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Improving Messaging to Airport Community Residents: An Application of Sentiment Analysis to Community Engagement

ABSTRACT

Natural Language Processing has made significant progress over the last decades with the development of open-source software and dedicated libraries. Sentiment analysis has become a best practice in both private and public industries. While airports have utilized sentiment analysis to assess their image and level of service, it has not been extensively used as a risk-mitigating tool to be proactive when airport operators engage community residents. This analysis shows how sentiment analysis can be used to anticipate residents' attitudes based on changes in key operational factors.

INTRODUCTION

Passenger traffic in many parts of the world is slated to increase barring any economic downturn or transmittable diseases such as the severe acute respiratory syndrome (SARS) and coronavirus, which may scare travelers away. In its June 2, 2019 press release, the International Air Transport Associated (IATA) stated that "total passenger demand, measured in revenue passenger kilometers, [was] expected to grow by 5.0% [in 2019] (down from 7.4% in 2018)."[1] With increasing passengers and airport operations, airports are often grappling with capacity management issues in the face of strong opposition from surrounding airport communities. Building new runways takes time because of environmental regulations and possible legal actions against construction.

Airport operators and planners frequently struggle to balance all parties' interests in their development plans. Airports are more than places where passengers come and go: They have become economic engines that provide jobs to surrounding communities and pump considerable money and resources into the local economy. While airports generate social benefits, others may argue they also generate social costs that may not always be easily measurable. In fact, it is difficult to survey communities on a regular schedule and define a representative sample of residents to monitor their sentiment on a regular and timely basis.

Noise usually comes to people's mind as the most important negative externality or social cost derived from airport activities. However, there are many other external costs residents and passengers have to deal with: traffic congestion, inefficient intermodal connections, as well as terminal and parking facility overcrowding. All these externalities are difficult to assess and it is important for airport operators, planners, regulators, and local governments to understand the impact of airport projects on communities. Surveys and interviews may provide an indication of residents' preferences. However, the conclusions may be biased by factors such as sample stratification, low response rate, reliability of respondents' opinions, socio-economic status, hidden agendas, among other factors. In an environment where information can change very rapidly, it is important to exploit data sources that better translate in-the-moment preferences, sentiments, and opinions. Therefore, sentiment analysis has gained so much attention lately.

Natural Language Process (NLP) and, more particularly sentiment analysis, has made significant progress over the last ten years. Open-source software such as Python and R have made it possible for a greater number of analysts to take advantage of a growing number of specialized libraries. The use of sentiment analysis in marketing as well as business intelligence is a best practice that has, nevertheless, not fully permeated the aviation industry. Understanding the sentiment of airport communities before engaging them or committing resources to projects may provide several benefits to airport operators and planners:

- It helps avoid costly overruns due to delays and legal actions from communities that may oppose them.
- It provides some understanding of stakeholders' attitudes and makes it possible to target messaging appropriately.
- It is important to capture people's sentiments before they become opinions, which is more difficult to change.

At this point, we need to define some key concepts. *Sentiment* represents an intermediate state between *feeling* as a vague and sometimes irrational emotional state and *opinion* as a view, belief, position, or judgment toward an issue. There are three methods to compute sentiment (S) based on positive words (P), negative words (N), and overall counts (C):

- Absolute proportional difference with bounds [0,1]: $S = (P - N) / (P + N + C)$
- Relative proportional difference with bounds [-1,1]: $S = (P - N) / (P + N)$
- Logit scale with bounds $[-\infty, +\infty]$: $S = \log(P + 0.5) - \log(N + 0.5)$.[2]

Since sentiment represents a view or attitude that is likely to change—sometimes very quickly—it needs to be monitored frequently so airport operators may be pro-active instead of reactive in their response to communities' concerns.

Sentiment analysis can deliver next-to-real-time communities' views on a subject that may minimize risks associated with specific actions such as runway construction or airport expansion projects. Sentiment analysis is all the more significant as it can prepare airport management to face three potential residents' strategies—based on Hirschman's[3] framework:

- Residents can exercise 'voice,' that is, express their discontent and opposition.
- They can remain 'loyal' to the airport's goals and objectives, that is, continue to support expansion projects.
- They may 'exit,' that is, not participate and deprive airport operators of valuable feedback that may minimize risk-taking. Airport operators do not want to be deprived of the voice of their surrounding communities. In fact, they need to listen to communities' 'voice' and measure the degree of emotion in the overall key topics that animate them.

Finally, sentiment analysis can represent a valuable predictive analytical tool to anticipate potential shifts in communities' views and beliefs given changes in some key variables. It can serve as a risk-mitigation tool to explore a community sentiment toward a project and anticipate sentiments. The purpose of this article is to evaluate whether some selected operational factors are likely to influence variations in sentiments based on the case of an unidentified airport in the U.S. East Coast. Airport operators may be caught by surprise if they do not have the availability to analyze digital media and detect shifts in sentiments.

