Predicting Indian Movie Ratings on IMDB

Team Project - Business Intelligence using Data Mining

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1 Executive Summary

The Indian movie industry produces the maximum number of movies per year at 1000/year, higher than any other country's movie industry. However, very few movies taste success and are ranked high. Given the low success rate, models and mechanisms to predict reliably the ranking and / or box office collections of a movie can help de-risk the business significantly and increase average returns. Various stakeholders such as actors, financiers, directors etc. can use these predictions to make more informed decisions. Some of the questions that can be answered using prediction models are given below.

1. Does the cast or director matter in the success or ranking of an Indian movie?
2. Is the genre of the Indian movie a key determinant of rank or success?
3. Does running time matter?

Further, a DVD rental agency or a distribution house could use these predictions to determine which titles to stock or promote respectively.

Data from the Internet Movie Database (IMDB) was gleaned and various data mining and prediction techniques such as multi-linear regression, regression tree and K-nearest neighbors were used to devise a model that can predict an Indian movie's ranking with an RMSE of 1.5 on a scale of 1 to 10.

2 Problem Description

While extensive description and data is available for Hollywood movies, detailed descriptions about movies from other countries are hard to find. India, especially, is an interesting case in point. The Indian movie industry produces approximately 1000 movies per year, one of the highest worldwide. However, a structured database or a central repository of Indian movie data is not available.

The objective of the project is to predict the ranking of Indian movies on www.imdb.com using information available from different sources including IMDB itself.

IMDB Rating / Ranking: IMDB offers a rating / ranking scale that allows users to rate films by choosing one of ten categories in the range 1–10, with each user able to submit one rating. The points of reference given to users of these categories are the descriptions "1 (awful)" and

"10 (excellent)"; and these are the only descriptions of categories. Due to the minimum category being scored one, the mid-point of the *range* of scores is 5.5, rather than 5.0 as might intuitively be expected given a maximum score of ten. This rating system has since been implemented for television programming on an episode-by-episode basis[1].

3 Data

3.1 Data Preparation

Initially, a total of 2.5 million records were collected from IMDB[2]. The data downloaded was a raw data dump of 15 list files with each list file containing the movie ID and one other potential predictor or movie attribute. The attributes are:

- Votes
- Month and year of release
- Genres – Drama, Action, Romance, Comedy, Other
- Running time
- Languages – Hindi, Telugu, Tamil, Other

As a first step, a database containing information about all the aforementioned attributes needed to be created in order to carry out further modeling or processing. Excel was unable to handle the large number of records. As an alternative to excel, the Java Movie Database (JMDB) tool provided a way to aggregate the information available on the IMDB into a relational database and search for information using SQL queries.

Note that the IMDB site predominantly contains data for Hollywood movies. However, of the millions of records, only 958 records had the country of origin as India and all other relevant information for the attributes listed above. Quite a few Indian movies had a few lines in a language, regional or English. In these cases, this language was also listed against the movie language attribute. Since this information is not relevant information for our purposes, these records were cleaned to reflect the language in which the movie was made or dubbed.

[1] http://en.wikipedia.org/wiki/Internet_Movie_Database#User_ratings_of_films Accessed on Dec 28, 2011

[2] Data source: ftp://ftp.fu-berlin.de/pub/misc/movies/database/

Based on domain knowledge and the palate of the Indian moviegoer, more attributes and interaction variables were added to the list. To do this, Filmfare award winning actors, actresses and directors were added to the database. The list was obtained from Wikipedia http://en.wikipedia.org/. After further processing, the number of award winning actors, actresses and directors were added to each movie record.

To summarize, the added attributes are:

- Interaction variables:
  - Romance & Comedy Genre (RomCom)
  - Action & Comedy Genre (ActCom)
  - Masala Genre – Drama, Action, Romance, Comedy
- Star power scores:
  - Star actor count
  - Star actress count
  - Star director count

3.2 Data Exploration

TIBCO Spotfire Visualization tool was used to explore the data and study relationships between the predictors or between a predictor and the predicted or “Y” variable, which is movie rank (1-10) for this project. Some relationships are illustrated using plots in the Appendix Data Exploration.

