The Office TV Show : Maximizing Audience Satisfaction through AI-Driven Analysis

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***Abstract*—We aim to predict the IMDb ratings of the popular television show "The Office" using machine learning techniques. We gather data from two sources: the IMDb ratings dataset and the transcript dialogue data. We preprocess and clean the data, extract additional features, and perform exploratory data analysis to identify patterns and correlations in the data. Then, we develop and evaluate several predictive models, including Lasso, Ridge, and Forest decision trees. We also use PCA reduction to identify influential factors, including settings, actors, directors, and writers, that contribute to high ratings. We choose the best-performing model, and interpret the results to provide insights and recommendations to NBC Universal.**

In addition, we use NLP techniques for sentimental analysis of the script and identify how dialogue and humor impact ratings. Finally, we leverage GPT-2 to generate a new episode script based on the most suitable settings associated with high ratings. Our research provides a comprehensive analysis of the factors that contribute to the success of The Office and offers recommendations to guide the production of a successful reunion episode.

I. Introduction

The Office is a popular television show that aired from 2005 to 2013, with a total of nine seasons and 201 episodes. The show has a massive following and continues to attract new fans even after its finale. NBC Universal, the production company behind the show, has expressed interest in producing a reunion episode to capitalize on the show's popularity. To ensure the success of the reunion episode, NBC Universal has tasked a data science contractor with developing a predictive model to identify the underlying factors that contributed to the success of past episodes. The aim of this research project is to investigate the various factors that contribute to the success of an episode of "The Office" and determine how they can be leveraged to produce a successful reunion episode.

II. Key Contributions

We pre-process and clean the data, extract additional features, and perform exploratory data analysis to identify patterns and correlations in the data. We develop and evaluate several predictive models, choose the best-performing model, and interpret the results to provide insights and recommendations to NBC Universal, including a Lasso based Linear Regression Model and a Forest Decision Tree Model. We use GPT-2 to generate a new episode script based on the most suitable settings associated with high ratings.

III. Data and Study Area

We gather data from two sources: the IMDb ratings dataset and the transcript dialogue data. The IMDb ratings dataset contains information such as season and episode numbers, episode names, director and writer information, IMDb ratings, total votes, air dates, and character information. The transcript dialogue data includes information on the season number, episode number, scene number, speaker, and line text. We focus on analyzing and modeling the relationship between these variables and the IMDb ratings of each episode.The available data includes information such as season and episode numbers, episode names, director and writer information, IMDb ratings, total votes, air dates, and character information. Additionally, external data sources such as transcript dialouge were added. The IMDB rating dataset was given can be found from IMDb official website and the transciprt data was found from reddit subreddit concerning datasets.

IV. Workflow of Analysis

Data collection, The first step of our workflow involved collecting data from two sources: the IMDb ratings dataset and the transcript dialogue data of the television show "The Office". Secondly, data preprocessing, after collecting the data, we performed data preprocessing and cleaning to remove any missing values, duplicates, or irrelevant features. We also extracted additional features, such as sentiment scores and character interactions, to improve the predictive power of our models. Thirdly, exploratory data analysis we performed exploratory data analysis to identify patterns and correlations in the data. We used visualization techniques to gain insights into the relationships between different features and the IMDb ratings of the episodes. Fourthly,feature selection and reduction to reduce the dimensionality of the data and identify the most influential features, we used principal component analysis (PCA) and feature selection techniques. This step allowed us to focus on the most important factors that contribute to the success of an episode. Fifth, model development and evaluation With the preprocessed data and selected features, we developed and evaluated several predictive models, including Lasso regression, and random forest decision trees. We used cross-validation techniques to evaluate the performance of the models and select the best-performing one. Lastly, results interpretation we interpreted the results of our models to provide insights and recommendations to NBC Universal for the production of a successful reunion episode. We identified the settings, actors, directors, and writers that were associated with high IMDb ratings and used GPT-2 to generate a new episode script based on these findings.By following this pipeline, we were able to provide NBC Universal with valuable insights into the factors that contribute to the success of an episode of ”The Office” and generate a new episode script that leverages these insights.