LITERATURE REVIEW

In the aviation industry, sentiment analysis has been mainly used to measure customer satisfaction. Airlines and airports make extensive use of sentiment analysis to rate services and customers' perceptions of their products. Gitto and Mancuso[4] used blog data to measure the level of customer satisfaction with food and drinks as well as shop services at five major European airports. The authors determined that measuring airport performance through purely operational approaches was not enough any longer. They pointed out that a growing literature on airport performance measurement focused on models to assess passengers' needs and their perception of the airport service quality. Perceptions are difficult to measure and traditional survey methodologies may not provide a timely and accurate picture of communities' perceptions compared with sentiment analysis, which takes advantage of digital media analysis.

Dhini and Kusumaningrum[5] analyzed customer reviews of services and facilities of Soekarno-Hatta Airport in Indonesia using the text mining approach of sentimental analysis. The authors used Support Vector Machine (SVM) and Naïve Bayes (NB) classification algorithms to identify positive or negative sentiments contained in review sentences. While the SVM algorithm makes it possible to identify classes of individuals performed better than NB, the outcomes of their analysis enabled them to evaluate the quality of airport services and facilities as well as to identify the key areas to address desired level of customer satisfaction

Martin-Domingo et al.[6] analyzed social media to identify areas of service quality improvement at London Heathrow. They supported the argument that sentiment analysis provided easier access to passengers than traditional survey methods did. The authors mined the airport's Twitter account dataset to identify key attributes in airport service quality. Ground transportation and wait times represented the two main issues of interest. The latest techniques in text mining related to the bag-of-words or n-gram algorithms allow analysts to associate words into topics as actionable areas for airport management decision makers. Presumably, the occurrence of a word or group of words can be predicted based on probability distributions.

Some social media such as Twitter are widely used to monitor and manage crises because they provide timely expression of sentiments. Hoste et al.[7] maintained that tweets offered valuable real-time information for decision-making illustrated by the case of the Germanwings Flight 9525 crash. They built a corpus (text to be analyzed) and they were able to classify emotions to help manage the crisis.

Twitter also provides a way of predicting and analyzing U.S. air traffic delays using publicly available data. Monmousseau et al.[8] leveraged a real-time publicly available passenger-centered data source. The same strategy could be used to predict sudden changes in communities' sentiments and make predictions before and after community engagements, for instance.

This article is original because it will illustrate how sentiment analysis can help airport operators predict changes in a community's mood based on some key variables. Sentiment analysis is a method to address perceptions and attitudes, which determine whether residents will use 'exit', 'voice', or 'loyalty'. There are two risks associated with ignoring or paying insufficient attention to residents' sentiments. If airport operators do not take the time to analyze communities' views and attitude, then they may not be able to prioritize resources to solve the right problem that concerns airport communities. Moreover, if airport operators do not analyze key topics and issues that communities' leaders convey to airport operators, they may not be able to communicate effectively to airport community residents. Sentiment analysis is important tool to identify influencers: they represent the key stakeholders who lead the conversation among groups of residents, help build coalitions, and have a significant impact on the political agenda through mobilization.

METHODOLOGY

Text mining and analysis make it possible to determine two key concepts in sentiment analysis:

- *Polarity* refers to sentiment orientation, which can be positive, neutral, or negative.
- *Subjectivity* determines whether the content of a *corpus* or text is more emotion- rather than fact-driven. This variable is not included in the model described next.

Data Sources and Text Preprocessing

This study illustrates how airport operators can use sentiment analysis to forecast sentiment polarity as a function of some selected dependent variables. The Aviation System Performance Metrics (ASPM) data warehouse represented the source of information for operations records[9]. ASPM contains data on operations and delays at the 77 largest U.S. airports. The analysis focused on monthly data from January 2016 to August 2018. The sample included 62,776 words.

Polarity measured sentiment based on the following sources: ~~(1)~~ 18 percent of the sampled data originated from social media (tweets in Twitter and posts in Facebook), ~~(2)~~ 61 percent from digital print articles (local newspapers), ~~(3)~~ one percent from blogs of politicians and community leaders, and (~~4)~~ 20 percent from local radio and television coverage of community residents' sentiment and opinion about airport activities. The overall polarity score was computed based on all digital media data collected for a specific month and served as the dependent variable. Although emotions can flare up at any time in response to a press article or public official actions, a month provides a reasonable period that can be match with operational factors mentioned earlier. All information included in the sample was publicly available and none was proprietary.

