# Predicting Box Office Success Through IMDB Scores

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## Abstract

This study covers how film ratings can be used to predict box office success for movies with similar characteristics of already published movies. This is beneficial for investors because it will indicate how much money they should spend on films in production. It could potentially a larger output of high quality films. I conducted different forms of descriptive statistics and regression analysis to test the theory. I concluded that there is a slightly positive correlation between IMDb scores and box office success, especially for film ratings above a 6.

## Introduction

The film industry is a multi-billion entertainment industry that significantly impacts culture, education, leisure, and inspiration. They are integral in many people's daily lives, and some may even develop deep connections and reach epiphanies from movies. However, an industry of that scale does not get to that size without a proper foundation. The average budget for a movie is about $65 million dollars, with an additional $35 million for marketing (Mueller). Unfortunately, the amount of money that goes into producing a movie does not guarantee success. Some people are genuinely passionate about a movie being brought to life, but the uncertainty of box office success leads to a lot of risk and concerns for film investors who are more concerned about the financial profits.

This leads to the main question of the research paper: how can we predict box office success for movies? There are a number of potential factors that can contribute to the prediction of a movie's box office success such as budget, cast, director, producer, trailer views, and movie ratings (Chakraborty et al). The most prominent factor that movie viewers focus on is movie ratings. It is one of the first things that viewers do before deciding to watch a movie because people only want to watch worthwhile movies. The Internet Movie Database (IMDb) is the most popular film review company. IMDb uses a 10-point scale for consumers to rate movies with a weighted average system that is intended to prevent people from rigging reviews (Stegner). The platform is also used for finding out more details about movies such as the cast, director, producer, synopsis, and trailer of a movie. Although IMDb has been a trusted platform for films for a long time, it does not mean that it is flawless. Their most significant problem is that consumers will only leave reviews if they have a very high or low opinion about a film. This leads to skewed ratings, so it is important to also look into the written movie review.

Nonetheless, IMDb has a lot of data to work with and is a reliable source for film reviews and ratings, so the platform's film ratings will be used primarily to predict box office success for this research paper. If there appears to be a correlation between IMDb ratings and box office success, investors could compare the characteristics of a movie that is already produced and had strong box office success to a movie that is in need of investment. The investors could choose how much to invest based on how the other similar movie performed at the box office. This approach would also be beneficial to consumers as it ensures that mostly only movies with characteristics that people have an interest in will be invested in to be created.

For this purpose, I will use data with 21 variables and 444 values on Walt Disney movies from 1937 to 2021 compiled by Diksha Bhati on Kaggle. I will be focusing on the effect of IMDb scores of movies on box office success. The reason why I will be focusing on Walt Disney movies is that the animation studio has been dominating its film category for decades, so it would be of interest to see the potential correlation between film ratings and box office success for a highly established animation company. It would also be worthwhile to learn more about why the company is so successful. It could be their reputation, storytelling, or appeal to emotion that compels so many viewers. Disney holds seven of the ten highest-grossing animated movies in North America (Whitten). It is fitting to analyze the box office success of the company referred to as the “king of the box office”.

For the data analysis, I first look over the summary statistics of the cross-sectional data set to understand what I will be working with. Box plots, a scatter plot with a fitted regression line, and quantiles are used to describe the data of interest. For the box plots, it is important to note that there are outliers at the high end of the quartiles, which represent the unusually successful Disney movies such as Frozen. On the other hand, there are outliers on the low end of the quartiles for the IMDb scores, which indicate that consumers oftentimes leave unreasonably negative reviews for films. For the scatter plot, we see that there is a moderately positive correlation between IMDb scores and box office success. However, the positive slope does not appear until after the IMDb score of 6. This shows that only films with a rating above 6 are exponentially successful.

I also regress IMDb scores on box office success using OLS regression. All of the variables were statistically significant, which is a good sign for the interpretation of the regression analysis. There is a lot of standard error, but that's partially because the box office success data is so large. The adjusted R-squared is very low at about 0.14, which indicates that the variation of the dependent variable is not explained by the independent variable well. This makes sense as the points are scattered around for the most part. The regression line's intercept starts at a negative number, which makes sense since a movie with an IMDb score of 0 would not be profitable at all.