All predictors listed in Data Preparation section were deemed valid except the year of release and the number of votes. The year typically is not expected to impact movie ranking or box office collection and the number of votes a movie receives is not available apriori and can only be used for profiling.

4 Results

Since the objective is to predict a numerical Y, i.e. movie rank, which ranges from 1 to 10, multi-linear regression, regression tree and K-Nearest Neighbor methods of prediction were used. Spotfire Miner was used to run the multi-linear regression and regression tree and XLMiner was used to run K-Nearest Neighbors.

Multi-linear regression

Movie rank = *5.29 (Intercept) + 0.17 Drama + 0.06 Action -0.06 Romance -0.18 Comedy + 0.04 Other Genre + .00209 Running - 0.31 Hindi - 0.05 Telugu -0.07 Tamil -0.17 English + 0.05 Other Language + 0.19 RomCom - 0.14 ActRom + 0.1 Masala + 0.05 Month + 0.04 Star Actress Count + 0.04 Star Actor count + 0.04 Star-pairing + 0.64 Star Director count*

The regression tree and K-Nearest Neighbor lift charts are provided in the Appendix, Prediction Models.

5 Performance

The performance of the three methods of prediction is similar. Given that the movie rank ranges from 1-10, an RMSE of 1.5 seems tolerable. Error variance of all three methods hovers around 1.5.

Prediction Method	RMSE Training	RMSE Validation
Multi-linear regression	1.3601	1.3892
Regression tree	1.2610	1.4526
K-Nearest Neighbors (50-30-20 partition)	0.0824 (Validation)	1.7433 (Test)

Table 1 Performance of prediction methods

6 Findings

1. Language related predictors: Movies from other languages or regional languages have a higher rank compared to movies in mainstream languages such as Hindi, Tamil or Telugu. While this seems like an interesting result, a caveat is that movies from regional languages are under represented in the dataset. Further, only the popular and better movies in regional languages are available in IMDB. Therefore, this result might not hold water in a dataset representative of the population.

2. Genre related predictors: While slapstick comedy alone doesn't improve a movie's rank, movies with comedy laced with romance (RomCom) have a higher rank on average. Given the number of movies with comedy as a central theme, this result could serve as a useful way to differentiate a movie from its competition and gain the popular vote. Further, masala movies hold their own with a higher rank amongst other Indian movies.

3. Star Power: Directors have much higher clout and influence a movie's rank more strongly compared to actors, actresses or the star pairing in a movie. While this is surprising, this is hinting at the potential of star directors to extract a quality performance from his / her cast and delivers a superior product after understanding the pulse of the audience.

7 Conclusion

The prediction model arrived at provides some key insights on the palate of the audience of an Indian movie and gives a sense for what governs the movie ranking on IMDB. The predictive accuracy can be improved if a better and more exhaustive listing of Indian movies were available on IMDB. Using Filmfare awards information for actors, actresses and directors, the predictive accuracy of the model was improved and brought to fore some interesting aspects.