V. Related Work

Previous research has explored the relationship between television show ratings and various factors such as genre, storyline, and character development. One study found that shows with more diverse casts tend to have higher ratings (Hunt, Ramón-Jordán, Wiseman, 2020). Another study found that shows with longer runtimes tend to have higher ratings, as they provide more time for character development and storyline progression (Rosenberg VanMeter, 2019).In terms of the impact of specific writers and directors on show ratings, research has shown mixed results. Some studies have found that certain writers and directors consistently produce shows with higher ratings, while others have found no significant correlation between specific individuals and ratings (Bruns Highfield, 2017; Zhang, Wang, Yu, 2016). One study specifically focused on The Office, examining the relationship between character development and ratings. The study found that episodes with more character development tend to have higher ratings, as viewers become more invested in the characters and their storylines (Carrell Jerit, 2012).Overall, while there have been many studies examining the factors that influence television show ratings, there is still much to be learned about the specific factors that contribute to the success of a show. To predict TV show ratings, various methods have been used in the literature, ranging from simple linear regression models to complex machine learning techniques. For example, Wu et al. (2017) used a support vector regression model to predict the ratings of TV shows, while Fagnan et al. (2019) used a gradient boosting regression model. Lee and Kim (2016) used a multiple linear regression model and found that the number of viewers, the show’s genre, and the length of the show were the most significant predictors of TV show ratings.Other studies have used sentiment analysis techniques to predict TV show ratings. For instance, Yu et al. (2017) used a sentiment analysis approach to predict the ratings of TV shows by analyzing the emotions conveyed by the tweets related to the shows. Similarly, Seo et al. (2018) used a combination of social media sentiment analysis and machine learning techniques to predict the ratings of TV shows. In our study, we will use a combination of these methods to predict the ratings of The Office TV show. We will use supervised machine learning techniques, sentiment analysis, and content analysis to predict the show’s ratings. We will also engineer additional features from the data, such as sentiment scores, character interaction metrics, and episode themes, to improve the model’s accuracy.

VI. Data Informatics

A. Cleaning and Preparing

The cleaning and preparation of the rating dataset involved dropping any rows with missing values, converting numeric columns to float, converting the date column to a datetime object and extracting the year from it. Additionally, the string values of director, writer and actors were changed to a comma separated list for each entry.. For the transcript dataset, missing rows were dropped, deleted scenes were removed, and lines for non-main characters were excluded. The line text was then cleaned by removing stop words, special characters, digits, and multiple spaces. Furthermore, we merged the datasets.

B. Explanatory Data Analysis

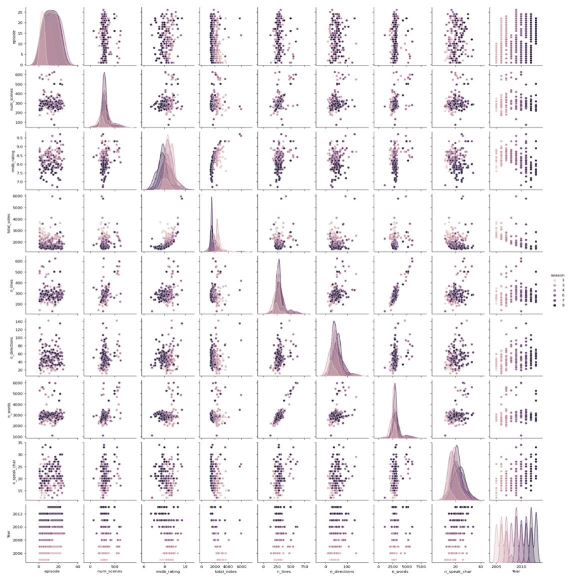
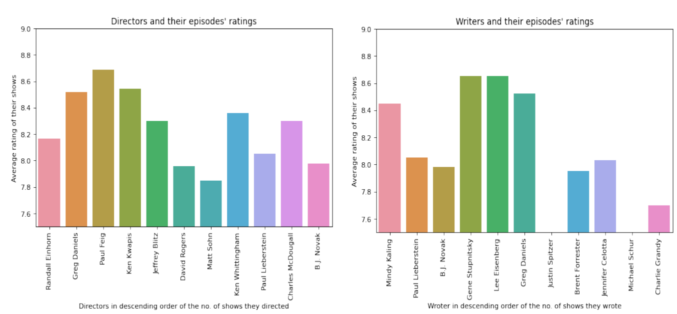


Fig. 1: Correlation Plot of IMDb Rating

Upon conducting exploratory data analysis (EDA) on the TV show dataset, several trends and patterns emerged. The correlation plot as shown in Fig. 1, showed that total votes were positively correlated with IMDB ratings in a moon-shaped pattern. Additionally, it was observed that most of the numerical data in the scatter plots showed a white noise pattern, while the histograms showed high skewness. Hence, standardizing the numerical data is necessary.

