**Rotten Tomatoes**

Movies Rating Prediction

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ABSTRACT

This project explores the development of a high-performing classification algorithm to predict the status of movies on Rotten Tomatoes—whether labeled as 'Rotten,' 'Fresh,' or 'Certified-Fresh.' Leveraging two distinct datasets, the project applies tree-based algorithms like Decision Tree Classifier and Random Forest to solve the classification problem using both numerical/categorical features and textual data. The first approach utilizes the movies dataset, which includes features like audience ratings, tomatometer scores, genres, and directors, while the second approach employs the critics dataset to analyze textual review data. The project aims to demonstrate the efficacy of tree-based models in handling varied data types and providing interpretable results for movie classification.

KEYWORDS

Prediction, Classification Algorithms, Tree-Based Models, Text and Numerical Analysis, Random Forest, Decision Trees

1 Introduction

Rotten Tomatoes is a trusted platform for movie ratings, hosting both audience scores and professional critic reviews. With an abundance of data available on movies and reviews, the task of predicting a movie's status ('Rotten,' 'Fresh,' or 'Certified-Fresh') presents an intriguing machine-learning challenge. By combining structured data from the movies dataset and unstructured textual data from the critics dataset, this project provides a comprehensive exploration of classification techniques. The focus lies on tree-based algorithms like Decision Tree Classifier and Random Forest, which are known for their flexibility and ability to handle complex data relationships. This study not only highlights the practical implementation of these models but also underscores the importance of feature selection and preprocessing in building robust classifiers.

2 Data

Rotten Tomatoes, a widely recognized platform for movie ratings, offers two distinct types of reviews: audience scores reflecting public opinion and professional reviews from certified critics affiliated with writing guilds and film associations.

2.1 Source of dataset

The datasets used in this project were scraped from the publicly accessible Rotten Tomatoes website as of October 31, 2020. These datasets provide a unique opportunity to analyze and predict a movie's classification—'Rotten,' 'Fresh,' or 'Certified-Fresh'—by leveraging both structured and unstructured data.

The **movies dataset** includes features such as audience ratings, tomatometer scores, genres, directors, and release dates, offering a structured perspective on the factors influencing a movie’s status. On the other hand, the **critics dataset** provides textual reviews, capturing nuanced opinions from professional critics, which can be processed for predictive insights. Together, these datasets facilitate a comprehensive exploration of classification techniques using tree-based algorithms, illustrating their ability to handle diverse data types and uncover the relationships underlying a movie's rating.

2.2 Characters of the datasets

The critic reviews dataset contains 50,000 rows and includes columns such as movie\_title, critic\_name, critic\_score, publication, review\_content, and review\_date. The critic\_score is a percentage ranging from 0 to 100, and the review\_date was standardized to a uniform datetime format for temporal analysis.

The movies dataset provides metadata about movies, including columns like movie\_title, release\_year, genre, runtime, box\_office, and tomatometer\_score. The runtime is recorded in minutes, and the box office earnings were cleaned to ensure a consistent numeric format by removing non-numeric characters such as $ and ,. Missing or null values in critical columns were removed to maintain data integrity.

To enable deeper insights, the datasets were combined using the movie\_title column as a common key. This merge allowed the association of critic reviews with movie metadata. New analytical categories were created to enrich the analysis. For example, a score\_category column was added to the critic reviews dataset, grouping scores into bins such as Excellent (≥80), Good (60–79), Average (40–59), and Poor (<40). Similarly, a release\_decade column was derived in the movies dataset by truncating release\_year to the nearest decade, facilitating trend analysis over time. These transformations ensured the datasets were clean, structured, and ready for detailed exploration.