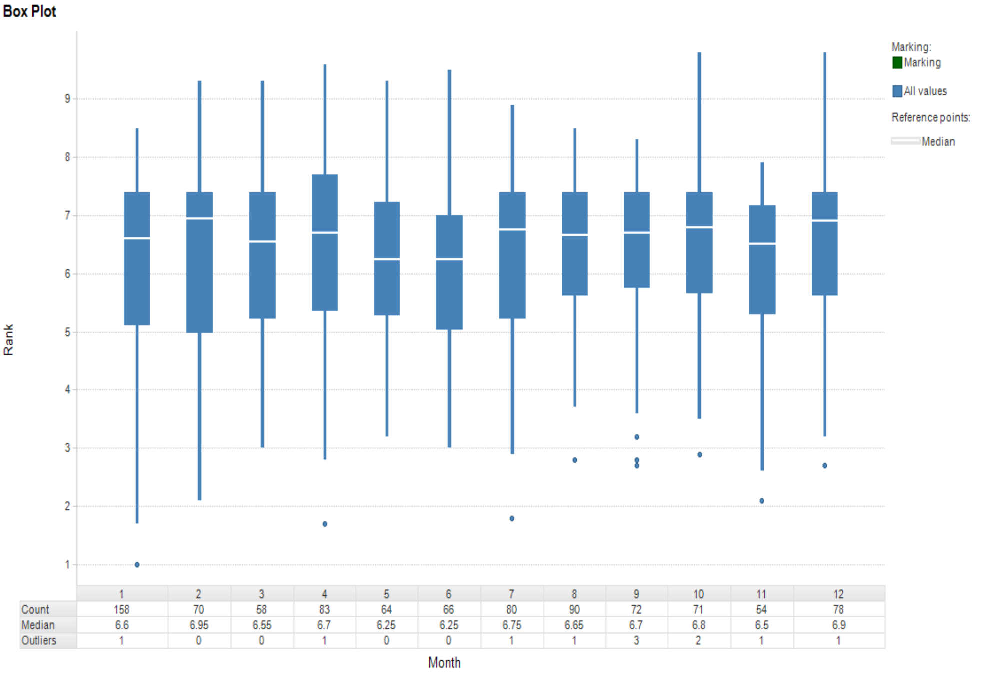
Similarly, the model can be improved by incorporating more social media information and capturing user sentiments and feedback such as Likes, Mentions, Referrals, Tweets and Re-tweets on platforms such as Facebook and Twitter.

A recent venture called Khyati Entertainment Pvt. Ltd[3] makes for interesting reading as the method they use for prediction uses similar predictors to those used in this project! This could potentially mark the beginning of yet another lucrative space for using data mining for business intelligence.

[3] http://articles.timesofindia.indiatimes.com/2011-12-26/bhopal/30558648_1_film-critic-box-office-bollywood-movie

8 Appendix

8.1 Data Exploration



	1	2	3	4	5	6	7	8	9	10	11	12
Count	158	70	58	83	64	66	80	90	72	71	54	78
Median	6.6	6.95	6.55	6.7	6.25	6.25	6.75	6.65	6.7	6.8	6.5	6.9
Outliers	1	0	0	1	0	0	1	1	3	2	1	1

Figure 1 Rank v/s Month of release

From Figure 1, it can be seen that movies that release towards the end of the year are ranked slightly higher. This improvement is quantified using regression and K-NN models.

