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Twitter sentiment analysis during Covid-19: The Case of Aegean Airways

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Abstract

While traditional word of mouth is used in small groups of people, electronic (Word of Mouth- eWoM) is considered one of the most influential informal media among consumers, businesses, and the population at large. We present how eWoM can be measured easily and economically, during a crisis period. For this purpose, we use a case study of the Greek airline "Aegean Airlines", in order to investigate what kind of sentiment dominates among users and therefore the type of eWoM that is spreading especially through the central hubs of the company's social network on Twitter. By performing text and sentiment analysis on the tweets text, we observe that even with the extreme measures in effect due to the COVID-19 pandemic, the general sentiment for Aegean remains positive over time. Moreover, we further highlighted the top users by frequency and context of tweets (influencers) regarding the airline and examined how they affect the spread of the eWoM, positive or negative, and what this means for the company's reputation. In conclusion, we argue that a substantial percentage of users are exposed to positive eWoM regarding Aegean, and therefore, it is more likely that those users might choose it for their future trips, and recommend it to others, further strengthening its brand name.

Keywords: Sentiment analysis, Electronic Word of Mouth, Covid-19, Airline, Greece

I. Introduction

Changes in communication, management and information technology (IT) technologies have transform business activities at least at the operational level and in some cases, strategically. One of the that has taken place in recent decades is the emergence and spread of social media. changes and explosive spread affected everyone and all activities, though not in the same way. In the following presentation we present the use of a simple analytical tool which was used during the appearance of the Covid-19 to measure the feelings of the customers of an airline. Sentiment analysis can be used as a tool to quickly and economically measure views and feelings in order for those interested to make at least an initial assessment of the above. There are many ways in which the elements of the method can be utilized, but in our case, they are limited. We do not consider sentiment analysis to be used as the basic tool for analyzing consumer behavior, but as a tool for recording the views of specific individuals and groups on specific issues. In the case where there is solid evidence that individuals are actively involved in the use of a social networking medium and are accustomed to honestly expressing their views through these social media, then we may be able to use the results of the data we have collected as analysis data behavior. However, this is not the purpose of the presentation.

Following the use of social media in corporate communication, companies have the ability to quickly collect data on the views and feelings of their customers who are expressed about them on popular social networking platforms. The purpose of the study is more to highlight the capabilities of the platform for the immediate, financially tolerable and useful collection of data on the views and feelings of the company's customers, rather than the ability to support the company's communication strategy on a digital platform. The second is a rather complex issue whose presentation goes beyond the objectives of this publication. In this post we will try to present the possibility of collecting data that can be used by the company in order to shape its communication strategy under crisis conditions.

In order to achieve this goal it was chosen to use the technical analysis of emotions from data extracted from Tweeter over a period of time and analyzing the text itself, we note that even with the extreme measures taken due to the COVID-19 pandemic, the general sentiment about Aegean remains positive over time. In addition, we highlighted the top users (influencers) based on the frequency and content of their tweets about the company and examined how they affect the spread of eWoM, positive or negative, and what this means for the company's reputation. Evaluating the findings we conclude that a significant percentage of users expressed positive about Aegean, and therefore, they are more likely to choose it for their future trips and recommend it to others, further strengthening Aeagean's brand name.

II. Literature Review

A. Sentiment Analysis

The roots of Sentiment Analysis can be traced to the studies of the analysis of public opinion at the beginning of the 20th century as well as to the analysis of a text's subjectivity in the 1990's. In recent years there has been a growing interest in emotion analysis because of the high availability of subjective texts on the Internet, and especially, social media.

In recent studies related to the analysis of emotions have faced new challenges such as the detection of more complex emotions, the identification of metaphorical uses of words, the multi-lingual adaptation and the identification of complex emotions. The sources of data used are print and electronic media, social networks, web content and images. The methodologies used for emotion analysis are generally categorized into three categories:

- Machine Learning
- Natural Languange Processing
- Special Methods of Sentiment Analysis

The following paragraphs of this chapter describe characteristics of emotion analysis, the purposes it serves as well as methodologies used (Mäntyläa, Graziotinb, & Kuutilaa, 2018).

Description & Definitions

Seth Grimes (2008) definiens sentiment analysis as the: "Emotion Analysis is a set of (systematic) methods that are typically (but not always) implemented in computer software, and detect, measure, and utilize attitudes, behaviors, opinions, and emotions in online social and business sources" (Grimes S., 2008). According to the definition by Liu, "sentiment (or an opinion) is a quintuple, (e, a, s, h, t), where e is the name of an entity, a is the aspect of e, s is the sentiment on aspect a of entity, e, h is the opinion holder, and t is the time when the opinion is expressed by h". In this definition, the sentiment s can be a positive, negative, or neutral, or a numeric rating score expressing the strength/intensity of the sentiment (e.g., 1–5 stars) such as in review sites like Yelp and Amazon. The entity can be a product, service, topic organization, or event (Bing Liu, 2012).