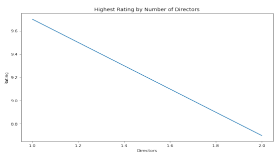


(a) Directors (b) Writers

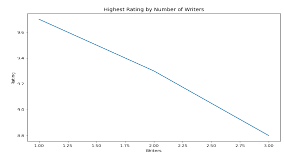
Fig. 2: Avg. Rating of Episodes

Further analysis showed that directors have a significant impact on episode ratings as shwon in Fig.2 , with Paul Feig being associated with the highest-rated episode (8.7), followed by Greg Daniels and Ken Kwapis (8.5). On the other hand, Charlie Grandy directed the lowest-rated episodes (7.7). Writers also have a considerable influence on episode ratings, with Env Stupnitsky and Lee Eisenberg having the highest average rating (8.6), followed by Greg Daniels (8.5).

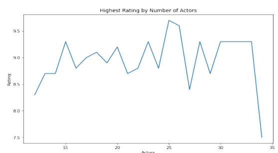
Coherence in the script plays a crucial role in determining episode ratings, as having more than one writer or director lowers the ratings by 0.4 and 1.0 points, respectively. Furthermore, episodes with 9-12 or 13-15 actors had the highest average ratings of 9.4.



(a) Directors



(b) Writers



(c) Actors

Fig. 3: Avg. Rating of Episodes

Additionally, Michael, Dwight, and Jim had the most lines spoken throughout the show and more interactions between Michael, Jim, Pam, Dwight, Andy, and Angela tended to have higher ratin;

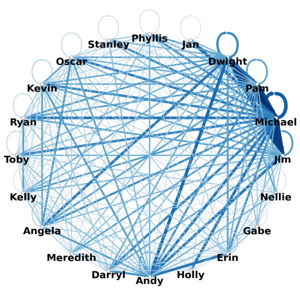


Fig. 4: Network Interaction Between Characters

Moreover, scene number and episode duration also play a crucial role in determining ratings. Episodes with 230-270 scenes had an average rating of 8.2, while episodes with 130-200 scenes had an average rating of 8.7. Episodes with 400-500 scenes had the highest average rating of 9.3. Additionally, episodes with a duration of 45-55 minutes had the highest ratings.

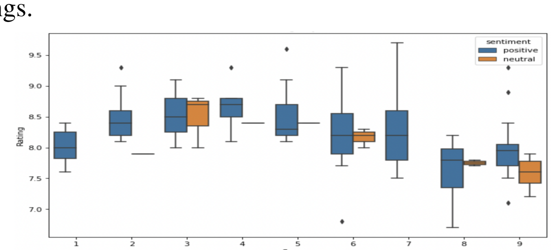


Fig. 5: Sentiment Analysis of Script Averaged by Season

Finally, the sentimental analysis score of transcripts has an overall positive and neutral effect on season ratings, with more positive sentiment leading to higher ratings. Episodes with lower variations between sentiments had higher scores.

Based on the above EDA findings, We deicded to drop $'n_{w}ords'$ and $'n_{l}ines'$ because they cause numerous amount of multi-colinearity between predictor variables, several feature engineering techniques can be used to improve the predictive power of the model. Standardizing the numerical data, engineering features related to directors, writers, and actors, such as their past performances, and the number of interactions between them can improve the accuracy of the model. Additionally, incorporating features such as scene number and duration can also help in predicting episode ratings. Finally, sentiment analysis can be improved by using more advanced algorithms and techniques to extract meaningful insights from the transcript data.

