Paper 2897-2018

# Twitter Sentiment Analysis: A Case Study of Comparative Advertising in the Airline Industry

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## ABSTRACT

The aviation industry today is in oligopolistic conditions where major airlines control the market and create entry barriers to low-cost domestic airlines and fast-growing rivals from other markets. This has led to stifling competition between the two groups, and when controversies such as service failures surround the oligopolies, competitors strike back by sharing comparative advertisements on social media platforms. The posters act as a catalyst for already dissatisfied customers resulting in a more negative attitude towards the mocked brand and indirectly building a substantial brand equity and loyalty for the competitors. This paper focuses on overall sentiment surrounding three major controversial passenger incidents in the airline industry from the year 2017 and how subsequent parody advertisements from competitors helped the latter gain an advantage over the market leaders and boost their brand value. For this case study, we extracted ~116,000 customer tweets from Twitter for thirteen airline brands during the time of the controversies. Base SAS® procedures were used to prepare the extracted data, and SAS® Enterprise Miner's Text Miner nodes were used to discover customer sentiments, topics and term relationships for different airlines during such unfortunate incidents.

## INTRODUCTION

The Airline Deregulation Act signed in 1978 changed the aviation industry. The act dissolved the Civil Aeronautics Board (CAB) that regulates airlines fares and resulted in carriers to innovate new business models with low fares. Because of low fare models, tough competition prevailed between airliners which led to losses and failures [1]. Consequently, airlines were consolidated into three to four large carriers through mergers or acquisitions. With only a few major airlines dominating the industry, oligopolistic conditions began to exist characterized by collusion, restrained competition and high entry barriers [2] making it difficult for rivals to penetrate the already concentrated market and that drove the rivals to take the route of comparative advertising.

Comparative advertising is a technique where an advertising message directly or indirectly names the advertising company's competitors (in this case, the few major airlines) and compares one or more of its characteristics by showing why their competitor's service is inferior [3]. The primary objective for the airline brands here is to make their potential customers look upon its service as rather different from the market leaders. The idea is to use advertising as a tool in lowering the elasticity of demand for the large carriers. When this happens, consumers will regard the brand as being more desirable than the substitute [4]. In order to make the advertising highly efficient, choosing the right platform to share the poster and seizing the perfect opportunity to publish it is of paramount importance.

Social media sites such as Twitter have evolved to become a prominent platform for advertising and marketing. It has also become one of the essential channels through which customers request and receive customer service. According to a recent survey, 90% of the customers have used social media in some way to communicate with a brand, and more than 1/3rd said they preferred social media to traditional channels like phone and email [5]. Therefore airline brands share their parody advertisements on Twitter to subvert their competitors' value and gain customer sentiments.

Airline brands build and maintain a bond with customers by offering dependable service. A single misstep such as service failure can be enough to keep their public relations departments scrambling as customers strongly voice their negative sentiments in social media platforms. Competitors target the other airlines with their adverts during such service failures and controversies to gain attention.

Figure 1 shows a simplified version of how competitors target the market leaders with their comparative advertising.

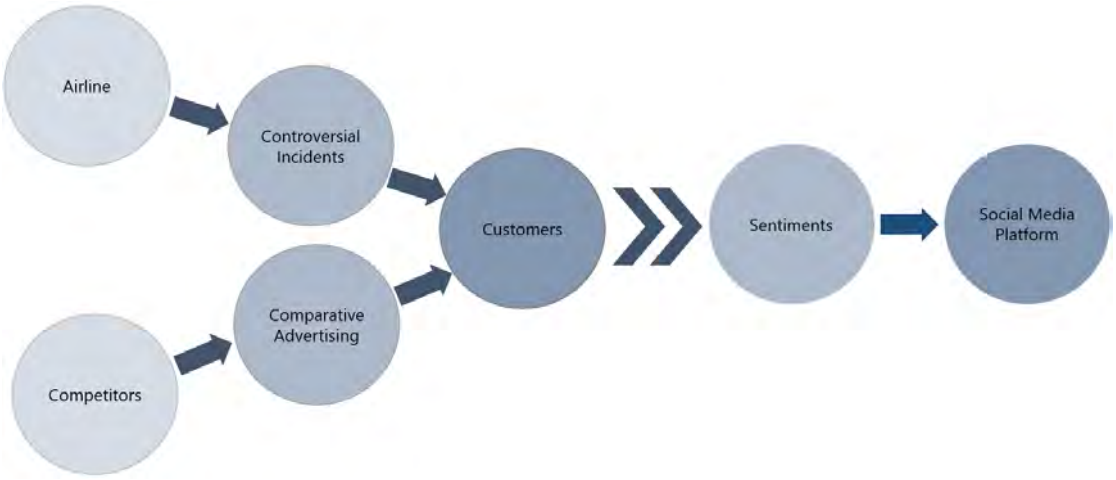


**Figure 1. Comparative Advertising in Airline Industry**

In the United States today, the four major airlines influencing the market are United Airlines, American Airlines, Delta Air Lines and Southwest Airlines who fly about 80% of all domestic passengers [7]. Low-cost domestic competitors such as Spirit Airlines and Frontier Airlines and fast-growing rivals from Middle East markets such as Emirates Airlines, Qatar Airways, and Etihad Airlines are trying to gain market share concentrated by these major four [8]. Similarly, the Indian market is dominated by IndiGo Airlines, Air India and Jet Airways and new entrants like Spice Jet and Go Air are finding it difficult to enter the domestic market [9].

In this paper, we discuss three major controversial passenger incidents of the year 2017 and how successive advertisements from competitors helped them gain an advantage over the market leaders to boost their brand value. The controversial cases analyzed in this study are as follows.

**CASE 1: UNITED AIRLINES LEGGINGS INCIDENT**

On March 26th, 2017, a gate agent for United Airlines denied entry to two girls onto a flight who were wearing leggings (a close-fitting garment worn over the legs typically by women). The incident set off a wave of online criticism with public calling the airline dress code policies as old-fashioned. Though United Airlines issued a statement [10] stating the passengers were ‘pass-riders’ who had to follow specific dress codes, women activists voiced that the leggings ban disproportionately affected women and girls.

**CASE 2: UNITED AIRLINES PASSENGER REMOVAL INCIDENT**

On April 9th, 2017, United Airlines Express flight 3411 from Chicago to Louisville was overbooked (more tickets sold than actual available seats) and with no volunteers to deplane to accommodate four crew members, the flight agent selected a passenger through an automated selection process. The chosen passenger refused to disembark the flight and was forcibly removed [11] by law enforcement officers and suffered injuries. The video footage of the forcible removal captured by other passengers was widely shared on social media causing public outrage. Many including the US government criticized the way this situation was handled by United Airlines.

**CASE 3: INDIGO AIRLINES PASSENGER MANHANDLE INCIDENT**

On October 15th, 2017, a ground crew associate of IndiGo Airlines (the largest airline in India) physically assaulted a passenger at Delhi airport following an altercation. The video captured by another IndiGo associate surfaced in social media on November 7th, 2017 and went viral. The incident received strong condemnation from public, and the Directorate General of Civil Aviation of India issued a show-cause notice to IndiGo airlines seeking explanation [12] on the episode.

Figure 2 shows a timeline of the three controversial incidents along with competitors’ advertisements.

