Predicting a Film's Rating Utilizing Machine Learning

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Abstract

We present a program that will utilize existing data on films that have been released in order to predict the rating of a film that has yet to be released. This prediction will be given to the film industries that created the film in order to give them a chance to improve the film if needed. The factors being used are IMDB rating, budget, USA gross, USA opening weekend gross, tomatometer, metascore, and worldwide gross. We used using linear regression, k-nearest neighbors, and logistic regression as our model for the project. K-nearest neighbors and logistic regression will utilize k-fold cross validation and will be used as a contender against our linear model. Our methodology to solve this problem included intense research and rigorous testing.

1 Problem Description

When a film industry decides to create a film, the creators have to factor in many attributes that are important to how the public will interpret and perceive the film. Some of these factors are the companys film budget, the film critic ratings, and how much the film makes on its first weekend.

This public interpretation is very important to the film company because how the public perceives the film ultimately determines how many people go and see the film. The amount of people who go see the movie ultimately determines if the film company makes a profit off of the movie, i.e. if it is a hit or a flop.

The fate of the film cannot be determined until after the film is released to the public making it too late to make any changes if it fails. Our program is aimed to fix this problem by analyzing factors of previous films in order to predict the audience rating the new film will receive. This audience rating will give the film company a general idea of how well their film will do before they release the movie. Based on the audience rating presented, the film company will be able to fix their film before release so they can maybe save the film from flopping.

The film industry is a staple in many cultures. It affects almost anyone you can think of. This, along with the fact that we are big fans of films and what it takes to create a work of art worth seeing, is what pushed us to pursue this problem.

2 Survey

To see how much of an impact this project would have with the general population, we asked 50 students their opinion.

Q: Do you believe this project will have an impact on which movies you will watch based on the rating generated?

37 students said it would have an impact. 9 students said it would not impact them. 4 students said they did not know.

3 Plan

March 8th - Understand the Problem in-depth

- Our group has got a now gotten a better understanding of how we can attack this problem. Our attributes will be able to help us use our model to estimate the probability of success (IMBD Rating, Budget, USA Gross, USA Opening Weekend Gross, Tomatometer, Metascore, Worldwide Gross).

March 14th - Develop a data base for the code
- We first created a database where we stored our
y attributes and our y audience rating (1.0.10.0) in

x attributes and our y audience rating (1.0-10.0) in excel.

- Our model first takes the data from the database (excel), then splits our data to a X and Y dataset. Our model will consist of a train/test split of the X and Y dataset. We used Linear Regression to find a relation between the X attributes and the rating, we then proceeded to use the K-Fold method to optimize our model.

March 29th - Complete Intermediate Project Report

- Done and done.

April 10th - Research ways to make algorithm more accurate

- This step took us some time. We found that doubling the size of our dataset was the most influential change that increased the accuracy of our models.

April 20th - Edit algorithm to be more effective and more precise

- We implemented cross validation in our k-nearest neighbors and logistic regression models in order to increase the precision of our predictor. In the end we saw an increase of about 20% using cross validation but our linear regression model continued to be the more accurate model of the three.

April 29th - Complete Final Project Presentation

- Done.

May 4th - Complete Final Project Report - This report is proof of completion.

4 Data

The data set contains seven attributes (or features, denoted by X1. . . X8) and one response (or outcomes, denoted by y1). The aim is to use these seven features to predict the outcome.

We specifically choose these seven features because the information is easy to find and open to the public. Some other attributes that we considered for the data was harder to come across on the internet and left many holes in our data. This would have required us to have to clean our data beforehand. With the attributes we are using there is no need to clean the data because we handpicked each movie individually to contain all or most of the attributes. Data was obtained from the Rotten Tomatoes website which provided us with the Tomatometer (Rotten Tomatoe's score of the movie), and the audience score (the value that we intend to predict.) We also utilized the IMDb website to obtain the gross USA (the amount of money that was made in the USA), the gross opening weekend USA (the amount of money that was made in the first week that the movie was released to the public), worldwide gross (the total amount of money made around the globe), budget (the amount of money the studio spent to create the movie), metascore (the IMDb user's score of the film), and IMDb rating (the score that IMDb critics gave the film.)