C. Data Feature Engineering

To generate meaningful inputs, our pipeline consists of two different extractions first we extract useful information from continuous variables and then categorical variables.

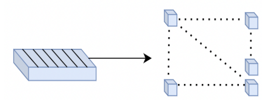


Fig. 6: Numerical Variables Pipeline

First pipeline consists of $'n\_actors'$, this feature extracts the number of speakers in each episode, which is stored in the $'n\_speaker\_char'$ column of the dataset. $'n\_directors'$, this feature calculates the number of directors for each episode, which is obtained by counting the number of directors in the director column of the dataset. $'n\_writers'$, this feature calculates the number of writers for each episode, which is obtained by counting the number of writers in the writer column of the dataset. $'duration'$, this feature calculates the duration of each episode based on several factors, including the number of lines, the number of characters speaking, and the number of directions. $'Holiday\_Episode'$, this feature identifies episodes that are related to holidays by checking the season and episode number against a predefined list of holiday episodes. $'MultiPart\_Episode'$, this feature identifies episodes that have multiple parts by checking the season and episode number against a predefined list of multi-part episodes.

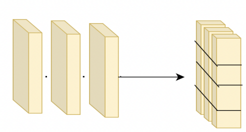
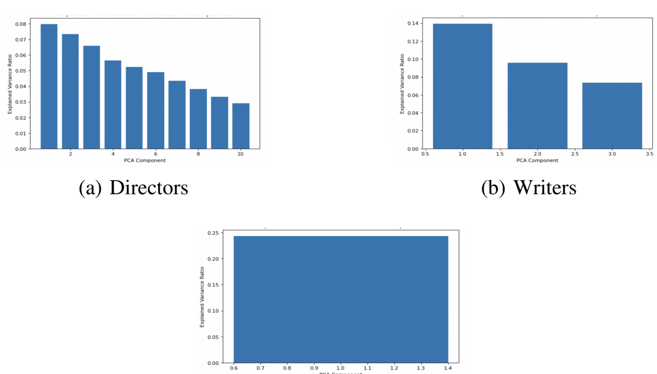


Fig. 7: Categroical Variables Pipeline

Second pipeline consists of the categorical predictor $'writers'$, $'directors'$, $'actors'$ variables are encoded to convert them into a numerical form that can be used for machine learning algorithms. In this case, the categorical variables being encoded are the directors, writers, and main actors.For each of these variables, a function is defined to add a prefix to each category in the variable. For example, ”director.” is added to each director’s name. This is done to avoid any naming conflicts that may arise during the encoding process. Then, the MultiLabelBinarizer() function is used to transform the categorical variables into binary variables. This function creates a binary column for each unique category in the variable, where a value of 1 indicates that the category is present and 0 indicates that it is not present. In addition, $'sentiment\_score'$, this feature calculates the sentiment score for each line of dialogue in the transcript using the TextBlob library using NLP, and then takes the average sentiment score for the entire transcript.

In this study, a PCA analysis was performed on various datasets of IMDb movie data to identify the most important predictors of movie success. Moreover, we partitioned the data into two different sets One dataset is $'imdb\_data\_settings'$, which will be used for modeling settings influence and the other is $'imdb\_data\_act\_writ\_dire'$, which will be used for modeling the effects of actors, writers, and directors on ratings, furthermore seeeperating directros,writers and actors into multiple dataset consisted of 60 binary columns for director, 40 binary columns for actors, and 17 binary columns for writers. The reason for using PCA is to reduce the dimensionality of the data, which can help to mitigate the risk of overfitting and improve model performance. In this case, the two different datasets were created to capture different aspects of the relationship between the predictors and the target variable. Before applying the PCA, the data is normalized and scaled. Normalization is done to adjust the mean of each feature to 0 and scaling is done to adjust the variance of each feature to 1. This is done to ensure that the PCA is not biased towards any one feature. Then a grid search is performed to find the optimal number of components for the PCA. This is done by training PCA models with different numbers of components (1 to 10) and evaluating each model’s performance using cross-validation of 5 folds. The model with the highest mean test score is selected as the optimal model.