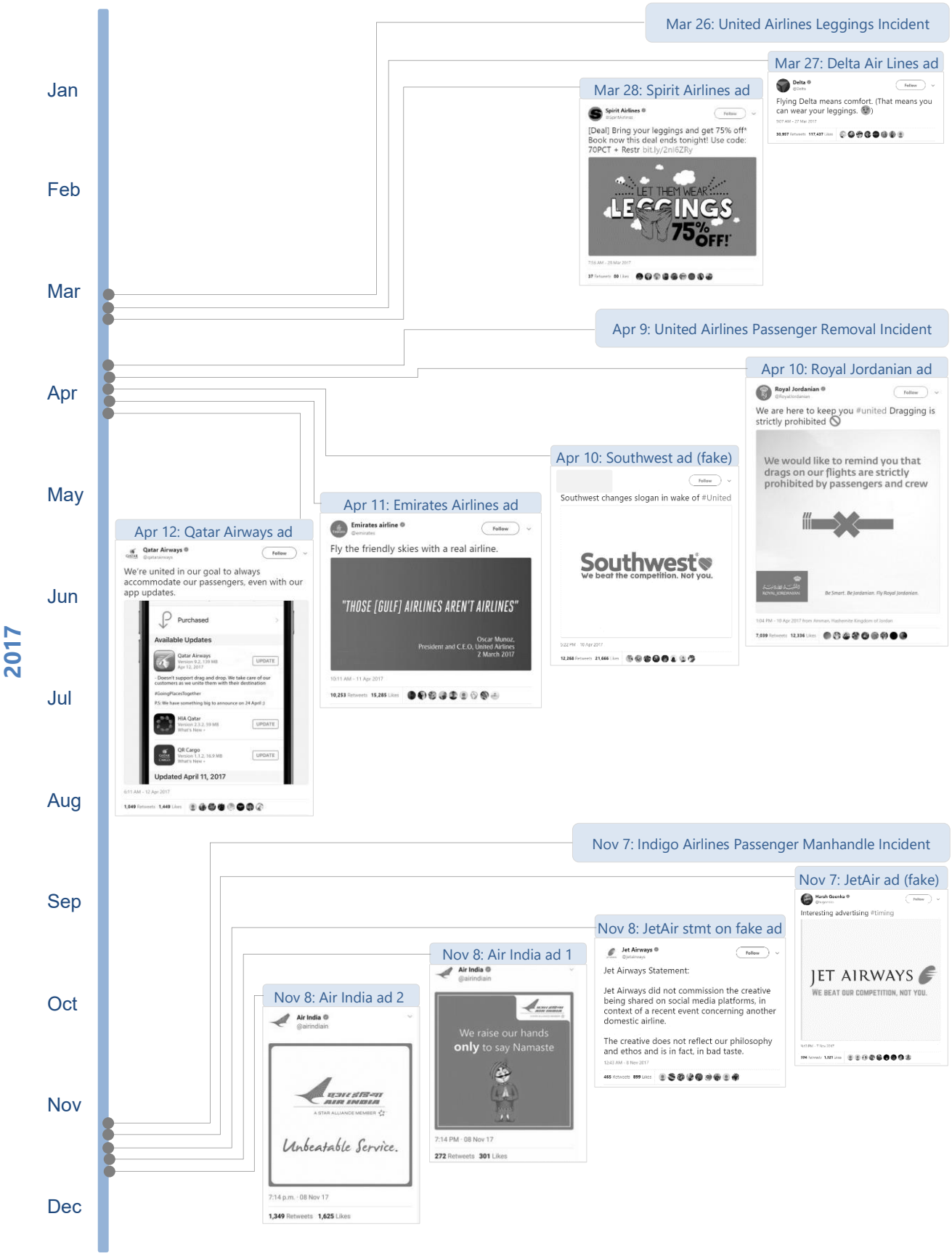


**Figure 2. Controversial Incidents and subsequent ads in the Airline Industry - 2017 Timeline**

## METHODOLOGY

For this study, we extracted customer tweets of thirteen airline brands over different time periods surrounding the three controversial incidents from Twitter using Python. The first step was to import the extracted csv files into SAS. With 151 csv files, it was impossible to import each file as a SAS dataset manually, so SAS macro code was created to import all csv files from a specified directory. Once the files were available in SAS format, three datasets (each specific to an airline incident) were merged and pre-processed using SAS procedures. The pre-processed data was then analyzed using SAS Enterprise Miner.

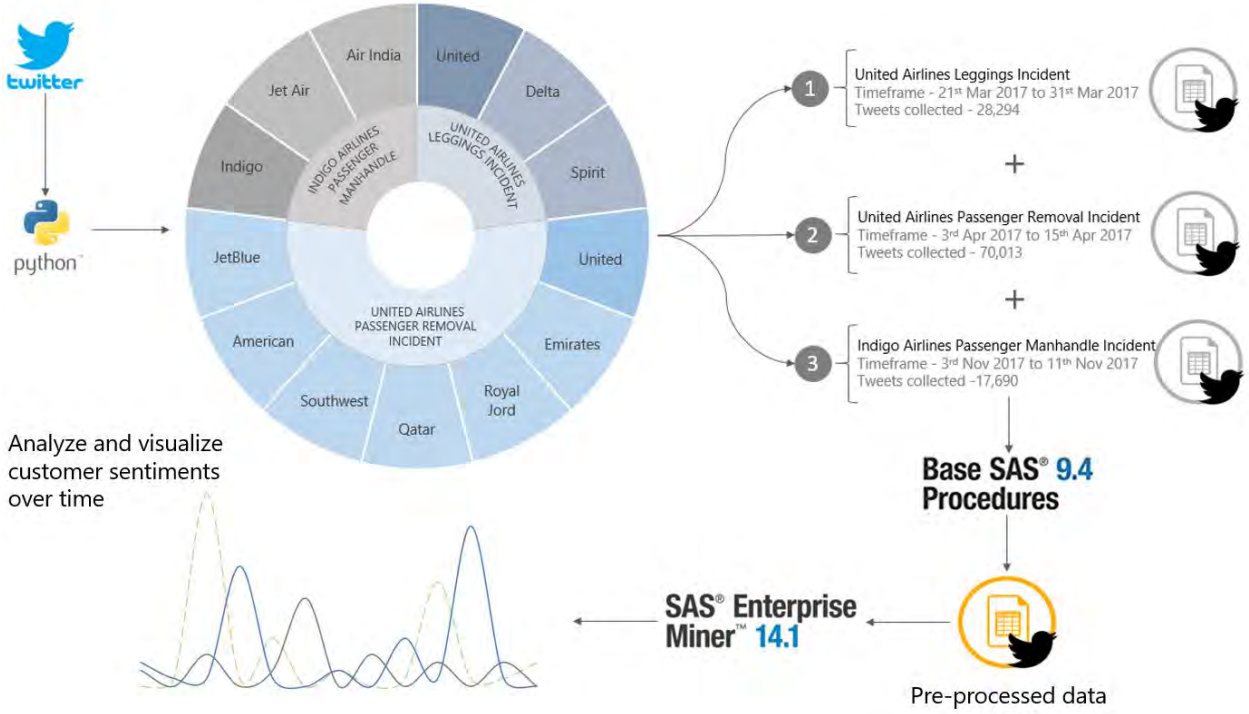


**Figure 3. Framework for Sentiment Analysis**

The metadata of the final SAS dataset imported from csv files is as shown below.

| Variable | Data Type | Data Format | Length | Details |
|---|---|---|---|---|
| ID | String | Char10 | 10 | The integer representation of the unique identifier for the tweet |
| Username | String | Char20 | 20 | Unique username of the tweeter |
| Date | Date | DATE9 | 8 | Date on which the tweet was posted |
| Retweets | Number | BEST12 | 8 | Number of times the tweet has been re-tweeted |
| Favorites | Number | BEST12 | 8 | Number of likes for the tweet |
| Text | String | Char500 | 500 | The text content of the tweet (max.280 characters) |
| Geo | String | Char54 | 54 | The geographical location of the tweet |
| Mentions | String | Char250 | 250 | Word preceded by a hash sign (#) used to identify messages on a specific topic |
| Hashtags | String | Char250 | 250 | Reference to other twitter username preceded by a at sign (@) |
| Permalink | String | Char250 | 250 | URL of the tweet |

**Table 1. Metadata of final SAS dataset used in the case study**

## DATA PRE-PROCESSING USING SAS® PROCEDURES

The first step in working with text data is to pre-process it. Social media data is highly unstructured with typos, bad grammar, usage of slang, the presence of special characters and unwanted content like URLs, etc. Analyzing such data can produce misleading results. In the data pre-processing stage, we removed reoccurring noisy data elements such as airline replies, URLs, special characters and flight numbers.

The customer tweets extracted had airline brand responses along with consumer messages. Such responses can skew the results of sentiment analysis. An example of how airline response can alter the result is shown in Figure 4 where a user tweet is in negative tone and response from the airline is in a positive tone. We removed all airline brand responses and subset the tweet corpus only for user tweets.

**Figure 4. Sample customer tweet with airline response highlighted in red**

From the tweet corpus, we saw that customers share web links and attach pictures to their tweet message. The web links and images appeared as embedded URLs in the tweet corpus. Removing all such URLs was achieved through Perl regular expressions (the PRX functions) in SAS. An example of customer tweet with embedded URL is shown in Figure 5.

**Figure 5. Sample customer tweet with embedded URL highlighted in red**

Tweet corpus also contained special characters and complex symbols. Therefore, for better analysis, it is necessary to have clean data without symbols and characters like @ and #. PRX functions were used to achieve this. A sample customer tweet with special characters is shown in Figure 6.

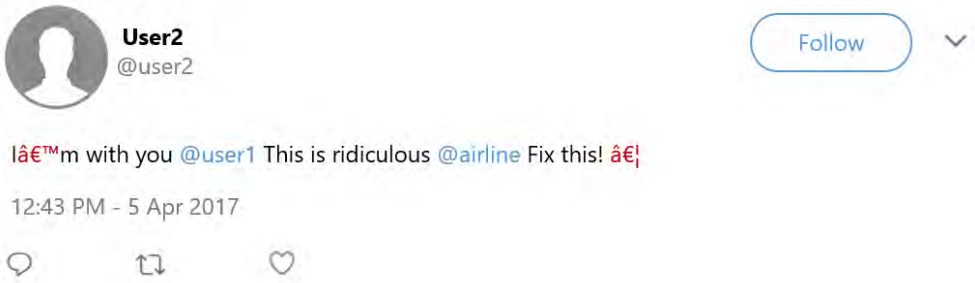


**Figure 6. Sample customer tweet with special characters highlighted in red**

Most of the customer tweets had flight numbers mentioned in the message. Replacing flight number patterns with custom term ‘flight’ was accomplished through PRXCHANGE function. Flight number patterns vary with different airline companies, so tweets were cleaned at airline level dataset and consolidated post cleaning. An example of customer tweet with flight number is shown in Figure 7.

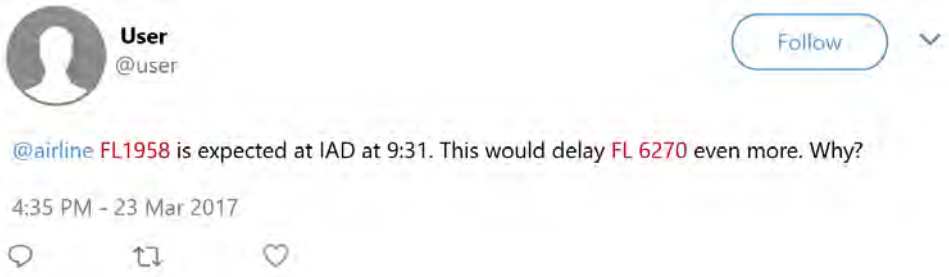


**Figure 7. Sample customer tweet with flight numbers highlighted in red**

**DATA PROCESSING USING SAS® ENTERPRISE MINER**

After cleaning data using SAS procedures, the prepared data was then processed using SAS Enterprise Miner. For this, we followed the text analytic approach suggested by Chakraborty, Pagolu, and Garla (2013). The procedure involved using appropriate NLP techniques, lemmatization, tokenization, concept linking, entity recognition, etc. In addition to that, we also defined custom entities to discover items specific to the airline industry.