Levels of Analysis

The research in Sentiment analysis is mainly performed at three levels of distinction: at document-level, sentence-level and at aspect- / feature level.

Document Level

When document-level analysis is performed, the whole document is treated as an entity. This means accepting that the text expresses only one opinion and carries a unique emotion. The goal is to recognize and if possible, quantify the general emotion that comes from the text. The most typical example of this type of analysis is its application to product or film reviews. One of the first problems studied with this method was aimed to find the emotional orientation of the critique, i.e., if the critique is positive (thumbs-up) or negative (thumbs-down) (Pang et al., 2002; Turney, 2002).

Sentence Level

At this level of analysis, the goal is similar to document-level, differentiating only in the scale of text in which the emotion is examined, in that case, a sentence. Once more, a simplistic assumption is made, that is, that each sentence expresses one (at most) opinion, about an entity. But unlike before we have a deeper level of analysis, which offers the opportunity to utilize much more information. By using the previous example, in this case we can distinguish for each sentence separately what is the emotion expressed. Also, if this information is combined with the identification of the entity (Topic / Target-based) for which emotion is expressed, then notable percentage of the available information is utilized.

Aspect Based Level

This level of analysis is the most interesting and the most difficult. In the previous two levels of analysis, some assumptions are made, such as how many opinions are contained in a text, to simplify the problem. However, in feature-level analysis, the goal is to identify the emotion for all entities or even aspects of them.

Sentiment Analysis Approaches

In this section, an overview of the basic approaches to SA applications will be made. The approaches will be divided based on the methodologies in use. A key criterion for grouping approaches is how they manage features for natural language modeling. Figure 3 shows the hierarchy of the various techniques. Techniques can be divided into two main categories, those that use Machine Learning (supervised and unsupervised) and those that use Semantic Orientation techniques (unsupervised).

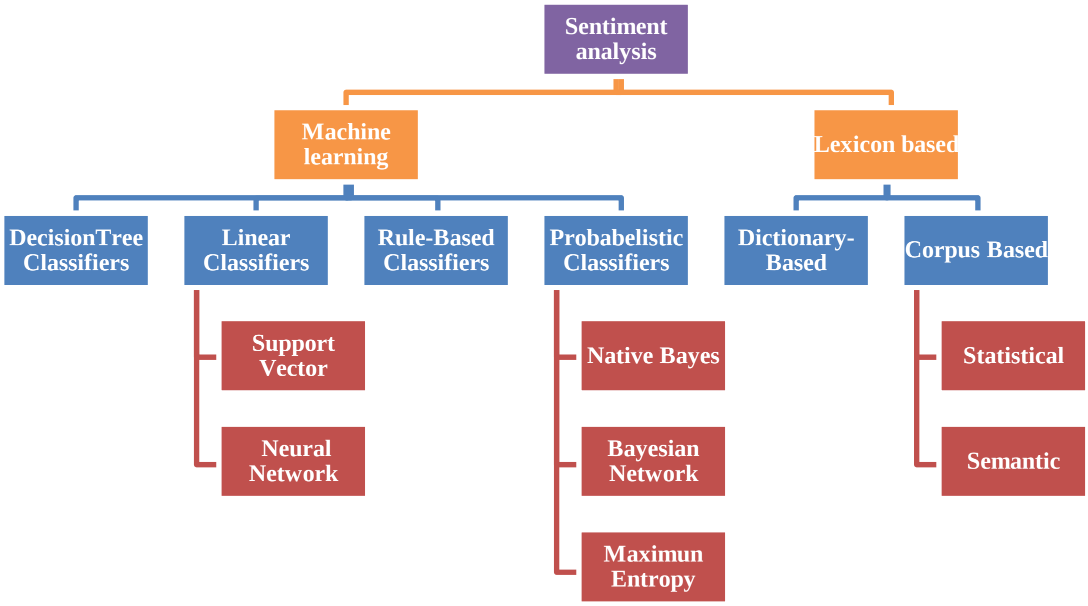

Figure 1. Approaches of Sentiment Analysis

Machine Learning

Machine Learning techniques aim to create algorithms that will allow a machine to learn to perform a task, through data. That is, without the specific actions explicitly planned in advance. This is done by creating statistical models which are based on a set of features that are extracted from the data. An important condition is the use of features that will best describe the data. In the context of machine learning, a feature is a measurable property of an entity.

Machine learning techniques are divided into three main subcategories, supervised, unsupervised and reinforcement learning techniques. In supervised learning techniques, for each example in the data the result or its class is known (e.g. which number is displayed in the image, whether the email is spam or not, etc.) and utilizing this information, in combination with the features given, the corresponding statistical model is built All of these techniques have been applied within the SA, with each focusing on different sub-problems. For example, in text classification problems based on emotional orientation (positive, negative, or neutral), supervised learning techniques are commonly used. In these problems sets of documents, sentences, and even single words are used, for which their orientation is known and the machine learning model learns to recognize the orientation of new texts based on patterns found in previous examples. On the other hand, in problems such as producing summaries of opinions expressed in a text, often unsupervised learning techniques are used (e.g., customer segmentation). The reason is that in such problems, it is difficult to produce recorded data. (Pang et al. 2002; Hu M. & Liu, B., 2004; Zhuang et al., 2006).

