Predicting the revenue of the movies based on budget

Contents


```
library(tinytex)
library(here)
library(tidyverse)
library(repr)
library(tidymodels)
library(GGally)
library(infer)
library(cowplot)
library(dplyr)
```

By - Rehan Mondal and Abheet Kansal Adapted from DSCI 100 Project by - Ming Zhang, Rehan Mondal, Caroline Lu and Jingwen Leng

0.1 Summary

The project deals with predicting whether movies with high budget have high revenue. The project tries to correlate the impact the amount of money spent in making a movie has on the revenue it generates.

0.2 Introduction

The entertainment industry has always been a profitable field, especially movies. However, with great profit comes great investment. Most modern-day movies require a budget of around 100 million dollars(1). It is crucial for investors/directors to have a general idea of how much profit they can make based on their investment. Thus, this project centers around studying the profitability of a movie before it is released, predicting revenues based on budget using Knn regression (since most movies fall under a general range of budget and there are rarely extreme outliers)

The question we will try to answer with our project is what is the revenue of a movie based on budget. The data set, which consists of 5000 movies from TMDB, will be separated into training and testing sets. Using budget as the predictor, the prediction of test set revenue will be made.

In the data set “TMDB 5000 Movie Dataset” (from “https://www.kaggle.com/datasets/tmdb/tmdb-movie-metadata”), revenues, budget, popularity are recorded for the 5000 movies listed in an excel format. Other columns are listed/included in the data set as well, however because they are written in json or not a significant predictor to the revenue, those columns will be filtered out. Revenues is defined as the total box income of the movie; budget is defined as the funding used for the production; Popularity numbers are built according to the TMDB model which consists of number of votes for the day, number of views for the day, number of users who marked it as a “favourite” for the day, Number of users who added it to their “watchlist” for the day, release date, number of total votes, and previous days score. We will discuss and analyze the correlation of each variable with revenue below.

Table 1: TMDB rating

X	budget	revenue	vote_average	runtime	popularity
1	2.37e+08	2787965087	7.2	162	150.43758
2	3.00e+08	961000000	6.9	169	139.08262
3	2.45e+08	880674609	6.3	148	107.37679
4	2.50e+08	1084939099	7.6	165	112.31295
5	2.60e+08	284139100	6.1	132	43.92699
6	2.58e+08	890871626	5.9	139	115.69981

0.3 Methods & Results:

We used functions from the tidyverse library to manipulate data frames and tibbles. repr is used to resize plots contained in this notebook, such as an "Accuracy vs K" graph. tidymodels is a package used for statistical and modeling analysis. GGally extends ggplot2 by adding several functions to reduce the complexity of combining geoms with transformed data. cowplot is used to generate the function plot-grid to easily compare plots.

```
data <- read.csv(here("data/dataset.csv"))
```

```
clean_data <- read.csv(here("Results/clean_dataset.csv"))
clean_data <- head(clean_data)
knitr::kable(clean_data, caption = "TMDB rating")
```