Airline customers use airport codes as a short form to refer locations. A sample tweet of user mentioning locations Houston, San Antonio and Denver as IAH, SAT and DEN respectively is shown in Figure 8. All such airport codes should be treated as synonyms. The pattern is three uppercase letters but using PRX functions to replace such instances with a common term might generalize too much and pick up random instances of uppercase words such as ‘AND’, ‘NOT’ etc.

**Figure 8. Sample customer tweet with airport codes highlighted in red**

To solve this, we compiled an exhaustive list of 8,900 IATA airport codes [13] as a SAS dataset as shown in Figure 10 and added it to the terms table of multi-word terms property option in text parsing node. This is a possible workaround for creating custom entities as synonyms without using SAS Enterprise Content Categorization.

| term | parent |
|---|---|
| AAA | location |
| AAB | location |
| AAC | location |

**Figure 10. Airport codes treated as synonyms**

Similar to airport codes, customers also tweeted aircraft codes in their messages. A sample user tweet with aircraft code mentioned is shown in Figure 11. Instances of aircraft codes should also be treated as synonyms, so we compiled a complete list of aircrafts codes for flights every airline company [14] considered in this study owns.

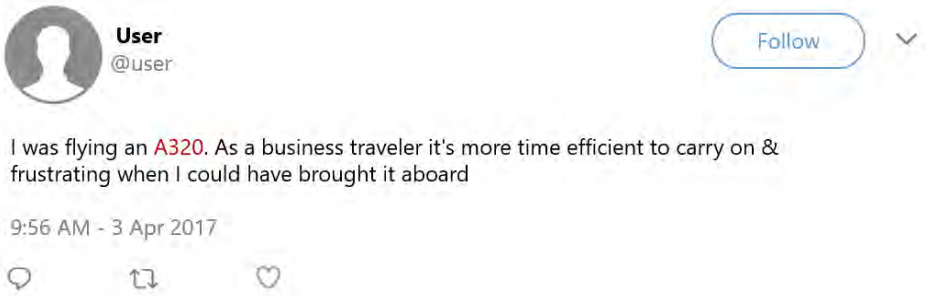


**Figure 11. Sample customer tweet with aircraft code highlighted in red**

Complied list of aircraft codes is then converted into a SAS dataset compatible and used in text parsing node to be treated as synonyms. A sample of the prepared aircraft synonym list is shown in Figure 12.

| term | parent |
|---|---|
| A310 | aircraft |
| A319 | aircraft |
| A320 | aircraft |

**Figure 12. Aircraft codes treated as synonyms**

Twitter being a microblogging platform limits a user to fit only 280 characters per tweet. Hence customers tend to use abbreviations instead of complete words. An example of a customer using abbreviation CS for customer service and abbreviation S/o for shout out is shown in Figure 13.

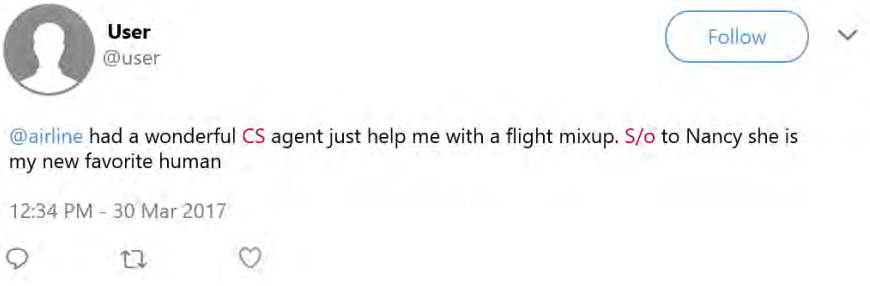


**Figure 13. Sample customer tweet with abbreviations highlighted in red**

A thorough synonyms-list of 150 slang terms and abbreviations used in Twitter was prepared as a SAS dataset and used in the text parsing process. A sample of the prepared abbreviation synonym list is shown in Figure 14.

| term | parent |
|---|---|
| ab | about |
| abt | about |
| b/c | because |

**Figure 14. Custom Synonyms list**

## CONCEPT LINKS

Once the data were cleaned and filtered, concept links were examined to understand how sentiments changed over time during the controversial incidents. Concept links help us view the terms that are highly associated with the word of interest. The selected term (in this case, the airline) from customer comments are surrounded by its strongest correlated terms in the form of a hyperbolic tree graph. Thick lines indicate a strong association between the terms. For each case, we analyzed concept links from one day's worth of customer tweets before and after a controversial incident had occurred. This helped us to comprehend how a controversial incident affects change in moods of the public.

## CASE 1: UNITED AIRLINES LEGGINGS INCIDENT

In the case of United Airlines leggings incident, we considered the airline's tweets from 25th March 2017 and 26th March 2017 for pre vs. post analysis. Figure 15 (left) shows that before the incident had occurred, people complained about customer service, flight delays, and other airline failures. However, Figure 15 (right) shows how customer mood changed overnight. People started to talk about the controversy of a girl being stopped at the gate for wearing leggings. Customers voiced their dissatisfaction with airline's service post-incident which is highlighted by the terms +service +spend and +flight.

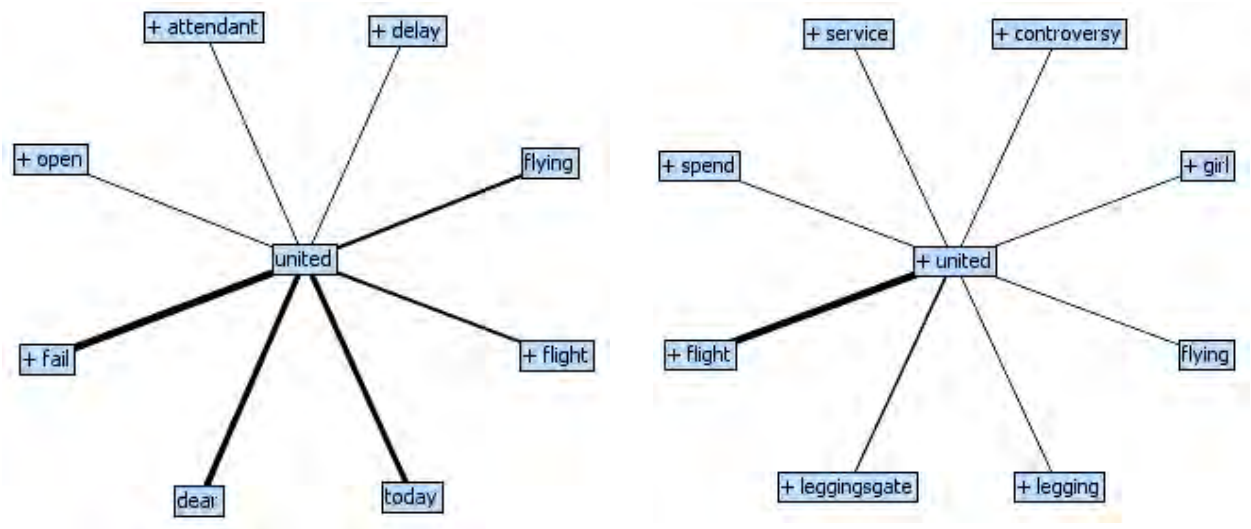


**Figure 15. Concepts links for United Airlines before (left) and after (right) the Leggings Incident**

## CASE 2: UNITED AIRLINES PASSENGER REMOVAL INCIDENT

For United Airlines passenger removal incident, we considered the airline's tweets from 9th April 2017 and 10th April 2017 for pre vs. post analysis. Figure 16 (left) shows how customers were still unhappy with the leggings incident and complained that the airline's service as terrible and perhaps the worst. Clearly, the airline's brand image had suffered quite a damage. Figure 16 (right) shows how the passenger removal incident compounded public's negative sentiments. People let the video talk (embedded in the tweet) and

tweeted briefly on how the airline decided to randomly pick a passenger from an overbooked flight and stopped him from flying back home.

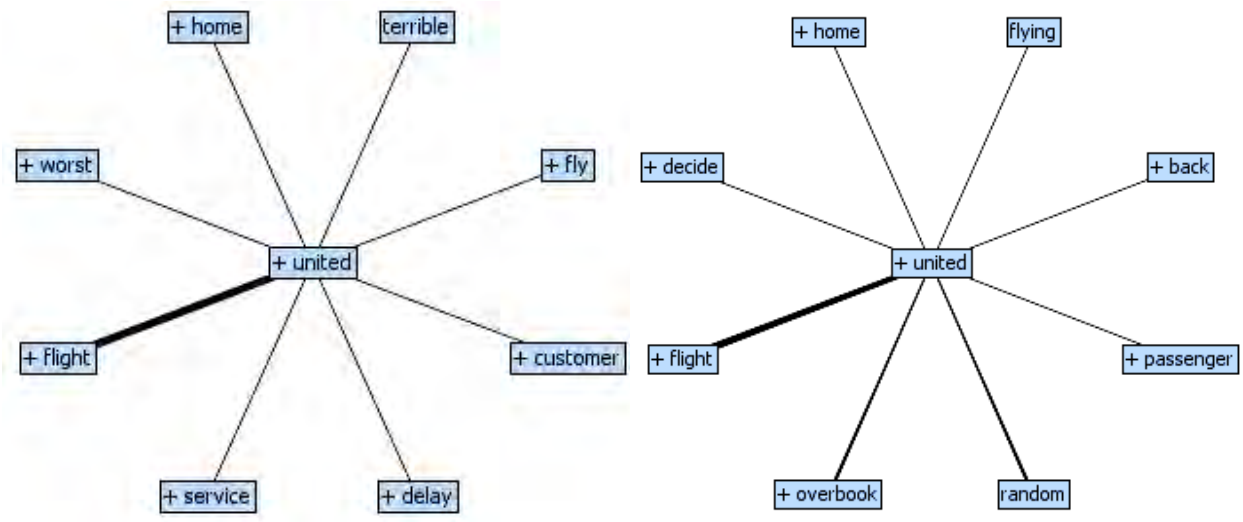


**Figure 16. Concepts links for United Airlines before (left) and after (right) the Passenger Removal Incident**

**CASE 3: INDIGO AIRLINES PASSENGER MANHANDLE INCIDENT**

Although IndiGo Airlines' passenger manhandle incident occurred on 15th October 2017, video of the episode surfaced in social media only on 7th November 2017. For this reason, we considered IndiGo Airlines tweets from 6th November and 7th November for pre vs. post analysis.

