TWITTER SHOWS INFLUENCE OF BUZZ ON MOVIES

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ABSTRACT

Previous research has found that word of mouth is perhaps the best predictor of a movie's success. This is evident by the absence of a formula to guarantee a predictable return on investment and the lack of other reliable predictors such as genre, cast and budget. As a result, recommendations from moviegoers, whether positive or negative, can have a significant impact on a movie's performance. Several studies have focused on how social media can be used to predict movie box office revenue. However, this has primarily been based on activity levels or the amount of buzz generated by these films. As a result, this study examines sentiment analysis on Twitter to determine the impact of word of mouth on a movie's success. It also evaluates the effect of tweet rate after a movie's release and its relationship to sentiment analysis.

INTRODUCTION

Researchers are continually finding ways to use social media as a predictive model for one purpose or another. For instance, Twitter has been used to predict changes in the Dow Jones Industrial Average and forecast movie box office revenue. In fact, one study found that the rate at which movie tweets are generated can be a more accurate predictor of a movie's performance than the Hollywood Stock Exchange, largely considered the gold standard. This study also found that the predictive power of tweet rates could be enhanced by using sentiment analysis in the regression model (Asur & Huberman, 2010). In addition to Twitter, researchers have even used Wikipedia activity to forecast the first weekend box office revenue of movies (Mestyán, Yasseri, & Kestész, 2013).

Another study used sentiment analysis to predict movie success by comparing the ratio of positive to negative tweets about a film to its profit ratio. While the researchers found that the positive tweet to negative tweet ratio curve had the same tendency as the profit ratio, they noted certain limitations to this study. For example, they indicated that the sentiment analysis software they used had rather low accuracy (Jain, 2013). This is not unusual as other previous studies have found mixed results regarding the impact of word of mouth through social media on sales outcomes (Oh, 2013).

The first part of this study builds on this previous work and conducts a more thorough sentiment analysis of posts about movies on Twitter to determine their correlation to weekly changes in box office revenue. This was not done to assess the impact of word of mouth on social media per se but as a means of determining the extent to which this relationship exists. This is an important

distinction for several reasons. First, only 7% of word of mouth occurs online (Berger, 2013). This is because most people share information with family and friends in face-to-face contexts. In fact, it is estimated that people have more than 16 conversations a day about products and services (Geller, 2013).

Another reason we did not attempt to analyze the impact of word of mouth on social media is because different channels have different levels of influence. For instance, one study analyzed the unique characteristics of microblogging word or mouth (MWOM) and the so-called "Twitter effect." Widely discussed by industry observers, this effect was thought to be the cause of the failure of the movie *Brüno* and the success of the movie *Inglourious Basterds* (Corliss, 2009; Singh 2009).

However, researchers were able to quantify the Twitter effect on movies during their opening weekends. In particular, they investigated whether MWOM on Twitter could influence early product adoption and whether differences could be found for positive and negative MWOM (Hennig-Thurau, Wiertz, & Feldhaus, 2014).

The researchers found that negative Twitter reviews shared on a movie's opening day decreased revenues on Saturday and Sunday, but that positive Twitter reviews did not have the inverse effect. This negativity bias was thought to be the result of the diagnosticity of information and prospect theory. That is, because consumers have only been exposed to producers' appeals at this point in the decision-making process, the negative messages have a more diagnostic value. Also, based on Kahneman and Teversky's prospect theory, consumers are more concerned about experiencing loss from a bad decision than they are concerned about benefitting from a good one (Hennig-Thurau, Wiertz, & Feldhaus, 2014).

This study illustrates how MWOM is distinct from both traditional word of mouth (TWOM) and electronic word of mouth (EWOM). For example, EWOM is generally less influential than MWOM because of the degree of trust that microbloggers have in their network. In contrast, EWOM is generally shared among users who have little to no relationship. Therefore, it is difficult for consumers to determine the quality and credibility of the recommendation.

In addition, research has also found that the platforms to which EWOM is posted can also affect consumer judgments. For example, some recommendations could be attributed to the circumstances under which a recommendation is made as opposed to the stimuli itself if they appear on personal blogs versus independent blogs. That is, recommendations on personal blogs are more likely to be construed as being biased (Lee & Youn, 2009).