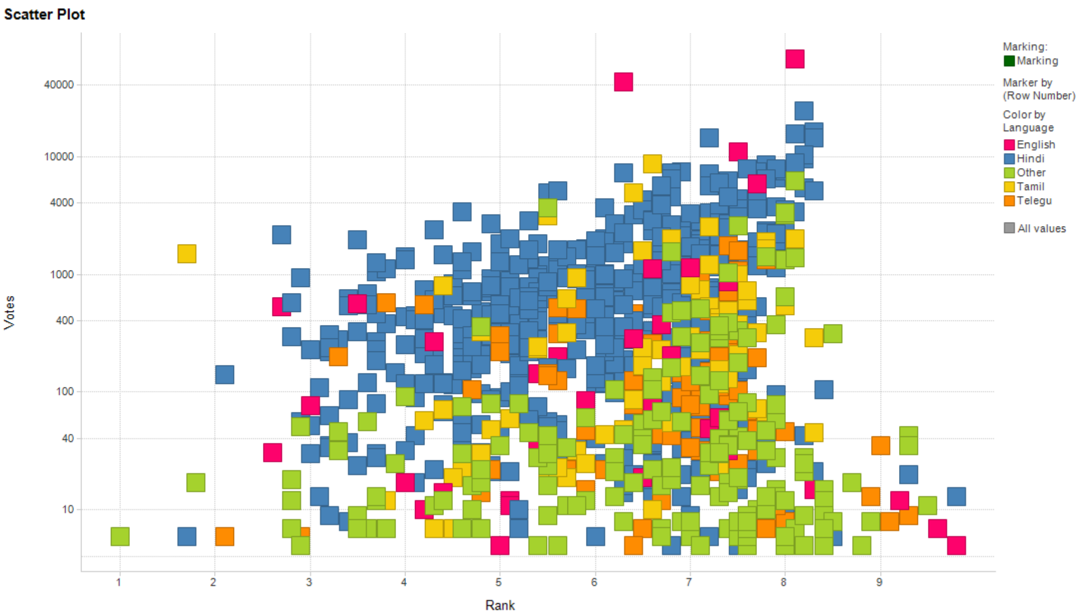


Figure 2 Votes v/s Rank

From Figure 2, it can be seen that better ranked movies have higher votes. However, since voting information is not available prior to release, this relationship is more useful for profiling and explanation.