A machine learning system consists of two parts:

1) **Features:** In this step the features for modeling the examples are created. In SA some common features are from simple bag-of-words to more sophisticated ones such as semantic, syntactic and cognitive features. This step usually consists of various submissions such as: extract the original features, selection of the most important features, production of new ones from the original, rendering significance on the characteristics based on their importance (based on some criteria).

2) **Machine Learning Algorithm:** This step involves applying one (or a combination of many) machine learning algorithms, which build one statistical model, using the features of the previous step.

<u>Advantages-Disadvantages</u>

Machine learning techniques have been successfully applied to most natural language processing problems, such as Translation, Dialog Systems, Question-Answering and of course Text Classification. SA is approached mainly as a problem of the latter, as in most applications the goal is to categorize texts according to their emotional-semantic orientation. These techniques allow the creation of quite sophisticated models, quite high accuracy. They have the ability to utilize complex sets of features and discover patterns and structures hidden in them. They are based on strong mathematical foundations.

Semantic Orientation

These techniques assume that the semantic orientation (positive, negative or neutral) of a text is determined by the offsetting of the orientation of the individual terms (words or phrases) that is composed of.
In general, they concern the process of calculating the semantic orientation of each term of a text. Once the orientation of the terms has been calculated, then their values are offset, and the total orientation of the text (document, sentence or phrase) is calculated. Depending on the way this calculation is done, it can be divided into two subcategories: (1) text-based (corpus-based) and (2) lexicon / dictionary-based.

Corpus Based

The text-based approach is built on the assumption that when a word co-appears, more often with positively oriented words (e.g., "excellent"), the value of its orientation tends to be positive, respectively when it co-appears more often with negatively oriented words (e.g., "poor"), the value of its orientation tends to be negative. Initially, a set of terms with already known orientation is selected, which belongs to one of two classes ("positive" or "negative"). Statistics of the frequency of co-appearance are then collected for each word with the ones of the two classes. Thus, if a word appears more often near "negative" words, we consider that this word is "negative" or ‘’positive’’ respectively. A major difficulty is that a large collection of texts is required to reliably identify the orientation of each word. That means, that a sufficient number of texts must be collected in order for the sample to be considered representative of the whole.

Lexicon Based

In this approach, pre-made dictionaries are used, in which for each word, the corresponding value of its semantic orientation is given. Such dictionaries, for example, are WordNet, SenticNet, SentiWordNet and many more. Usually, these dictionaries, contain the positive or negative disposition of a specific word, as well as sometimes even how intense this orientation is. The fact that a source that provides orientation values (sentiment polarity) is used for each word, means that there is no need for large set of texts (Miller, 1995; Cambria et al., 2016; Esuli et al., 2007).
The main difficulty in this approach is to create a large enough dictionary that covers several fields (reviews of movies, electronic products, books, etc.). This is usually achieved through a combination of individual dictionaries. Also, something that is often overlooked is the importance of the various keywords. This can be addressed by applying weights to the features, through a mechanism that assesses their importance.

Advantages-Disadvantages

The advantage of these techniques is that they do not require the creation of a statistical or machine learning model, as nowadays there is a variety of open-source lexicons available to sentiment analysis practitioners. It is also quite easy to implement models that utilize these techniques.

B. Aegean Airlines

Aegean Airlines is the largest Greek airline that offers high quality short and medium range flight services, both within the Greek borders as well as in a great variety of locations abroad, mainly in the European Union. Aegean, since its founding, has followed a growth strategy in order to claim the largest possible market share and has become a leader in the Greek aviation market and an important player in the international market. With the rapid increase in its size, Aegean managed to achieve significant scale economies, while before the purchase of the Olympic Air it had a clear cost advantage over the latter. The company was one of the few that managed to survive in this incredibly competitive environment, while the nature of the product is such that significant investments in equipment are required to the extent that Aegean can be classified as a capital-intensive company. In addition, due to its high operating cash flows, the company was able to lease part of the equipment. For many years, the airline followed the strategy of horizontal integration which enabled it to acquire similar companies to expand its size and to gain a dominant position in the market. The brand name is mostly based on those characteristics that establish it in the consciousness of the consumer. The company has invested significantly in creating a strong brand name which is based on safety and punctuality.