I include a polynomial regression and a step function for additional analysis as well. The polynomial regression was to provide a non-linear fit to the data. The graph's intercept started at a high intercept, while the IMDb regression coefficient became negative, which was the complete opposite of the normal OLS regression. However, the polynomial variable was positive. The step function used a K of 2 for the K-Nearest-Neighbors cross-validation. I fit a linear regression model with a step function which had steps at the 5.45 and 8.51 values. The summary results showed that the regression intercept is statistically insignificant.

Principle component analysis was performed to draw the proportion of variance explained. Box office success captured most of the data with a proportion of variation explained (PVE) of 0.7. On the other hand, IMDb scores had a PVE of 0.3.

Regression trees were used for specialized regression to predict continuously valued outputs. The biggest takeaway was that all movies with an IMDb score above 6.35 was indicated to have positive box office success.

A Least Absolute Shrinkage and Selection Operator (LASSO) model was used to potentially shrink and regularize coefficients to avoid overfitting of the data. The best tuning parameter (lambda) was large but partially due to a data set with large numbers. The graph starts off flat and goes upward at about a lambda of 18. There is a sizeable standard error around the red dots.

## Data

I use data with 21 variables and 444 values on Walt Disney movies from 1937 to 2021 compiled by Diksha Bhati on Kaggle. I will be focusing on the effect of IMDb scores of movies on box office success. That data set was initially scrapped from Wikipedia and compiled to do exploratory analysis and make a movie recommender system. I will be using the data set to predict the box office success of Disney movies using IMDB scores.

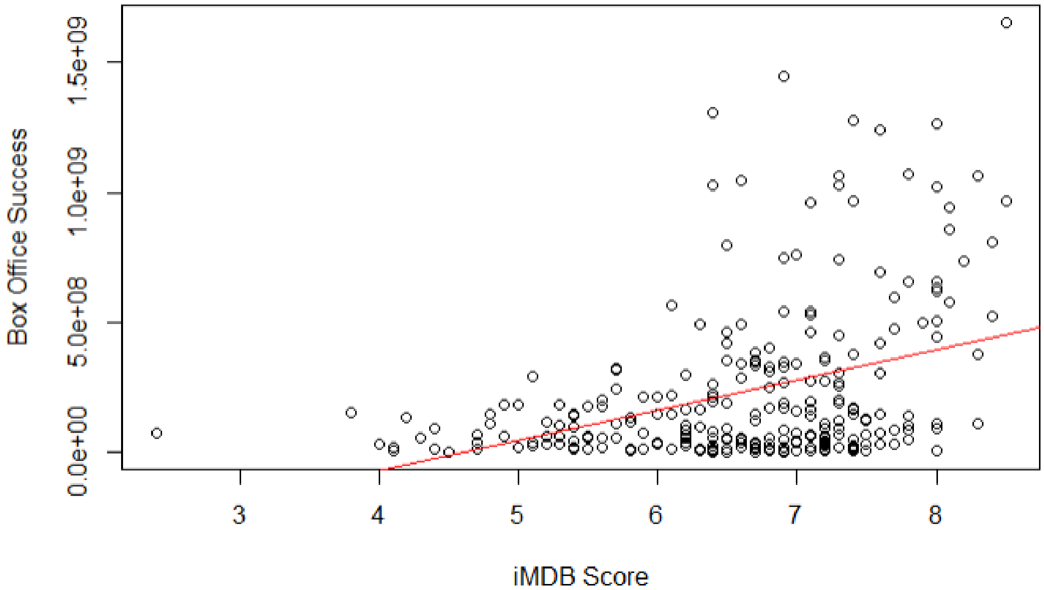
The 21 variables used in the data set are title, production company, country, language, running time, budget, box office, release date, IMDb, metascore, rotten_tomatoes, directed by, produced by, based on, starring, music by, distributed by, cinematography, edited by, and screenplay by. I will be focusing on the IMDb scores and the box office success as IMDb scores are the most popular film rating system and consumer-based, which is ultimately important for determining box office. Film critics are a tiny percentage of the consumer base for movies, so it would be ideal to target consumer reviews. The other major film review platforms, Rotten Tomatoes and Metacritic, both incorporate some aspect of film critic review (Stegner).