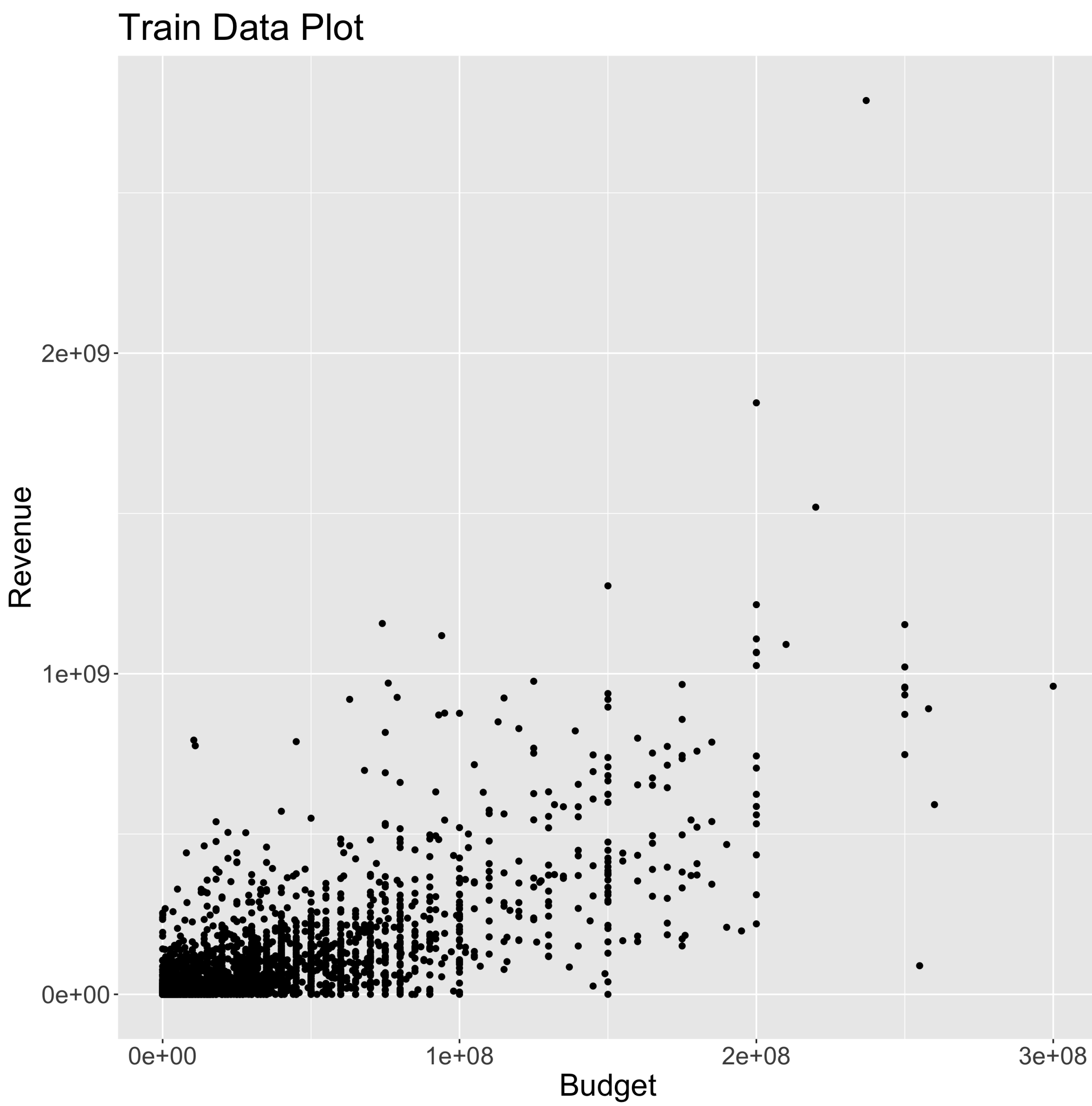
As of now, we have a single giant data frame consisting of all the data of TMDB movie. If we pass all of the revenue data into our model, we would not have any data to use as a measure of how accurate the model is. If we use the data that we have used to train the model before, the model will recognize that data because it has "seen" it before and will most likely produce a faulty accuracy that is higher than reality.

Therefore, to allow a fair process of measuring the model's accuracy, we must calculate its accuracy based on how accurate it is at predicting revenues that it hasn't "seen" before. To do this, we split the data into training and testing datasets and only use the training dataset to create our regression model. By doing so, we will have a set of data that the machine learning hasn't seen before.

To do this, we will use the golden ratio which is a 75-25% ratio of training and testing datasets respectively. The strata statement can shuffle and ensure the data is not split unrepresentatively.

To make sure that this process is replicable, we use set.seed().

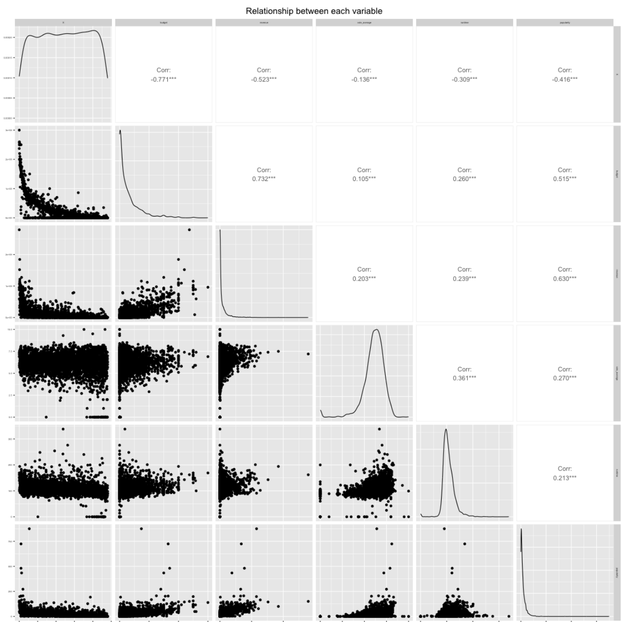
```
# Graph for train data


knitr::include_graphics(here::here("Results/initial_scatter_plot.png"), rel_path = FALSE)
```



Below we use ggpairs to analyze the correlation between revenues and the predictors "vote_average", "budget", "runtime", and "popularity".