To improve its product, the airline provides high quality food during the flight, while to improve ground handling, it introduced services such as electronic check in and RSS feeds. The accuracy of the arrival and departure times and the excellent service of the staff towards the passengers are other important features of the product. Regarding its product promotion, the company posts advertisements on websites related to tourism services, travel agencies, banks, etc. Advertising campaigns and sponsorships also used as part of the company’s promotional mix.
Aegean’s pricing is higher than low-cost competitors operating in the same markets such as Ryanair. The relatively high price is justified by the great quality of the services offered, especially on-board. Distribution refers to the way

in which the final product is delivered to the consumer. This sector is one of the most difficult and controversial marketing departments of an airline. Airlines, including Aegean, use travel agents to distribute their product. It is estimated that 80% of the tickets worldwide are sold through travel agents. The product is also distributed with the CRS electronic booking system. This system provides the possibility of ticket and luggage control, automatic issuance of tickets and distribution of passenger seats.

C. Word of Mouth and Social Media

Word of Mouth leads to possibilities that are linked to network effects. The rise of online media and communication means have remarkably increased the speed of sharing messages in social networks. Also, it appears to be less expensive in contrast to other marketing methods. Additionally, the explosion of media and the changing pattern of consumption have made the marketing communication reality quite challenging. Consumers are exposed daily to an abundance of advertising messages while the impact of conventional communication is getting gradually reduced.
It has also been proven that Word of Mouth accelerates the purchasing process. Silverman (2001) stated that all forms of marketing, advertising and communication should be considered possibilities for generating Word of Mouth, without implying that traditional marketing is without sense. In other words, he suggests looking at everything from a WoM point of view can provide interesting and valuable insights. One advantage of Word of Mouth is that it accelerates the decision to purchase a product. The main reason is because consumers usually trust the person who commends a product, therefore the timeframe of decision making shortens, mainly because they reduce their own research time on the product. Silverman also states that the acceleration in the purchase process is a direct route to more sales and this is exactly where Word of Mouth gets its strength.

III. The Study: Sentiment Analysis using Twitter data

Data Collection
Data from Twitter were collected via a text scrapper created in Python. This tool, which was created for the scope of this research, can scrape and download data from Twitter based on a keyword (as a general search mode), a hashtag, or by using a specified username. Twitter was selected mostly because large volumes of data are published daily and each post is short and concise due to the 280-character limit set by the platform. Moreover, the posts mainly contain text, unlike other social networks that posts can be comprised entirely by videos or images. In addition, tweets are written and published in simple and spontaneous everyday speech, which reflects the sincerity of the sentiment and opinions. Furthermore, tweet data are easily accessible via the company’s API (Application Programming Interface).

Data Description
With the use of the abovementioned tool, data were collected from the official Twitter account of the company, from relevant searches via hashtags mentioning the company’s username, and from a broad search of the ‘aegean’ and ‘airlines’ keywords at a full scale.

The total amount of Tweets sampled, before the basic cleaning, is 18.681 non distinct Tweets, spanning in the period from November 2019 until December 2020, with the purpose to also get a sample period before the major COVID-19 outbreak, so it can be used as a benchmark.

Data Cleaning
The initial cleaning procedure of the data, included but was not limited to:

- Deduplication of the dataset via two methods, the Tweet ID, which is also used as the primary key of the database and the text of the Tweets.
- Removal of the Tweets that contain only emojis, links, pictures or username mentions.
- Removal of all the non-English Tweets (because all the open-source lexicons mainly support the English language).
- Removal of irrelevant tweets, that happened to contain the specific keywords or hashtags but are referring to a different subject (e.g., Aegean Sea).

Moreover, we applied the following cleaning procedure to the text of the remaining Tweets in order to have a more reliable result in the sentiment analysis part of this work:

- Removal of hyperlinks.
- Removal of the hashtag symbol and its corresponding text (analyzed separately).
- Removal of mentions, and the following username.
- Removal of emojis, special characters, numbers, and punctuation.
- Conversion of the text to lowercase.

Data Exploration and descriptive results

After applying the proper data cleaning, 8.118 clean and distinct tweets remain for analysis, all written in the English language. In general, the majority of tweets scraped are written in English. Specifically, as shown in Figure 4, 55% of tweets are in English, 35% in Greek and 10% are written in other languages. 80% of the utilized tweets came from the users who tweeted about Aegean and 20% came from the company's Twitter account.

Furthermore, by analyzing the data, we have extracted the following observations:

- Tuesday is the day with the highest frequency of Tweets, followed closely by Wednesday and Friday. (Figure 1)
- Interestingly, the time of posts follows a distribution very similar with the Gaussian one, with the mean centered around 10 and 12 o'clock (Figure 2).
- Figure 3, depicts the 20 most prevalent countries regarding the number of originating tweets. As expected, Greece holds the first place with approximately 1700 tweets, followed by the United Kingdom and France. From figure 8 we can safely assume that most of the passengers are Greeks and additionally we are able to observe that Aegean is well perceived and trusted by other European Countries as well.