Disney movies were chosen to work on as a data set because of the undisputed international acclaim and box office success of the animation studio. The company has been at the forefront of animation films, holding seven of the ten highest-grossing animation movies of all time. It would be very informative to learn more about how the “king of the box office” is so successful financially and receptively.

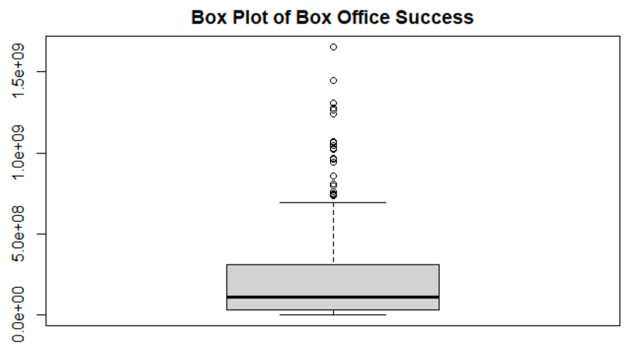
| Release.date <chr> | imdb <dbl> | metascore <chr> | rotten_tomatoes <chr> |
|---|---|---|---|
| 1937-12-21 | 7.6 | 95 | |
| 1940-02-07 | 7.4 | 99 | 73% |
| 1940-11-13 | 7.7 | 96 | 95% |
| 1941-06-20 | 6.9 | N/A | 68% |
| 1941-10-23 | 7.2 | 96 | 98% |
| 1942-08-09 | 7.3 | 91 | 90% |
| 1943-07-17 | 6.5 | N/A | 54% |
| 1946-04-20 | 6.3 | 60 | 70% |
| 1946-11-12 | 7.1 | 54 | 50% |
| 1948-05-27 | 6.3 | 69 | 80% |

1-10 of 257 rows | 10-13 of 21 columns — Previous 1 2 3 4 5 6 ... 26 Next

**Scatter Plot With Line of Best Fit**

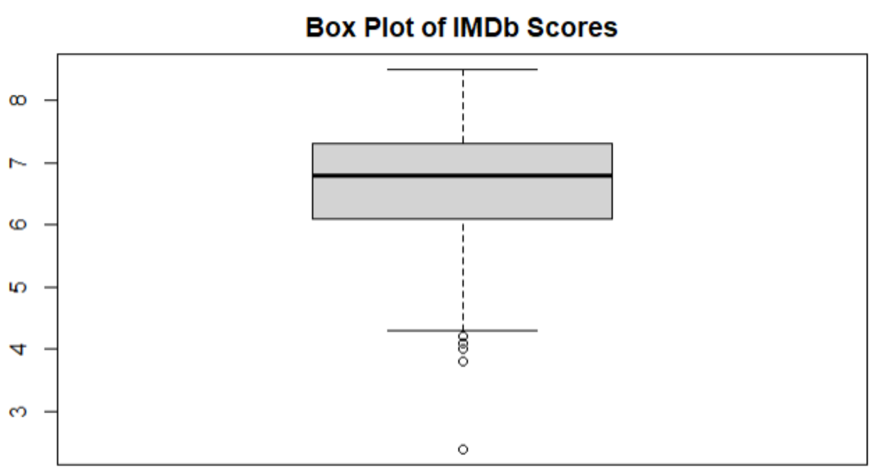



I created a scatter plot with a fitted regression line using IMDB score as the independent variable and Box Office Success as the dependent variable. It appears that there is a positive correlation between IMDb score and Box Office Success. There is a plateau of box office success points from an IMDb score of 4 to 6. The box office success increases dramatically beyond an IMDb score of 6. However, most movies are clustered below a box office success of $500,000,000.




| 0% | 25% | 50% | 75% | 100% |
|---|---|---|---|---|
| 3.600e+01 | 3.060e+07 | 1.064e+08 | 3.100e+08 | 1.657e+09 |

There are outliers at the high end of the quartiles, which represent the unusually successful Disney movies such as Frozen. This indicates that a lot of Disney movies boom outside of their typical range.




| 0% | 25% | 50% | 75% | 100% |
|---|---|---|---|---|
| 2.4 | 6.1 | 6.8 | 7.3 | 8.5 |

There are outliers on the low end of the quartiles for the IMDb scores, indicating that consumers leave unreasonably negative reviews for films occasionally. This is the typical inconvenience of allowing the general public to leave reviews.