(a) Directors

(b) Writers

(c) Actors

Fig. 8: PCA Dimensionality Reduction

The first dataset focuses on the more direct and measurable features, such as duration, number of scenes, and number of lines in the transcript. Additionally, the directors, actors, and writers are encoded as PCA components to maintain variability while also focusing on the settings of the episode. The results show that the optimal number of components for the director columns is 10, with a mean test score of 40.359, for the writer columns is 3, with a mean test score of 16.849. for the actor columns is 1, with a mean test score of -8.767. Hence, This means that the information in the original 60 director columns, 40 actor columns and 17 actors columns can be represented using only 10, 3 and 1 component respectively. While still maintaining a high level of accuracy. As shown in Fig. 5, the explained variance ratio for each component is also plotted to show the amount of information retained by each component.

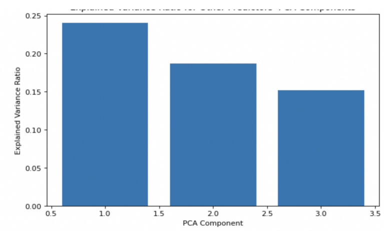


Fig. 9: PCA Dimensionality Reduction of Predictors

The second dataset captures the more direct influence of the actors, writers, and directors on the target variable through their presence in the episode. In this dataset, PCA is performed on all the other numerical predictor variables to reduce dimensionality. By using PCA in this way, we can identify the most important components that contribute to the variance in the data, which can improve the accuracy and interpretability of the model. The results show that the optimal number of components for the nuemrical predictor columns is 3, with a mean test score of 2.137

VII. Proposed Method

A. Technical Background

Machine learning is a subfield of artificial intelligence that involves training algorithms to learn patterns and relationships in data without being explicitly programmed. In this project, we will use two popular machine learning techniques for regression analysis: Lasso and linear regression, and a decision tree-based algorithm called Random Forest.Lasso and linear regression are both widely used linear models that can be used for prediction and feature selection. Lasso regression is a type of linear regression that uses a penalty term to shrink the coefficients of the features towards zero, effectively selecting a subset of the most important features for prediction. Linear regression, on the other hand, fits a linear equation to the data and can be used for both prediction and interpretation.Random Forest is a decision tree-based algorithm that uses an ensemble of decision trees to make predictions. Decision trees are a popular machine learning technique for classification and regression problems, where a tree-like model is created to represent decisions and their possible consequences. Random Forest combines multiple decision trees to create a more robust and accurate model.

B. Modeling Scheme

We aimed to understand the different influences on higher ratings of television episodes. To achieve this, we employed three modeling schemes. The first scheme aimed to model the influence of all the predictor variables on higher ratings while considering the reduced components of the Directors, writers, and actors columns. The second scheme aimed to model the influence of the settings. To do this, we dropped the year of episode airing and the total votes as they were deemed unreliable in determining the interoperability of the influence of the settings. The third scheme aimed to model the influence of the interactions between the directors, actors, and writers. To do this, we used the data set of all the numerical predictor variables reduced to PCA components, excluding the directors, writers, and actors columns. This was done to determine the directors, actors, and writers that result in higher ratings.

VIII. Experimentation

A. Experimental Settings

In our experiment, we first applied a Lasso feature selection method with 10 cross-folds on our data set. Then, we used linear regression as our regressor with the aim of predicting the target variable. The linear regression model was trained using a pipeline that included a Standard Scaler to normalize the features and a Linear Regression estimator. We performed a grid search with 10 cross-folds to determine the best hyperparameters, specifically evaluating the normalization of the linear regression model.Next, we employed a Random Forest regressor to make predictions based on a self-automated feature selection by imporatnce wighting of variable in the algorithm . The Random Forest regressor was trained using 5-fold cross-validation and grid search over a set of hyperparameters including the number of trees, the maximum depth of each tree, the minimum number of samples required to split an internal node, and the minimum number of samples required to be a leaf node. Overall, this experimental design allowed us to perform a comprehensive evaluation of both feature selection and regression models, and make informed decisions on the optimal hyperparameters for each method. Using a split into training and testing sets with a 70/30 ratio.