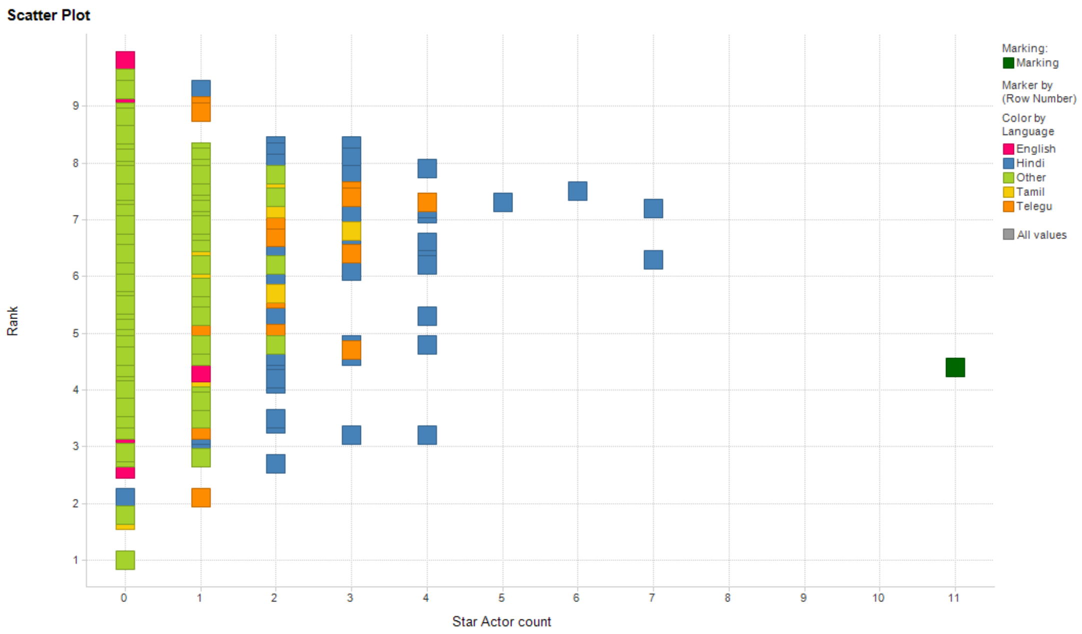


Figure 3 Rank v/s Star Actor Count

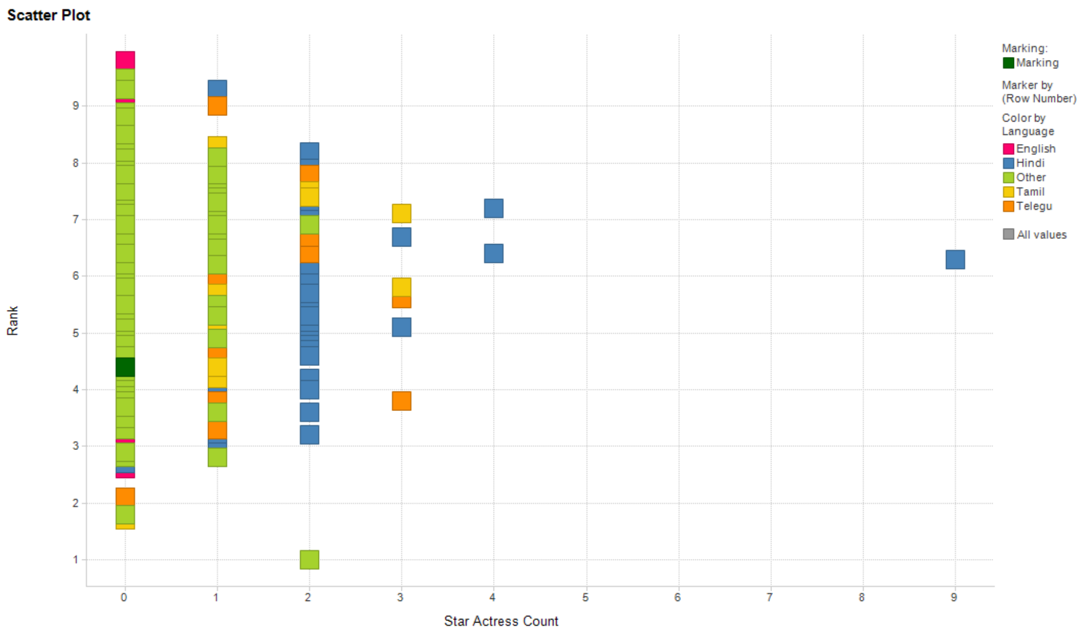


Figure 4 Rank v/s Star Actress Count

From Figure 3 and Figure 4, it can be noted that the minimum rank increases as more star actors and actresses are cast in a movie. Most of the outliers that show more than 5 stars in the same movie are because of special appearance by Filmfare award winners, e.g.: Raj Kapoor documentary (1987), Om Shanti Om (2007).

8.2 Prediction Models

8.2.1 Spotfire Miner setup

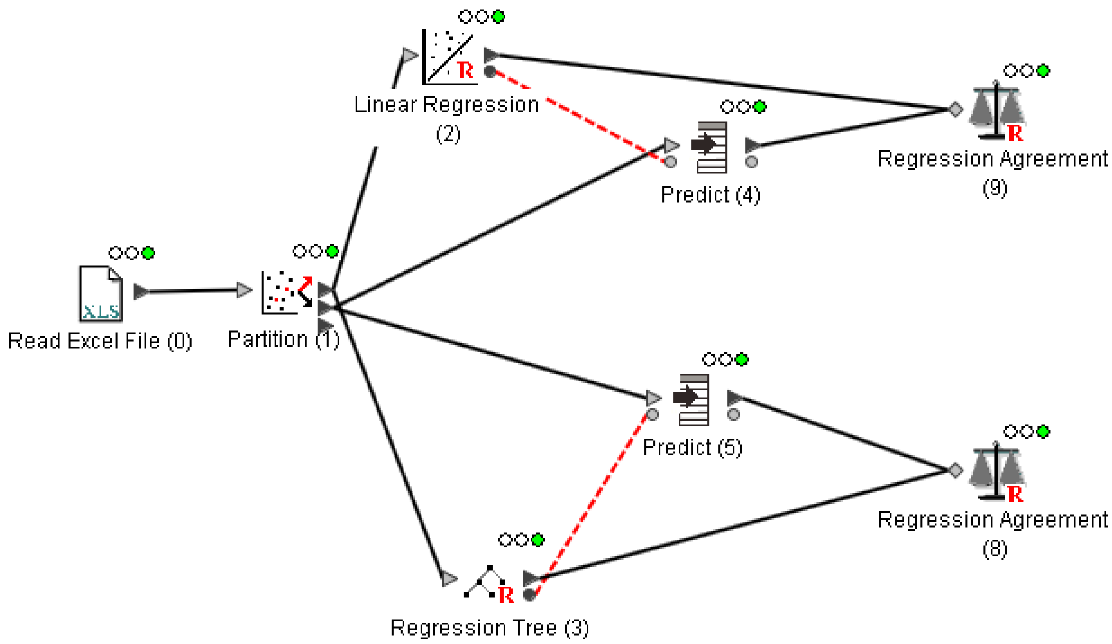


Table 2 Spotfire Miner workspace

Table 2 shows the workspace indicating the modeling process for multi-linear regression and regression tree on the cleaned dataset.

