

Final Project Marketing Analytics

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Presentation Agenda

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Introduction

- IMDb is an online database that provides detailed information about millions of films and television programs
- Our data set takes 1000 of the most popular movies from IMDb from 2006 to 2016

We seek to answer:

- **Where is the movie industry headed?
How can the movie industry optimize
revenue and ratings through its selection
of genres and other factors in the future?**



Advantages and Limitations of Our Dataset

- Why our dataset?
 - Our dataset allows us to analyze multiple factors that may affect movie success including: genre, recency and run time, and predict how these factors affect future movie trends
 - Our data includes several measures of movie success: votes, rating, revenue, and metascore, allowing us to measure movie success more holistically
- Potential limitations:
 - The production time of movies:
 - Because movies are produced over a span of a few years, it takes a couple of years to see if a trend has taken place in the movie industry
 - Our data only spans 10 years, so it may be limited in finding some trends



IMDb Movie Data

Dataset from Kaggle.com consisted of 12 attributes/columns and 1000 observations.

Rank - the ranking of each movie (from 1 to 1000)

Title - the title of each movie

Genre - the label each movie can be classified under. Each movie can have more than one genre label. There are 20 Genres and 195 different combinations shown in the data set

Description - the biography of each movie that highlights what the movie is about.

Director - the name of the main director of the movie

Actors - the names of the leading actors in the movie.

Year - the year in which the movie was made (from 2006-2016)

Runtime - the movie runtime (in minutes)

Rating - the movie's rating determined by IMDB registered users (on a scale from [1,10])

Votes - the number of IMDB registered users that provide a rating for a movie on IMDB

Revenue - the gross revenue of each movie in millions of dollars.

Metascore - the movie's rating determined by professional movie critics (on a scale from [1, 100]).

Preparing our Data - Operative Results

The raw IMDB movie data consisted of 12 attributes/columns and 1000 observations. Of these observations, 13.3% of our Dependent variable Revenue had NULL values. From this, we deleted the records with NULL revenue values in our dataset to be able to analyze 867 observations.
Ratings had 0.

Rank	Title	Genre	Description	Director	Actors	Year	Runtime	Rating	Votes	Revenue	Metascore
1	Guardians of Action, Adventure	A group of in	James Gunn	Chris Pratt, Vin Diesel, Z	2014	121	8.1	757074	333.13	76.00	
2	Prometheus	Adventure, Mystery	Following closely	Ridley Scott	Noomi Rapace, Michael Fassbender	2012	124	7	485820	126.46	65.00
3	Split	Horror, Thriller	Three girls are	M. Night Shyamalan	James McAvoy, Anya Taylor-Joy, Malin Akerman	2016	117	7.3	157606	138.12	62.00
4	Sing	Animation, Comedy	In a city of hi	Christophe Léotard	Matthew McConaughey, Anne Hathaway, Tessa Thompson	2016	108	7.2	60545	270.32	59.00
5	Suicide Squad	Action, Adventure	A secret government	David Ayer	Will Smith, Jared Leto, Margot Robbie	2016	123	6.2	393727	325.02	40.00
6	The Great Wall	Action, Adventure	European master	Zhang Yimou	Matt Damon, Jing Tian, Pedro Pascal	2016	103	6.1	56036	45.13	42.00
7	La La Land	Comedy, Drama	A jazz pianist	Damien Chazelle	Ryan Gosling, Emma Stone	2016	128	8.3	258682	151.06	93.00
9	The Lost City of Z	Action, Adventure	A true-life dr	James Gray	Charlie Hunnam, Robert Pattinson, Ewan McGregor	2016	141	7.1	7188	8.01	78.00
10	Passengers	Adventure, Drama	A spacecraft	Morten Tyldum	Jennifer Lawrence, Chris Pratt	2016	116	7	192177	100.01	41.00

Preparing our Data: Adding Columns for Genre & Recency

The IMDB movie data consists of 20 different genres that movies can be labeled under. We used binary values to code each record of being labeled with that genre (1) or not (0)

Action	Mystery										
Adventure	Romance	N	O	P	Q	R	S	T	U	V	W
Animation	Sci-Fi	Adventure	Biography	Comedy	Crime	Drama	Family	Fantasy	Horror	Thriller	Western
Biography	Thriller	1	0	0	0	0	0	0	0	1	0
Comedy	Western	1	0	0	0	0	0	0	0	0	1
Crime	Sport	0	0	0	0	0	0	1	0	0	0
Drama	History	0	0	1	0	0	0	0	1	0	0
Family	War	1	0	0	0	0	0	0	1	0	0
Fantasy	Music	0	0	1	0	1	0	0	0	0	0
Horror	Musical	1	1	0	0	0	1	0	0	0	0

The raw IMDB movie data consists of movies made from 2006 to 2016. We encoded each record with numerical values in number of years from 2021 that the movie was made.