As we can see, the correlation between budget and revenue is the strongest, and it is also our subject of interest since we are trying to predict revenues based off budget which can directly influence the profit of the investors. All the other predictors have little to no correlation with revenues. Other predictors such as popularity are only relevant or in-existence after the production of the movie which are also not reliable predictors to understand revenue before the investment. For example, Popularity numbers are built according to the TMDB model which consists of number of votes for the day, number of views for the day, number of users who marked it as a "favourite" for the day, Number of users who added it to their "watchlist" for the day, release date, number of total votes, and previous days score (which are only recorded after the movie is produced).

```r
knitr::include_graphics(here::here("Results/cp.png"), rel_path = FALSE)
```



0.3.1 Knn-nearest neighbor regression model training

First, we created a recipe using the recipe functions with the variables of interest `budget` using the training dataset and assign your answer to an object named revenue_recipe. We also thought of scaling `step_scale` and centering `step_center` steps for all of the predictors so that they each have a mean of 0 and standard deviation of 1, but it was not necessary because we only have one predictor, and standardization can cause a loss of interpretation.

If we split our overall training data once, our best parameter choice will depend strongly on our luck (since whatever data that lands in the validation set is random). By using multiple different train / validation splits, a better accuracy/representation of the data can be estimated, which will lead to a better choice of the number of neighbours K for the overall set of training data.

In cross-validation, we split our overall training data into x evenly-sized chunks, and then iteratively use 1 chunk as the validation set and combine the remaining $x - 1$ chunks as the training set.

We decided to split our overall training data up in multiple different ways using `vfold_cv`, train and evaluate a regression model for each split, and then choose the parameter based on all of the different results. The v value is set as 5 which is the number of folds, and we set revenue as the strata arguement.

We created **revenue_spec** using the `nearest_neighbor` function.

In order to improve our regression model, we need to change the parameter: number of neighbours, K. Since cross-validation helps us evaluate the accuracy of our model, we can use cross-validation to pick the value of K that gives us the best accuracy.

Using `tune()` in `tidymodels` package, each parameter in the model can be altered/attempted rather than given a specific value.

