**Final Exam Report**

**Maximizing Movies Revenue**

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## Introduction

Movies play an important role in consumer entertainment since they offer everyone an intense, dramatic, and funny experience. Follows (2018) points out that the average time for developing a movie between first public announcement and eventual theatrical release is around two years and some blockbusters' production budgets often exceed hundreds of millions. How different activities can help studios maximize movie performance under such tremendous pressure is a key consideration for many. This report mainly employs conjoint analysis and multiple linear regression analysis to explore the impact of movies' inherent features and online advertising on movie performance.

## Analysis methods and reasons

In the given dataset, many variables seem to have a relationship to movie sales during the first week. Multiple linear regression is employed to generate precise judgment on variables that significantly connect with the movie performance. And this analysis will include all variables to prevent the omission of essential elements. The result of this analysis can help studios know the impact extent of different activities on movie sales and provide them some practical insights to maximize profit.

For the business to run effectively, the studio needs to understand the value its movies bring to consumers. This understanding allows film producers to make new movies in the future with a more informed strategy. But the inherent characteristics of different movies are heterogeneous such as various genres, the extra allure of main actors, a sequel or not, the number of trailers, the release season, and so much. The conjoint analysis provides a way to understand how customers value different features of movies. And this dataset has a critic rating variable that describes professional critic movie evaluation from one to a hundred. Thus, conjoint analysis is employed to find the relationship between the movie's features and its critic rating.

One of the most crucial stages of film distribution is to determine the influence of advertising on box office performance and, as a result, selecting the optimal advertising level, as pointed out by Yan (2020).

In other words, understanding the relationship between advertising budgets and movie performance enables studios to manage the movie profit better. So, based on the given four years' records, I adopted the ADBUDG response function to formulate a linear model between advertising level and first-week sales. In addition, in this model natural logarithm is used to scale advertising budget and sales revenue since they have huge variance.

**Interpretation of analysis results**

Firstly, the multiple linear regression analysis is employed to study the significance of each activity on the box office performance; the selected models' outcomes are movie sales during the first day of release, during the first weekend, and during the first week, respectively. The coefficients table is provided below (Table 1) that include the main findings, and the original outputs of linear models are attached in Appendix1 – 3.

| Highest significance variables: p-value ≤ 0.001 (Coefficients Table) | | | | | | |
|---|---|---|---|---|---|---|
| | Model P-value | Intercept | Sequel | View count | Star power | Critic rating |
| First Day | 4.89648E-76 | -12.84 | 6.80 | 0.40 | 22.60 | 62.95 |
| First Weekend | 2.00161E-82 | -33.17 | 14.78 | 0.96 | 49.45 | 18.10 |
| First Week | 2.10108E-76 | -44.26 | 19.45 | 1.24 | 66.42 | 25.13 |

Note: Intercept and Sequel unit in millions;
Star power and Critic rating unit in thousands

Table 1

Three linear regression models are significant and homogeneous since they have almost zero P-value and the same highest significance variables. The value of intercepts is an enormous negative number; it seems inconsistent with intuition as the box office sales cannot be negative. However, these models are still reasonable since other significant variables save the negative intercept and make the model back positive. The most worth noting activity is view count, which holds the lowest p-value; it indicates the number of people who watched a movie trailer on YouTube. Referring to the coefficients table, the table implies that each additional view count brings in an average of 40 cents more in the first-day box office sales. If the time interval is extended to the first week, the viewing will affect the box office by more than 1 dollar, and the figure is 1.24 dollars on average. Focusing on the movie's inherent features, consumers are more likely to be attracted by sequel films, and the expected ticket sales of the first weekend can increase by more than 10 million. In addition, the blockbuster usually attracts more moviegoers since many reputable actors play roles in the movie; the table shows that each additional star-power score can bring more than 22 thousand sales on the first-day box office. The last finding is that professional critic movie evaluation – also known as critic rating played an important role in consumer choice; each additional rating score brings more than 25 thousand ticket sales in the first week.