All this would come together to predict what an average person watching the film would rate it. Because this score is given by a person and not so calculating machine these scores have an entropic nature. Some may give a low score while others may give a high score. To combat this problem, we have simple stuck to the audience score from Rotten Tomatoes that takes the average of all user's scores.

Specifically:

5 Results

X1 Gross USA

X2 Gross Opening Weekend USA

X3 Worldwide Gross

X4 Budget

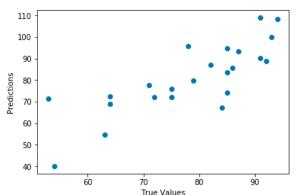
X5 Metascore

X6 IMDb rating

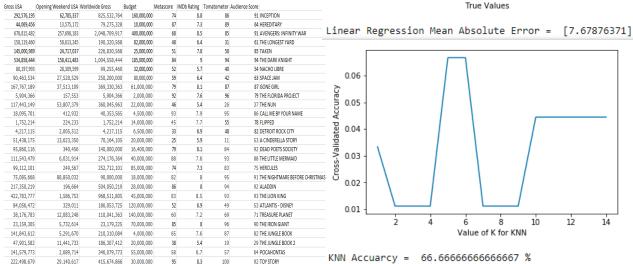
X7 Tomatometer

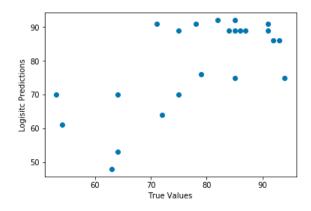
y1 Audience Score

Below is a screenshot of the first few lines in the dataset that we are utilizing for our model. As you can see, most attributes are filled in and few are null. We intend to expand the size of the dataset as we continue to work on the project. Much of the data is gathered by hand and requires a large amount of time to find. Fortunately, the doubling of our dataset was enough to increase our accuracy dramatically so we felt that there was not much benefit in adding much more data to our set.



Predicting Infinity War: score = ~91, Predicted = 89





model=regr.fit(X_train, y_train) predictions=regr.predict(X_test)

regr=linear_model.LinearRegression()

Log Reg Accuarcy = 55.555555555556 %

Considering the fact that predicting a score exactly correct is very difficult we decided to take a different approach as to how to calculate the accuracy of our linear regression model. We decided on allowing a small window of +3/-3 to the model's prediction. For example, if our prediction was either 71, 72, 73, 74, 75, 76, or 77 for a film with a score of 74 it would be considered as a accurately predicted audience score. When you take this into consideration, our accuracy increased dramatically.

This is an acceptable method of reading our data because film ratings are all based on biased opinions and many other factors that cannot be considered. The window covers the high variance that comes with predicting this type of data.

print("Linear Regression Mean Absolute Error =
", mean_absolute_error(y_test, predictions, multioutput='raw_values'))

k_scores=[]
for k in k_range:
knn=KNeighborsClassifier(n_neighbors = k)
scores=cross_val_score(knn, X, y, cv=3, scoring='accuracy')
k_scores.append(scores.mean())