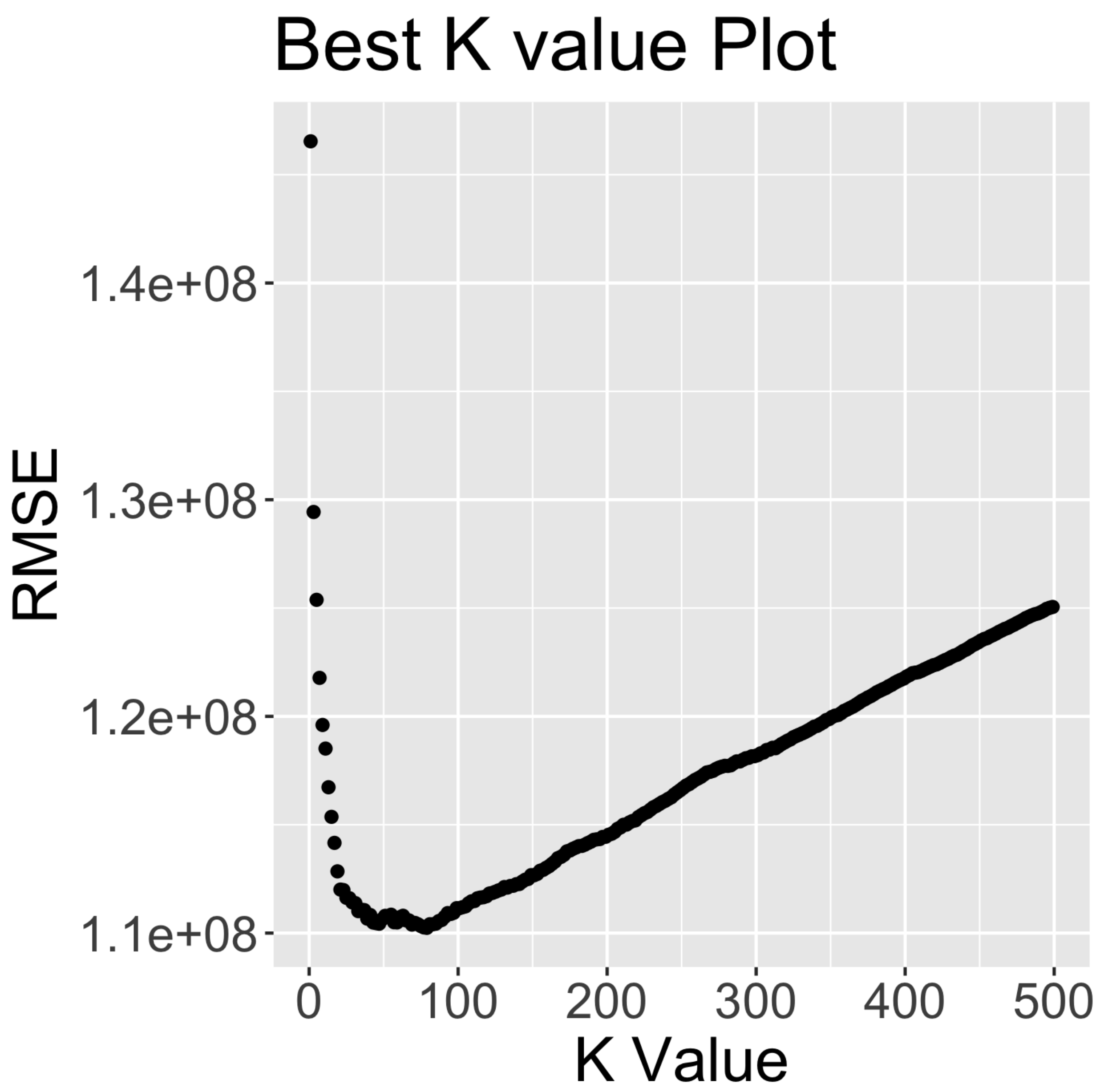
Using `workflow`, we can chain together multiple data analysis steps without a lot of otherwise necessary code for intermediate steps. We use the **revenue_recipe** and **revenue_spec** we have created previously in the workflow.

We can use `tibble` to create a set of values we will be using for the grid arguement (the range of parameter we will be testing). Here, we indicated the K value to range from 1 to 500, and step by 2.

We can then use the tune_grid function to fit the model for each value in a range of parameter values. For the resamples argument, we input the cross-validation revenue_vfold we created earlier. The grid argument specifies that the tuning should try X amount of values of the number of neighbors K when tuning, we input the gridvals object we created earlier to indicate the range of parameters we would like to try.

We then used filter to only list out rmse (which represent $RMSE$: root mean square prediction error) to use to evaluate for the best k value.

```
# Plot K Values
knitr::include_graphics(here::here("Results/K-value_plot.png"), rel_path = FALSE)
```



Here we can see neighbor $K = 85$ gives us the minimum $RMSE$.

```
# Exact K value
minK <- read.csv(here("Results/minK.csv"))
knitr::kable(minK, caption = "Minimum Value of K")
```

Table 2: Minimum Value of K

X	neighbors	.metric	.estimator	mean	n	std_err	.config
1	79	rmse	standard	110240792	5	6949925	Preprocessor1_Model040

Table 3: Summary data of analysis

X	.metric	.estimator	.estimate
1	rmse	standard	1.161874e+08
2	rsq	standard	5.197549e-01
3	mae	standard	5.745618e+07