*2021-year movie was made =
recency. _____

AG
Recency

Exploratory Data Analysis - Rows and Variables

There are 867 observations

After preparing our data there are 33 columns

Exploratory Data Analysis - Data Types, Zeros, NULL

	variable	q_zeros	p_zeros	q_na	p_na	q_inf	p_inf	type	unique
1	Rank	0	0.00	0	0	0	0	integer	867
2	Title	0	0.00	0	0	0	0	character	866
3	Genre	0	0.00	0	0	0	0	character	195
4	Description	0	0.00	0	0	0	0	character	867
5	Director	0	0.00	0	0	0	0	character	535
6	Actors	0	0.00	0	0	0	0	character	863
7	Year	0	0.00	0	0	0	0	integer	11
8	Runtime	0	0.00	0	0	0	0	integer	91
9	Rating	0	0.00	0	0	0	0	numeric	50
10	Votes	0	0.00	0	0	0	0	integer	866
11	Revenue	0	0.00	0	0	0	0	numeric	810
12	Metascore	0	0.00	0	0	0	0	integer	82
13	Action	583	67.24	0	0	0	0	integer	2
14	Adventure	616	71.05	0	0	0	0	integer	2
15	Biography	794	91.58	0	0	0	0	integer	2
16	Comedy	612	70.59	0	0	0	0	integer	2
17	Crime	738	85.12	0	0	0	0	integer	2
18	Drama	431	49.71	0	0	0	0	integer	2
19	Family	818	94.35	0	0	0	0	integer	2
20	Fantasy	774	89.27	0	0	0	0	integer	2
21	Horror	775	89.39	0	0	0	0	integer	2
22	Mystery	778	89.73	0	0	0	0	integer	2
23	Romance	738	85.12	0	0	0	0	integer	2
24	Sci.Fi	757	87.31	0	0	0	0	integer	2
25	Thriller	716	82.58	0	0	0	0	integer	2
26	Western	862	99.42	0	0	0	0	integer	2
27	Sport	851	98.15	0	0	0	0	integer	2
28	History	842	97.12	0	0	0	0	integer	2
29	War	857	98.85	0	0	0	0	integer	2
30	Animation	820	94.58	0	0	0	0	integer	2
31	Music	847	97.69	0	0	0	0	integer	2
32	Musical	862	99.42	0	0	0	0	integer	2
33	Recency	0	0.00	0	0	0	0	integer	11

How many movies are labeled with each genre?