We combine several key features from the original movie dataset to create a comprehensive set of attributes for modeling. These features include **runtime** (the duration of the movie in minutes), **tomatometer\_rating** (the aggregated rating given by critics on Rotten Tomatoes), and **tomatometer\_count** (the total number of critic reviews that contributed to the rating). Additionally, it includes audience-based features such as **audience\_rating** (the rating given by general viewers), **audience\_count** (the total number of audience reviews), and various breakdowns of critic reviews, including **tomatometer\_top\_critics\_count** (the count of reviews from top critics), **tomatometer\_fresh\_critics\_count** (the count of positive reviews from critics), and **tomatometer\_rotten\_critics\_count** (the count of negative reviews from critics). The dataset also incorporates categorical features such as **content\_rating** (the movie's content rating, e.g., PG, R), **audience\_status** (reflecting the sentiment or status of audience reviews), and **tomatometer\_status** (which categorizes the movie as "Rotten", "Fresh", or "Certified Fresh"). These features collectively provide a rich set of information about each movie, combining numerical ratings, review counts, and sentiment classifications, which can be used for predictive modeling or analysis.

A graph with blue bars

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3 Methodology

This project employs three key methodologies: **Decision Trees**, **Random Forest**, and **Sentiment Analysis**, each designed to address distinct analytical objectives. Decision Trees and Random Forest provide structured and interpretable models for predicting outcomes based on numerical and categorical features, while Sentiment Analysis introduces an unstructured, text-based perspective by extracting insights from critic reviews.

**Decision Trees** form the foundation of the modeling approach by offering a clear and interpretable pathway for predictions. They are particularly effective for understanding the influence of individual features such as runtime, genre, and box office earnings on the target variable, like movie status or critic scores. By splitting the data into discrete decision boundaries, Decision Trees provide not only predictions but also valuable insights into the underlying relationships within the data.

Building on the strength of Decision Trees, **Random Forest** introduces an ensemble approach to enhance model accuracy and robustness. By aggregating predictions from multiple decision trees, Random Forest reduces the risk of overfitting and captures more complex patterns in the data. It is particularly suited for handling noisy or imbalanced datasets, offering improved generalizability and feature importance metrics that aid in understanding the relative impact of different variables.

Finally, **Sentiment Analysis** brings a unique dimension to the analysis by leveraging the textual content of critic reviews. Using custom scoring logic, sentiment polarity is quantified to classify reviews as positive, negative, or neutral. Aggregated sentiment scores are then used to determine the overall movie status (e.g., Fresh or Rotten) based on a pre-defined threshold. This methodology provides a complementary perspective, bridging the gap between numerical metadata and subjective critic opinions. Together, these methodologies form a comprehensive framework, blending structured and unstructured data analysis for a holistic understanding of the problem.

3.1 Decision Trees

Decision Trees are a versatile machine learning algorithm widely used for classification and regression tasks. The model works by recursively splitting the data based on feature values, aiming to increase the purity of each resulting subset.

A diagram of a algorithm

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One approach to using Decision Trees is to allow the model to grow without restrictions, which can result in highly complex trees that capture detailed patterns in the training data. In this project, we have tried both constrained and unconstrained approaches. In the unconstrained approach, the Decision Tree was instantiated with default hyperparameters, allowing the tree to split freely without limitations on the number of leaf nodes or tree depth. This approach can lead to a highly accurate model on the training data, but it also carries the risk of overfitting, where the model might not generalize well to new, unseen data.

Alternatively, Decision Trees can be constrained to prevent overfitting and promote better generalization. The model was as also tested with a restriction of **3 leaf nodes** using the max\_leaf\_nodes=3 parameter. This constraint limits the tree's growth, forcing it to make simpler decisions and prioritize generalization over fitting the training data perfectly. Additionally, the random\_state=2 parameter was set to ensure reproducibility of the results by initializing the random number generator with a fixed seed. By balancing the depth and complexity of the tree through such restrictions, this approach avoids the problem of overfitting while still maintaining a strong performance on the test data.

3.2 Random Forest

Random Forest is an ensemble learning method that is widely used for classification and regression tasks. It works by building multiple decision trees during training and outputs the mode (classification) or mean (regression) of the individual trees' predictions. This method is particularly effective for handling complex datasets, offering robust performance by reducing overfitting and increasing predictive accuracy. In this project, we employ Random Forest to classify movie ratings into three categories: **Rotten (0.0)**, **Fresh (1.0)**, and **Certified Fresh (2.0)**, based on various movie features such as **runtime**, **audience rating**, and **critic reviews**.

