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Glitz Investments: Predicting a blockbuster

Shelly Bajaj and Sean Bandyopadhyay wrote this case under the supervision of Srini Krishnamoorthy and Kyle Maclean solely to provide material for class discussion. The authors do not intend to illustrate either effective or ineffective handling of a managerial situation. The authors may have disguised certain names and other identifying information to protect confidentiality.

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**RYLEE SMITH**

Investment manager Rylee Smith was thinking about the meeting she had just held with her team at Glitz Investments, an investment firm based in the United States that focused on the entertainment industry. Specifically, Smith was pondering the comments that her fellow investment manager had made:

We’re forgoing a lucrative opportunity by not investing in the east. Some international movie industries are seeing high growth rates. It will be a mistake to not shift our investment focus to that region. Specifically, I’ve gathered some information on Bollywood—the Indian movie industry—and Rylee, I think you should look over it. We’ve got some potential movies lined up, we just have to choose one if we decide to give this project a go.

Smith knew that investing in the Indian film industry for the first time would be a risk for Glitz Investments. However, such a move, if executed properly, could become a critical turning point for the company. Another colleague who had attended the meeting agreed. “This could be a great opportunity for us,” stated the colleague. “Capitalizing on these trends could provide us with access to an untapped market.”

From the research that was given to her, Smith understood that if Glitz Investments wanted to expand its investment focus geographically, Bollywood would be the perfect place to begin. The main challenge was choosing the right movies as investment vehicles. Although it was an attractive industry for investment, many movie projects across the world resulted in failure. Smith decided that she had to gain a better understanding of the unique features of the Indian movie industry.

Smith studied the report that the analysts at the firm had compiled for her (see Exhibits 1 and 2). She noticed that the team had collected data only for movies with a budget of ₹100 million[[1]](#footnote-2) or higher, which was consistent with the firm’s policy to invest in movies with a minimum level of production quality. She wondered if she could determine a quantitative relationship between box office performance and the factors that the analysts had identified. Could Glitz Investments selectively choose movies based on Smith’s analysis? Half an hour later, she had created a couple of log linear regression models (see Exhibits 3 and 4). It was time to share some conclusions with her boss, Carl Irving. Smith reached for her phone and called Irving.

CARL IRVING

On the other end of the phone line, Smith’s boss listened carefully to her conclusions before replying, “This is good Rylee, but I want something more. It shows how we can improve our average return but I want an analysis that guarantees or at least improves the odds that we strike a jackpot Bollywood movie.”

Smith shook her head to herself and spoke into her phone: “If there was such a thing, Carl, then everyone would be using that magic formula to guarantee sky-high ROIs [returns on investment].”

Irving replied with his own assessment of the situation:

Of course, that’s a given. But come on, in a world where analytics is providing so many different ways to look at data, surely something as straightforward as log linear regression cannot be the only analytical technique we can use. I want more refined analysis and I want it by the end of this week. I mean, look at the trends of the Bollywood market. The ₹1B Club of box office earnings is going to be superseded by a new ₹2 billion benchmark. That’s what I want to identify—a ₹2 billion movie that sets the precedent for forthcoming blockbusters. Nothing else.

And without warning, Smith heard the phone click on the other end. What was she going to do? And how was she going to further dissect the analysis she had conducted?

Smith felt frustrated, but as she logged into Facebook and started to mindlessly go through her newsfeed, something caught her eye. A former classmate from her master of business administration (MBA) studies had posted a new status. More important than the Facebook status was the name of the classmate that caught her attention. Ian Thomas had been widely known as the “analytics wizard” of the MBA program. If anyone could expertly interpret the Bollywood data, it was him. Without hesitating, Smith picked up her phone and called Thomas.

**IAN THOMAS**

Thomas agreed to meet with Smith two days later at a nearby coffee shop. After exchanging pleasantries, the two former classmates got down to business.

“Okay so show me what you’ve got,” stated Thomas.