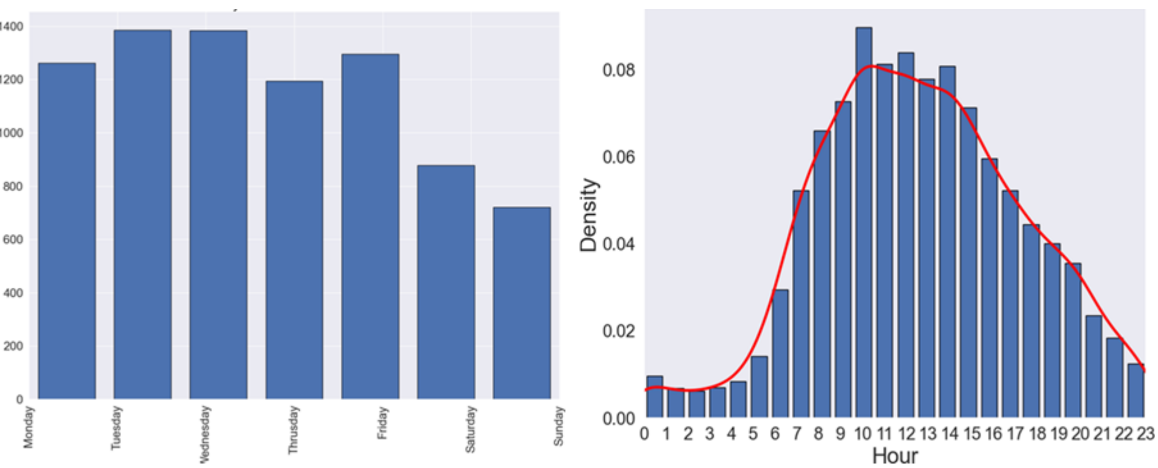

Figure 2: Daily and hourly distribution of Tweets

Table 1 presents the usernames, number of tweets and number of followers of each user which positively correlate with faster and wider spread of eWoM. Specifically, these users are the ones with the greatest effect on the reputation of the company and are considered hubs from which information and news regarding the company passes on to the broader public. Usernames are collected, but their names remain unpublished, as this information has no relevance to the study.

Name	Tweets	Followers
Aegean-Tweeter #1	93	2576
Aegean-Tweeter #2	83	1240
Aegean-Tweeter #3	77	213
Aegean-Tweeter #4	73	4680
Aegean-Tweeter #5	67	2035
Aegean-Tweeter #6	59	2229
Aegean-Tweeter #7	54	18872
Aegean-Tweeter #8	35	1629
Aegean-Tweeter #9	33	2662
Aegean-Tweeter #10	32	51
Aegean-Tweeter #11	30	521
Aegean-Tweeter #12	27	30
Aegean-Tweeter #13	26	7790
Aegean-Tweeter #14	26	46
Aegean-Tweeter #15	25	7839
Aegean-Tweeter #16	24	6406
Aegean-Tweeter #17	23	26665
Aegean-Tweeter #18	23	16
Aegean-Tweeter #19	23	9836
Aegean-Tweeter #20	22	13593

Table 1: Top 20 users with the highest number of tweets

The same type of analysis was used to identify the 20 most frequent hashtags, tweeted by the company and its followers (table 2). The hashtags with the higher frequency, are common and refer to expected topics for a Greek airline (e.g., Greece, aviation, travel, flights etc.). Apart from the obvious tags, there are two more categories worth mentioning. Firstly, we can identify two hashtags coming from the company's account regarding the purchase of two new types of airplanes, namely the A320neo and the A321neo, which caused a positive increase in the total sentiment of the period that they were getting 'tweeted'. Considering the hastags, we can draw the conclusion that Twitter, together with other forms of social media, can be considered as a medium of information, used by companies to achieve their marketing goals and in reaching a target audience regarding their new products and services.

The second category we can identify are the hashtags related to the COVID-19 pandemic. The insights we can derive by analyzing the data regarding their corresponding tweets are that the there are four very frequent hashtags that can be considered as neutral in terms of sentiment and source ('COVID19','COVID_19','coronaviruspandemic', 'coronavirusupdates') as they can either be included in tweets from the company regarding flight updates, safety rules and legislation, either from passenger accounts that enquire information concerning their flights. We have identified three hashtags that we could consider negative in terms of sentiment polarity. Specifically, 'boycottaegean', 'CustomerService' and 'Refundpassangers' generally stem from user tweets addressing the company regarding flight cancellations and refunds and in general are strictly correlated with the period in the beginning of the pandemic where most of the flights were cancelled and the customer service of the company was too busy to reply in a swift manner. The above analysis leads us to the conclusion that Twitter can act as a medium of information in both-ways, meaning that users can address the company via the platform, and in many cases affect the company's image negatively (or positively), in the same way that the company can use the platform for marketing its new products and services. This negative effect is greatly augmented when the negative eWoM is spread by central hubs, such as the top 20 users mentioned above, in the 'social network' that is created via following and friend connections in the platform.