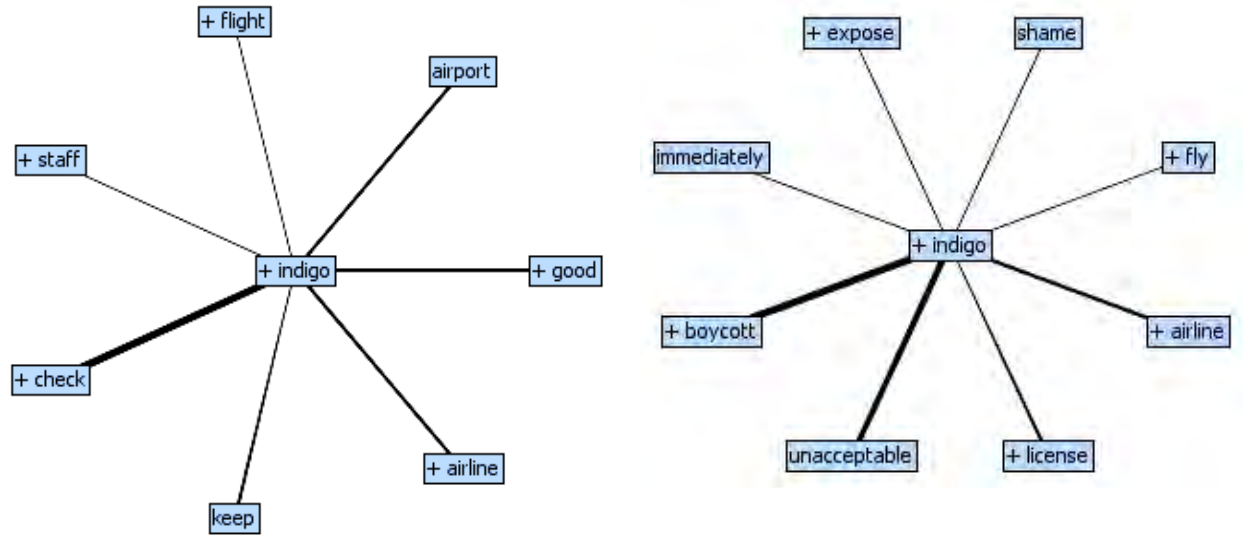


**Figure 17. Concepts links for Indigo Airlines before (left) and after (right) the Passenger Manhandle Incident**

Concept links in Figure 17 (left) shows that before the video had surfaced people felt happy about excellent customer service provided by the airline's flight and airport staff. However, Figure 17 (right) shows how public emotion changed after the release of the video of passenger manhandled by the airline staff. People felt that the airline's real attitude towards customers had been exposed and called the passenger assault incident as unacceptable. Customers considered the episode a shameful act and

called others to boycott the airline. Furthermore, some people emphasized to cancel the airline's license immediately.

## BUILDING A RULE BASED MODEL USING SAS® ENTERPRISE MINER

Concept links helped us understand how controversial incidents can swiftly make a reputed airline brand infamous among customers. To examine how competitors influenced the already unhappy customers with their advertisements, customer sentiment trend was analyzed. This was accomplished by building a rule-based model using the 'Text Rule Builder' node in the SAS Enterprise Miner that automatically generates an ordered set of rules for predicting customer sentiment as either positive or negative.

Rules generated by the Text Rule Builder node are defined for each category (positive/negative). The rules contain conjunction that indicates the presence or absence of one or subset of terms (for example, "term1" AND "term2" AND (NOT "term3")). A particular customer comment will match this rule to be categorized as either positive or negative if and only if it contains at least one occurrence of term1 and term2 and no occurrences of term3.

From concept links, it is possible to note that affected airline brand can skew the prediction of customer comment as positive/negative. So it is crucial to replace airline names and airline handles with custom term **'airline'** before feeding the data (training, validation, and scoring) to the rule-based model. It was a project within itself, and we used a SAS macro [15] that finds airline handles from a list and replaces it with the custom term **'airline'** [16]. To achieve this, we compiled an exhaustive list of 170 airline handles identified from the customer tweets to be used as a lookup table from which each handle is searched and replaced in the tweet corpus. A sample of how actual tweet is fed as a masked tweet to the model is as shown in Figure 18.

| Actual Tweet | Masked Tweet |
|---|---|
| **@united** I support you guys and love your airline | **airline** I support you guys and love your airline |
| Shame on you **@united** | Shame on you **airline** |
| Dear **@SouthwestAir** thank you for going above my expectations once again proving why you're my fave airline | Dear **airline** thank you for going above my expectations once again proving why you're my fave airline |
| **@SouthwestAir** so frustrating 30 minutes on hold and disconnected. Currently holding 35 minutes and looks like my flights are gone | **airline** so frustrating 30 minutes on hold and disconnected. Currently holding 35 minutes and looks like my flights are gone |

**Figure 18. Sample data with Airline handles masked**

To train the model we took a random sample of around 3,000 tweets and two different reviewers read through each of the tweet diligently to code it as positive or negative. After comparison, we considered only those tweets for modeling that were unanimously coded as either positive or negative. Overall, we used 1,005 positive tweets and 1,008 negative tweets as the training dataset for the rule based model. We used a data partition node to split the data 70:30 for training and validation.

The set of rules created by the model can be used for both descriptive and predictive purposes. When scoring new tweets as positive or negative, the model scans thorough the ordered set of rules and chooses the target when the first scanned rule is found in the tweet and if not proceeds to the following rules.

The top ten rules describing positive and negative comments are as shown in the Figures 19 and 20 respectively.

| Rule # | Rule | True Positive/Total | Precision | Recall | Valid True Positive/Total | Valid Precision | Valid Recall |
|---|---|---|---|---|---|---|---|
| 56 | awesome | 40/40 | 100.0% | 5.69% | 8/8 | 100.0% | 2.65% |
| 57 | amazing | 19/19 | 100.0% | 8.25% | 3/3 | 100.0% | 3.64% |
| 58 | shout | 13/13 | 100.0% | 9.96% | 1/1 | 100.0% | 3.97% |
| 59 | love | 65/69 | 97.74% | 18.49% | 20/20 | 100.0% | 10.60% |
| 60 | great | 55/59 | 97.30% | 25.60% | 25/26 | 98.21% | 18.21% |
| 61 | love | 22/23 | 97.54% | 28.17% | 9/10 | 96.92% | 20.86% |
| 62 | choice | 9/9 | 97.64% | 29.45% | 0/0 | 96.92% | 20.86% |
| 63 | glad | 7/7 | 97.72% | 30.44% | 3/3 | 96.97% | 21.19% |
| 64 | birthday | 9/9 | 97.79% | 31.44% | 2/2 | 97.01% | 21.52% |
| 65 | favorite | 8/8 | 97.85% | 32.43% | 6/6 | 97.22% | 23.18% |

**Figure 19. Top 10 positive rules derived by Text Rule Builder**

| Rule # ▲ | Rule | True Positive/Total | Precision | Recall | Valid True Positive/Total | Valid Precision | Valid Recall |
|---|---|---|---|---|---|---|---|
| 1 | cancel | 34/34 | 100.0% | 4.82% | 15/15 | 100.0% | 4.95% |
| 2 | pay | 19/19 | 100.0% | 7.52% | 15/16 | 96.55% | 9.24% |
| 3 | rude | 20/20 | 100.0% | 10.07% | 7/7 | 97.22% | 11.55% |
| 4 | bad & ~rock | 61/63 | 98.51% | 18.72% | 19/21 | 94.55% | 17.16% |
| 5 | shame | 15/15 | 98.65% | 20.71% | 9/9 | 95.24% | 19.80% |
| 6 | terrible | 14/14 | 98.76% | 22.55% | 2/2 | 95.31% | 20.13% |
| 7 | money | 11/11 | 98.82% | 23.83% | 4/5 | 94.03% | 20.79% |
| 8 | horrible | 13/13 | 98.88% | 25.11% | 4/5 | 94.37% | 22.11% |
| 9 | worst | 11/11 | 98.93% | 26.24% | 4/4 | 94.59% | 23.10% |
| 10 | pathetic | 9/9 | 98.97% | 27.38% | 4/4 | 94.81% | 24.09% |

**Figure 20. Top 10 negative rules derived by Text Rule Builder**

The fit statistics of the text rule-based model showed that the validation misclassification rate is 21%. This is as desired and the model used to score the entire dataset. The fit statistics of text the rule-based model is shown in Figure 21.

| Target | Fit Statistics | Statistics Label | Train | Validation |
|---|---|---|---|---|
| tgt | _ASE_ | Average Squared Error | 0.068903 | 0.080925 |
| tgt | _DIV_ | Divisor for ASE | 2816 | 1210 |
| tgt | _MAX_ | Maximum Absolute Error | 0.495383 | 0.497393 |
| tgt | _NOBS_ | Sum of Frequencies | 1408 | 605 |
| tgt | _RASE_ | Root Average Squared Error | 0.262495 | 0.284474 |
| tgt | _SSE_ | Sum of Squared Errors | 194.0319 | 97.91983 |
| tgt | _DISF_ | Frequency of Classified Cases | 1408 | 605 |
| tgt | _MISC_ | Misclassification Rate | 0.184659 | 0.209917 |
| tgt | _WRONG_ | Number of Wrong Classifications | 260 | 127 |

**Figure 21. Fit statistics of the text rule based model**

As Twitter is used as a complaining platform by the airline customers, it would not be appropriate to use the default cut off value of **0.50** as predicted probability for decision making. So considering customer behavior and taking into account the trade-off between sensitivity, specificity, and false positivity values we used the Cutoff node to change the threshold probability to **0.41** to predict the negative tweets.