Nevertheless, word of mouth is widely regarded as the most effective form of marketing. According to McKinsey & Company, "word of mouth generates more than twice the sales of paid advertising in categories as diverse as skincare and mobile phones" (McKinsey, 2010). In light of the effectiveness of word of mouth, our first hypothesis was that a strong correlation would be found between Twitter sentiment and movie revenue over a broader period of time.

The second part of this study evaluated the relationship between the tweet rate after a movie's release and its box office performance. For instance, we know from previous research that tweet

rate is a reliable predictor of opening weekend box office revenue. We also know that tweet rate can be a reliable predictor of successive weekends as well (Asur & Huberman, 2010). What is not known, is the qualitative difference between sentiment analysis and tweet rate. Therefore, we conducted a more thorough evaluation of tweet rate using the same methodology as our sentiment analysis so that we could compare these results and better understand this relationship. Our second hypothesis was that a strong correlation would also be found between tweet rate of box office performance.

METHODOLOGY

The first part of this study was conducted using a two-stage sampling method. We first collected and archived tweets discussing movies over the first four weeks after their release using the data mining platform Tweet Archivist. Specifically, we utilized a hashtag-based sampling approach and only considered tweets comprising at least one hashtag used by studios to promote their films. This enabled us to define a pool of tweets related to these movies. Our universe was comprised of 17 movies that were released in the fall of 2016. The only criteria for the selection of these movies were that they were scheduled for wide release and were not holiday-themed to eliminate the possibility of considering data skewed by unique audiences. This resulted in the collection of 800,739 tweets.

Secondly, we narrowed down the initial sample by randomly selecting tweets from week to week. The data was then coded manually by three coders including the principal investigator and two co-investigators. This design was utilized to ensure accuracy in the analysis of the data and to foster a better understanding of sentiments' effects on movie outcomes. Moreover, Cronbach's alpha was used to ensure intercoder reliability. For this assessment, 10% of the sample was tested which resulted in a reliability measure of .93.

To conduct our analysis, a random sample of 400 hashtags were analyzed each week after the release of each movie for as many weeks up to four weeks that the data would allow. For several low performing movies, we were only able to gather a week of data and, in other cases, we were not able to gather any data at all. In the end, out of the 17 movies for which we collected tweets, we were only able to analyze 11 that had at least a week of data that met our sample size criteria.

For these 11 movies, we coded 12,000 tweets manually, which is the equivalent of 30 weeks of data. To create a more representative sample of individuals sharing their sentiments, as opposed to simply retweeting content from others, we eliminated retweets from the data sets before our random selection. That is, our review of retweets consistently revealed that an overwhelming number of them were multiple retweets that contained only original content without any further editorializing. Moreover, in cases where there were not multiple retweets, it was difficult to discern which content was original and which wasn't. Therefore, we opted to eliminate this potential error by removing retweets from our universe. Then, once the random sample was created, we coded the tweets for their positive or negative reviews of the movie. Specifically, we used both keywords and emojis to discern sentiment and code the data using pre-established criteria.

Once the tweets were coded, we then compared the average weekly sentiments with the average weekly percentage change in revenue for each movie. Weekly sentiments were defined as those expressed on Twitter from the initial Friday of a movie's opening to the following Thursday, and then Friday to Thursday in subsequent weeks. Revenue figures were obtained via the website The Numbers, which is owned and operated by Nash Information Services, LLC, a leading film analytics company. Twitter data was analyzed for as many weeks as the samples would allow up to four weeks. Weekly revenue was defined as the percentage change from weekend to weekend to allow us to compare this data to another study which used this methodology.

We then compared hashtag sentiments, Audience Score, and CinemaScore ratings with average weekly revenue. The Audience Score is a viewer rating sponsored by Rotten Tomatoes based on the percentage of positive and negative ratings by audiences. The CinemaScore is based on surveys of movie audiences on opening night to gauge a movie's appeal by rating it on a scale of A to F. We then assigned a numerical value to the CinemaScore ratings for analysis purposes.

The second part of this study also consisted of a two-stage sampling method. We again collected and archived movie tweets over the first four weeks using the same hashtag-based sampling approach. Our universe was comprised of 8 movies that were released in the spring of 2017. Though we used the same criteria for the selection of these movies, the difference in the number of movies in each universe was due to the number of weeks with sufficient data. That is, the volume of tweets was much more prevalent than the sentiments of tweets in each of these data sets. Our second universe was comprised of 471,492 tweets.