8.2.2 Multi-linear regression

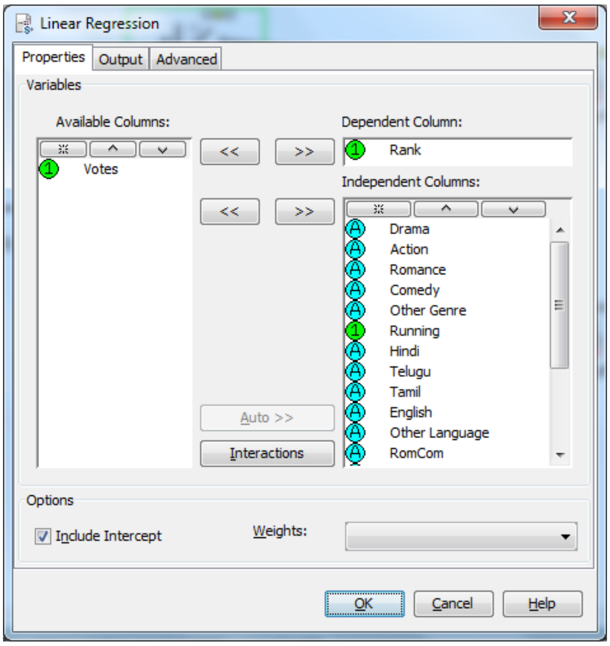


Figure 5 Multi-linear regression settings

Error! Reference source not found. shows that votes was excluded as a predictor for multi-linear regression model. Year of release was excluded in the cleaned dataset itself.

Votes and Year of use have been excluded in the other prediction models as well.

Multi-linear regression coefficient estimates:

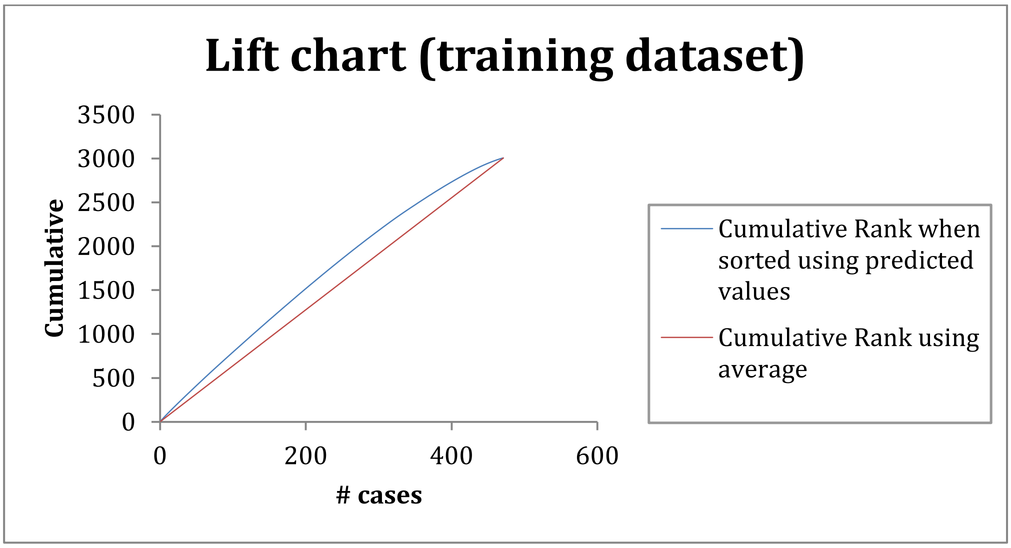
Variable	Estimate	Std.Err.	t-Statistic	Pr(|t|)
(Intercept)	5.29	0.54	9.78	0.00
Drama(1)	0.17	0.06	2.92	3.61E-3
Drama(0)	-0.17	0.06	-2.92	3.61E-3
Action(0)	-0.06	0.08	-0.74	0.46
Action(1)	0.06	0.08	0.74	0.46
Romance(1)	-0.06	0.08	-0.73	0.46
Romance(0)	0.06	0.08	0.73	0.46
Comedy(0)	0.18	0.08	2.26	0.02
Comedy(1)	-0.18	0.08	-2.26	0.02
Other Genre(1)	0.04	0.06	0.78	0.44
Other Genre(0)	-0.04	0.06	-0.78	0.44
Running	2.09E-3	2.31E-3	0.91	0.37
Hindi(1)	-0.31	0.15	-2.11	0.04
Hindi(0)	0.31	0.15	2.11	0.04
Telugu(0)	0.05	0.15	0.35	0.73