Next, the conjoint analysis is employed to study how consumers value the movie with different features. That is the relationship between movie features and critic rating. The partworth of critic rating is provided below (Table 2); all coeffects are rounded to two decimal places.

| The partworth of critic rating | | | | | | | |
|---|---|---|---|---|---|---|---|
| Intercept | Genre | Sequel | Star power | Teaser trailer | Teaser | Number trailer | Season |
| 52.71 | 11.63 | -3.82 | 0.03 | 0.40 | -1.16 | 0.10 | -2.53 |
| Production | Advertising | Fox | Paramount | Warnerbros | Columbia sony | Disney | Universal |
| -0.01 | 0.00 | 3.79 | 0.47 | -2.95 | -0.10 | 24.16 | 2.12 |

Table 2

The average critic rating is around 57.3 based on the four years of records, but it varies between different movie's characteristics. According to the partworth table, the coefficient of movie genre is the second-highest number among variables, and action movies usually can be awarded 11.63 scores more than the drama movie. The concrete reasons behind this phenomenon cannot be interpreted. But the possible reason could be that since the action movie gives the person short-term excitement or stress, viewers have more impression to mark the critic rating. Another element about the movie's inherent features is whether it is a sequel movie or not; the table shows that a sequel movie has an average 3.82 score lower than the prequel movie on critic score. The reason probably is that consumers usually add more expectations and higher requirements on the sequel movie. In general, the allure of the main actors has a significant impact on the movie's reputation. However, the partworth table indicates that star power has no considerable influence on critic rating; it only climbs 3 points, increasing one hundred star power. This result correlates to the intrinsic problem of the movie, such as what kind of actors would be best suited for such a script and what kind of script would be best suited for such actors. In terms of external activities of a movie, the production budget and advertising level almost have no impact on film rating, the coefficient of both is near zero. Moreover, the partworth table shows that the number of trailers also has no remarkable impact on critic rating. Thus, a movie's critic rating is mainly affected by its quality and influence rather than production budget, star power, and trailers, which is the simple assertion concluded from the partworth table. The most important attribute of the critic rating is the film producer, and the impact value is more than 24 scores. Disney seems to have its brand aura. This absolute advantage in film critics must be related to his successful marketing strategies and high consumer loyalty.

Lastly, the ADBUDG response function is employed to study the relationship between advertising level and box office performance. Two ADBUDG models are provided below (Figure 1 – 2), the advertising budget and box office performance in the first week are scaled by nature logarithm. The response functions are attached on Appendix 4.

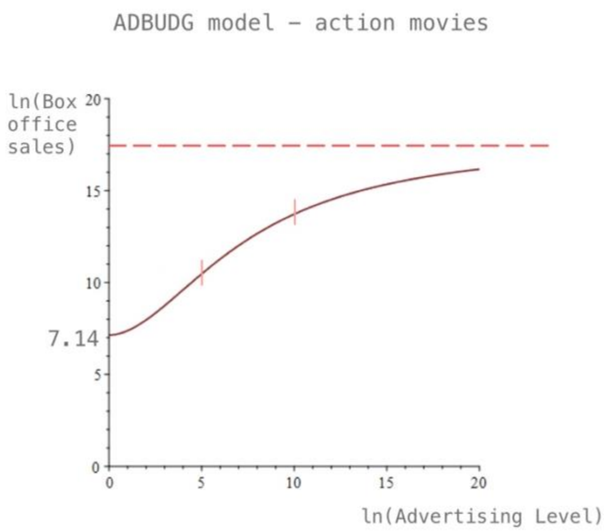


Figure 1

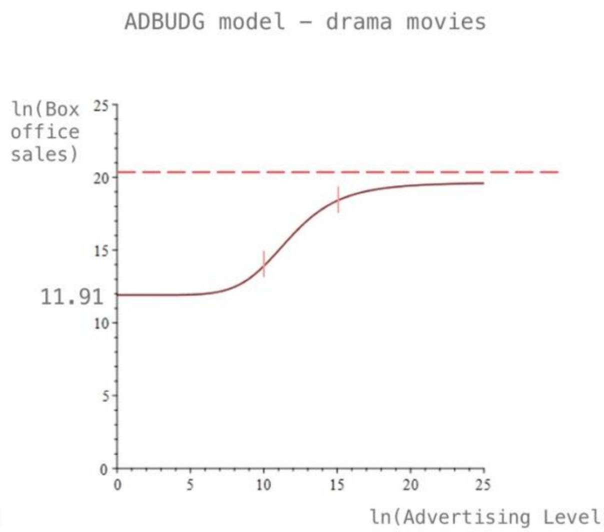


Figure 2

The linear models between action movies and drama movies are different. The minimum box office sales of the action movie in the first week is roughly 7.14 (scaled by nature logarithm), and the corresponding monetary value is around 1261 dollars. In contrast, the drama movie has a more excellent performance in ticket sales, and its minimum level is 149 thousand dollars (11.91 in nature log). Moreover, the box office performance of action movies can be expected to rapidly climb when the advertising budget is increased from 5 to 10. However, the requirement for drama movies is strictly higher in five magnitudes to experience a similar increase in sales (between 10 and 15). Both models will enter the dormancy period after this exciting period (the segment closed by two small red lines), which means additional advertising incentives will generate fewer box office sales and adversely affect the studio's financial performance.