Sentiment analysis depends on text preprocessing, which includes four important steps:

- *Tokenization* transforms words into tokens (minimal meaningful units) before they have converted them into vectors.
- *Stopword Removal*. Stopwords are the most common words in a language such as ‘the’, ‘a’, ‘an’, and ‘in’, which are generally filtered out before analyzing a text or *corpus*.
- *Stemming* refers to the process of reducing a word to its stem. The result of the stemming process represents the *lemma*. For instance, ‘mak’ is the lemma for ‘making’, while ‘good’ is the lemma for ‘better’. Stemming is useful in information retrieval systems such as search engines or in domain analysis. While the goal of stemming algorithms is to cut off the end or the beginning of the words, lemmatization takes into consideration the morphological analysis of the words.
- *Punctuation Removal* is the process of eliminating all punctuation from the corpus.

The Model Variables

The Dependent Variable

The dependent or target variable was *polarity* or *orientation* or *valence*, which is usually measured on a scale from -1 to +1 (negative, neutral, and positive). Based on Wang et al.[10], the formula for polarity is

$$ps(w) = \frac{sw(p(w))^{ocr(w,=)+1} - sw(p(w))^{ocr(w,+)+1}}{1-sw(p(w))} \quad (1)$$

with the following parameters:

- w: a word that appears in a text
- p(w): the part of the speech of the word w
- sw(p): the sentiment weight for the part of the speech p
- ocr(w,+): the number of positive text data that contain w
- ocr(w,-): the number of negative text data that contain w.

We used the Quantitative Discourse Analysis Package library or QDAP[11] in the open-source software R to derive the polarity. Readers interested in in-depth review of key sentiment analysis concepts are referred to Liu's[12] extensive treatment of the subject.

The Independent Variables

- *Runway Configurations* are the hourly arrival and departure runways that the Federal Aviation Administration (FAA) airport facilities report to the Air Traffic Control System Command Center and are recorded in ASPM. In this analysis, we measure the impact of not using the preferred configuration on polarity. The airport located on the U.S. East Coast has a preferred and alternate configuration. In the former, flights arrive from the south (southwest/northwest runway) and depart to the east (east/west runway). In the latter, flights arrive from the west (east/west runway) and depart from the south (southwest/northwest runway). The configuration in use is coded 'A' when it is preferred and 'B' when it is an alternate configuration.

- *Total Volume of Operations* represents the sum of arrivals and departures reported by FAA's airport tower staff.
- *Delays Due to Weather* are the delays associated with weather events at the airport such as rain, snow, thunderstorm, and heavy wind that preclude the normal flow of arrivals and departures.
- *Percentage of Periods in Instrument Approach Conditions* (IAC) refers to the periods when ceiling and visibility were below the airport's minima. The variable was coded as '1' for IAC and '0' for visual approach conditions or VAC.
- *Meeting* refers to the occurrence or not of a community meeting during the period of observation. It is '0' for no meeting and '1' for the case when airport officials, regulators, and community representatives met.

The Tobit Model

The Tobit model[13] is a type of censored regression that can be summarized as follows (equation 1 to 3):

$$y_i^* = \boldsymbol{x}_i'\beta + \epsilon_{i,}, \; for\ i = 1,2,\dots,n\ with\ \epsilon_{i,}|\boldsymbol{x} \sim Normal(0,\sigma^2) \text{ (2)}$$

$$y = y^*\ if\ y_i^* > 0\ (polarity > 0, thus\ positive, left\ censored) \text{ (3)}$$

$$y = 0\ if\ y_i^* \leq 0\ (polarity\ is\ either\ neutral\ (0)\ or\ negative, right\ censored) \text{ (4).}$$

Left-censored refers to the lower limit of a distribution, while right-censored refers to upper limit. Censoring the data makes it possible for analysts to compare models and predict how selected independent variables are likely to influence the variation of polarity only when it is it is positive (equation 2), or only when it is neutral or negative (equation 4). Tobit regression makes it possible to estimate a linear relationship between variables when the dependent variable (polarity) is either left- or right-censored as characterized in equation (3) and (4) respectively. Polarity is scaled from -1 to 1. We tried to predict the significance of selected operational variables and their interactions when polarity is greater than zero (equation 2) or less than or equal to zero (equation 3). An ordinary least-squares (OLS) model would not be optimal in the present case because it will be biased.

The Tobit Model Outputs

The intercept is the expected value of polarity when all the variables are set to zero. In Table 1 and 2, intercept 1 represents the intercept of the Tobit model. Intercept 2 is the log-standard deviation of the latent variable.