Once the cutoff was changed we used the score node to score the entire dataset for classifying customer tweets as positive or negative. We then used as SAS code node to export the scored dataset.

## RESULTS

From the scored dataset we studied the affected airline's sentiment pattern over time for each one of the three cases.

### CASE 1 AND 2: UNITED AIRLINE INCIDENTS

The graph below (Figure 22) shows the percentage of negative tweets for United Airlines from 21st March 2017 to 15th April 2017. It is clear from the display that United Airlines initially had negative sentiment around 87%, but from 26th March 2017 to 30th March 2017 the percentage of negative tweets soared to 92%. This is highlighted in the graph with a strong hue of red. Evidently, customers were disappointed with the airline brand after the leggings incident that occurred on 26th March 2017. Percentage of negative tweets then declined after 30th March 2017 and remained around 87% for next few days.

**Figure 22. United Airlines negative sentiment trend**

However, the airline's negative tweets escalated to 93% on 10th April 2017 because of the controversial passenger removal incident that had occurred on 9th April 2017. The airline's negative sentiments stayed at around 93% for next several days.

To investigate how these incidents affected the airline's Twitter following and to examine the brand's tweet pattern during the time of controversies, we gathered supporting evidence from online resources [17].

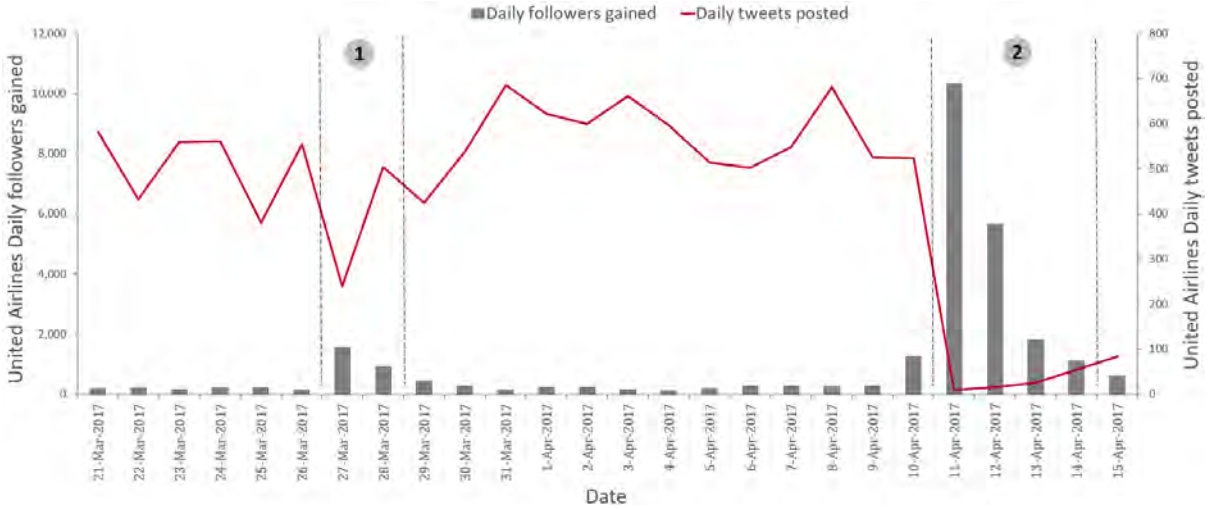


**Figure 23. United Airlines Daily followers gain and Daily tweets posted trend**

The dual axis graph as shown in Figure 23 with daily followers gained by the brand on primary axis and tweets posted by the brand on secondary axis over time tells an interesting story. Contrary to common opinion that a brand loses followers during negative incidents, United Airlines, as a matter of fact, gained an additional 1,600 followers on 27th March 2017 and 10,340 followers on 11th April 2017 following the leggings incident and the passenger removal incident. This is about 9 and 61 times greater than its average gain of 168 followers per day. Also from the graph, we clearly note that the brand continued to add new followers post-incident for next few days and this sudden follower gain subsided only after some time.

Both these incidents truly affected the airline's reputation and the gain in followers was a direct result of negative publicity. People started to follow the brand out of curiosity to know the airline's response to such controversies. Ironically the airline brand decided to do exactly the opposite. Realizing the followers gained are due to the negative publicity the brand remained hesitant to tweet during controversial incidents. United Airlines on average posts about 271 tweets per day and following the passenger removal incident the airline brand posted just 9 tweets on 11th April 2017 and continued to post limited tweets until the followers gain declined.

**CASE 3: INDIGO AIRLINES PASSENGER MANHANDLE INCIDENT**

IndiGo Airlines controversial incident also shows similar results. Immediately after the unfortunate incident the airline's percentage of negative sentiment increased and continued to remain highly negative for the following days.

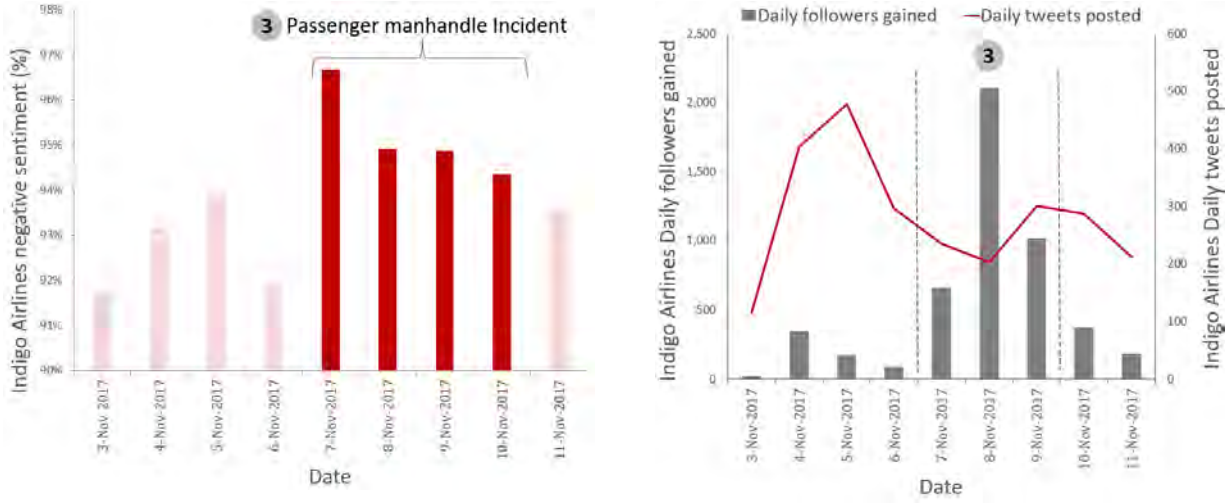


**Figure 24. IndiGo Airlines negative sentiment trend (left), Daily followers gain and Daily tweets posted trend (right)**

IndiGo Airlines on an average gains 94 new followers each day. However, the airline added 2,110 followers to its account on 8th November 2017 following the passenger manhandle incident. Similar to United Airlines, IndiGo reduced its tweet posts on Twitter for few days after the controversy.

1. From the above cases we see that after controversial incidents, an airline's negative sentiment immediately soars and continuous to remain highly negative for next few days.
2. We see a strong inverse relationship behavior between the followers gained and tweets posted for an airline brand.

**THE EFFECTS OF COMPARATIVE ADVERTISING**

This section discusses how comparative advertising from the competitors affects the already tarnished brand, induces a more negative attitude towards the mocked airline and indirectly builds a substantial brand equity and loyalty for the competitors through comparative advertising.

## CASE 1: UNITED AIRLINES LEGGINGS INCIDENT

To study the effects of comparative adverting we graph the negative sentiments of affected airline and a competitor as a comparison chart during the same date range. Figure 25 shows negative sentiment trends for United Airlines in comparison with Delta Air Lines (left-top) and Spirit Airlines (right-top) who released creative advertisements on Twitter mocking United Airlines. From the graph, we clearly see that for both Delta and Spirit there is a drop in negative sentiments subsequent to posting advertisements that parodied United on the leggings incident.