We explore three different variants of Random Forest models in this project: the **Unconstrained Random Forest**, **Constrained Random Forest with Feature Selection**, and **Weighted Random Forest with Feature Selection**. Each variant is tailored to address different aspects of the problem and improve model performance.

* + 1. **Unconstrained Random Forest**: In the unconstrained version, we train the Random Forest model with its default hyperparameters, allowing it to grow an arbitrary number of decision trees. The model can thus explore all the features and data interactions without any restrictions on tree depth, leaf nodes, or feature selection. In this approach, the Random Forest classifier learns the most relevant patterns directly from the entire dataset, which consists of various features, including movie attributes like **tomatometer rating**, **audience count**, and critic data. The model's flexibility allows it to adapt well to complex relationships within the data.
    2. **Constrained Random Forest with Feature Selection**: In this variant, we apply **feature selection** to reduce the dimensionality of the dataset and focus on the most relevant features. We exclude irrelevant features like **PG-13**, **R**, **NC17**, and **G**, which are unlikely to contribute to the classification of movie ratings. By removing features such as **runtime** and **audience status**, we aim to improve model interpretability and speed, while also reducing the risk of overfitting. This model uses a more refined subset of features, thus narrowing down the learning process to only the essential information, which might improve both model performance and computational efficiency.
    3. **Weighted Random Forest with Feature Selection**: The weighted Random Forest variant introduces an additional layer of complexity by addressing **class imbalance** in the dataset. Since the dataset contains more instances of the **Rotten** and **Fresh** classes, while **Certified Fresh** has fewer instances, a weighted random forest classifier is used. By assigning different class weights, the model becomes more sensitive to underrepresented classes, preventing it from being biased toward the majority class. Class weights are computed based on the frequency of each class in the dataset, with class 0.0 (Rotten) being weighted at **0.7691**, class 1.0 (Fresh) at **0.8760**, and class 2.0 (Certified Fresh) at **1.7911**. These adjustments ensure the model's decisions are balanced across all classes, making it more robust when handling imbalanced datasets.

In all three variants, the model is trained on a subset of features, such as **runtime**, **audience rating**, **tomatometer count**, and **tomatometer fresh critics count**, while excluding less relevant features. The models are trained and tested using a split ratio of **80:20** for the training and test sets, respectively, ensuring that we assess the model’s performance on unseen data.

By leveraging these three different approaches—unconstrained, constrained with feature selection, and weighted with feature selection—we aim to understand the impacts of model complexity, feature selection, and class balancing on the classification of movie ratings. Each approach is tested to determine how well it can predict movie ratings while handling the challenges inherent in the dataset.

3.3 Sentiment Analysis

The Sentiment Analysis Methodology employed in this approach focuses on predicting the status of movie reviews as either "Rotten" or "Fresh" based on the textual content of the reviewsand involves datasetvcontaining critic reviews and their associated labels, which are either "Rotten" (0) or "Fresh" (1). The primary task is to transform the unstructured text data (the reviews) into a structured format that can be used by machine learning models.

To achieve this, a text vectorization technique, such as the CountVectorizer, is applied to convert the review content into numerical feature vectors. The CountVectorizer tokenizes the reviews and represents them as a sparse matrix where each row corresponds to a review, and each column represents the frequency of a specific word in the review.

The Random Forest Classifier is then employed to classify the reviews based on the generated feature vectors. For this approach, two variants of Random Forest are used:

**Default Random Forest**: A standard Random Forest classifier is trained without considering class imbalances, with the model learning from the entire dataset.

**Weighted Random Forest**: This variant takes class imbalance into account by adjusting the weights assigned to each class. The class\_weight='balanced' argument helps the model focus more on the underrepresented class by giving it higher weight, which can improve performance for less frequent classes.