Action = 32.76%

Adventure = 18.95%

Animation = 5.42%

Biography = 8.42%

Comedy = 29.41%

Crime = 14.88%

Drama = 50.29%

Family = 5.65%

Fantasy = 10.73%

Horror = 10.61%

Mystery = 10.27%

Romance = 14.88%

Sci-Fi = 12.69%

Thriller = 17.42%

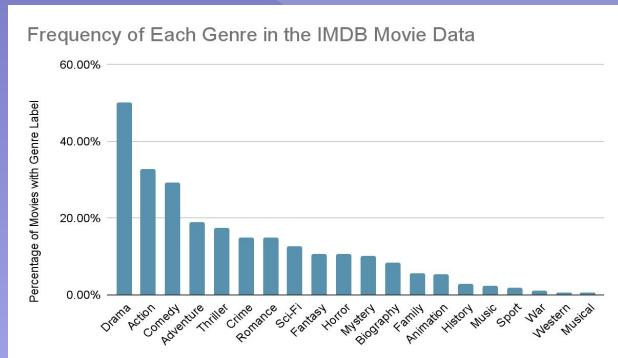
Western = .58%

Sport = 1.85%

History = 2.88%

War = 1.15%

Music = 2.31%



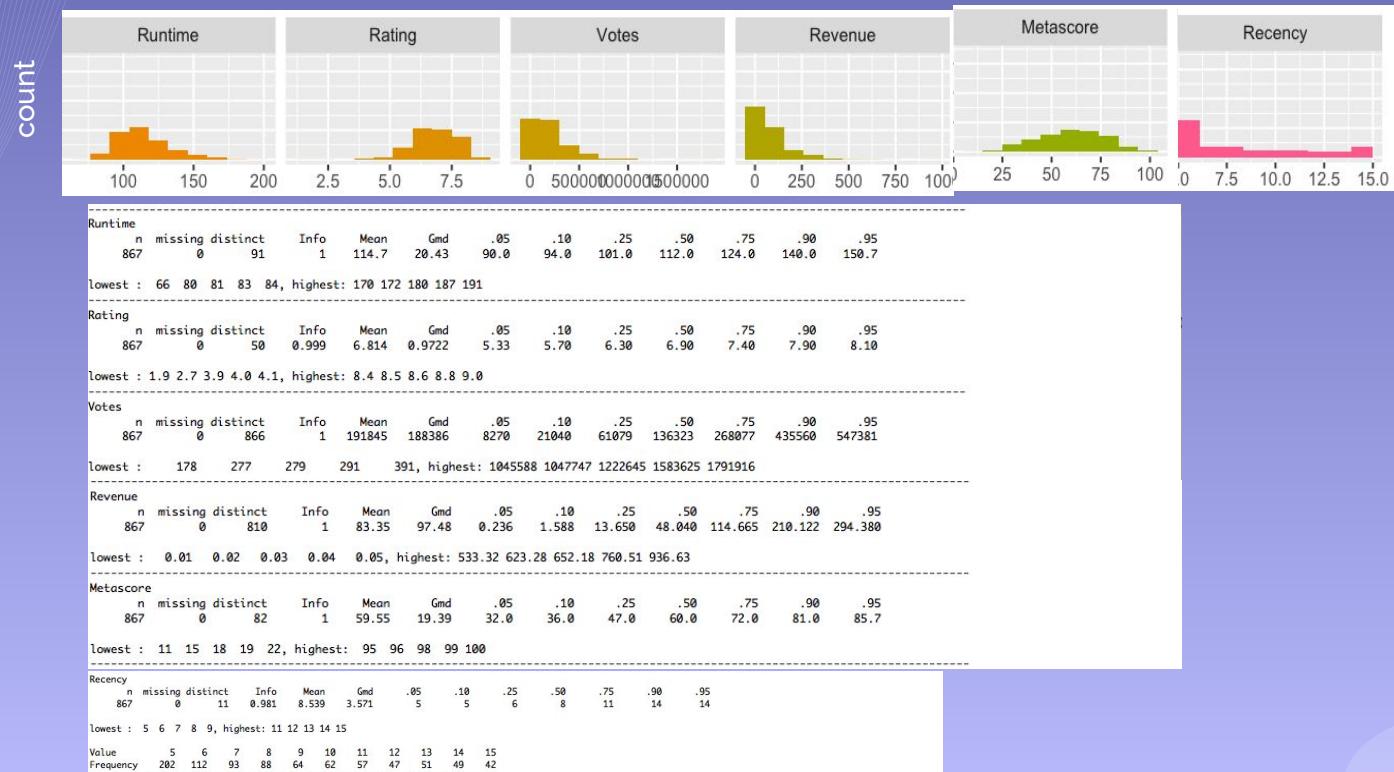
Exploratory Data Analysis - Frequency

freq(data)

	Genre	frequency	percentage	cumulative_perc
1	Action, Adventure, Sci-Fi	50	5.77	5.77
2	Comedy, Drama, Romance	33	3.81	9.58
3	Drama	31	3.58	13.16
4	Drama, Romance	30	3.46	16.62
5	Action, Adventure, Fantasy	26	3.00	19.62
6	Animation, Adventure, Comedy	26	3.00	22.62
7	Comedy	26	3.00	25.62
8	Comedy, Drama	24	2.77	28.39
9	Comedy, Romance	23	2.65	31.04
10	Crime, Drama, Mystery	18	2.08	33.12
11	Action, Adventure, Drama	17	1.96	35.08
12	Crime, Drama, Thriller	17	1.96	37.04
13	Action, Crime, Drama	16	1.85	38.89
14	Action, Adventure, Comedy	14	1.61	40.50
15	Adventure, Family, Fantasy	14	1.61	42.11
16	Biography, Drama	14	1.61	43.72
17	Action, Comedy, Crime	12	1.38	45.10
18	Biography, Drama, History	12	1.38	46.48
19	Drama, Thriller	12	1.38	47.86
20	Action, Adventure, Thriller	11	1.27	49.13
21	Action, Crime, Thriller	11	1.27	50.40
22	Horror, Thriller	11	1.27	51.67
23	Animation, Action, Adventure	9	1.04	52.71
24	Action, Thriller	8	0.92	53.63
25	Adventure, Comedy, Drama	8	0.92	54.55
26	Biography, Crime, Drama	8	0.92	55.47
27	Biography, Drama, Sport	8	0.92	56.39
28	Crime, Drama	8	0.92	57.31
29	Comedy, Crime, Drama	7	0.81	58.12
30	Horror	7	0.81	58.93
31	Horror, Mystery, Thriller	7	0.81	59.74
32	Action, Adventure, Crime	6	0.69	60.43
33	Action, Biography, Drama	6	0.69	61.12
34	Action, Drama, Thriller	6	0.69	61.81
35	Action, Sci-Fi, Thriller	6	0.69	62.50
36	Biography, Comedy, Drama	6	0.69	63.19
37	Drama, Mystery, Romance	6	0.69	63.88
38	Drama, Mystery, Thriller	6	0.69	64.57
39	Horror, Mystery	6	0.69	65.26
40	Mystery, Thriller	6	0.69	65.95
41	Action, Adventure, Mystery	5	0.58	66.53
42	Action, Comedy	5	0.58	67.11
43	Action, Horror, Sci-Fi	5	0.58	67.69
44	Adventure, Drama, Fantasy	5	0.58	68.27
45	Animation, Comedy, Family	5	0.58	68.85
46	Comedy, Crime	5	0.58	69.43

Overall, there are 195 different genre combinations between the 20 categories that we have (Action, Adventure, and Sci-Fi) are the most frequent combination next to (Comedy, Drama, and Romance.)

Exploratory Data Analysis - Histograms and Numerical and Categorical Representations



Methodology- Agenda of Tests

#01.

K-means
clustering

#02.

Regression
analysis

#03.

Logistic
regression
analysis

#04.