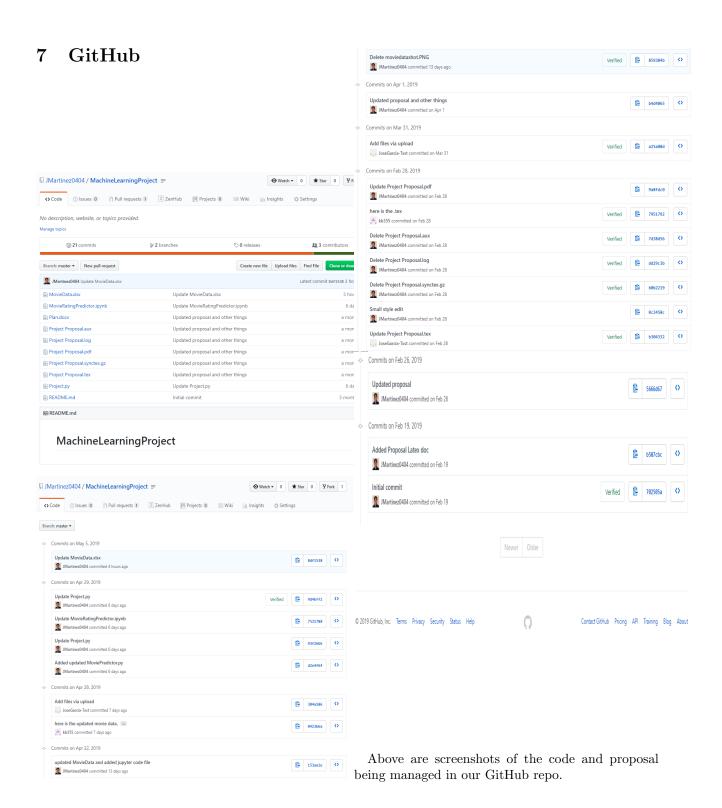
6 Code

df=pd.DataFrame(df,columns=['Gross USA','Opening Weekend USA','Worldwide Gross','Budget','Metascore','IMDb Rating','Tomatometer','Audience Score'])

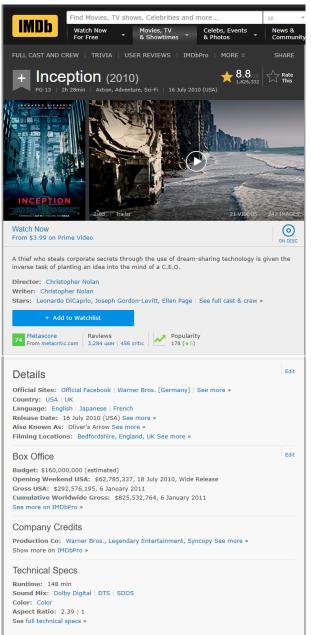
X=df[['Gross USA','Opening Weekend USA','Worldwide Gross','Budget','Metascore','IMDb Rating','Tomatometer']]
y=df['Audience Score']

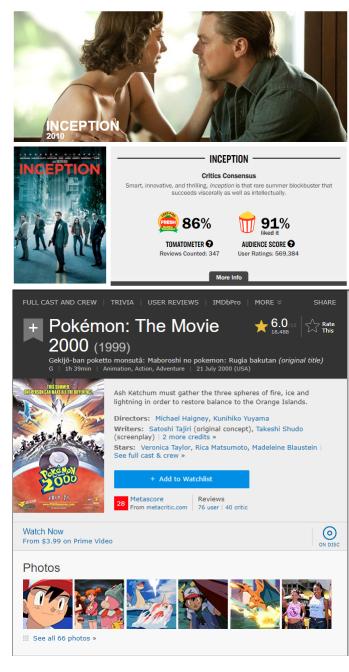
X_train, X_test, y_train, y_test train_test_split(X, y,test_size=0.5) knn=KNeighborsClassifier(n_neighbors=6) print("KNN Accuarcy = ", (cross_val_score(knn, X, y, cv=3, scoring='accuracy').mean()) * 1000, "

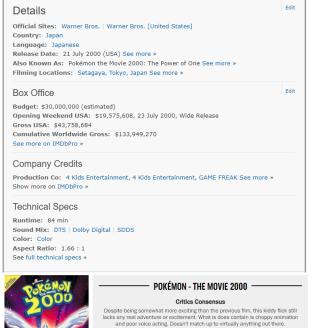
logreg=LogisticRegression()
logmodel=logreg.fit(X_train, y_train)
logpreds=logreg.predict(X_test)

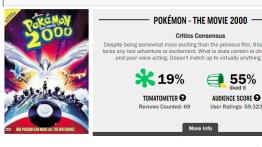


8 Films













Post

MOVIE INFO

In this action-packed anime film, fearless Pokemon trainer Ash Ketchum and his pals must try to save Earth from destruction. An evil collector schemes to procure three coveted Pokemon – Moltres, Zapdos and Articuno – whose capture will unleash mystical sentinel of the sea Lugia. When the villain snares the trio, nature gets thrown out of whack, causing a series of natural disasters. Can Ash and friends prevent an environmental cataclysm?