We then created random samples of tweets from week to week to analyze. Similar to our sentiment analysis, this data was also coded manually. Two coders were used in this process, including the principal investigator and a co-investigator, and Cronbach's alpha was used to ensure intercoder reliability. Ten percent of the sample was used in this assessment, resulting in a reliability measure of .95.

A random sample of 400 hashtags was created for each week for as many weeks up to four weeks that data was available. Some low performing movies fell short of this threshold and would only allow a few weeks of data. However, all 8 movies had at least two weeks of data that met our sample size criteria.

We manually coded 11,600 tweets, or 29 weeks of data, for these 8 movies. Unlike our sentiment analysis, we included promotional tweets and retweets. We only coded this data to discern whether the tweets were related to specific movies.

After coding the tweets, we determined the aggregate number of relevant tweets per week for each movie and compared this number with the movie's weekly gross revenue. This is an important distinction relative to our sentiment analysis. Our sentiment analysis only compared the average weekly sentiments with the average weekly percentage change in revenue for each movie over their initial four weeks. We used these aggregate numbers in the sentiment analysis since overall sentiments about a movie are not likely to change from week to week.

DISCUSSION

Our research found a significant relationship between positive word of mouth on Twitter and changes in average weekly revenue. Specifically, the more highly a movie was rated on Twitter the more revenue the film was expected to garner from week to week. These findings are significant because of the random sample design and the scientific approach to evaluating this data. In addition, these findings provide an alternative measure to other movie ratings, some of which have been shown to be skewed and unreliable.

For instance, one study of Fandango's ratings found them to be greatly inflated, which appeared suspicious because Fandango is also in the business of selling tickets to consumers (Hickey, 2015). In addition, ratings can also be skewed by other factors such as the number of male and female reviewers, and by the binary heuristic that some ratings use. A binary heuristic aggregates ratings as either positive or negative and, therefore, does not include levels of intensity. To illustrate, a rating on Rotten Tomatoes can result in a positive or negative review exceeding a film's average score and vice versa (Hickey, 2016).

Nevertheless, we compared our findings with the ratings of Rotten Tomatoes and CinemaScore due to the popularity of these reviews. For instance, a correlation analysis between tweet sentiments and revenue found an r value of .75, which indicates a strong relationship since a correlation coefficient of .5 is considered high, .3 is considered medium, and .1 is considered low. And, even though the sample size of 11 movies is small, this analysis found a p value of less than .01 which means that there is a 99 percent chance of it being accurate.

By comparison, correlation analyses for Audience Score and CinemaScore with revenue found r values of .44 and .36, respectively. However, both the Audience Score and CinemaScore had p values of greater than .05. Therefore, these correlations were not found to be significant as .05 is considered the threshold for determining statistical significance. The relationship between hashtags and revenue is immediately apparent when visually represented. For example, Exhibit 1 below shows the relationship between the average movie rating based on hashtag sentiments and average percentage change in weekly revenue.