## Linear Regression Model

I fit a linear regression model with box office as the response variable and the IMDB scores as the predictors. I use the summary function to see the summary statistics.

### Regression Summary Table

```
Call:
lm(formula = disney_clean$Box.office ~ disney_clean$imdb, data = disney_clean)

Residuals:
       Min         1Q     Median         3Q        Max 
-388183854 -207625705  -50396562   99221532 1204170704 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)       -540743214  118436424  -4.566 7.75e-06 ***
disney_clean$imdb  116890884   17715139   6.598 2.39e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 286700000 on 255 degrees of freedom
Multiple R-squared:  0.1458,	Adjusted R-squared:  0.1425 
F-statistic: 43.54 on 1 and 255 DF,  p-value: 2.389e-10
```

The regression summary table above was obtained through the summary function in R. I regressed IMDb scores on box office success. The three asterisks next to the very small p-values indicate that the intercept of the regression line and IMDb score variable are both statistically significant. The regression and individual variables have large standard errors, but it is important to consider that this data set is working with very large numbers in the hundreds of millions.

If the IMDb score predictor variable was 3, then the predicted box office success would be -540743214 + 3(116890884), which is -190070562. This makes sense because we would not expect a movie with a 3/10 score to be lucrative. If the IMDB predictor was 7, then the predicted box office success would be -540743214 + 7(116890884), which is 277492974. This further proves the observation that Disney movies with scores above 6 are exponentially more successful at the box office.

I do the same as I did for the linear regression model above, but I include a polynomial for the predictor. The polynomial regression is intended to extend the linear model by adding an extra predictor obtained by raising the predictors by an exponent. The goal is to provide a non-linear fit to the data. The intercept and predictor variables are still all statistically significant, but the graph starts much higher now at 1,211,851,629 instead of starting at a negative number. The IMDb score has a negative coefficient now, which is not expected because I anticipated that an increase in the score would lead to higher box office success for movies. However, the squared polynomial variable for the IMDb score has a positive coefficient, which suggests that higher scores might have more accurate box office predictions compared to lower scores that have a higher than expected prediction in this model. I will not be using this model to interpret conclusions.

```
Call:
lm(formula = disney_clean$Box.office ~ disney_clean$imdb + I(disney_clean$imdb^2),
    data = disney_clean)

Residuals:
       Min         1Q     Median         3Q        Max
-482393830 -183378366  -46715089   97366873 1217184911

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)            1211851629  450694633   2.689  0.00764 **
disney_clean$imdb      -464822707  145655745  -3.191  0.00159 **
I(disney_clean$imdb^2)   46801935   11636683   4.022 7.62e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 278500000 on 254 degrees of freedom
Multiple R-squared:  0.197,	Adjusted R-squared:  0.1907
F-statistic: 31.15 on 2 and 254 DF,  p-value: 7.95e-13
```

If the IMDB predictors were 5, the predicted box office success would be 1211851629 - 464822707(5) + 46801935(5), which is -878252231. This means that movies with an IMDb score of 5 or lower are likely to not profit at the box office, which supports the observation that a score of 6 is the threshold for positive box office performance.