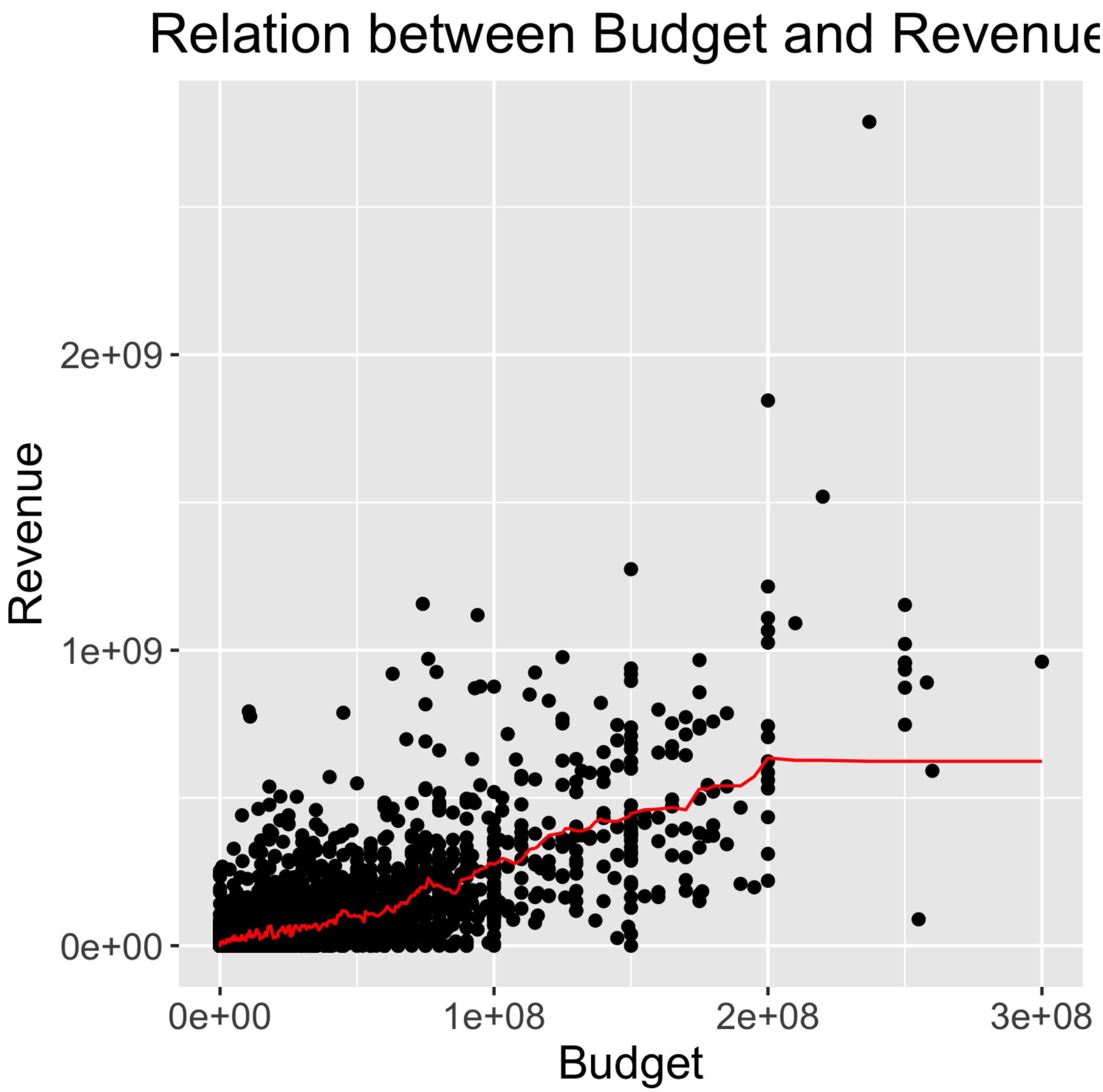
We assigned the best K to `k_min`, and use the best K value to recreate our model following the same steps as before.

Finally, we will pass the testing dataset into our final regression model. The model will predict the revenue using the `predict()` function function, and be use `bind_cols` to combine with the revenue_test column for readability. We will compare its predictions with the actual labels.

```
# Summary data
revenue_summary <- read.csv(here("Results/revenue_summary.csv"))
knitr::kable(revenue_summary, caption = "Summary data of analysis")
```

At last, we visualize our prediction using ggplot functions to evaluate if our model is overfitting, underfitting or a good fit for our target.

```
# Regression Plot
knitr::include_graphics(here::here("Results/revenue_Budget_plot.png"), rel_path = FALSE)
```



0.4 Discussion:

0.4.1 Expected outcome

This project centers around studying the profitability of a movie before it is released, predicting revenues based on budget using Knn regression. By analyzing the data set, which consists of 5000 movies from TMDB, a correlation between budget and revenue can be established. According to the market feedback, a larger production (budget) will usually indicate higher qualities of production, indicating a higher revenue. However, as budget exceeds a certain limit, it will reach its total capacity for revenue feedback due to the limited resources of the market. Thus, we hypothesize that a revenue and budget will have a positive correlation, but our model will streamline at a maximum capacity of revenue since that is the limitation of KNN nearest neighbor regression(which lose accuracy beyond the range of the training data).