## Recommendations

### Embrace social media

Social media is becoming an increasingly effective way to get the audience involved and build a sticky personal relationship with them. It allows people to share different marketing campaigns and discuss what they think and feel about movies with others. A study conducted by Tejada (2015) shows that studios will be able to implement new marketing strategies using social media as a platform to interact with viewers. In addition, the above analysis provides a strong indication that the view count of the movie trailer on YouTube has the most significant relationship with box office sales. Therefore, a series of suggestions are provided to improve the effectiveness of marketing campaigns. Firstly, the movie's trailer should be distributed on different social media to catch the audience's attention and create hype around the movie. Secondly, actors or crews could be invited to share their experiences while making the movie since these celebrities already have some reputation and influence on social media. Thirdly, keeping the audience engaged during the film's production by disclosing information on filming locations, looks, and clothing is an exciting method to keep their attention.

### Make a strategic decision on release date and advertising budget

Yan (2020) discovered that a film's release date is set in advance, and studios employ advertising to influence customer choice and push potential audiences to the theatres, especially during crucial opening weekends. However, the decision of release date is an incomplete information game between film producers since they can only evaluate the quality of their movies and have no ideas about other studios. The practical approach uses the consumer response to advertising such as view count on trailers, the frequency of topic conversation on social media, and one question survey, "Are you expect this movie?"  to study the demand for this new film and estimate the market share with the same period movies. Thus, an optimal release date can be scheduled to minimize the probability of engaging in fierce competition in the theatre. The above partworth critic rating model (Table 2) can be used to evaluate the quality of the movie and help the studio understand whether their films have the edge over the box office competition. Moreover, the ADBUDG model (Figure 1 – 2) can also predict ticket sales based on the advertising budget.

### Take a portfolio approach to movie distribution

Movie studios derive almost half of their revenues from theatrical releases if theatres have a diminished role in the windowing system and how rearranging distribution channels is a key consideration for movie producers, as pointed out by Arkenberg, Cutbill, Loucks, and Westcott (2020). The tendency in the future is for studios to offer streaming services in diverse ways. They not only make box office revenues and expect the revenue generated from subsequent windows such as mobile video channels and premium TV networks. Thus, studios need to improve their business models to meet the digital world's demands better.

**Reference**


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Yan, W.C. (2020). *Strategic Advertising and Release in the Movie Industry,* [Doctoral Dissertation, New York University]. Retrieved from https://www.anderson.ucla.edu/sites/default/files/documents/areas/fac/marketing/Seminars/Fall%202019/JMP%20Weichen%20Yan.pdf

**Appendix**

**First day model** Appendix 1

SUMMARY OUTPUT

| *Regression Statistics* | |
|---|---|
| Multiple R | 0.838305287 |
| R Square | 0.702755754 |
| Adjusted R Square | 0.691503606 |
| Standard Error | 8456388.004 |
| Observations | 330 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 12 | 5.35945E+16 | 4.46621E+15 | 62.45525269 | 4.89648E-76 |
| Residual | 317 | 2.26688E+16 | 7.15105E+13 | | |
| Total | 329 | 7.62633E+16 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | |
|---|---|---|---|---|---|
| **Intercept** | -12840385.38 | 2564459.338 | -5.007053608 | 9.18995E-07 | *** |
| screens | 1618.827207 | 797.6088634 | 2.029600323 | 0.043232193 | * |
| production | 3825.871752 | 2262.573776 | 1.690937901 | 0.091831551 | . |
| **viewcount** | 0.395891916 | 0.030150739 | **13.13042186** | **9.55408E-32** | *** |
| teasertrailer | 416655.9232 | 1093543.767 | 0.381014401 | 0.703447784 | |
| teaser | 1018135.316 | 2664344.58 | 0.382133499 | 0.702618397 | |
| numbertrailer | 717386.675 | 696325.6193 | 1.030245987 | 0.303679954 | |
| **sequel** | 6795901.193 | 1333349.6 | 5.096863712 | 5.94722E-07 | *** |
| **star_power** | 22597.0883 | 4733.631538 | 4.77373199 | 2.76632E-06 | *** |
| genre | -503401.9466 | 1227200.632 | -0.410203461 | 0.681933796 | |
| season | 722452.9604 | 357971.7873 | 2.018184075 | 0.04441407 | * |
| **critic_rating** | 62951.71935 | 17807.39878 | 3.535144021 | 0.000468276 | *** |
| advertising | 0.063637685 | 0.622549767 | 0.10222104 | 0.918645858 | |