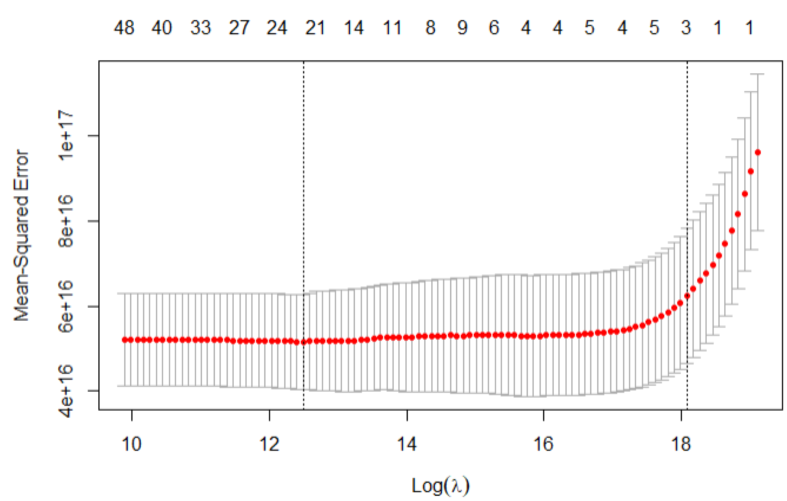
## OLS Regression With Step Function

I used the K-Nearest-Neighbors method for cross-validation of the data, which is a nonparametric method used to solve classification and regression problems. Cross-validation is used to test a model's ability to predict new data. I found that there is no difference in using a K of 1, 2, 3, or 4 when comparing the cross-validation results, so it does not matter which K we proceed with for the OLS regression with a step function. Using a K of 2, I fit a linear regression model with a step function. I created a regression summary table that has steps at the 5.45 and 8.51 values. The summary results indicate that the regression intercept is statistically insignificant, which logically makes sense since the coefficient is a positive large number, so it suggests that even low IMDb scores would perform well at the box office. On the other hand, the IMDb score coefficient is statistically significant at a value of 181160299. The regular OLS regression appears to be more reliable for interpreting results.

```
Call:
lm(formula = disney_clean$Box.office ~ cut(disney_clean$imdb,
    2), data = disney_clean)

Residuals:
       Min         1Q     Median         3Q        Max
-258569034 -213669070  -84569070   71891229 1398430930

Coefficients:
                                       Estimate Std. Error t value Pr(>|t|)
(Intercept)                            77408771   49220283   1.573 0.117028
cut(disney_clean$imdb, 2)(5.45,8.51] 181160299   53319812   3.398 0.000789 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 303400000 on 255 degrees of freedom
Multiple R-squared:  0.04331,	Adjusted R-squared:  0.03956
F-statistic: 11.54 on 1 and 255 DF,  p-value: 0.0007885
```

## LASSO Model

I will create a model matrix and cross-validate the lasso model to ultimately find the best tuning parameter (denoted by lambda) and plot the model. The optimal lambda will be found by sorting through the lambdas in the LASSO model to find the smallest one. The best lambda is 268028.4, which seems large but we also have to consider that the data set works with very large numbers.



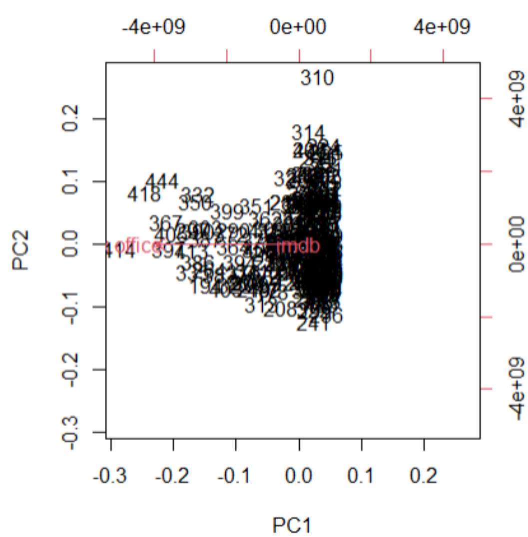

The red dots in the LASSO model graph are the mean from the cross-validation. It starts off flat and scales upward at about a lambda of 18. There is a sizeable standard error around the red dots.

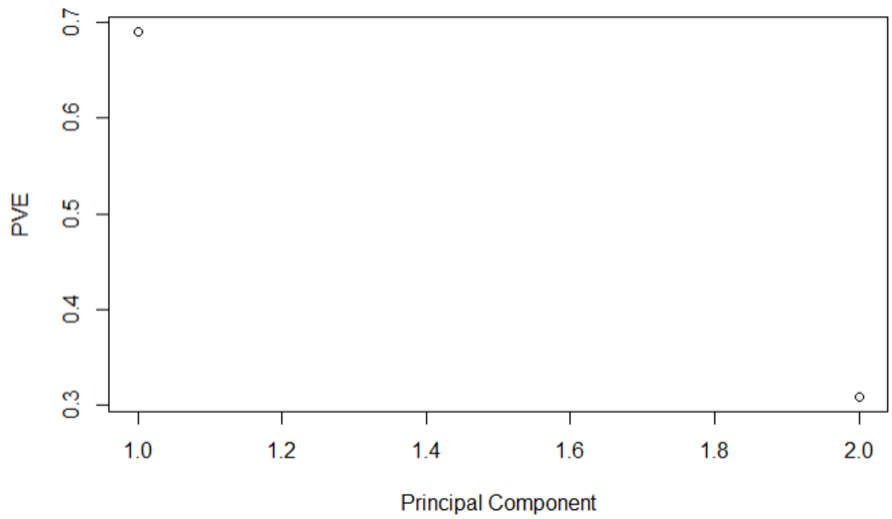
The coefficients of the LASSO model are below. They are split just about even for positive and negative coefficients.