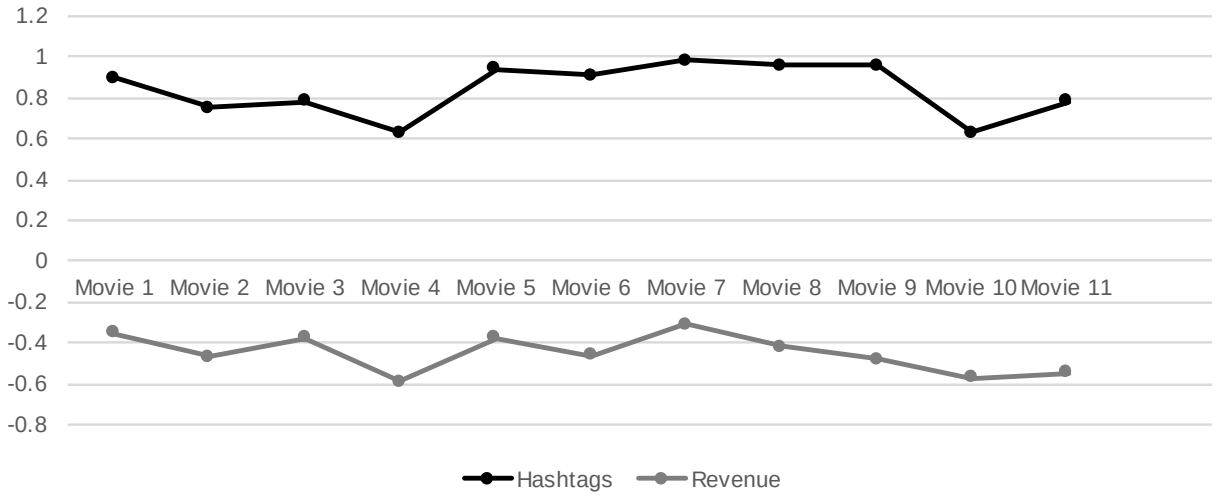

EXHIBIT 1: HASHTAGS V. REVENUE

Moreover, this study was developed to further confirm the findings of another study on the relationship between word of mouth and movie revenue. Since word of mouth is thought to be a primary determinant of movie success, this earlier study used revenue as a proxy for word of mouth to see if significant differences could be found between high-performing films versus low-performing films (Eagan, 2016).

Conducted in the fall of 2015, this study analyzed the role of word of mouth on both successful and unsuccessful movies over the previous 20 years. Specifically, the study characterized high performers as Oscar-nominated movies and low performers as Razzie-nominated movies which resulted in a sample size of over 200 movies. Then these movies' average percentage change in revenue over their initial four weekends was averaged over a 20-year period. This analysis revealed very consistent findings among these movies (Eagan, 2016).

As Exhibit 2 demonstrates, the average percentage change for high performers was -24 percent, -26 percent, -25 percent, and -21 percent over the first four weeks. This was in sharp contrast to the average percentage change for low performers, which was -54 percent, -56 percent, -53 percent, and -54 percent. Over this period, the average percentage change between Oscar nominees and Razzie nominees was -30 percent.

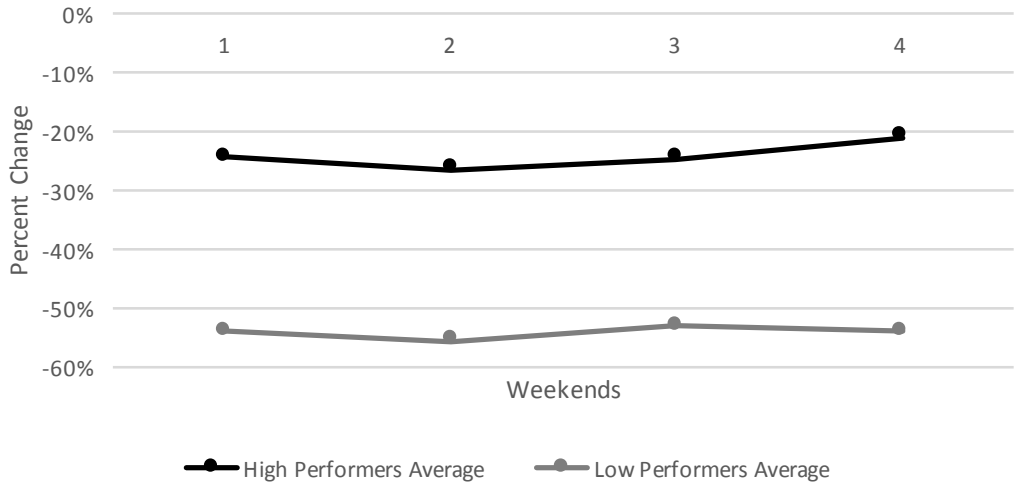

EXHIBIT 2: HIGH V. LOW PERFORMERS

Also evident in Exhibit 2 are the clear patterns and trends that emerged in this data. Thus, this study concluded that weekly average percentage change in revenue seemed to be a good proxy for estimating the influence of word of mouth. Taken together with the results of the Twitter sentiment study, this presents compelling evidence of the role that word of mouth plays on a movie's success.

To prevent our sample from being skewed, we statistically eliminated outliers in our analysis. That is, once averages were obtained for Twitter sentiments and weekly percentage changes for each movie, we used a statistical method to remove these numbers from our data sets. However, there was only one outlier among the data.

The outlier was the movie *Bleed For This*. Written and directed by Ben Younger, this movie is based on a true story about the life of former world boxing champion Vinny Pazienza. Martin Scorcese also served as the film's executive producer.

According to our review of Twitter sentiment, audiences loved this film. In fact, it earned a positive rating of 98% over its first three weeks, which is the only period our sample would allow. However, at the same time, its revenue plunged by an average of -69% per week. As Exhibit 2 above illustrates, even some of the worst movies only lose an average of -54% per week in their initial weeks after release.