Hastag	Count
Greece	213
aviation	208
travel	133
COVID19	95
A329neo	95
Flights	74
aviationphotography	46
RefundPassengers	37
takeoff	33
Traveler	26
planespotting	23
tourism	23
Milesandbonus	21
A321neo	20
COVID_19	17
coronaviruspandemic	16
coronavirusupdates	15
VisitGreece	15
boycottagean	13
CustomerService	11

Table 2: Top 20 Frequent Hashtags.

Word clouds

Our analysis included the creation of two word clouds that present the most frequent words adopted by users and by the airline. Our main goal is not only to distinguish the most popular words, but also to attempt to extract an initial assessment of the sentiment polarities. In figure 11 we present the most popular words found in the follower's tweets. The words with the highest frequency, among others, are: "refund", "flights", "cancelled", "voucher" and "booking". Considering the extreme circumstances and the precautionary measures taken for the coronavirus, it is expected from the passengers to use these words, as they represent the majority of their requests and issues at the time.

In Figure 11, we present the word cloud that is generated from the airline's tweets. The most frequent words are: "booking", "check", "disposal", "reference", "replied". These words mostly depict the company's efforts in handling this crisis.

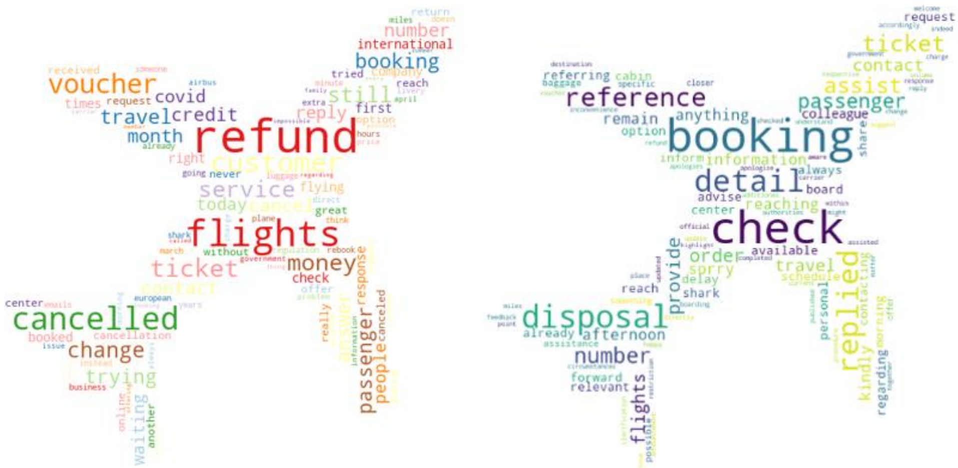

Figure 3: Most frequent Tweets by users Vs Tweets by the company

We can argue that the two, from a certain perspective, constitute a “dialog” between user’s and company’s tweets. Specifically, we recognize that the most repeated words follow the pattern of ‘question and answer’. The “red” cloud in figure 3 constitutes the user’s “questions” and the blue one, the airline’s answers. Following this dialogue, it is safe to assume that the users clearly use Twitter as a distribution channel for expressing their complaints, or their positive feedback. Consequently, we could assume that via this communication channel, a company has the opportunity to achieve immediate interaction with current and potential customers and possibly take action to avoid further spread of negative eWoM.

Event tracking

By investigating the Twitter content, we can get public opinion trends of events related to the company. For example, on February 2020, the tweeted content originating from Aegean was high, mainly because the airline unveiled the addition of a number of the state-of-the-art, Airbus A320 neo aircraft to its fleet. On May 2020, the ease of restrictions regarding air transportation, resulted in high Twitter activity. The new standards of travelling in combination with summer holiday season, have also led to the elevated number of tweets presented in figure 4.

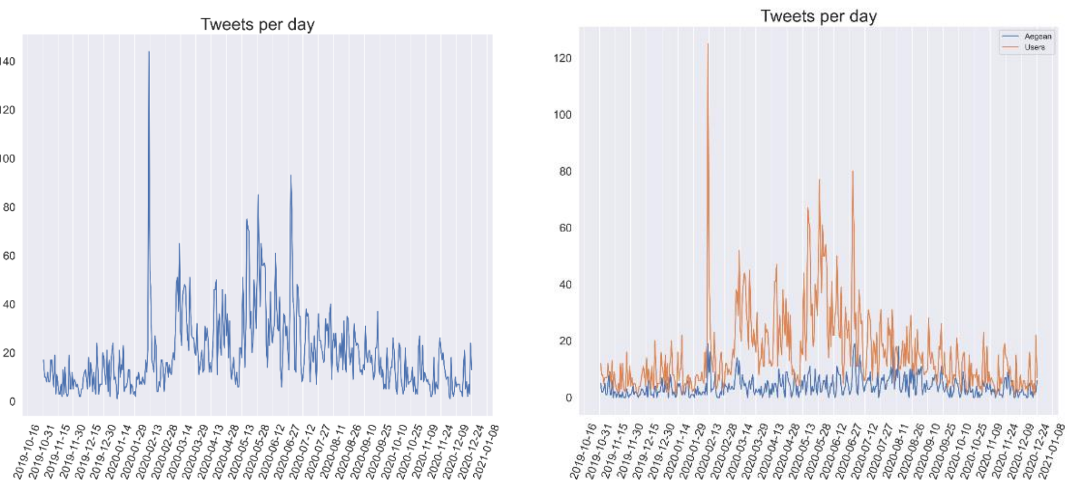

Figure 4: Event tracking: Tweet/day (the second graph presents users vs Aegean tweets)