**Principle Component Analysis**

I will perform principal component analysis, which reduces data set dimensionality and increases interpretability. From the scree plot, we see that box office success captures most of the data with a proportion of variation explained (PVE) of 0.7. IMDb scores are less effective at this, as they have a PVE of 0.3.

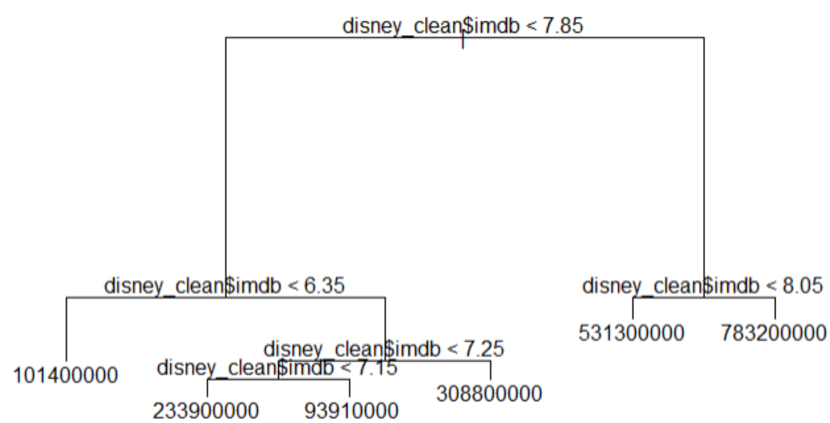
The biplot shows that most values on the principal component one axis (box office success) are clustered on the positive side but many drift to the negative side. There appears to be an outlier on the principal component two axis that is past 0.2. The points are well-clustered which suggests that they respond to the system uniformly.






**Regression Tree**

I created a regression tree to predict continuously valued outputs for the regression model. My observation of all movies with an IMDb score above 6 is supported by the regression tree having all positive values for scores above 6.35. It appears that movies with an IMDb score of 8.05 are on another level of box office success.




**Results**

Upon completing the data analysis, the OLS regression shows statistically significant data and a slightly positive correlation between IMDb scores and box office success. The additional regression functions such as the polynomial regression, LASSO model, and step function did not contribute much to the theory of IMDb scores predicting box office success as there was statistical insignificance and contradictory regression coefficients, so the OLS regression was the main source of information. Overall, the data support the prediction of high IMDb scores suggest high box office success.

## Conclusion

There are many facets to film ratings and reviews. One can argue that film critics do not truly capture the consumer audience well while consumers are biased and review subjectively. However, one thing that is for sure is that most people will continue to use film ratings to decide whether a film is worth watching or not. Although not exactly, this gives us some indication on how much box office success a movie will have. We can use film rating models to roughly predict how profitable movies will be so that investors can be well-informed for future similar movies that need funding. If this model is adopted, it ideally will ensure that the quality of movies in the future will be top notch.