The reasons for this occurrence are open to speculation. For instance, it could be that the movie might have a limited audience and, while popular among that audience, it does not have broad-based appeal. Regardless of the reasons, this is an important caveat for these findings. That is, even though a strong relationship can be established between word of mouth and revenue, there are exceptions to this rule.

In addition, there was another outlier that was removed for different statistical reasons. We removed the movie *Miss Sloane* from our data set because we were unable to accurately code its tweets. That is, this movie's plot involved a Washington, DC lobbyist who takes on the gun

lobby for stricter gun control measures. Consequently, the political nature of this film resulted in numerous tweets from second amendment advocates who criticized the content of the movie and the liberal bias of Hollywood. In the midst of these tweets, it was not clear which of these individuals had actually seen the movie.

Here again is another exception to the rule regarding the strong relationship between word of mouth and revenue. However, it does seem reasonable to suggest that movies which tackle controversial political issues are likely to alienate certain audiences. In fact, this could be a significant factor in the movie's poor box office performance. Although, without the data, it is hard to say for sure.

It is worth noting that there is a market for politically-oriented films. This is evident in the appeal of movies like *Fahrenheit 9/11*, the top grossing documentary of all time, and the Oscar-winning *An Inconvenient Truth* (Goldstein, 2017). However, these films are billed and marketed as such.

Though the impact of word of mouth on movies based on these findings seemed clear, the question regarding the impact of buzz in general also needed to be addressed. Buzz, in this sense, we simply defined as volume or the amount of chatter about a movie. For example, since previous studies had found that tweet rate was an accurate predictor of movie success both before and after a film's release, we wanted to assess its influence relative to word of mouth using the same methodology.

To that end, we also found a significant relationship between tweet rate and weekly gross revenue. That is, the more buzz a movie experienced on Twitter the more revenue it generated from week to week. In particular, our correlation analysis between tweet rate and revenue resulted in an r value of .69. Like the word of mouth correlation, the tweet rate correlation is considered a strong relationship. This relationship was also found to be significant with a p value of less than .01 and, therefore, an accuracy of 99 percent.

We again used a statistical method to remove outliers from our sample to prevent our results from being skewed. This was done by comparing the ratios of gross revenue to tweet rate for each week and resulted in the elimination of 3 of the 29 weeks. For example, *Fifty Shades Darker* continued to generate an inordinate number of tweets even into its fourth week despite its declining revenues. The reason for this is uncertain, but it could have been due to the popularity of the books and movies among a dedicated fan base or simply due to the sensational nature of the film.

The other weeks that were eliminated from the sample were the third week for *The Space Between Us* and the second week for *A Cure For Wellness*. In both cases this was the final week for which data was available. The disparities in these cases was not due to a large volume of tweets as was the case with *Fifty Shades Darker*. Rather, these disparities were due to a rapid decline in revenue in these movies' latter weeks. Exhibit 3 below shows the strong positive relationship between tweet rate and revenue for the 26 weeks we evaluated.