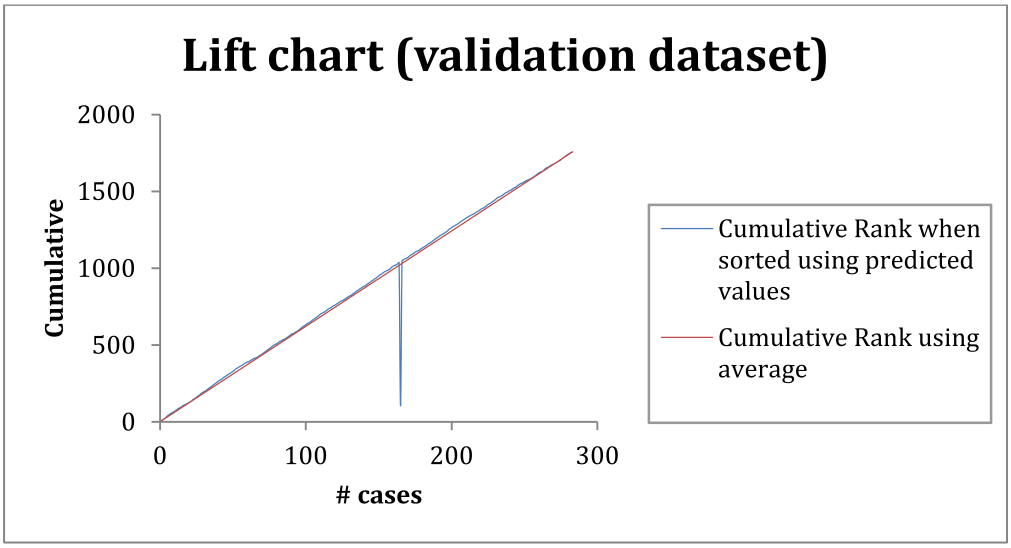
Telugu(1)	-0.05	0.15	-0.35	0.73
Tamil(0)	0.07	0.15	0.49	0.62
Tamil(1)	-0.07	0.15	-0.49	0.62
English(0)	0.17	0.17	0.98	0.33
English(1)	-0.17	0.17	-0.98	0.33
Other Language(1)	0.05	0.13	0.36	0.72
Other Language(0)	-0.05	0.13	-0.36	0.72
RomCom(0)	-0.19	0.13	-1.50	0.14
RomCom(1)	0.19	0.13	1.50	0.14
ActRom(0)	0.14	0.14	0.97	0.33
ActRom(1)	-0.14	0.14	-0.97	0.33
Masala(0)	-0.10	0.27	-0.37	0.71
Masala(1)	0.10	0.27	0.37	0.71
Month	0.05	0.02	3.41	6.90E-4
Star Actress Count	0.04	0.12	0.35	0.73
Star Actor count	0.04	0.07	0.56	0.58
Star-pairing	0.04	0.07	0.49	0.62
Star Director count	0.64	0.15	4.35	1.61E-5

Table 3 Multi-linear regression coefficient estimates

8.2.3 K-Nearest Neighbors

Lift charts: Results on test data are only marginally better than the naïve rule.