Genre
perception
map

#01. K-Means Clustering

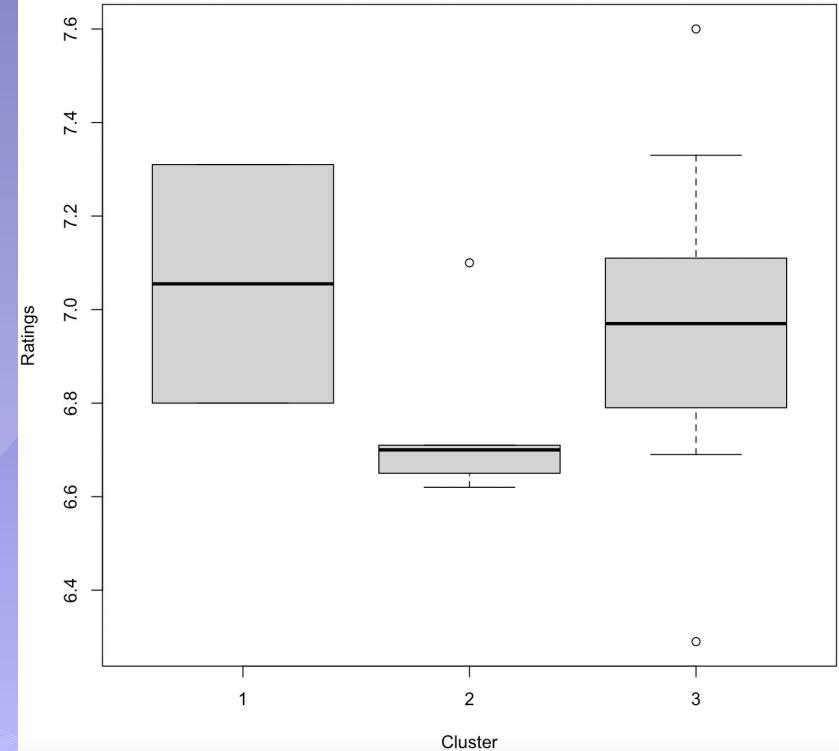
1. For our clustering data, we took the average revenue and average rating for each genre (20 total)
2. We selected 3 clusters for our analysis
3. In conducting this analysis, we discovered the following 3 clusters
 - a. Cluster 1: 2 genres
 - b. Cluster 2: 5 genres
 - c. Cluster 3: 13 genres

Cluster Genres

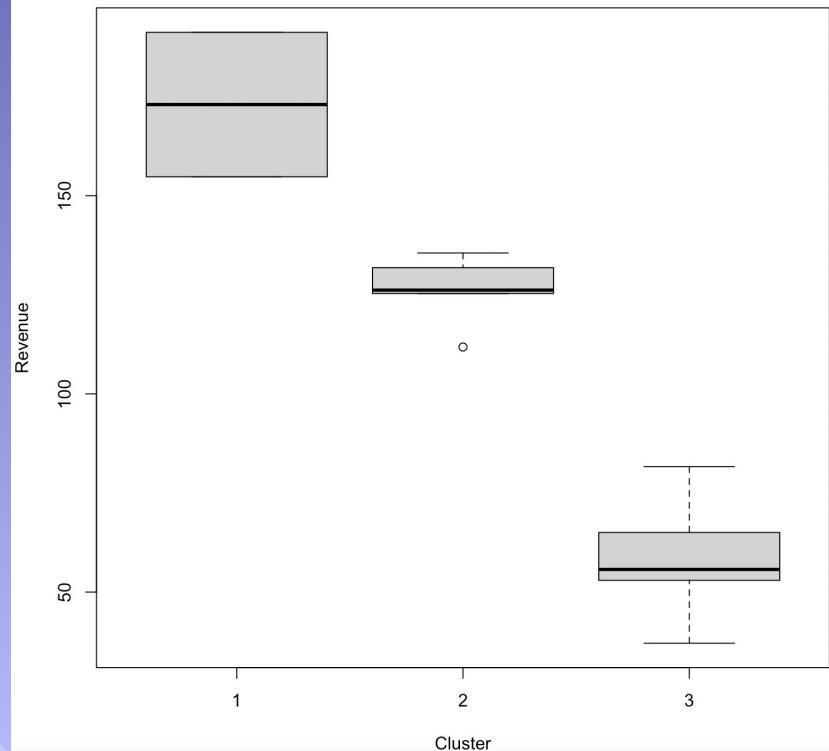
Cluster Features	Most Grossing; Popular	Grossing; Least Popular	Least Grossing; Popular
Cluster Number	1	2	3
Genres	<i>Adventure, Animation</i>	<i>Action, Family, Fantasy, Sci-Fi, Western</i>	<i>Biography, Comedy, Crime, Drama, Horror, Mystery, Romance, Thriller, Sport, History, War, Music, Musical</i>
Average Revenue (millions) [Avg Overall = 83.35]	173	126.14	58.24
Average Rating (out of 10) [Avg Overall = 6.814]	7.06	6.76	6.98

Cluster Boxplots

Cluster x Ratings Boxplot



Cluster x Revenue Boxplot



Test Implications

1. Movies in the adventure & animation genres have the highest average revenues & ratings
2. Cluster 3 holds a significant amount of movie genres that lag behind the rest in terms of amount of gross revenue
3. The difference between average revenue of each cluster is significantly large, especially clusters 2 and 3
4. The difference between average rating of each cluster is significantly small, as they are each saturated with similar ratings