Table 1 Tobit Model Estimates (When $y_i^* \leq 0$)

Variables	Estimate	Std. Error	z value	Pr(>lzl)	Sig. Level
(Intercept):1	2.047	0.987	2.074	0.038	*
(Intercept):2	-1.341	0.125	-10.718	<2e-16	***
Operations	-0.085	0.046	-1.869	0.062	.
Volume Delays	-0.159	0.078	-2.042	0.041	*
Weather Delays	0.004	0.004	1.255	0.210	
Pct Operations in IAC	-0.005	0.011	-0.492	0.623	
Meeting (TRUE)	0.080	0.115	0.693	0.488	
Preferred Configuration A	-0.450	0.271	-1.659	0.097	.
Preferred Configuration B	-0.054	0.304	-0.176	0.860	
Alternate Configuration A	-0.364	0.152	-2.394	0.017	*
Alternate Configuration B	-0.250	0.274	-0.914	0.361	
Interaction (Operations*Volume Delays)	0.008	0.004	2.137	0.033	*
Interaction (Weather Delays*IAC)	0.000	0.000	-0.949	0.343	

Significance codes: p ≤ 0.000 '***' / p ≤ 0.001 '**' / p ≤ 0.01 '*' / p ≤ 0.05 '.' / p ≥ 0.1 ' '

It is important to remember that the β coefficients estimate the effect of the independent variables on y*, the latent variable, and not y. According to McDonald and Moffit[14], the interpretation of the coefficients requires some care: "Tobit can be used to determine both changes in the probability of being above the limit and changes in the value of the dependent variable if it is already above the limit."

When $y_i^* \leq 0$, Table 1 shows that the intercept 1, volume delays, the use of the alternate configuration, and the interaction between operations and volume delays were significant at a 95% level. The volume of operations and preferred configuration were significant at a 90% confidence level. The intercept 2 was significant at a 99.9% level.

The expected polarity changed by 0.008 for each unit increase in the variation that measured the interaction between operations and volume delays, while holding the other variables constant. The expected polarity changed by -0.149 for each unity increase in the variation that measured volume delays, holding other variables constant. Among the significant variables, the expected polarity changed by 0.260 for each unity increase in the variation that measured operations not using the second preferred configuration, holding other variables constant.

When $y_i^* > 0$, Table 2 shows that the interaction of operations and volume delays were significant at a 90 percent level. The expected polarity changed by 0.004 for each unit increase in the variation that measured the interaction between operations and volume delays, while holding the other variables constant.

Table 2 Tobit Model Estimates (When $y_i^* > 0$)

Variables	Estimate	Std. Error	z value	Pr(>|z|)	Sig. Level
(Intercept):1	0.608	1.119	0.543	0.587	
(Intercept):2	-1.827	0.136	-13.481	<2e-16	***
Operations	-0.026	0.055	-0.481	0.631	
Volume Delays	-0.074	0.045	-1.631	0.103	
Percent Ops in IAC	0.009	0.062	0.144	0.885	
Weather Delays	0.001	0.002	0.321	0.748	
When Preferred Configuration 1 is Used	0.030	0.110	0.269	0.788	
When Preferred Configuration 2 is not Used	0.142	0.091	1.557	0.120	
When there was no Monthly Meeting	0.006	0.068	0.086	0.931	
Interaction of Ops*Volume Delays	0.004	0.002	1.767	0.077	.
Interaction of IAC*Weather Delays	0.000	0.000	0.077	0.939	
Interation of Operations and Percent Ops in IAC	-0.001	0.003	-0.177	0.859	

Significance codes: $p \leq 0.000$ '***' / $p \leq 0.001$ '**' / $p \leq 0.01$ '*' / $p \leq 0.05$ '.' / $p \geq 0.1$ ' '

From a community engagement standpoint, the fact that community and airport representatives met did not have an impact on the latent variable y*, whether $y_i^* > 0$ or $y_i^* \leq 0$. When $y_i^* \leq 0$), the use of preferred and alternate configurations was significant at a 95 and 99 percent level, respectively. However, when $y_i^* > 0$, no runway configuration was significant at any level.

FINAL REMARKS

Understanding the sentiment of communities before, during, and after implementation of airport projects is important to ensure their completion and success. Sudden changes in sentiments can catch airport operators and planners by surprise and result in project delay or even cancellation. Sentiment is usually measured by the direction of attitudes and beliefs (negative, neutral, or positive) as well as the emotional content of residents’ expressions in digital media (percent of subjectivity). Sentiment analysis makes it possible to monitor community sentiment and be proactive before sentiments turn into opinions. It is more difficult to change community residents’ attitudes and beliefs when they became opinions, which requires more communication efforts and targeted messaging.

This analysis illustrated how sentiment analysis can be used to predict polarity among community residents based on the case of a U.S. East Coast airport. However, it can be applied to any airport, regardless of size and location. While the percent of operations in instrument approach conditions did not appear to influence positive, neutral, and negative sentiments, the use of preferred and alternate runway configurations appeared to impact the negative sentiment of community residents. It is likely that residents who were not used to see and hear flights over their house were more likely to complain, as the tweets and Facebook comments suggested. While aircraft engines have become much quieter over the last two decades with the introduction of modified fans and nacelles, the visualization of increased overflights is likely to impact negative polarity whether airport operators engage or not with their community.

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