Smith reached for her notes and started explaining the situation:

Definitely. Here’s what I’ve done already. I performed a log linear regression between the net gross of Bollywood movies over the past five years and the following factors: budget, number of screens, and star factor. While I found significant relationships between these factors and the net gross, this information is not enough. My boss wants more insight on this information. The thing is that he wants to invest in a movie that is not only going to be a success but a game changer for the industry—one that has the potential to break all the Indian box office records. I just don’t know what else to do with this information to answer his question. Frankly, I’m not sure if it can be answered at all.

“Hmmm. Let’s see. Do you remember the concept we learned at school—quantile regression?” asked Thomas.

“Oh yeah. I do remember that concept. Quantile regression helps us model the relationship between an independent variable ‘X’ and the specific percentiles or quantiles of the response variable ‘Y. I also recall that quantile regression is especially useful to identify relationships in markets where outcomes are highly uncertain, as is the case with many cultural industries. My word, it will be perfect for our Bollywood data.”

“Exactly. Averages don’t mean much in the film industry because producers and investors care only about blockbusters. No wonder your boss is so antsy about hitting the jackpot.”

“Well he’s antsy in general, so don’t make excuses for him. Do you want to apply quantile regression to the data?” asked Smith.

“Yeah, definitely,” confirmed Thomas.

Smith and Thomas got to work. A few hours later, they had the output from their analysis in front of them (see Exhibit 4). “Okay,” Thomas started, “now that we have performed further analysis using quantile regression, it’s time to understand what all these numbers mean. Hopefully, by the end of today, you’ll be able to give your boss some insights.”

Exhibit 1: Indian Film Industry Analysis Report

*The Bollywood Report*

Based in Mumbai, the Indian movie industry, known widely as “Bollywood,” is one of the fastest growing movie industries in the world. In 2013, the value of the entire industry was estimated at ₹125 billion. Each year, box office milestones are created by Bollywood movies—not only in India, but across the world. The domestic film industry market was expected to grow at an annual compound annual growth rate (CAGR) of 11.4 per cent until 2018, while the overseas market was projected to grow at a CAGR of 8.9 per cent. Two other significant revenue streams for Bollywood movie production companies are cable and satellite television rights and ancillary revenue streams. Cable and satellite television rights were expected to grow at an annual rate of 10.7 per cent, whereas ancillary revenue streams were expected to grow at a rate of 24.7 per cent.

*The 1B Club*

In 2008, the Indian movie industry released a blockbuster movie that earned a staggering ₹1.14 billion in domestic revenues. This marked the creation of the coveted “1B Club,” which consisted of movies that earned over ₹1 billion domestically. Year over year, an increasing number of movies recorded earnings above that benchmark. Currently, 25 movies hold a place in the 1B Club. Analysts predict that the 1B Club will eventually be replaced by a “2B Club,” as more movies break box office records set by predecessors.

*Hollywood’s Interest in Bollywood*

Foreign investment in the Indian movie industry is not new. Many Hollywood production companies have already entered Bollywood, contributing to this lucrative industry. For example, 20th Century Fox Film Corporation entered the industry as a joint venture and later acquired the leading Indian media and entertainment company Star India Private Limited to distribute and produce over 25 Indian movies. Similarly, Viacom started a joint venture with the India-based media company Network 18. Disney has a majority stake in UTV Software Communications, one of the top Indian movie production companies.

Source: KPMG*, The Stage Is Set: FICCI-KPMG Indian Media and Entertainment Industry Report, 2014*, accessed May 31, 2019, https://assets.kpmg/content/dam/kpmg/pdf/2014/03/FICCI-Frames-2014-The-stage-is-set-Report-2014.pdf; Nyay Bhushan, “Disney Acquires Controlling Stake in India’s UTV,” The Hollywood Reporter, February 1, 2012, accessed May 31, 2019, www.hollywoodreporter.com/news/disney-acquires-controlling-stake-indias-286342.