#02. Regression (Runtime, Genre, Recency on Revenue)

```
lmformula = revenue ~ Runtime + Recency + Action + Adventure +  
Biography + Comedy + Crime + Drama + Family + Fantasy + Horror +  
Mystery + Romance + SciFi + Thriller + Western + Sport +  
History + War + Animation + Music + Musical, data = Movie)
```

Residuals:

Min	1Q	Median	3Q	Max
-196.45	-43.31	-8.83	29.18	744.63

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-141.6268	23.8594	-5.936	4.26e-09 ***
Runtime	1.7237	0.1731	9.959	< 2e-16 ***
Recency	2.5803	0.9084	2.840	0.00461 **
Action	17.5673	8.0995	2.169	0.03037 *
Adventure	39.0748	8.6288	4.528	6.80e-06 ***
Biography	0.3827	11.9170	0.032	0.97439
Comedy	3.2748	8.9218	0.367	0.71367
Crime	-5.3842	9.1784	-0.587	0.55762
Drama	-38.6647	8.2387	-4.693	3.14e-06 ***
Family	11.7811	13.4215	0.878	0.38031
Fantasy	27.0761	10.6869	2.534	0.01147 *
Horror	-23.4960	11.0051	-2.135	0.03305 *
Mystery	-16.8083	10.3834	-1.619	0.10587
Romance	-12.0237	9.5594	-1.258	0.20882
SciFi1	33.2466	10.1570	3.273	0.00111 **
Thriller	3.6896	9.0477	0.407	0.68426
Western	-12.4619	37.8205	-0.330	0.74186
Sport	3.5707	22.0086	0.162	0.87115
History	-18.6364	18.2702	-1.020	0.30800
War	-13.2715	27.0873	-0.490	0.62429
Animation	103.9028	14.3659	7.233	1.06e-12 ***
Music	2.8530	22.2079	0.128	0.89781
Musical	-1.0256	43.1852	-0.024	0.98106

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 83.08 on 845 degrees of freedom
Multiple R-squared: 0.3706, Adjusted R-squared: 0.3542
F-statistic: 22.61 on 22 and 845 DF, p-value: < 2.2e-16

1. Genres are dummy coded (0=no, 1=yes)
2. Animation, Adventure, Sci-Fi, Fantasy & Action genres all have significantly positive effects on revenue
3. Drama & Horror genres have significantly negative effects on revenue
4. Recency & Runtime have significantly positive effects on revenue
5. Low R-Squared value

Regression (Runtime, Genre, Recency on Ratings)

```
lm(formula = Rating ~ Runtime + Recency + Action + Adventure +
  Biography + Comedy + Crime + Drama + Family + Fantasy + Horror +
  Mystery + Romance + SciFi + Thriller + Western + Sport +
  History + War + Animation + Music + Musical, data = Movie)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.4588 -0.3921  0.0631  0.4831  1.8623 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.345545  0.212560 20.444 < 2e-16 ***
Runtime     0.016987  0.001542 11.016 < 2e-16 ***
Recency     0.035524  0.008093  4.389 1.28e-05 ***
Action      -0.150750  0.072157 -2.089  0.03699 *  
Adventure   -0.023570  0.076873 -0.307  0.75922  
Biography   0.348277  0.106167  3.280  0.00108 ** 
Comedy      0.073522  0.079483  0.925  0.35523  
Crime       0.015582  0.081770  0.191  0.84892  
Drama       0.332838  0.073398  4.535 6.60e-06 ***
Family      -0.065177  0.119570 -0.545  0.58583  
Fantasy     -0.102566  0.095208 -1.077  0.28166  
Horror      -0.288337  0.098043 -2.941  0.00336 ** 
Mystery     0.208074  0.092505  2.249  0.02475 *  
Romance    -0.176018  0.085163 -2.067  0.03905 *  
SciFi       0.150163  0.090487  1.659  0.09739 .  
Thriller    0.085410  0.080605  1.060  0.28963  
Western     0.145587  0.336938  0.432  0.66579  
Sport       -0.027582  0.196072 -0.141  0.88816  
History    -0.056118  0.162767 -0.345  0.73035  
War        0.679248  0.241317  2.815  0.00499 ** 
Animation   1.011826  0.127984  7.906 8.29e-15 ***
Music       0.355444  0.197847  1.797  0.07276 .  
Musical     -0.517002  0.384731 -1.344  0.17937 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7402 on 845 degrees of freedom
Multiple R-squared:  0.3048,    Adjusted R-squared:  0.2867 
F-statistic: 16.84 on 22 and 845 DF.  p-value: < 2.2e-16
```

1. Genres are dummy coded (0=no, 1=yes)
2. Animation, War, Mystery, Drama, & Biography genres all have significantly positive effects on rating
3. Action, Horror, & Romance genres have significantly negative effects on rating
4. Runtime & Recency have significantly positive effects on rating
5. Low R-Squared value

Regression (Runtime & Recency on Revenue & on Rating)

Call:

```
lm(formula = Revenue ~ Runtime + Recency, data = Movie)
```

Residuals:

