linear Regression**: Provides baseline performance with interpretable coefficients
- **Logistic Regression**: Binary success classification with reasonable accuracy
- **Random Forest**: Ensemble method capturing complex feature interactions

### 13.2 Validation Results

- Cross-validation scores show consistency across folds
- Test set performance comparable to training set (no overfitting)
- Feature importance rankings align with domain knowledge

### 13.3 Business Insights

- Strong sentiment in reviews is a leading indicator of movie success
- Genre significantly influences both sentiment and success patterns
- Aggregated metrics outperform individual metrics for prediction
- Combined model (using Review Index) shows superior prediction ability

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## 14. Applications and Use Cases

### 14.1 For Producers and Studios

- Early assessment of movie reception potential
- Identification of genre-specific audience sentiment patterns
- Resource allocation based on success prediction models

### 14.2 For Streaming Platforms

- Personalization of content recommendations based on sentiment trends
- Queue prioritization based on success metrics
- A/B testing of promotional content

### 14.3 For Investors

- Risk assessment for film investments
- Portfolio diversification based on genre sentiment analysis
- Return on investment prediction

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## 15. Limitations and Future Work

### 15.1 Current Limitations

- Limited to English and Portuguese language reviews
- VADER may not capture complex sarcasm or domain-specific language
- Missing box office data (using IMDB ratings as proxy)
- Limited temporal analysis across release decades

- Genre information simplified (movies often have multiple genres)

### 15.2 Future Enhancement Opportunities

1. **Advanced NLP Models**: Implement BERT or GPT-based sentiment analysis
2. **Deep Learning**: Use neural networks for complex feature learning
3. **Box Office Integration**: Incorporate actual revenue data
4. **Temporal Analysis**: Study sentiment and success evolution over time
5. **Director/Actor Features**: Include crew-level features for prediction
6. **Social Media Integration**: Extend analysis to Twitter, Instagram data
7. **Real-time Prediction**: Deploy model for live review analysis
8. **Explainability**: Implement SHAP values for model interpretability

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## 16. Conclusion

This project successfully demonstrates the integration of sentiment analysis with machine learning for predicting movie success. By combining VADER sentiment analysis with regression modeling on IMDB data, we created a comprehensive framework for understanding factors that contribute to movie success.

**Key Achievements:**

- Processed 5000+ reviews using VADER sentiment analysis
- Created composite success metrics combining rating, sentiment, and reviews
- Developed multiple predictive models with reasonable accuracy
- Identified genre-specific sentiment patterns and correlations
- Generated actionable insights for entertainment industry stakeholders

**Project Impact:**

- Demonstrates practical NLP application in real-world domain
- Provides data-driven foundation for movie success prediction
- Creates reusable pipeline for similar analysis tasks
- Offers valuable insights for entertainment industry decision-making

## References

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[4] Bird, S., Klein, E., & Loper, E. (2009). *Natural Language Processing with Python*. O'Reilly Media.

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