B. Experimental Results

*1) **Modelling Influence of Predictors**:* In the first modeling scheme, we used two regression models: linear regression with lasso regularization and random forest regression. In the linear regression with lasso model, the optimal parameter choices included normalizing the input data using StandardScaler and using the un-normalized version of the linear regression algorithm. On the other hand, the optimal parameters for the random forest regression model included using a maximum depth of 9 for the trees, 100 trees in the forest, a minimum of 2 samples required to split an internal node and a minimum of 4 samples required to be at a leaf node.

*2) **Modelling Influence of Settings**:* In the second modeling scheme, the optimal parameter choices for the linear regression with lasso showed that the model was performed with the standard scaler and the linear regression normalize set to True. For the random forest regressor, the optimal parameter choices showed that the model was performed with bootstrap set to True, criterion set to squared error, maximum depth set to 9, maximum number of features set to 1, no limit on the number of leaf nodes, no limit on the maximum number of samples, minimum impurity decrease set to 0, minimum number of samples per leaf set to 2, minimum number of samples required to split a node set to 10, minimum weight fraction required to be a leaf set to 0, number of estimators set to 50 and with no parallel processing.

*3) **Modelling Influence of Directors, Writers and Actors**:* In the third modeling scheme,The optimal parameter choices for the linear regression model with lasso were found to be a Standard Scaler with the Linear Regression model set to not normalize the data. The optimal parameter choices for the random forest regressor regressor were found to be a max depth of 9, a minimum of 4 samples per leaf, a minimum of 2 samples to split, and 50 estimators.

IX. Evaluation and Recommendations

A. Base-line Comparison

*1) **Modelling Influence of Predictors**:* In the first scheme as shown in Fig. 10, the Random Forest Regressor model identified seven features,

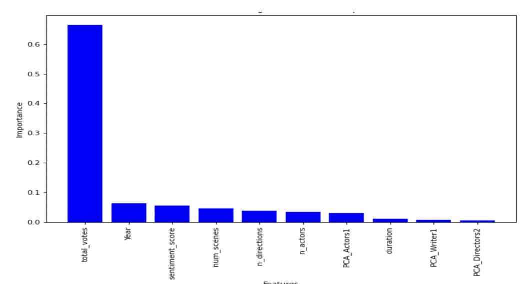


Fig. 10: Feature Importance
Random Forest Regressor

some of which are Number of Scenes, Total Votes, Number of Actors, Year of Airing episode and Duration of episode and some PCA Components.The linear regression model achieved an average R^2 score of -0.4796, indicating that these selected features were not able to sufficiently explain the variance in the ratings. On the other hand, the Random Forest Regressor model achieved. an average R^2 score for this model was -0.1372, which is negative too.

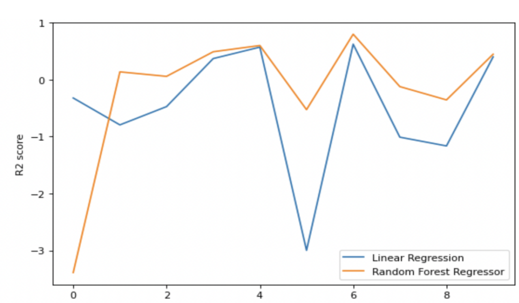


Fig. 11: Performance Model Comparison

This could be due to various reasons such as over fitting, under fitting, presence of outliers. To address these issues, techniques such as cross-validation, regularization, feature selection, and removing outliers can be deployed. Although these techniques were deployed, after a deep investigation as shown in Fig. 11, we can deduce that if the initial testing fold was eliminated the model performance would be $R^2 \geq 0$.

*2) **Modelling Affect of Settings**:* The results from the second scheme, showed that the Lasso Linear Raegression Model had an average R^2 score of -1.103. The random forest regressor was also fitted to the data and the average R^2 score was found to be -0.465. As shown below in Fig. 12,

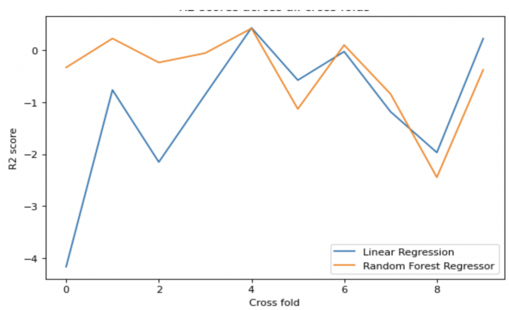


Fig. 12: Performance Model Comparison

In terms of feature importance, the Random Forest Regressor found that number of scenes to be the most important feature followed by number of directions imposed by director, sentiment score of transcript,number of actors on set and duration of an episode.