## First weekend model    Appendix 2

SUMMARY OUTPUT

| *Regression Statistics* | |
|---|---|
| Multiple R | 0.854058659 |
| R Square | 0.729416193 |
| Adjusted R Square | 0.719173273 |
| Standard Error | 19518449 |
| Observations | 330 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 12 | 3.25554E+17 | 2.71295E+16 | 71.21174283 | 2.00161E-82 |
| Residual | 317 | 1.20767E+17 | 3.8097E+14 | | |
| Total | 329 | 4.46322E+17 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | |
|---|---|---|---|---|---|
| **Intercept** | -33169270.59 | 5919107.398 | -5.60376225 | 4.55941E-08 | *** |
| screens | 5237.990125 | 1840.985526 | 2.845209835 | 0.004727055 | ** |
| production | 9532.454501 | 5222.316055 | 1.82533083 | 0.06889195 | . |
| **viewcount** | 0.956191617 | 0.069591846 | **13.73999499** | **5.03227E-34** | *** |
| teasertrailer | 355670.1984 | 2524041.972 | 0.140912949 | 0.888028212 | |
| teaser | 922649.5501 | 6149655.595 | 0.150032719 | 0.880834215 | |
| numbertrailer | 1253652.829 | 1607210.558 | 0.780017791 | 0.435962407 | |
| **sequel** | 14781000.19 | 3077545.183 | 4.802854 | 2.41632E-06 | *** |
| **star_power** | 49449.26973 | 10925.84041 | 4.525900791 | 8.51746E-06 | *** |
| genre | -1483727.755 | 2832539.488 | -0.523815382 | 0.60077297 | |
| season | 1751811.52 | 826245.6818 | 2.120206567 | 0.03476512 | * |
| **critic_rating** | 180953.6156 | 41101.80431 | 4.402571094 | 1.46416E-05 | *** |
| advertising | 0.791186621 | 1.436926247 | 0.550610459 | 0.58228854 | |

**First week model** Appendix 3

SUMMARY OUTPUT

| *Regression Statistics* | |
|---|---|
| Multiple R | 0.839261143 |
| R Square | 0.704359266 |
| Adjusted R Square | 0.693167818 |
| Standard Error | 27106138.83 |
| Observations | 330 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 12 | 5.54913E+17 | 4.62427E+16 | 62.93728087 | 2.10108E-76 |
| Residual | 317 | 2.32913E+17 | 7.34743E+14 | | |
| Total | 329 | 7.87826E+17 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | |
|---|---|---|---|---|---|
| **Intercept** | -44255742.64 | 8220127.886 | -5.383826536 | 1.42203E-07 | *** |
| screens | 6523.657752 | 2556.658537 | 2.551634353 | 0.011190975 | * |
| production | 14532.22068 | 7252.462736 | 2.003763578 | 0.045946017 | * |
| **viewcount** | 1.238073981 | 0.096645294 | 12.81049423 | 1.46005E-30 | *** |
| teasertrailer | 298512.5887 | 3505249.424 | 0.085161583 | 0.932186692 | |
| teaser | -1148701.775 | 8540300.427 | -0.134503673 | 0.893089664 | |
| numbertrailer | 1039710.039 | 2232004.835 | 0.465818901 | 0.641665024 | |
| **sequel** | 19451847.27 | 4273923.969 | 4.551285286 | 7.60746E-06 | *** |
| **star_power** | 66417.39707 | 15173.20085 | 4.377283194 | 1.63375E-05 | *** |
| genre | -2063894.78 | 3933673.655 | -0.524673616 | 0.600176811 | |
| season | 2931331.802 | 1147444.152 | 2.554661852 | 0.011096105 | * |
| **critic_rating** | 251262.4863 | 57079.90497 | 4.401942968 | 1.46816E-05 | *** |
| advertising | 1.061212862 | 1.995523433 | 0.531796743 | 0.595239255 | |

**ADBUDG Response Functions (scaled by nature logarithm)**

Action movies

$$Y = 7.14 + 10.53 * \frac{X^{1.85}}{42.49 + x^{1.85}}$$

Total squared error: 656.26

Drama movies

$$Y = 11.91 + 7.73 * \frac{X^{6.67}}{13463723.24 + x^{6.67}}$$

Total squared error: 183.20

Note: X indicates the advertising level (scaled by ln)
Y indicates the box office sales in the first week (scaled by ln)

Appendix 4