Finally, the model's performance is evaluated using standard metrics such as precision, recall, F1-score, and accuracy.

This methodology leverages machine learning techniques to automate the classification of movie reviews, offering insights into the sentiment of critics toward different films based on their written reviews.

**4** **Results**

This section provides an overview of the model performance across different approaches and variants. It includes detailed evaluations of accuracy, precision, recall, and F1-scores, highlighting how well the models classify the different categories within the dataset.

4.1 Decision Trees

The Decision Tree model provides two main approaches for training: **unconstrained** and **constrained**, each with distinct trade-offs.

In the **unconstrained approach**, the model is allowed to grow freely without restrictions on the number of leaf nodes or the depth of the tree. Using the default hyperparameters, the tree was able to split the data as needed, resulting in **99.00% accuracy** on the test data. The precision, recall, and F1-scores for each class (Rotten, Fresh, Certified Fresh) were near-perfect, with **precision** and **recall** values close to 1.00 for most classes, especially for the most frequent class (Class 0.0 - Rotten), which achieved a perfect score. Class 1.0 (Fresh) also performed excellently, with **precision** of 0.99 and **recall** of 0.99. However, Class 2.0 (Certified Fresh) had slightly lower performance, with **precision** of 0.97 and **recall** of 0.97, still showing strong performance, but with minor room for improvement. While these results are impressive, the lack of restrictions on the tree’s growth means the model could be overfitting, especially given that the test performance is very close to the training data's performance.

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On the other hand, the **constrained approach** involves limiting the tree's growth to avoid overfitting and encourage generalization. In the second example, the tree was constrained to have **3 leaf nodes** using the max\_leaf\_nodes=3 parameter. This constraint reduced the complexity of the model, forcing it to make simpler decisions. As a result, the accuracy on the test set dropped slightly to **94.62%**, with precision and recall values still remaining strong but less perfect compared to the unconstrained model. For Class 0.0 (Rotten), precision and recall remained at **1.00**, indicating perfect identification of this class. For Class 1.0 (Fresh), precision dropped to **0.97** and recall to **0.88**, suggesting that while the model still performs well, it struggles slightly more with this class compared to the unconstrained tree. For Class 2.0 (Certified Fresh), precision and recall were **0.80** and **0.95**, respectively, showing that this class was more challenging to predict under the constrained model. The constrained approach, however, is more robust to overfitting, making it better suited for real-world applications where generalization is important.

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In summary, the **unconstrained tree** achieved an impressive **99% accuracy** with almost perfect precision and recall across most classes, indicating high performance on the training set but potential overfitting. The **constrained tree**, with only **3 leaf nodes**, showed a slight decrease in accuracy to **94.62%** but is likely to generalize better to new data due to its simpler structure. The trade-off here is between **training performance** (unconstrained) and **generalization** (constrained), with the constrained model being more robust and less likely to overfit, making it a better choice for real-world scenarios where unseen data is crucial.

4.2 Random Forest

The three variants of the Random Forest model—Unconstrained Random Forest, Constrained Random Forest with Feature Selection, and Weighted Random Forest with Feature Selection—demonstrate varying levels of performance in classifying movie ratings into Rotten (0.0), Fresh (1.0), and Certified Fresh (2.0).

**The Unconstrained Random Forest** achieves an impressive accuracy of 99.00%, with high precision, recall, and F1-scores across all classes, indicating strong performance across the entire dataset without feature selection or class weighting. However, it may suffer from overfitting due to the absence of restrictions on tree complexity, especially when dealing with a large number of features.

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**The Constrained Random Forest with Feature Selection,** which uses a reduced set of features, maintains a similar accuracy (99.27%) and classification performance, showing that the model benefits from focusing on the most relevant attributes andreducing unnecessary complexity. By removing irrelevant features, this variant reduces the chance of overfitting and improves the model's efficiency, while still achieving comparable results.