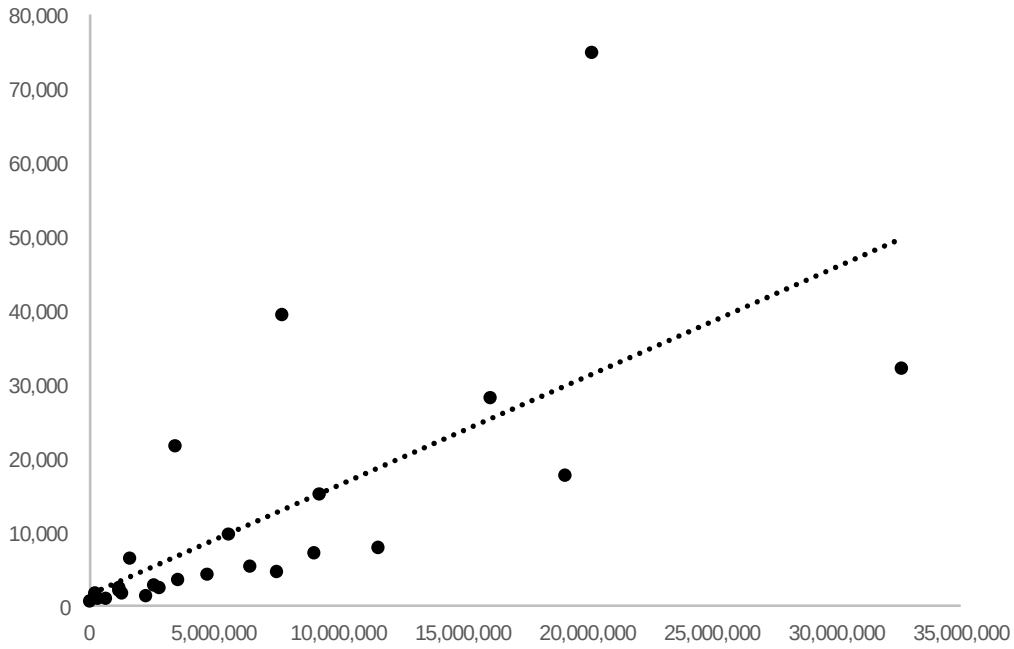

EXHIBIT 3: TWEET RATE V. REVENUE

Taken together, these studies seem to indicate how buzz can influence movies in two ways. First, these results offer more evidence of the influence of positive and negative word of mouth on movies. Second, we have further confirmation that the amount of buzz about a movie can affect its performance even after its release. This could be due to the level of awareness that this social media activity continues to generate. Or, it could be reflective of the amount of buzz about a movie in general.

Another interesting finding from this research was that those movies that had more positive buzz also had more buzz in general. That is, it seems that the more audiences enjoy a movie, the more likely they are to talk about it. On the other hand, it seems that those who do not have a favorable experience are less likely to share their sentiments.

This appears reasonable in light of the ability of tweet rate to predict a movie's performance. However, this is an issue that warrants further research.

CONCLUSION

This study confirmed our hypotheses that there are strong relationships between both Twitter sentiment and movie revenue, and tweet rate and movie revenue. While word of mouth has always thought to be a primary contributor to the success of movies, social media now provides us with a means of both confirming this relationship and the extent to which this relationship exists.

In addition, while prior research has confirmed that the level of social media activity can predict a movie's performance, it seems that buzz can continue to contribute to movie outcomes. This is apparent in not only the degree to which movies are reviewed positively by audiences but also in the number of tweets that are shared.

Practically speaking these findings allow us to better understand how word of mouth influences movies. For instance, the movie *John Carter*, a science fiction movie released in 2012 by Walt Disney Studios, has become shorthand for a box office disaster (Mendelson, 2015). In fact, Rich Ross, the company's chairman, resigned a month after Disney reported that they would lose $200 million on the film (Nakashima, 2012).

The film only earned $30 million on its domestic opening weekend, which is likely attributable to some marketing challenges, but word of mouth did not help it thereafter, as the movie lost an average of -59% in revenue per week over its first four weekends (The Numbers, 2017). This was especially problematic for the movie since it cost $307 million to produce (Sylt, 2014).

Conversely, *Paranormal Activity*, the most profitable movie ever made, had a production budget of only $15,000 yet earned $194 million at the box office (Avila, 2010; Frankel, 2009; The Numbers, 2017). Following its release in 2009, the movie experienced exceptional revenue growth over its first four weeks (The Numbers, 2017).

More recently, Twitter announced that *Wonder Woman* had become the most tweeted about movie of 2017 (Wagmeister, 2017). This is no surprise since its revenue only dropped 45% in its second weekend. This may not seem significant on its face value but *Batman v. Superman: Dawn of Justice* lost 69 percent in revenue between its first and second weekends. As further context, at the time of this writing it had the best second weekend of any superhero movie (Abad-Santos, 2017).

When *Batman v. Superman* opened, it garnered $166 million at the box office during its first weekend. However, the movie continued to shed screens in its first few weeks just as *Deadpool* was adding them (Pressberg, 2016). Compared to the highly-anticipated *Batman v. Superman* movie, *Deadpool* might not have even been made but for the attention that was generated by fans from leaked footage online (Setoodeh, 2017).

In light of our research, it is clear that these outcomes are largely the result of word of mouth. Specifically, we know that a movies' percentage change in revenue from week to week can be a good proxy for word of mouth given the patterns of high and low performers. Moreover, we know that this word of mouth consists of both positive and negative sentiments, as well as the amount of buzz that a movie generates.

Now, when people talk about movie buzz, we have a better understanding of its constituent parts and its impact. We also have a better appreciation for the predictive value of Twitter in this process.

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