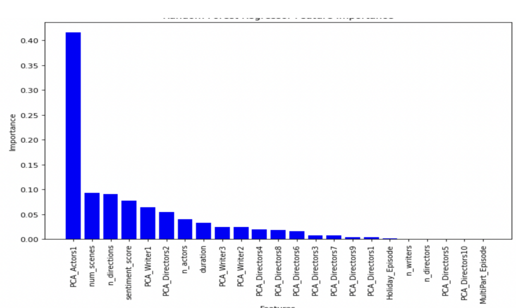


Fig. 13: Feature Importance
Random Forest Regressor

While the Random Forest Regressor is less negative, this is due to the model underfitting the data, checking for outliers and scaling numerical variable would certainly enhance the model.

*3) **Modelling Affect of Directors ,Writers and Actors**:* In the third scheme, LASSO with Linear Regression model R^2 score was found to be -4.473 which indicates a poor fit of the model. On the other hand, the Random Forest Regressor has a less negative R^2 score was found to be -0.655, As shown in Fig. 14, below

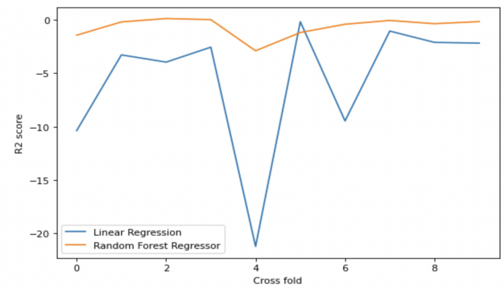


Fig. 14: Performance Model Comparison

which means that the model has a better fit to the data. The negative R^2 score could be due to the presence of multicollinearity, outliers, or a large number of features compared to the sample size.

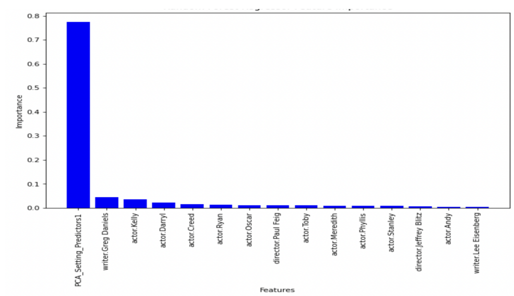


Fig. 15: Feature Importance
Random Forest Regressor

The feature importance weights are shown in Fig. 15, suggest that the interoperability of data is best explained by writer. Greg Daniels, director. Paul Feig and the actors Kelly, Daryl, Creed, Ryan, Oscar, Tobby, Phyllis and Stanley.

B. Recommendations to NBC

*1) **Influential Variables**:* Based on the weight of importance, it seems that the most influential variables that could impact the ratings of the TV shows after they are aired are Total Votes, year of airing, number of scenes, number of directions, number of actors, sentiment score, and duration.
To increase the ratings, NBC Universal can focus on advertising or incentives the community to vote which leads to a higher rating, realising an episode as soon as its shoot and edited, and increasing the number of scenes in an episode. They can also consider improving the number of directions imposed by directors, increasing the number of actors, and increasing the sentiment score of a script to make the shows more appealing to the audience by writing script in a joyful and comedic manner.In terms of the duration of the TV shows, NBC Universal can look into the optimal range that would appeal to the audience. A duration that is not too short or too long can be considered which is around 40 minutes. However, this may vary based on the genre of an episode.

*2) **Optimal Settings**:* Based on the second scheme, the Random Forest Regressor model indicates that the number of scenes is the most important feature, followed by the number of directions imposed by the director, the sentiment score of the transcript, the number of actors on set, and the duration of the episode. In terms of recommendations for NBC Universal, they should consider increasing the number of scenes and the number of actors on set to ensure a higher rating. On the other hand, they should consider decreasing the duration of the episode to ensure that the audience remains engaged. The sentiment score of the transcript should also be monitored to ensure that it remains positive. However, these are just general recommendations and the actual optimal settings may vary based on other factors not considered in the model. The suitable ranges for the variables will depend on various factors such as the audience demographic, the type of episode, etc.