## References

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## Code Appendix

```
disney <- read.csv("C:/Users/justi/Documents/Datasets/walt_disney_movies.csv")
disney$imdb <- as.numeric(as.character(disney$imdb))
disney$Box.office <- as.numeric(as.character(disney$Box.office))
disney_clean <- na.omit(disney)
attach(disney_clean)
plot(disney_clean$imdb, disney_clean$Box.office, xlab = 'IMDB Score', ylab = 'Box Office
Success')
disney_lm = lm(disney_clean$Box.office ~ disney_clean$imdb, data=disney_clean)
summary(disney_lm)
disney_poly_lm = lm(disney_clean$Box.office ~ disney_clean$imdb + I(disney_clean$imdb^2),
data=disney_clean)
summary(disney_poly_lm)
proj_glm_fit = glm(Box.office ~ imdb, data=disney)
cv.err = cv.glm(disney, proj_glm_fit)
cv.err$delta
proj_glm_fit = glm(Box.office ~ poly(imdb,2), data=disney)
```

```
cv.err = cv.glm(disney, proj_glm_fit)

cv.err$delta

library(class)

train = (imdb > 7)

disney.10 = disney[!train, ]

Box.office.7 = Box.office[!train]

imdb1 = (imdb <= 7)

imdb2 = (imdb > 7)

train.X = cbind(imdb1, imdb2)[train, ]

test.X = cbind(imdb1, imdb2)[!train,]

train.Box.office = Box.office[train]

set.seed(1)

knn.pred1 = knn(train.X, test.X, train.Box.office, k=1)

knn.pred2 = knn(train.X, test.X, train.Box.office, k=2)

knn.pred3 = knn(train.X, test.X, train.Box.office, k=3)

knn.pred4 = knn(train.X, test.X, train.Box.office, k=4)

table(knn.pred1, Box.office.7)

mean(knn.pred1 == Box.office.7)

table(knn.pred2, Box.office.7)

mean(knn.pred2 == Box.office.7)

table(knn.pred3, Box.office.7)

mean(knn.pred3 == Box.office.7)

table(knn.pred4, Box.office.7)
```

```
mean(knn.pred4 == Box.office.7)

y <- disney_clean$Box.office

x <- data.matrix(disney_clean[, c('imdb', 'Budget')])

library(glmnet)

ridge_model <- glmnet(x, y, alpha = 0)

summary(ridge_model)

cv_model <- cv.glmnet(x, y, alpha = 0)

best_lambda <- cv_model$lambda.min

best_lambda

plot(cv_model)

best_model <- glmnet(x, y, alpha = 0, lambda = best_lambda)

coef(best_model)

plot(ridge_model, xvar = "lambda")

y_pred<- predict(ridge_model, s = best_lambda, newx = x)

sst <- sum((y - mean(y))^2)

sse <- sum((y_pred - y)^2)

rsq <- 1 - sse/sst

rsq

x_matrix <- model.matrix(y ~ poly(x, 10, raw = T), data = disney_clean)[, -1]

lasso_mod <- cv.glmnet(x_matrix, y, alpha = 1)

best_lambda <- lasso_mod$lambda.min

best_lambda

best_model <- glmnet(x_matrix, y, alpha = 1)
```

```
predict(best_model, s = best_lambda, type = "coefficients")

library(pls)

x <- model.matrix(disney_clean$Box.office ~ disney_clean$imdb, data = disney_clean)[, -1]

pcr_train <- sample(c(TRUE, FALSE), nrow(disney_clean),replace = TRUE)

pcr_model <- pcr(disney_clean$Box.office ~ disney_clean$imdb + disney_clean$Budget, data =
disney_clean ,subset = pcr_train,scale=TRUE,validation="CV")

validationplot(pcr_model, val.type = "MSEP")

summary(pcr_model)

set.seed(1)

knn.pred1 = knn(train.X, test.X, train.Box.office, k=1)

knn.pred2 = knn(train.X, test.X, train.Box.office, k=2)

knn.pred3 = knn(train.X, test.X, train.Box.office, k=3)

knn.pred4 = knn(train.X, test.X, train.Box.office, k=4)

table(knn.pred1, Box.office.7)

mean(knn.pred1 == Box.office.7)

table(knn.pred2, Box.office.7)

mean(knn.pred2 == Box.office.7)

table(knn.pred3, Box.office.7)

mean(knn.pred3 == Box.office.7)

table(knn.pred4, Box.office.7)

mean(knn.pred4 == Box.office.7)

disney_step_lm <- lm(disney_clean$Box.office ~ cut(disney_clean$imdb, 2), data =
disney_clean)
```

```
summary(disney_step_lm)

disney_subset <- subset(disney_clean, select = c(Box.office, imdb))

pr_out <- prcomp(disney_subset)

biplot(pr_out)

plot(pr_out$sdev^2 / sum(pr_out$sdev^2),ylab="PVE",xlab="Principal Component")
```