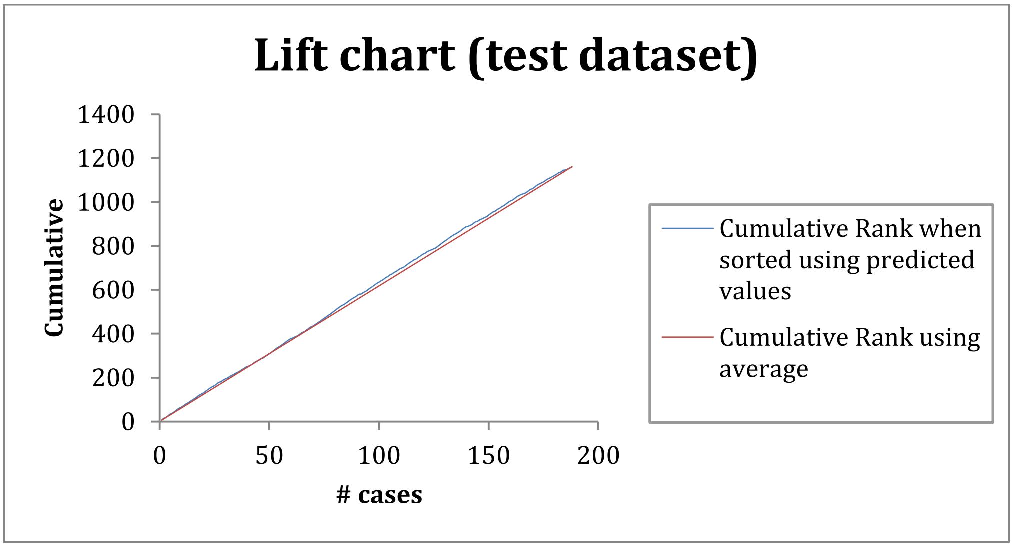


Figure 6 Lift charts - K-Nearest Neighbors

8.2.4 Regression Tree

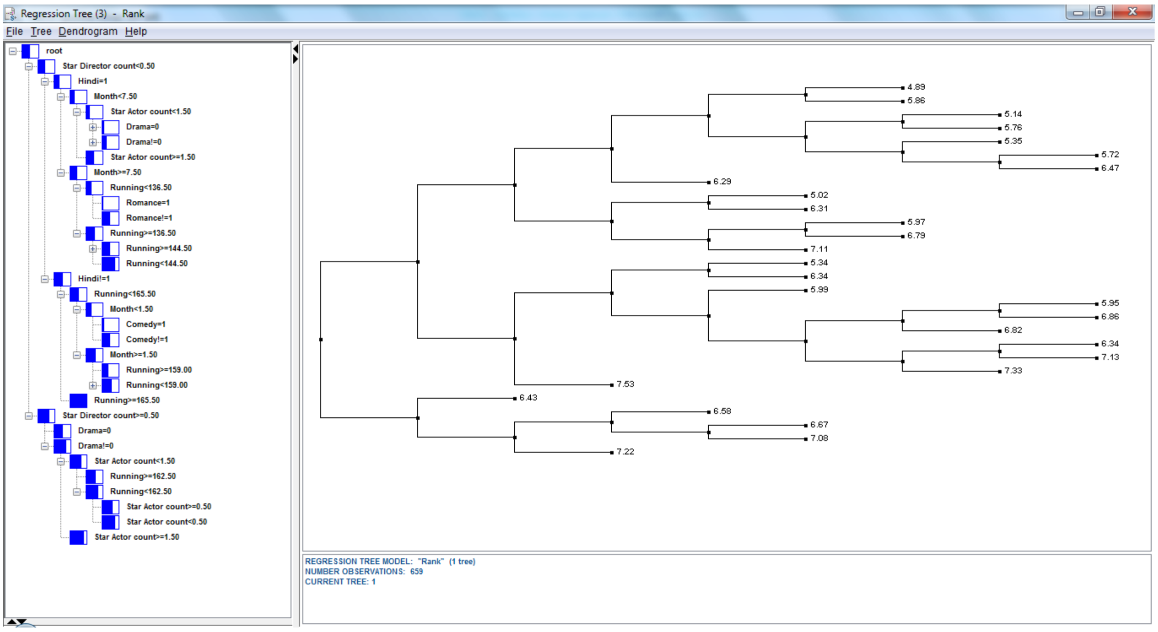


Figure 7 Regression tree with splits to determine movie rank