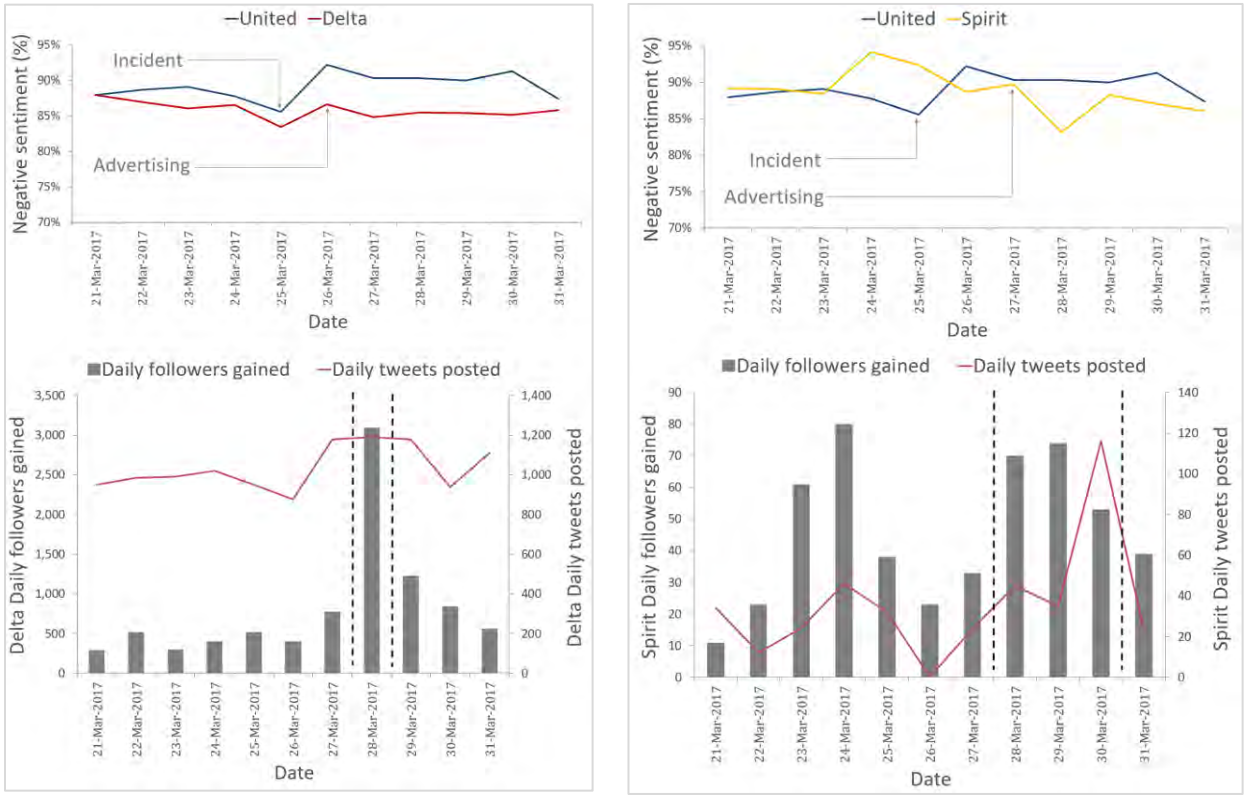


**Figure 25. United vs. Delta Comparison (left) and United vs. Spirit Comparison (right)**

The graph (left-bottom) tells us that Delta Air Lines gained 3,100 new followers on 28th March 2017 after sharing a creative poster on Twitter on 27th March 2017. This is 8 times more than its average daily follower growth of 330. The Twitter advertisement which said "Flying Delta means comfort. (That means you can wear your leggings☺)" burlesqued United Airlines and at the same time emphasized how it treats customers better. The tweet received 117,437 likes and was shared 30,957 times on Twitter.

Likewise, Spirit Airlines too saw a drop in negative sentiments from 90% to 83% (right-top) after releasing its advertisement on Twitter that said customers would receive 70% discount on their airfare for wearing leggings when boarding Spirit Airlines flights. The airlines also saw an increase in followers (right-bottom) days after the advertising but not as well as Delta. This is understandable given the fact that Spirit is a low-cost domestic airline with a small market share on Twitter and in the airline industry.

One other interesting finding from the graph (right-bottom) is that Spirit Airlines posted 116 tweets on 30th March 2017, two days after sharing their comparative ad. This is almost twice its daily average posts of 60 tweets. Analyzing tweets from 30th March 2017, we see that Spirit Airlines used this popularity gain to increase its brand equity by posting offers and loyalty by addressing customer grievances.

## CASE 2: UNITED AIRLINES PASSENGER REMOVAL INCIDENT

The comparative advertisings from Emirates Airlines, Qatar Airways and fabricated tweet showing Southwest Airlines parodying United Airlines on the passenger removal incident had a longer positive effect for the mentioned brands. From Figure 26 (left-top) we see that Emirates Airlines negative sentiment dropped and stayed low even few days after sharing their poster on Twitter. Emirates comparative ad focused on why their brand is considered better than United and received 15,285 likes with 10,253 retweets.

Southwest Airlines did not create any comparative advertisings targeting United Airlines. However, a fabricated ad mocking United with Southwest's brand name was shared widely on Twitter and received 21,666 likes, retweeted 12,268 times ultimately creating a positive impact for the brand. The airline's negative sentiments dropped from 81% to 76% and continued to stay around 77% for next few days.

In both cases, we see an increase in negative sentiment for the affected airline and a decrease in negative sentiment for the competitor airlines.

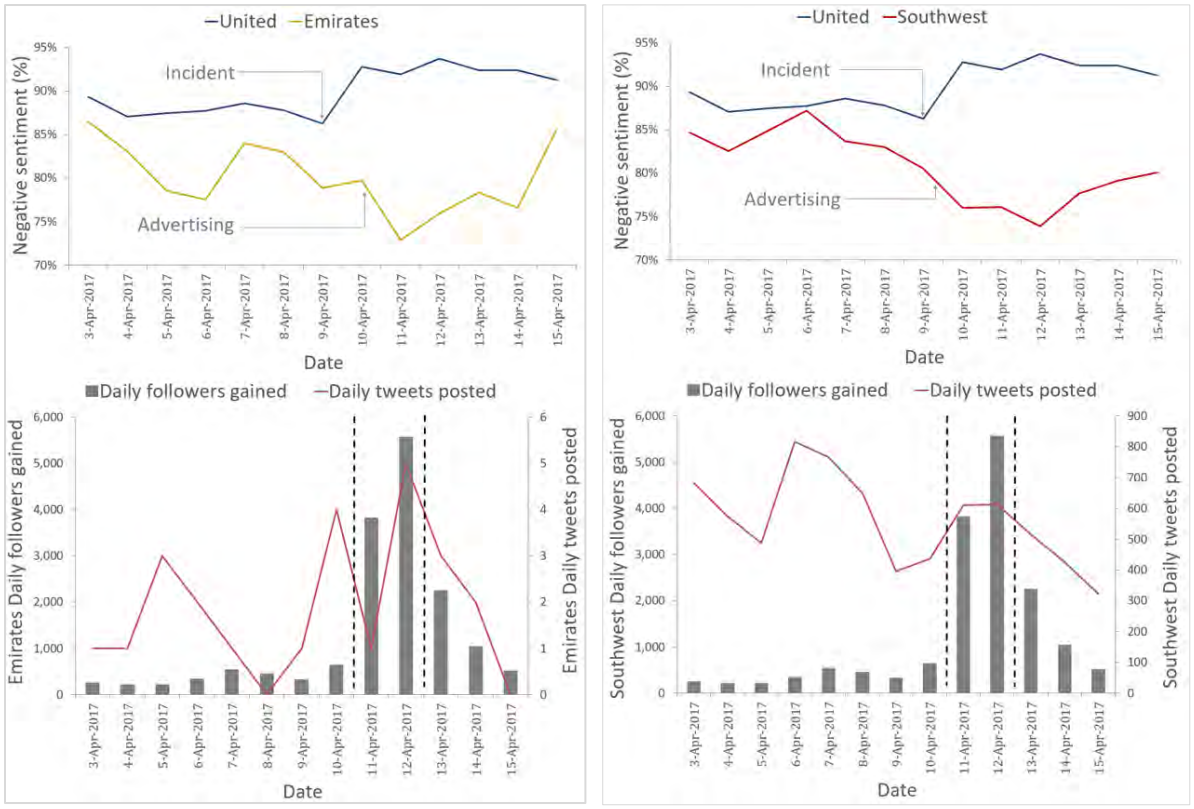


**Figure 26. United vs. Emirates Comparison (left) and United vs. Southwest Comparison (right)**

Both these airlines also saw a very steep increase in the follower gain after advertisements were shared on Twitter. Emirates follower gain increased about seven times than its usual growth rate of 477 followers and Southwest received a maximum follower gain of 5,570 on 12th April 2017 which was 16 times greater than its follower gain of 332 on 9th April 2017.

Similar trend was seen for Qatar Airways as well. However, the airline did not receive a significant number of likes and retweets alike Emirates and Southwest nor gained many followers in spite of being active on social media platforms and having a considerable market share. The possible reason could be because of sharing its advertisement a little later than occurrence of the incident (about three days after the incident).

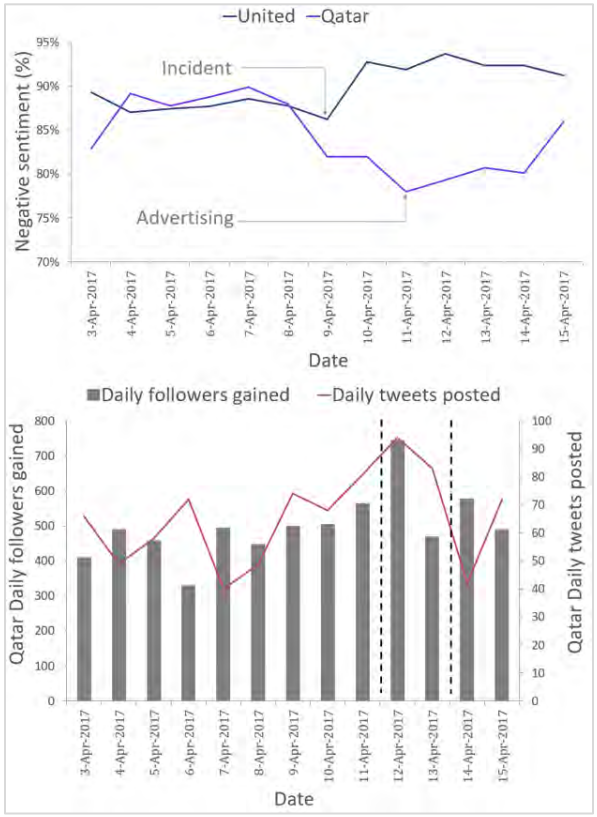


**Figure 27. United vs. Qatar Airways Comparison**

From the graph, we see that Qatar Airways posted 90 tweets on 12th April 2017 which is five times greater than its daily average tweets of 17. Most of these tweets were either offers or the airline addressing customer grievances.

**CASE 3: INDIGO AIRLINES PASSENGER MANHANDLE INCIDENT**

In the case of IndiGo Airlines passenger manhandle incident, Jet Airways saw a sharp decline in negative sentiments. Though Jet Airways did not create an advertisement, a fabricated tweet with the airline name was shared on Twitter, and the airline reaped the benefits out of the unexpected marketing campaign.