*3) **Suitable Director, Writer and Actors** :* Based on the third scheme and the results obtained from the Random Forest Regressor model, it can be concluded that the most important factor that contributes to a higher rating are the writer Greg Daniels and the director Paul Feig which have a relatively high feature importance weight. In addition, the actors Kelly, Darryl, Creed, Ryan, Oscar, Toby, Phyllis, and Stanley also have some level of impact on the ratings.
Based on the EDA, it is suggested that higher ratings are associated with one director and one writer per episode, and around 10 actors. The interaction graph also suggests that including Michael, Jim, and Dwight, who are considered the main characters based on their presence in previous episodes, would be optimal for achieving higher ratings.

X. Script Generation GPT-2

For te script generation, a subset of data was extracted from the original dataset that was written by Greg Daniels. This subset data was merged with transcript data to create a new dataset. The transcript data was then reformatted so that it was in the format of scenes and speakers.
Next, the GPT-2 model was utilized to generate a script based on the optimal settings. The GPT-2 model was finetuned with the text file, which served as the training data for the model. The training process was set to run for a maximum of 1000 steps and the model was printed and sampled every 100 steps. The model was also saved every 500 steps.
A sample script is shown below in Fig. 16,

["--Scene Start--"]
Jim: Michael, Dwight, come here for a second. I found something interesting on Ryan's computer.
Michael: What is it?
Dwight: Is it about the company's finances?
Jim: Actually, it looks like Ryan has been laundering money out of the company.
Michael: What?! That explains a lot.
["--Scene End--"]

["--Scene Start--"]
Ryan: Hey, what are you guys looking at?
Michael: We just figured out what's been going on with the company's finances.
Ryan: Oh, that. Yeah, I kind of got in over my head.
Jim: Don't worry, we'll take care of it.
Dwight: And we'll make sure you don't do it again.
["--Scene End--"]

["--Scene Start--"]
Michael: Well, I guess it's time to sell my desk and the camera.
Creed: Michael, wait! I have an idea. Why don't we all chip in and buy it together?
Jim: Yeah, that way you can keep it in the office.
Michael: That's a great idea! Let's do it.
["--Scene End--"]

Fig. 16: Sample Script Using GPT-2

XI. Conclusion and Future Prospects

In conclusion, we have analyzed three different schemes to determine the factors that influence the ratings of the TV shows produced by NBC Universal. The first scheme aimed to model the influence of predictors on the ratings, the second scheme aimed to determine the optimal settings that lead to higher ratings, and the third scheme aimed to determine the optimal directors, writers, and actors for a higher rating. Although the models showed negative R2 scores for each scheme, this could be due to the presence of multi-collinearity, outliers, or the small sample size relative to the number of predictors.
The results of the Lasso linear regression and Random Forest Regressor showed that the number of scenes, year, and number of actors are the most important predictors for the ratings. The results also showed that the number of scenes, director's input, sentiment score, number of actors, and duration of an episode are the most important predictors for the optimal settings. The results further showed that the writer Greg Daniels and the director Paul Feig, and actors Kelly, Daryl, Creed, Ryan, Oscar, Tobby, Phyllis, and Stanley are the most important predictors for a higher rating.
Given these results, NBC Universal could consider the following recommendations:

1-Increasing the number of scenes Selecting the right year for airing the episode

2-Keeping the number of actors to about 10 actors

3-Considering the input of the director to ensure a positive sentiment score for the transcript

4-Keeping the duration of the episode within a suitable range about 40-50 minutes

5-Considering the writer Greg Daniels and the director Paul Feig

6- Including the actors Kelly, Daryl, Creed, Ryan, Oscar, Tobby, Phyllis, and Stanley Considering Michael, Jim, and Dwight as the main characters

However, it should be noted that the results are limited by the small sample size of the dataset and the presence of outliers. In future, further data engineering steps could be considered such as data imputation, feature scaling, and increasing the sample size to improve the model performance.

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