Rating: G

Genre: Animation, Anime & Manga, Art House & International, Kids & Family

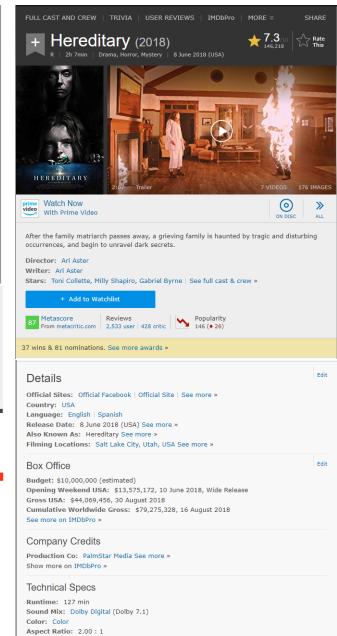
Directed By: Kunihiko Yuyama, Michael Haigney
Written By: Norman J. Grossfeld, Michael Haigney, John Touhey, Takeshi Shudo

In Theaters: Jul 21, 2000 Wide

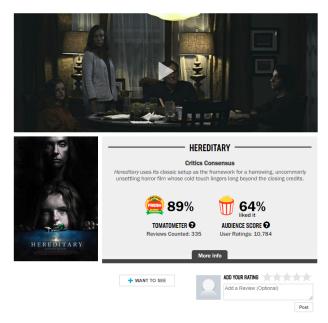
 On Disc/Streaming:
 Nov 14, 2000

 Box Office:
 \$2,119,065

 Runtime:
 102 minutes



See full technical specs ×



quality dataset. They're are a couple of movie database API's on the internet that we could have utilized to create our dataset but in order to ensure a clean set of data creating our own seem the logical step.

Something else we learned from this experience was the importance of understanding the multitude of algorithms available and which cases call for which algorithms. Machine learning is a broad subject as there is much room for improvement.

When it comes to the contributions of the team members they are as follows:

Joel Martinez: worked on program code; worked on report; worked on dataset

Kameron Bush: worked on report; worked on dataset; worked on presentation

Jose Garcia: worked on program code; worked on report; worked on presentation

9 Future Work

Obviously, there is much room for improving the accuracy of our models. Different algorithms or combinations of algorithms could increase our accuracy. Maybe, at some point we would be able to rid our evaluation of the +3/-3 score window altogether. More data and a better understanding of bias trends could help us attack this problem more efficiently.

There are other methods of handling our data that we could attempt. For example, there could be a way to combine regression and classification models in order to create different labels for low, mid-low, mid, mid-high, and high scoring films.

Our main focus for continuing this project would be able to increase the accuracy of our model and make the model more user friendly. One could say that a user interface or app could be marketable to a target audience.

10 Conclusion

One important observation that we came across when creating our project is the importance of a

References

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- [2] Sharda, Ramesh & Delen, Dursun Predicting boxoffice success of motion pictures with neural networks. Expert Systems with Applications. 30. 243-254. 10.1016/j.eswa.2005.07.018.
- [3] B. R. Litman & H. Ahn Predicting financial success of motion pictures. In B. R. Litman (Ed.), the motion picture mega-industry. Boston, MA: Allyn & Bacon Publishing, Inc. (1998)
- [4] M.H Latif & H. Afzal Prediction of Movies popularity Using Machine Learning Techniques. National University of Sciences and technology, H-12, ISB, Pakistan.