Min	1Q	Median	3Q	Max
-187.60	-58.01	-27.24	26.39	829.99

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-112.1557	22.1732	-5.058	5.17e-07 ***
Runtime	1.4703	0.1825	8.057	2.59e-15 ***
Recency	3.1399	1.0621	2.956	0.0032 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 99.05 on 865 degrees of freedom

Multiple R-squared: 0.0842, Adjusted R-squared: 0.08208

F-statistic: 39.76 on 2 and 865 DF, p-value: < 2.2e-16

Call:

```
lm(formula = Rating ~ Runtime + Recency, data = Movie)
```

Residuals:

Min	1Q	Median	3Q	Max
-4.5888	-0.4812	0.0471	0.5427	2.0488

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.599788	0.181078	25.402	< 2e-16 ***
Runtime	0.016886	0.001490	11.330	< 2e-16 ***
Recency	0.032307	0.008674	3.725	0.000208 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8089 on 865 degrees of freedom

Multiple R-squared: 0.1501, Adjusted R-squared: 0.1482

F-statistic: 76.39 on 2 and 865 DF, p-value: < 2.2e-16

1. Genres were left out of analysis
2. Runtime & Recency have significantly positive effects on rating and revenue
3. Even lower R-Squared values without genre

Models at a Glance

	Model #01	Model #02	Model #03	Model #04
Independent Variables	Runtime, Recency, Genre	Runtime, Recency, Genre	Runtime, Recency	Runtime, Recency
Dependent Variable	Revenue	Ratings	Revenue	Ratings
Significant Positive	Runtime & Recency Animation, Adventure, Sci-Fi, Fantasy & Action	Runtime & Recency Animation, War, Mystery, Drama, & Biography	Runtime & Recency	Runtime & Recency
Significant Negative	Drama & Horror	Action, Horror, & Romance	N/A	N/A
R-Squared Value	0.3706	0.3048	0.0842	0.1501

Test Implications

1. Runtime & recency both have significantly positive effects on revenue & ratings, as indicated in all 4 models
2. Genre can more accurately predict revenue and ratings, as indicated by the R-Squared values in each model
3. Being classified in the animation genre has a significantly positive effect on movie revenue and rating
4. Being classified in the horror genre has a significantly negative effect on movie revenue and rating

#03. Logistic Regression

1. We used logistic regression to learn how genre is dependent on rating, revenue, and metascore
2. We ran regression on each specific genre as the dependent variable
3. Criteria:
 - a. Regression analysis for each genre must include at least 2 or more statistically significant variables
 - b. Model AIC must be less than 540

Logistic Regression

(Revenue, Rating, and Metascore based on Biography Genre)

Call:

```
glm(formula = Biography ~ Revenue + Rating + Metascore, family = binomial("logit"),
  data = Movie)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.9971	-0.4660	-0.3210	-0.2252	3.2403

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-8.998603	1.371513	-6.561	5.34e-11 ***
Revenue	-0.005678	0.001735	-3.274	0.001062 **
Rating	0.845000	0.229964	3.674	0.000238 ***
Metascore	0.016181	0.010217	1.584	0.113267

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 501.14 on 867 degrees of freedom
Residual deviance: 451.37 on 864 degrees of freedom
AIC: 459.37

Number of Fisher Scoring iterations: 6

1. Revenue and rating are statistically significant
 - a. Revenue negatively associated with biography genre
 - b. Rating positively associated with biography genre
2. Metascore is not statistically significant

Logistic Regression

(Revenue, Rating, and Metascore based on Animation Genre)

```
Call:  
glm(formula = Animation ~ Revenue + Rating + Metascore, family = binomial("logit"),  
    data = Movie)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.1462	-0.3401	-0.2461	-0.1808	2.9752

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-6.34026	1.53715	-4.125	3.71e-05 ***
Revenue	0.00537	0.00109	4.926	8.39e-07 ***
Rating	0.04780	0.28150	0.170	0.86516
Metascore	0.03853	0.01438	2.679	0.00738 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 365.52 on 867 degrees of freedom
Residual deviance: 316.20 on 864 degrees of freedom
AIC: 324.2

Number of Fisher Scoring iterations: 6

1. Revenue and Metascore have a significantly positive association with the animation genre
2. Rating is not statistically significant