Exhibit 2: Indian Film Industry Financial Analysis Report

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Movie Name** | **Total Net Gross (INR)** | **Budget (INR)** | **Screens** | **Star** |
| *Dhoom 3* | 2,612,100,000 | 1,500,000,000 | 3,800 | 1 |
| *Ra. One* | 1,139,475,000 | 1,300,000,000 | 2,900 | 1 |
| *Chennai Express* | 2,076,900,000 | 1,100,000,000 | 3,600 | 1 |
| *Once Upon a Time in Mumbai Dobaara!* | 584,900,000 | 1,000,000,000 | 2,300 | 1 |
| *Aatma* | 83,450,000 | 110,000,000 | 1,300 | 0 |
| *Mickey Virus* | 78,050,000 | 110,000,000 | 1,000 | 0 |
| *Rabba Main Kya Karoon* | 10,575,000 | 110,000,000 | 400 | 0 |
| *London Paris New York* | 63,800,000 | 105,000,000 | 550 | 0 |

Note: Budget refers to the cost of producing and releasing the movie; Screens represents the number of film screens that show the movie after its release; Star is based on the historical box office performance of an actor’s movies.

Source: “BoxOffice Reports, India,” BOI: Box Office India, accessed March 2014, www.boxofficeindia.com.

Exhibit 3: LOG Regression OUTPUTS

Log Regression 1: Predicting the mean log(*Box Office)* using *Star*, log(*Budget)* and log(*Screens)*

Loge (*Box office*) = *Intercept* + (Coefficient1) × (*Star*) + (Coefficent2) × (Loge *Budget*)

+ (Coefficient3) × (Loge *Screens*)

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Estimate | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | 5.7687 | 1.9197 | 3.005 | 0.002885 \*\* |
| Star | 0.3943 | 0.1115 | 3.537 | 0.000471 \*\*\* |
| Budget | 0.1482 | 0.1215 | 1.220 | 0.223479 |
| Screens | 1.4706 | 0.1026 | 14.334 | < 2e-16 \*\*\* |

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

Residual standard error: 0.7682 on 293 degrees of freedom

Multiple *R*-squared: 0.6959, Adjusted *R*-squared: 0.6928

*F*-statistic: 223.5 on 3 and 293 DF, *p*-value: < 2.2e-16

Log Regression 2: Predicting the mean log(*Box Office)* using *Star* and log(*Screens)*

Loge (*Box office*) = *Intercept* + (Coefficient1) × (*Star*) + (Coefficient2) × (Loge *Screens*)

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Estimate | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | 8.03146 | 0.49504 | 16.224 | < 2e-16 \*\*\* |
| Star | 0.44233 | 0.10439 | 4.237 | 3.03e-05 \*\*\* |
| Screens | 1.55758 | 0.07384 | 21.095 | < 2e-16 \*\*\* |

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

Residual standard error: 0.7688 on 294 degrees of freedom

Multiple *R*-squared: 0.6944, Adjusted *R*-squared: 0.6923

*F*-statistic: 334 on 2 and 294 DF, *p*-value: < 2.2e-16

Note: All log regressions were done using the statistical software and programming language R.

Source: Created by authors.

Exhibit 4: Quantile Regression OUTPUTS

Quantile Regression 1: Predicting the 10th percentile of log(*Box Office)* using *Star*, log(*Budget*), and log(*Screens)*

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | –1.11150 | 2.93688 | –0.37846 | 0.70536 |
| Star | 0.60504 | 0.14961 | 4.04415 | 0.00007 |
| Budget | 0.50483 | 0.19516 | 2.58669 | 0.01017 |
| Screens | 1.32462 | 0.16840 | 7.86597 | 0.00000 |

Quantile Regression 2: Predicting the 25th percentile of log(*Box Office)* using *Star*, log(*Budget),* and log(*Screens)*

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | 1.77625 | 2.09388 | 0.84831 | 0.39696 |
| Star | 0.52088 | 0.12253 | 4.25117 | 0.00003 |
| Budget | 0.30617 | 0.13925 | 2.19864 | 0.02869 |
| Screens | 1.52156 | 0.13155 | 11.5622 | 0.00000 |

Quantile Regression 3: Predicting the 50th percentile of log(*Box Office)* using *Star*, log(*Budget),* and log(*Screens)*

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | 7.13596 | 2.53504 | 2.81493 | 0.00521 |
| Star | 0.37228 | 0.14405 | 2.58433 | 0.01024 |
| Budget | 0.02935 | 0.15518 | 0.18911 | 0.85014 |
| Screens | 1.60742 | 0.11144 | 14.42373 | 0.00000 |