**External Research Article Summary**

Although the movie industry is a large and prime industry for investors to get into, it is very tricky when deciding which movies to invest in. With the rapid growth of the industry, there is an increasingly large amount of data to work for data analysis. It is difficult and subjective to determine a movie's box office success, but this paper determines success as box office profit. The authors' proposed model uses pre-released features and post-released features of movies, but only the pre-released features for the predictions. A scale of 5 categories ranging from flop to blockbuster is used for the film success ranking. The authors' system uses Support Vector Machine (SVN), Neural Network, and Natural Language Processing to predict the box office success. The paper shows that Neural Network has a prediction accuracy of 84.1% for pre-released features and 89.27% for post-released features. SVM has 83.44% and 88.87% respectively when one away prediction is considered. IMDb votes and number of screens were concluded to be the most important predictors of movie box office success.

```
66 x 1 sparse Matrix of class "dgCMatrix"
                                      s1
(Intercept)              -2.264220e+08
poly(x, 10, raw = T)1.0   8.001005e+07
poly(x, 10, raw = T)2.0   8.321906e+00
poly(x, 10, raw = T)3.0   .
poly(x, 10, raw = T)4.0   .
poly(x, 10, raw = T)5.0  -2.633805e+04
poly(x, 10, raw = T)6.0  -9.809658e+02
poly(x, 10, raw = T)7.0   .
poly(x, 10, raw = T)8.0   .
poly(x, 10, raw = T)9.0   .
poly(x, 10, raw = T)10.0  1.205288e+00
poly(x, 10, raw = T)0.1   5.480157e-02
poly(x, 10, raw = T)1.1   .
poly(x, 10, raw = T)2.1   5.416761e-03
poly(x, 10, raw = T)3.1   .
poly(x, 10, raw = T)4.1   .
poly(x, 10, raw = T)5.1   .
poly(x, 10, raw = T)6.1   .
poly(x, 10, raw = T)7.1   .
poly(x, 10, raw = T)8.1   .
poly(x, 10, raw = T)9.1  -7.700572e-08
poly(x, 10, raw = T)0.2   .
poly(x, 10, raw = T)1.2   .
poly(x, 10, raw = T)2.2   .
poly(x, 10, raw = T)3.2   .
poly(x, 10, raw = T)4.2   1.484796e-12
poly(x, 10, raw = T)5.2   2.409400e-12
poly(x, 10, raw = T)6.2   5.412914e-14
poly(x, 10, raw = T)7.2   3.235666e-19
poly(x, 10, raw = T)8.2   .
poly(x, 10, raw = T)0.3  -2.053265e-17
poly(x, 10, raw = T)1.3  -3.061512e-18
poly(x, 10, raw = T)2.3  -8.624221e-20
poly(x, 10, raw = T)3.3  -8.806843e-22
poly(x, 10, raw = T)4.3   .
poly(x, 10, raw = T)5.3   .
poly(x, 10, raw = T)6.3   .
poly(x, 10, raw = T)7.3  -4.032478e-23
poly(x, 10, raw = T)0.4   .
poly(x, 10, raw = T)1.4   .
poly(x, 10, raw = T)2.4   .
poly(x, 10, raw = T)3.4   .
poly(x, 10, raw = T)4.4   .
poly(x, 10, raw = T)5.4   .
poly(x, 10, raw = T)6.4  -1.651652e-30
poly(x, 10, raw = T)0.5   .
poly(x, 10, raw = T)1.5   .
poly(x, 10, raw = T)2.5   .
poly(x, 10, raw = T)3.5   .
poly(x, 10, raw = T)4.5   .
poly(x, 10, raw = T)5.5   .
poly(x, 10, raw = T)0.6   5.793022e-43
poly(x, 10, raw = T)1.6   .
poly(x, 10, raw = T)1.6   .
poly(x, 10, raw = T)2.6   .
poly(x, 10, raw = T)3.6   .
poly(x, 10, raw = T)4.6   .
poly(x, 10, raw = T)0.7   9.179179e-52
poly(x, 10, raw = T)1.7   .
poly(x, 10, raw = T)2.7   .
poly(x, 10, raw = T)3.7   .
poly(x, 10, raw = T)0.8   .
poly(x, 10, raw = T)1.8   .
poly(x, 10, raw = T)2.8   .
poly(x, 10, raw = T)0.9   .
poly(x, 10, raw = T)1.9   .
poly(x, 10, raw = T)0.10 -5.022882e-78
```