Passenger geographical distribution

As shown in figure 8, the 5 countries with the largest number of tweets are:

- Greece
- United Kingdom
- France
- Cyprus
- Spain

Passengers living in Greece comprise a substantial percentage of tweets, as Aegean is a Greek airline and has a great reputation amongst the country’s citizens. Moreover, we can observe that most of the tweets regarding the company originate from Europe, with some activity being detected in the United States and Asia.

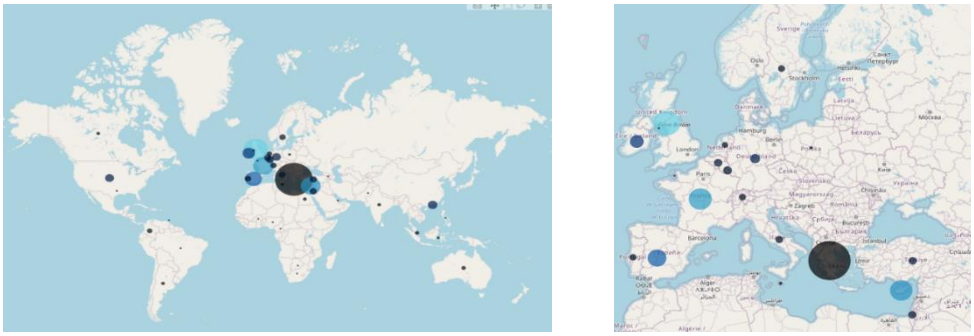

Figure 5: Tweets from the world & Tweets from Europe

Sentiment analysis

We have performed sentiment analysis, in sentence level, using a lexicon-based approach. In this approach, a pre-prepared sentiment lexicon is used to calculate the polarity score of a text, by aggregating the sentiment scores the whole sentence. We use open-source Lexicon TextBlob for this analysis. Initially, we are going to present the most important results obtained from the sentiment analysis of the data, such as the tweet sentiment count, subjectivity versus polarity and geographical distribution of the sentiment worldwide.

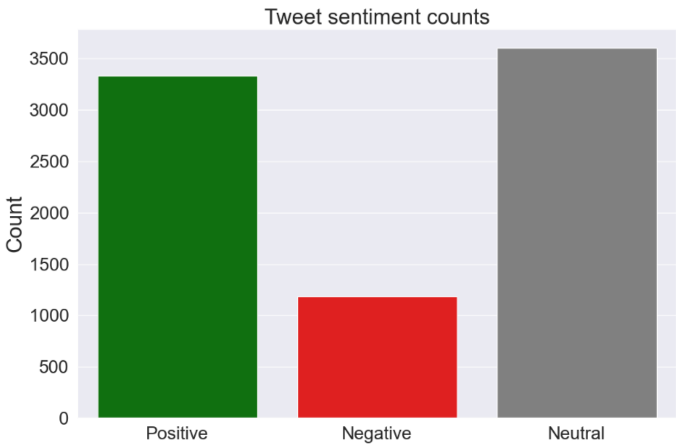

Figure 6: Sentiments counts and classified

Figure 17 shows the aggregated sentiment from the users and the company grouped by category. The dominant sentiment is neutral, which probably means that most of the tweets either do not contain any sentiment and mostly refer to facts, either the net polarity score sums in a range close to zero. The positive sentiment category comes second in the ranking with a marginal difference, while the negative category is last. In order to improve our understanding of the sentiment, it would be appropriate to provide a breakdown by source.