A few hours later Jet Airways officially tweeted saying the airlines did not create any advertisement parodying IndiGo and also mentioned that mocking a brand at the time of crisis was not part of its philosophy and ethos. However, the fabricated tweet continued to be shared on Twitter and Jet Airways gained 812 followers on 8th November 2017 which is about eight times greater than its usual daily average follower gain of 98.

On the other hand, Air India shared two tweets successively mocking IndiGo Airlines manhandle incident. The first tweet claimed Air India's provides an 'unbeatable service' and the second tweet said 'we raise our hands only to say namaste' which assured people that the airline will treat its customers kindly. The tweet helped Air India gain a follower count of 871 and 664 on 8th and 9th November 2017 which was eleven and nine times greater than its daily average follower gain of 76.

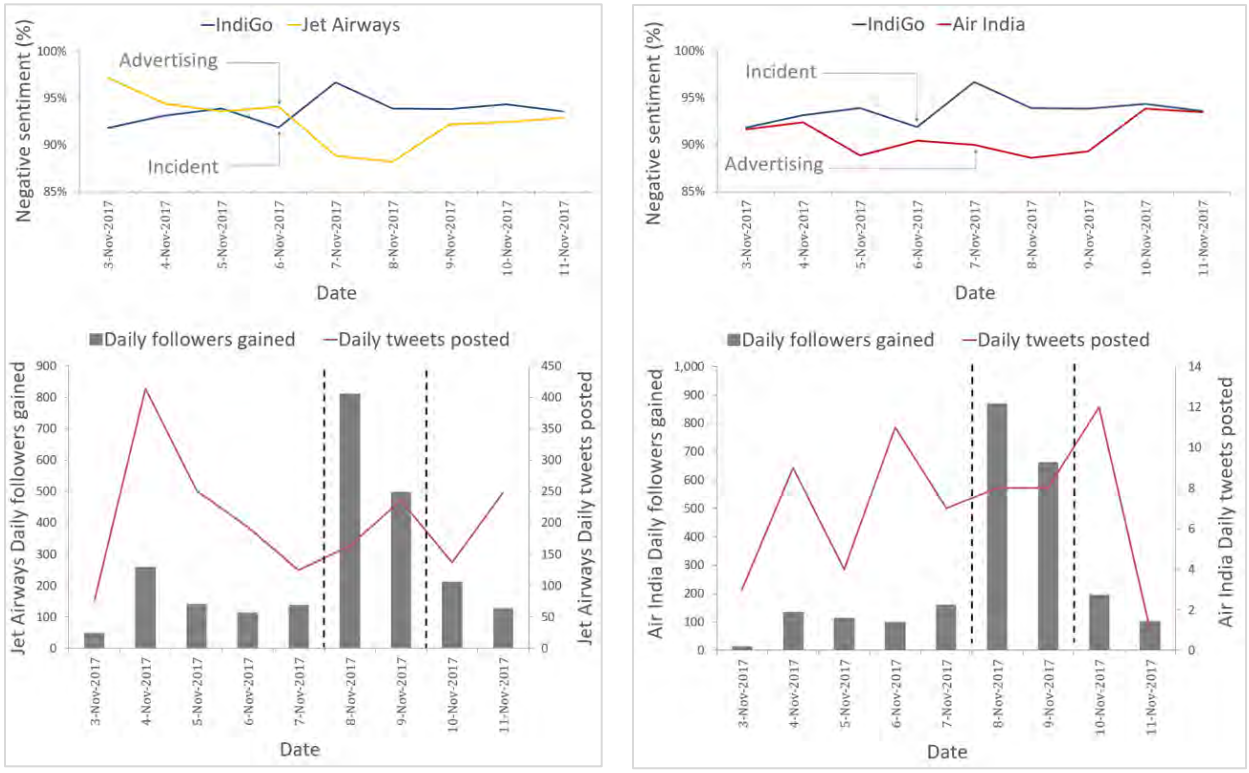


**Figure 28. IndiGo vs. Jet Airways Comparison (left) and IndiGo vs. Air India Comparison (right)**

## STUDY TO ANALYZE THE IMPACT OF COMPARATIVE ADVERTISING

The above section discussed how comparative advertising in three different cases helped each one of the competitor airlines gain a competitive advantage over the mocked brand and boost their brand equity which ultimately resulted in a decline in negative sentiments. In order to further prove that decrease in negative sentiments is a direct result of comparative advertising, there is a need to study other airlines behavior during the same time period that did not share any comparative tweets targeting the affected brand.

For this study, we consider the case of United Airlines passenger removal incident and choose two airlines that 1) have an almost equal market share as other competitors, 2) active in social media platforms and 3) did not share any comparative advertising after the controversial incident. American Airlines and JetBlue Airlines falls into this category and are selected for this comparative study. We follow the same methodology as discussed in the earlier sections of the paper to prepare both these airlines' data and predict sentiments for the same date range.

Figure 29 shows a multi-line graph with negative sentiments trend over time. The airlines examined are United Airlines (brand involved in the controversy), Emirates Airlines, Southwest Airlines, Qatar Airways (brand with comparative advertisements that targeted United Airlines), American Airlines and JetBlue Airlines (brand that did not share any competitive advertisement on United Airlines during the controversy).

The comparison involves multiple trend lines in a single graph, so for easy visualization, we have used smoothed curves instead of straight lines (not to be confused as polynomial curves). Airlines that shared comparative advertising are color coded in the hues of red and airlines that did not share any advertising are color coded in the hues of blue. The vertical line on 9th April 2017 indicates the day of the controversial incident.

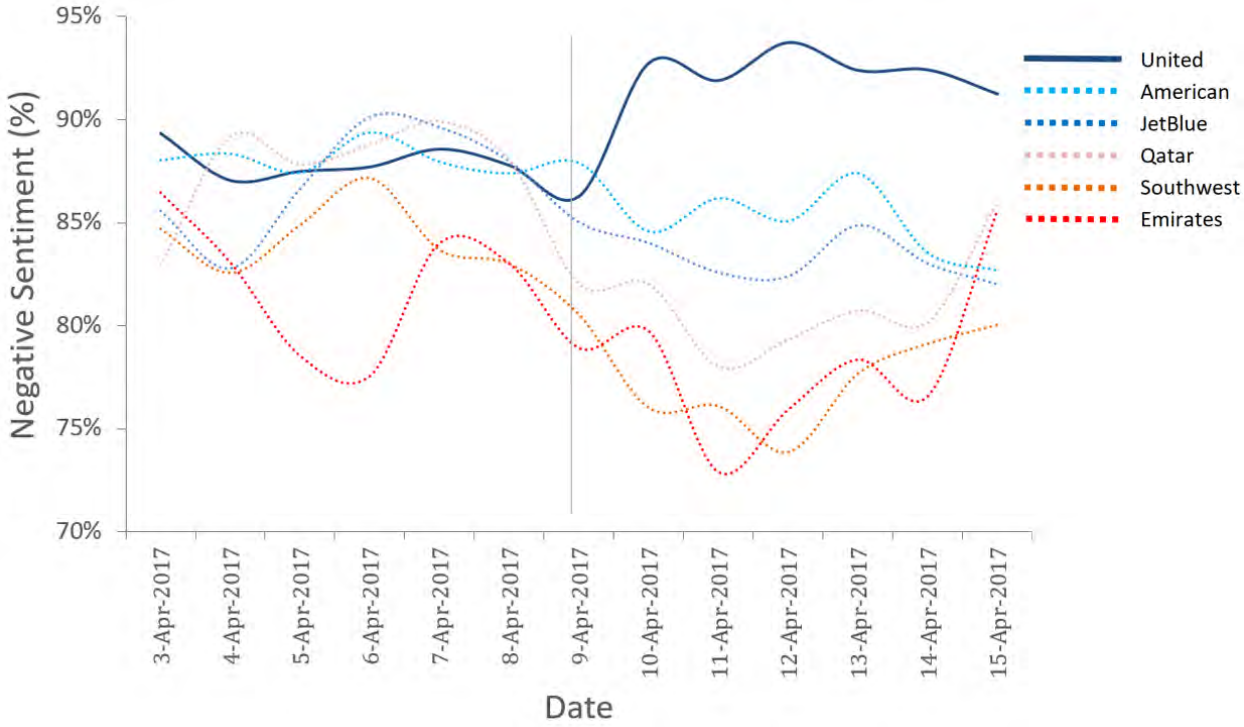


**Figure 29. Effect of Comparative Advertising on passenger removal incident**

From the above graph, we see that there is forking out of negative sentiments between the affected airline and rest of the airlines post controversial incident. After 9th April 2017 negative sentiments of United Airlines increases sharply whereas for all other airlines negative emotions take a dip. The graph also indicates deviance in negative sentiment drop between the airlines color-coded in shades blue vs. airlines color-coded in shades of red. Though sentiments of airlines from both groups, advertising and non-advertising, take a dip, there is a definite difference in slope of the sentiments - a steep downward dip for the advertising airlines and a gradual descent for the non-advertising airlines. The extra downward slope for the advertising airlines is a direct result of the comparative marketing. However, to prove that the extra fanning out for advertising airlines is because of comparative advertising it is vital to examine the reasons behind it. So we decided to analyze the customer tweets in depth.

## COMPARISON OF ADVERTISING VS NON ADVERTISING AIRLINES

To understand what causes the extra drop in negative sentiments for the advertising airlines over non-advertising airlines, we utilized the text topic node of SAS Enterprise Miner. Text Topics discover themes and assign each customer tweet to zero or more of the themes. This is different from Text Clustering which assigns each comment to only one of the themes. So Text Topics ensures customer tweets go into multiple themes, unlike Text Clustering that forces tweets to pick the most appropriate theme. As Twitter is a microblogging platform where people talk about multiple concepts in a single tweet, it is preferred to use Text Topics over Text Clustering.