Quantile Regression 4: Predicting the 50th percentile of log(*Box Office)* using *Star* and log(*Screens)*

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | 7.67060 | 0.67662 | 11.3361 | 0.00000 |
| Star | 0.41186 | 0.12539 | 3.28468 | 0.00114 |
| Screens | 1.60951 | 0.10029 | 16.04832 | 0.00000 |

Quantile Regression 5: Predicting the 75th percentile of log(*Box Office)* using *Star*, log(*Budget),* and log(*Screens)*

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | 8.25137 | 0.70655 | 11.67844 | 0.00000 |
| Star | 0.25278 | 0.09772 | 2.58690 | 0.01017 |
| Budget | 0.04560 | 0.05858 | 0.77844 | 0.43694 |
| Screens | 1.48199 | 0.13629 | 10.87396 | 0.00000 |

**exhibit 4 (continued)**

Quantile Regression 6: Predicting the 75th percentile of log(*Box Office)* using *Star* and log(*Screens)*

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | 8.78914 | 0.71381 | 12.31308 | 0.00000 |
| Star | 0.24419 | 0.11584 | 2.10804 | 0.03587 |
| Screens | 1.53469 | 0.10157 | 15.11001 | 0.00000 |

Quantile Regression 7: Predicting the 90th percentile of log(*Box Office)* using *Star*, log(*Budget),* and log(*Screens)*

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | 8.68576 | 1.10943 | 7.82901 | 0.00000 |
| Star | 0.14172 | 0.07807 | 1.81527 | 0.07050 |
| Budget | 0.14964 | 0.08446 | 1.77180 | 0.07747 |
| Screens | 1.18726 | 0.14779 | 8.03332 | 0.00000 |

Quantile Regression 8: Predicting the 90th percentile of log(*Box Office)* using *Star* and log(*Screens)*

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | 10.96996 | 0.73463 | 14.93263 | 0.00000 |
| Star | 0.18845 | 0.13059 | 1.44299 | 0.15009 |
| Screens | 1.27688 | 0.10444 | 12.22618 | 0.00000 |

Quantile Regression 9: Predicting the 90th percentile of log(*Box Office)* using log(*Budget)* and log(*Screens)*

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | 7.43025 | 1.32027 | 5.62784 | 0.00000 |
| Budget | 0.19819 | 0.10532 | 1.88187 | 0.06084 |
| Screens | 1.23842 | 0.15100 | 8.20143 | 0.00000 |

Quantile Regression 10: Predicting the 90th percentile of log(*Box Office)* using Star and log(*Screens)*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | t value | Pr(>|t|) |
| (Intercept) | 10.96996 | 0.73463 | 14.93263 | 0.00000 |
| Star | 0.18845 | 0.13059 | 1.44299 | 0.15009 |
| Screens | 1.27688 | 0.10444 | 12.22618 | 0.00000 |

Quantile Regression 11: Predicting the 90th percentile of log(*Box Office)* using log(*Screens)*

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | 9.66798 | 0.85738 | 11.27622 | 0.00000 |
| Screens | 1.47248 | 0.11578 | 12.71833 | 0.00000 |

**exhibit 4 (continued)**

Quantile Regression 12: Predicting the 90th percentile of log(*Box Office)* using log(*Budget)*

Coefficients

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | *t* value | Pr(>|*t*|) |
| (Intercept) | -1.15978 | 1.59321 | –0.72795 | 0.46722 |
| Budget | 1.09204 | 0.07921 | 13.78673 | 0.00000 |

Quantile Regression 13: Predicting the 90th percentile of log(*Box Office)* using Star

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Value | Standard Error | t value | Pr(>t) |
| (Intercept) | 19.95097 | 0.09972 | 200.06023 | 0.00000 |
| Star | 0.96062 | 0.17897 | 5.36738 | 0.00000 |

Note: All quantile regressions were done using the statistical software and programming language R.

Source: Created by authors.

1. ₹ = INR = Indian rupee; US$1 = ₹61.88 on January 1, 2014; all currency amounts are in ₹ unless otherwise specified. [↑](#footnote-ref-2)