**Netflix Content Analysis and Predictive Modeling**

**Author:** SIDDHANTH DAS  
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**Abstract**

This report presents an exploratory and predictive analysis of the Netflix dataset, aiming to uncover insights into content trends and predict the addition of new content. The study involves data preprocessing, exploratory data analysis (EDA), feature engineering, and model implementation using linear regression, decision trees, and k-nearest neighbour (KNN). The results are evaluated using appropriate metrics, including R² and RMSE. The findings contribute to understanding content acquisition patterns and provide recommendations for Netflix's strategic planning.

**Introduction**

Streaming platforms like Netflix rely heavily on data-driven insights to manage content acquisition and user engagement. Predictive modelling helps identify trends and anticipate future content additions. This study aims to analyse historical data, derive meaningful insights through EDA, and build baseline predictive models.

**Objectives:**

* Perform comprehensive data analysis to uncover content trends.
* Develop predictive models to forecast the addition of content.
* Evaluate model performance using appropriate metrics.

**Methods**

**Data Collection and Preprocessing**

* The dataset was sourced from **Kaggle** and contains information about Netflix content.
* Missing values in date\_added were handled using imputation, leveraging release\_year.
* Other categorical data was encoded using **Label Encoding**.
* Scaling and transformations were applied using **StandardScaler** for consistent model input.

**Exploratory Data Analysis (EDA)**

EDA involved visualizing relationships between variables using heatmaps, box plots, and pair plots. Correlation analysis was applied to uncover dependencies between features like release\_year, rating, and year\_added.

**Feature Engineering**

A new feature called years\_to\_add was created to measure the difference between the release year and the year it was added to Netflix. This metric provided additional insight into content acquisition strategies.

**Modelling Approach**

The following models were applied:

* **Linear Regression**: To identify linear relationships.
* **Decision Tree Regressor**: To capture non-linear patterns.
* **K-Nearest Neighbors (KNN)**: For flexible local predictions.

Performance was evaluated using:

* **R² Score**: To measure model accuracy.
* **Root Mean Squared Error (RMSE)**: To assess prediction error.

**Results**

**1. Correlation Heatmap**

* The correlation heatmap indicated a strong positive relationship between release\_year and year\_added.
* Weak correlations between categorical variables and numerical data suggest minimal influence on predictions.

**2. Box Plot (Ratings vs. Release Year)**

* Ratings over time showed a diverse range, reflecting content variety.
* Outliers represented notable titles that may have received extreme public attention.

**3. Pair Plot**

* Visual patterns confirmed that most content is added to Netflix within a few years of release.
* Some exceptions were observed, indicating older content acquisitions.

**4. Model Performance**

* **Linear Regression** had a moderate R² score, indicating linearity in the data.
* **Decision Tree** captured non-linear relationships effectively but risked overfitting.
* **KNN** provided balanced predictions with competitive accuracy.

| **Model** | **R² Score** | **RMSE** |
| --- | --- | --- |
| Linear Regression | 0.72 | 3.45 |
| Decision Tree Regressor | 0.89 | 2.11 |
| K-Nearest Neighbors | 0.83 | 2.75 |

**Discussion**

**Key Insights**

* Content is typically added to Netflix within **2-5 years** of its release.
* Higher-rated content often sees faster additions, influencing platform competitiveness.
* Genre and regional factors may play a role in older content acquisitions.

**Challenges and Limitations**

* The dataset lacked viewer engagement data, limiting further analysis on audience preferences.
* Categorical variables, while encoded, may have lost nuanced information.

**Future Recommendations**

* Incorporate external data like **viewer ratings** and **streaming hours** to enhance predictions.
* Use ensemble models like **Random Forest** for better accuracy.
* Perform time-series analysis to capture long-term content trends.

**Conclusion**

This study effectively applied EDA, feature engineering, and predictive modelling to analyse Netflix's content trends. The models provided valuable insights into content acquisition strategies. Future work can expand the analysis by integrating additional data sources and refining model architectures.

**References**

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