Logistic Regression

(Revenue, Rating, and Metascore based on Horror Genre)

```
Call:  
glm(formula = Horror ~ Revenue + Rating + Metascore, family = binomial("logit"),  
    data = Movie)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.8081	-0.5151	-0.3887	-0.2310	2.9813

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	2.868102	0.838193	3.422	0.000622 ***
Revenue	-0.009587	0.002408	-3.982	6.84e-05 ***
Rating	-0.826390	0.164334	-5.029	4.94e-07 ***
Metascore	0.017039	0.008663	1.967	0.049185 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 586.86 on 867 degrees of freedom
Residual deviance: 523.90 on 864 degrees of freedom
AIC: 531.9

Number of Fisher Scoring iterations: 6

1. Revenue, rating, and metascore are statistically significant
2. Revenue and rating have a negative association with the horror genre
 - a. Rating has a large association
3. Metascore has a positive association with Horror genre

Models at a Glance

	Model #01	Model #02	Model #03
Independent Variables	Revenue, Rating, Metascore	Revenue, Rating, Metascore	Revenue, Rating, Metascore
Dependent Variable	Biography	Animation	Horror
Revenue	Statistically Significant Negatively Associated	Statistically Significant Positively Associated	Statistically Significant Negatively Associated
Rating	Statistically Significant Positively Associated	Not Statistically Significant Positively Associated	Statistically Significant Largely Negatively Associated
Metascore	Not Statistically Significant Positively Associated	Statistically Significant Positively Associated	Statistically Significant Positively Associated
AIC	459.37	324.2	531.9

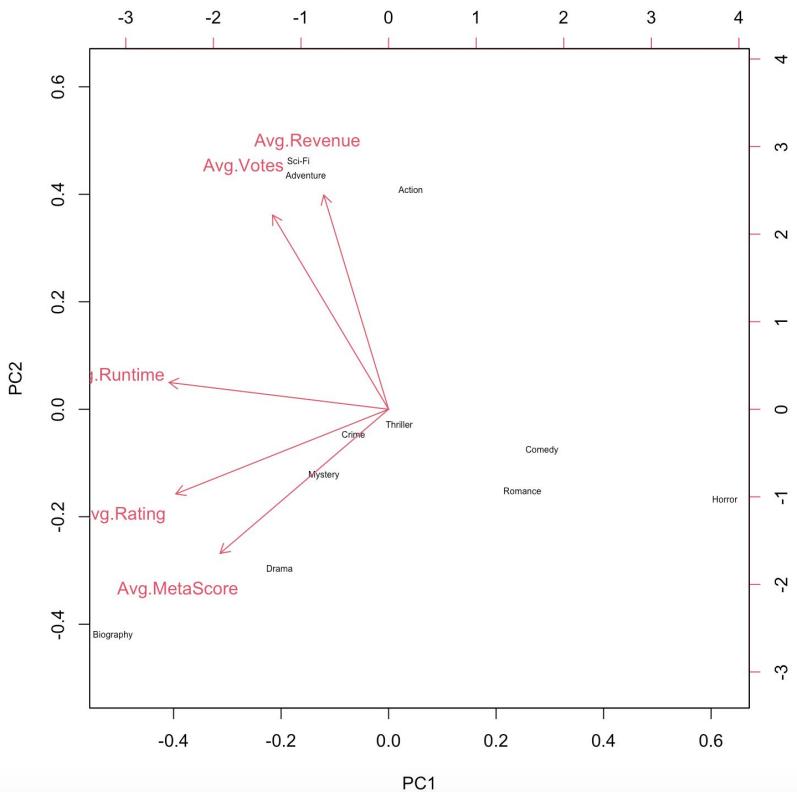
Test Implications

1. Only 3 genres were statistically relevant according our criteria
 - a. Biography
 - b. Animation
 - c. Horror
2. Rating has a significantly large positive impact on the Biography genre
3. Both metascore and revenue have a significantly large positive impact on the Animation genre
4. Both rating and revenue have a significantly large negative impact on the Horror genre

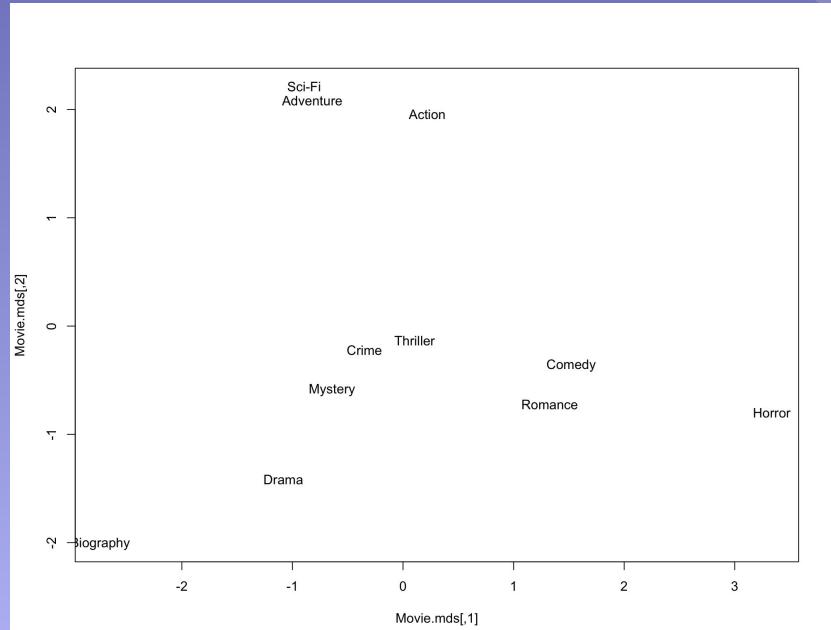
#04. Genre Perception Map

- Sorted data - using only genres that have more than 50 movies (12)
 - All variables have calculated averages to create a brand perception map

Genre Perception Map

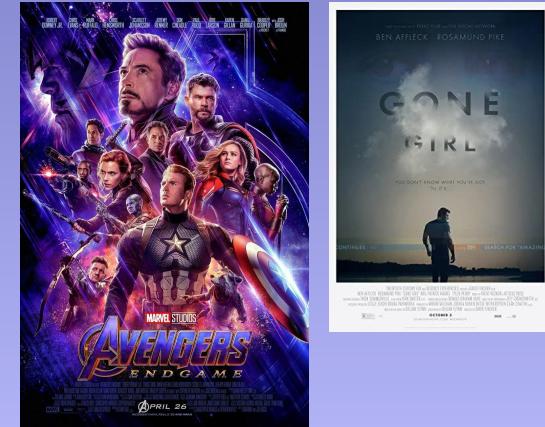


Genre Distance Map



Test Implications