In this study, we analyze how sentiment change over a period for both advertising and non-advertising airlines. So we create two datasets A and B for advertising and non-advertising airlines respectively. Both these datasets contain an equal number of tweets for three different time frames - 1) before the passenger removal incident occurred, 2) after the occurrence of passenger removal incident but before the airline released comparative advertisement and 3) after the release of comparative advertising. Also as there are multiple airlines within each of the category and each airline has a different number of tweets, we random sample an equal number of tweets for every airline and for every timeframe so that the total tweets in both datasets match. This removes any bias from the analysis. The framework is as shown in Figure 30.

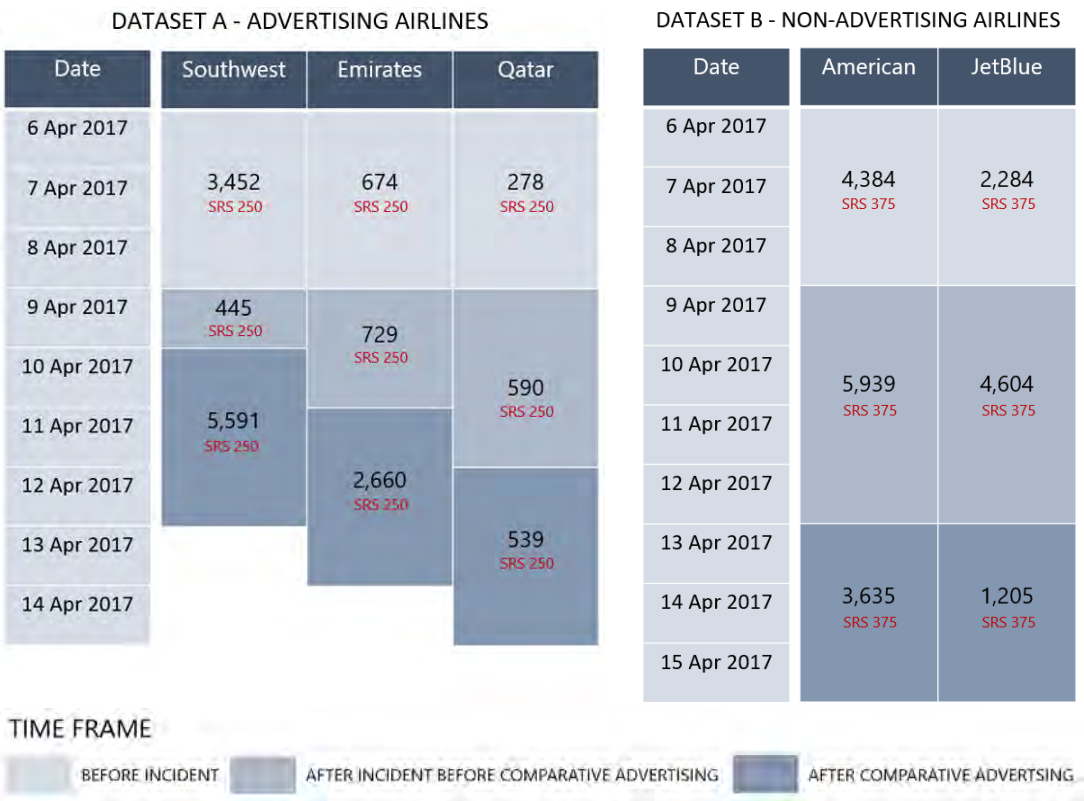


**Figure 30. Text Topics - Framework for data preparation**

Once the datasets are prepared, we use custom topics option of the Text Topic node and use the terms shown in the table below. The terms used in the custom topics were decided after a clear understanding of terms generated by default Text Topic node for each of the participating airline.

| TOPIC | TERMS |
|---|---|
| Flight Delays | cancel, delay, hour, always, time, wait, hope, miss, gate |
| Brand Love | love, happy, best, world, class, business, excellent |
| Positive Review | help, great, drink, crew, shout, good, back, staff, experience |
| Negative Review | bad, worst, service, problem |
| Passenger Removal Incident | overbook, removal, drag, beat, random |

**Table 2. Table depicting the categorization of terms into five topics**

When we examine the distribution of tweets in five different topics for each category – advertising airlines and non-advertising airlines, we can clearly see how the sentiment and opinions change over the three different time frames.

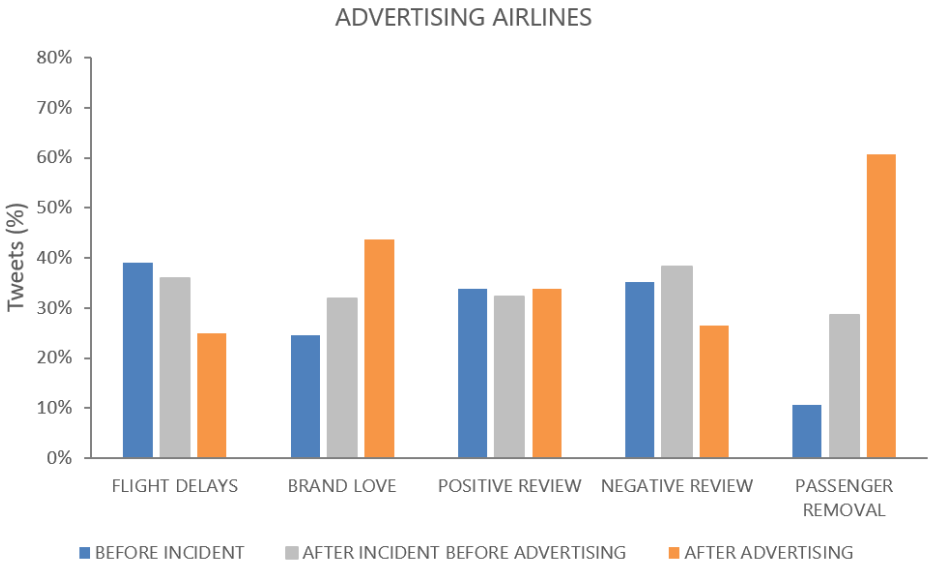


**Figure 31. Percentage of tweets by topic using clustering for advertising airlines**

Figure 31 shows the customer sentiments trend for the advertising airlines. Before the incident occurred, people were talking about flight delays. After the comparative advertising was released on Twitter people regarded the airline as more desirable rather than the mocked airline. This is evident from the increase in brand love over the period. Though positive reviews on the advertisement remained almost same, the negative reviews considerably decreased after promotion. Also, marketing created a negative attitude for the people towards the mocked brand as they spoke more about passenger removal incident after such advertisement than before.

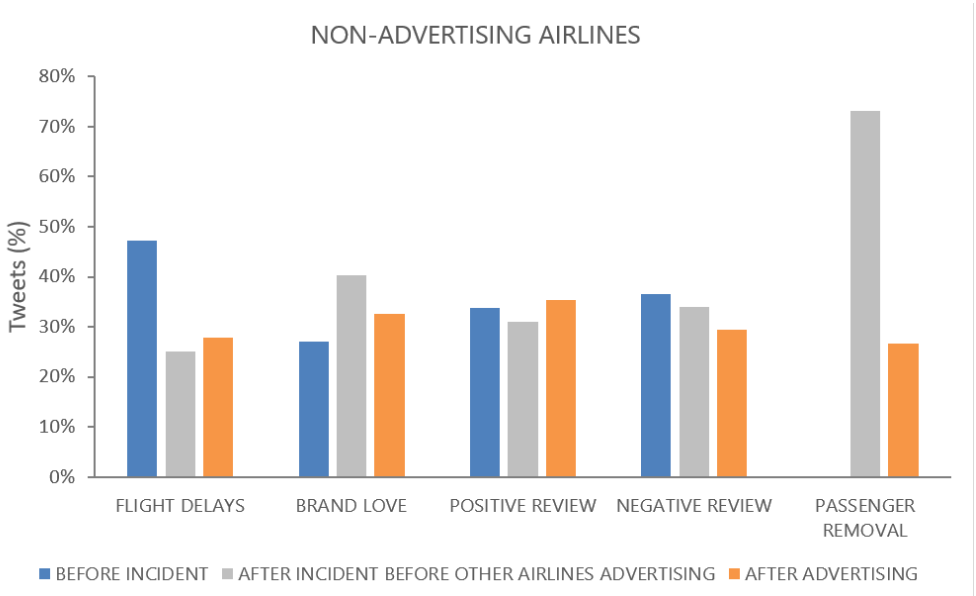


**Figure 32. Percentage of tweets by topic using clustering for non-advertising airlines**

Figure 32 focuses on non-advertising airlines. Tweets on flight delays decreased during the controversial incidents but slowly picked up when other airlines shared a comparative advertisement. People talked

about their brand love for non-advertising airlines prior burlesque advertisings, and this decreased after other airlines' marketing. Positive reviews for the non-advertising airlines almost remained the same (similar to advertising airlines) nevertheless negative reviews decrease was not as significant as compared to advertising airlines. Also a number of people tweeting about passenger removal incident reduced after other airline's advertisements.

## CONCLUSION

Comparative advertising is essential in the airline industry dominated by few market leaders. To make a point of differentiation new entrants, low-cost airlines and rivals from other markets adopt this advertising technique to captivate customer attention and to strengthen their brand equity. Good advertising is about competing smart and smart competitiveness requires choosing the right place and the right time. Prominent customer engagement platform such as Twitter proves to be the perfect stage for such advertisings, and there is no better time than moments surrounding controversial incidents.

This paper presents how comparative advertising is used as a competitive marketing tool in the airline industry to target the market leaders. Concept links helped us understand how a brand perception of the airline involved in controversy can change quickly. Text mining and sentiment analysis of customer tweets helped us realize the effects of comparative advertisings on lowering the brand value of the large airline carriers. Finally, Text Topics helped us understand how comparative advertisings assure customers that the advertiser's brand is different from other airlines and influence customers in making decisions.

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