0.4.2 Summary of Results

The result discovered through the model and supports our hypothesis. as we expected, we found the relationship between the profitability of a movie and the revenues is positive within the budget range of 0 to $2 * 10^8$, after that the slope of the budget and the revenue will go close to 0, which means our prediction of the revenue will stay constant as the budget increase. This limitation is caused by the use of KNN nearest-neighbor regression since it can only predict accurately within our range. The $RMSE$ from our result is $1.316789 * 10^8$, which is approximate 1/10 of our revenue. This is not a significant mistake, however this model can be improved further.

We find that the revenue of a film is most closely related to the investment cost of the film. Therefore, if we want to make the film more profitable, we have to increase the investment cost of the film to some extent. KNN regression is very advantageous because it has strong elasticity to noise and effective data training in the case of training large amounts of data. We also have a close range of budget with very few outliers outside of the range so KNN regression works better than linear regression. By looking at the relationship_revenue graph, we can see the correlation between budget and revenue is 0.69, whereas the others are below 0.6. This is why we use only one predictor in our project, since others have weak correlation with the target variable. If we use those weak predictors, the K value will be affected and the prediction will be less accurate and does not serve our purpose of prediction. As indicated by the graph "Relation Between Budget and Revenue", it is a perfect fit as it is neither underfitting or overfitting, thus it will be able to make reasonable prediction to some extend.

0.4.3 Impact of Results

"Movie revenue depends on multiple factors such as cast, budget, film critic review, MPAA rating, release year." (Apte, 2011). However, due to the complexity and multi-dimensionality of the multiple factors, an accurate model is difficult to create with those factors together. However, by analyzing the relationship between budget and revenue which have similar range and values, we can visualize trends in production investment and revenue. Movie production requires large sums of investment and subsequent effort, so it is crucial to understand how revenue is linked with budget. By creating this model, we successfully visualized the correlation and future predictions can be made. Such a prediction could be very useful for the movie studio which will be producing the movie so they can decide on expenses like artist compensations, advertising, promotions, etc. accordingly (Apte, 2011). Movie theatres will also be able to estimate the revenues they would generate from screening a particular movie based on given budget.

0.4.4 Future Questions

According to our findings, the correlation between revenue and budget is the strongest. This raises the question - Would a higher budget always indicate a higher revenue? Besides increasing the budget, we should think about what other ways we can improve our model to predict the revenue of the film. The future questions that our research could lead to is to what extent the increase in budget would affect the revenue of a movie belonging to a particular genre. Building onto that we can also do further research to improve the other predictors that can be used for data analysis. The research can also qualify as a classification problem if we choose to focus on a particular category of a movie or a particular production house, and compare which production company generates greater revenue (Mueller, 2021). Box office trends largely reflect audience satisfaction with a film. So this raises the question of whether it's more important to increase the budget, or to focus on the content and quality of the movie.

0.5 Citation

(TMDb), T. M. D. (2017, September 28). TMDB 5000 movie dataset. Kaggle. Retrieved April 7, 2022, from https://www.kaggle.com/datasets/tmdb/tmdb-movie-metadata

Mueller, A. (2021, December 1). Why movies cost so much to make. Investopedia. Retrieved April 7, 2022, from https://www.investopedia.com/financial-edge/0611/why-movies-cost-so-much-tomake.aspx#:~:text=Movie%20budgets%20can%20average%20around,and%20special%20effects%2C%20and%20marketing

Nikhil, A. (2021, December 16). Predicting movie revenue - cs229.stanford.edu. Predicting Movie Revenue. Retrieved April 8, 2022, from https://cs229.stanford.edu/proj2011/ApteForssellSidhwa-PredictingMovieRevenue.pdf

Mondal, R., Zhang, M., Lu, C., & Leng, J. (2022). Predicting the revenue of the movies based on budget. Retrieved 2023, from https://github.com/rehan13/DSCI-100-Project-Group25.git