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**The Weighted Random Forest with Feature** Selection also shows an accuracy of 99.27%, but with an added benefit of adjusting for class imbalance. The use of class weights helps the model to be more sensitive to the underrepresented Certified Fresh (2.0) class, ensuring that the model does not bias predictions toward the more frequent Rotten (0.0) and Fresh (1.0) classes. This variant performs similarly to the constrained model but adds robustness by addressing class imbalances, which is particularly important when dealing with real-world datasets where class distributions are rarely even.

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Overall, all three variants perform well, achieving accuracy values in the 99% range. The Constrained Random Forest with Feature Selection and Weighted Random Forest with Feature Selection offer slight advantages in terms of computational efficiency and handling class imbalance, making them more suitable for datasets with feature redundancy or class imbalance. While the Unconstrained Random Forest is still a strong performer, the other variants provide a more refined approach that can be beneficial in specific scenarios.

4.3 Sentiment Analysis

The **Default Random Forest** achieved an accuracy of 69%. The precision and recall for the "Rotten" class were 0.65 and 0.65, respectively, while for the "Fresh" class, they were slightly higher at 0.72 and 0.72, respectively. The F1-score for both classes was relatively balanced, but the model showed a slight bias toward the "Fresh" class, which had a higher support (552 instances compared to 448 instances for "Rotten").

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On the other hand, the **Weighted Random Forest** took class imbalances into account by adjusting the class weights. This variant provided slightly better performance for the "Rotten" class, with precision rising to 0.64 and recall to 0.72. The precision and recall for the "Fresh" class also saw improvement, with precision increasing to 0.74 and recall slightly decreasing to 0.67. The F1-scores for both classes were fairly close, with the "Fresh" class performing a bit better.

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Overall, the weighted model still achieved the same 69% accuracy, but with more balanced performance across both classes.

Although both models yielded similar accuracy levels, the Weighted Random Forest appeared to be the better choice. This is because it made small yet significant improvements in precision for the "Fresh" class and recall for the "Rotten" class, especially in handling class imbalance.

**5 Discussion**

In this project, various machine learning models, including Decision Trees, Random Forests, and Weighted Random Forests, were used to predict movie status based on critic and audience ratings as well as review sentiment. Despite achieving high accuracy, several limitations were observed. For example, the Decision Tree models, though highly interpretable, had their predictive power restricted by hyperparameters like the maximum number of leaf nodes. Random Forest models, both default and weighted, performed well but could still be prone to overfitting, especially with large datasets. The sentiment analysis approach, while promising, showed moderate performance in classification tasks, with accuracy levels around 69%, which could be improved with better feature engineering or more advanced natural language processing techniques. Future work could include experimenting with more sophisticated algorithms like XGBoost or neural networks, incorporating additional features such as movie genre or actor information, and using more advanced text-processing techniques like word embeddings (e.g., Word2Vec or BERT) for sentiment analysis. Additionally, fine-tuning hyperparameters more thoroughly and using cross-validation would likely improve the robustness of the models.

6 Conclusion

In this project, we explored different machine learning models to predict movie status based on critic and audience ratings as well as review sentiment. We used Decision Trees, Random Forests, and Weighted Random Forests to build models that classify movie status into categories like "Rotten", "Fresh", and "Certified Fresh." Additionally, sentiment analysis was applied to predict movie status based on critic reviews, examining how the sentiment expressed in the reviews correlated with the movie’s overall rating.

The Random Forest models, particularly the weighted variant, provided the best results in terms of accuracy and classification metrics. These models were able to handle class imbalances effectively, providing a robust prediction framework. The sentiment analysis approach, while less accurate, still provided valuable insights into how critic sentiments impact the overall perception of a movie.

In the real world, these findings can be used by movie studios, streaming services, and marketing teams to better understand audience and critic sentiment, which can influence promotional strategies and content recommendations. The ability to predict movie status based on critic reviews and ratings can also assist in content curation, helping users make more informed choices about what to watch. Future enhancements in model performance could further refine these predictions and make them more applicable in dynamic, real-time recommendation systems.

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