1. The Sci-fi and Adventure, and to an extent Action, genres are leaders in generating revenue and votes for all top genres sampled
2. The Comedy and Romance, and to an even larger extent Horror, genres are not representative of the any of the attributes for all top genres sampled
3. The Biography and Drama genre gets the highest ratings out of all top genres sampled
4. Similar consumer perception of genres:
 - a. Comedy and Romance
 - b. Crime, Mystery and Thriller
 - c. Sci-fi, Adventure and Action



Results/Interpretations

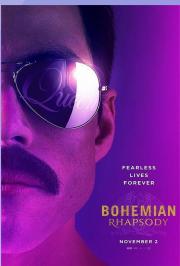
Where is the movie industry headed? How can the movie industry optimize revenue and ratings through its selection of genres and other factors in the future?

1. Genre on revenue
 - a. Adventure (18.95%) and Animation (5.42%) lead the movie industry with the highest impact on revenues with Sci-Fi (12.69%), Fantasy (10.73%), Action (32.76%) following behind
 - b. Drama (50.29%) & Horror (10.61%) have a significantly negative impact on revenue
2. Genre on ratings
 - a. Animation and War (1.15%) lead the movie industry with the highest impact on ratings with Biography (8.42%), Drama, and Mystery (10.27%) following behind
 - b. Horror, Romance (14.88%), and Action have a significantly negative impact on ratings
3. Other factors
 - a. Movies with increased runtimes and older years tend to do better

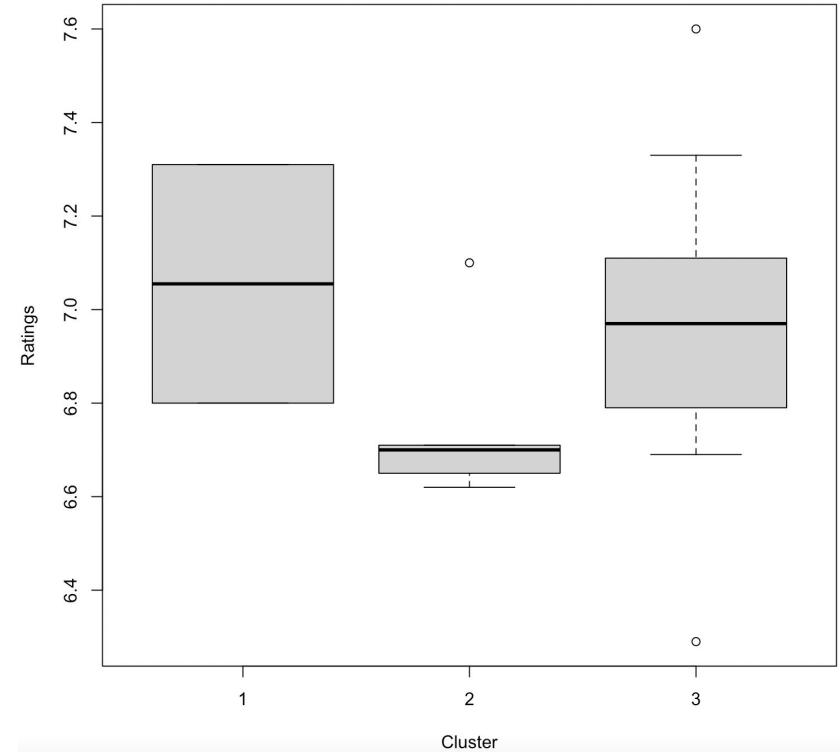
Managerial Implications

- Producers will need to curate their content based on whether they want to be part of the market trends or differentiate from what has been created
 - The top four genre combinations are: "Action, Adventure, and Sci-Fi" (50), "Comedy, Drama, Romance" (33), "Drama" (31), "Drama, Romance" (30)
 - Based our genre distance map. Other perceived combinations that could find success are: "Comedy and Romance" and "Crime, Mystery, and Thriller"
- Regardless of choice, the success of a movie will increase over time as it can reach viewers outside of the cinema and streaming services
 - In addition, an increased runtime may make viewers feel like they are getting more for their money

	Mainstream	Niche
Positive Revenues	Sci-Fi, Adventure	Animation, Fantasy
Positive Ratings	Biography, *Drama	War, Biography
Avoid	Romance, Comedy, Horror	Generally other genres



Cluster x Ratings Boxplot



Cluster x Revenue Boxplot