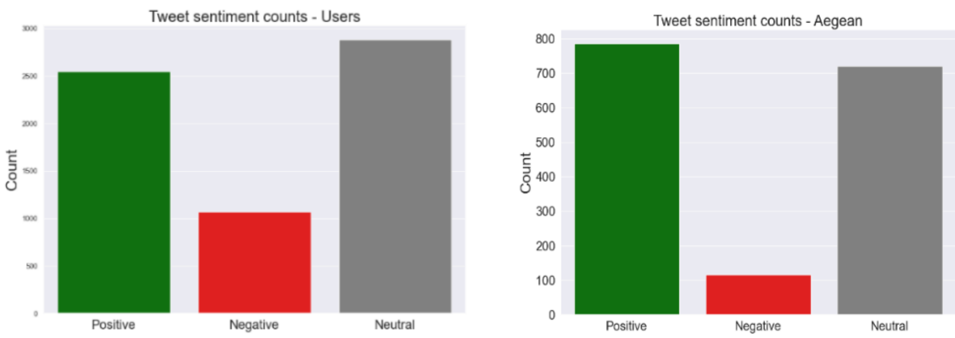

Figure 7: Sentiments by Users vs sentiments by the company

Figure 7 indicates that most of the tweets could not be clearly classified as positive or negative, either because they contain facts, or because their sentiment is mixed, and the net polarity score is close to zero. From the classified tweets, the dominant category is the positive, while the negative tweets comprise the smallest category, with less than half the volume of the positive ones. This sizable difference between the volumes of positive and negative tweets coming from the followers of the company, clearly shows that even in volatile periods of customer sentiment, such as the COVID-19 crisis, Aegean is well respected, and its good reputation still holds.

Moreover, although neutral is the prevalent sentiment, that is not necessarily translated as a non-opinion. Neutral sentiment may include only facts and can possibly be beneficial for the company. The importance of neutral tweets is hidden in the fact that the company brand is spreading through eWoM, regardless its sentiment. Consequently, it is likely for a potential passenger to choose this airline, only because he is already familiar with this company and he has read about it multiple times.

In the second half of the figure, the sentiment is extracted from tweets originating from Aegean. As expected, the prevalent sentiment is positive, while the negative is almost non-existent. The small number of negative tweets that can be found amongst the company's own tweets possibly refer to external factors with a negative meaning, such as the covid pandemic and restrictions, and while the company have used these as information to their passenger, the negative words in the text drive the polarity score in the negative range, and thus the text is classified as negative.

Figure 8 shows a comparison between the polarity and the subjectivity scores of the tweets. Regarding polarity, a score close to zero indicates a neutral sentiment and moving towards one, the sentiment becomes positive.

Figure 8. Subjectivity VS Polarity

Moving towards the left, the sentiment is classified as negative. Moving towards a higher subjectivity score, the range of the polarity score increases. This observation could provide strong evidence that the most subjective a tweet,

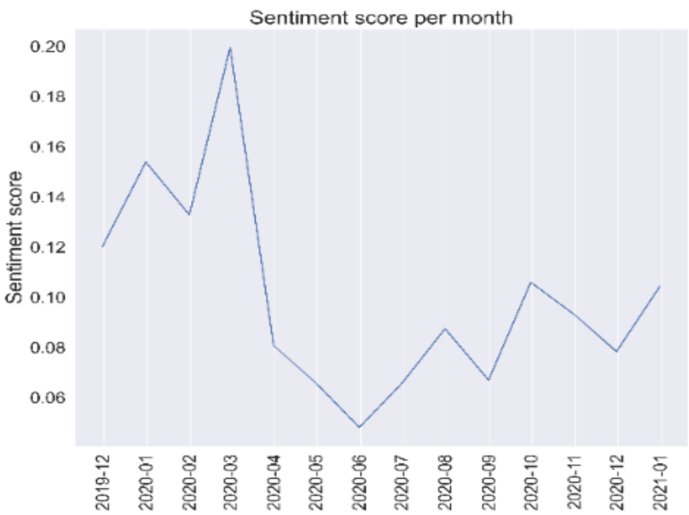

Figure 9: Sentiment Polarity per month (Aegean & Users)

the more intense its measured sentiment. Additionally, it is noted that in terms of frequency, the chart is denser from the center below, which means that most of the tweets are objective and therefore more reliable.

In order to study the sentiment dynamics regarding the company in the COVID-19 period, the monthly compound sentiment scores were calculated, and compared with a benchmark period before the start of the pandemic (figure 21). By studying the time series of scores, we observe that while there was a steadily increasing trend in the period from 12-2019 to 03-2020, which was also related to the purchase of brand-new aircraft by the company, a steep decline occurred right after the initial flight restrictions were announced, with the first signs of trend reversal appearing at the beginning of the summer, when some flying restrictions were lifted. This immense decline can be mostly explained by events directly related to the pandemic, such as flight cancellations, delayed refunds and fewer flights, as well as a general disbelief in airline companies from the broad public, mostly because of delays in call centers and customer service.

While the downturn of compound sentiment is well explained and considering that Twitter can be regarded as a two-way communication channel, it would be of great interest to study the company's responses to the negativity of the public.

In figure 10, a breakdown of sentiment score by user's and company's tweets is presented, in an attempt to study Aegean's reactions in terms of marketing and correcting the negative eWoM created and spread by its passengers. As observed, the company's sentiment is in a parallel downwards trend together with the one of user's until 06-2020. This can be mostly explained by the 'negative context tweets' published by the company, related to refunds and flight cancellations. In the beginning of summer, when the restrictions regarding air travel were partially or completely lifted, Aegean had the opportunity to implement a positive marketing policy promoting cheaper flights,

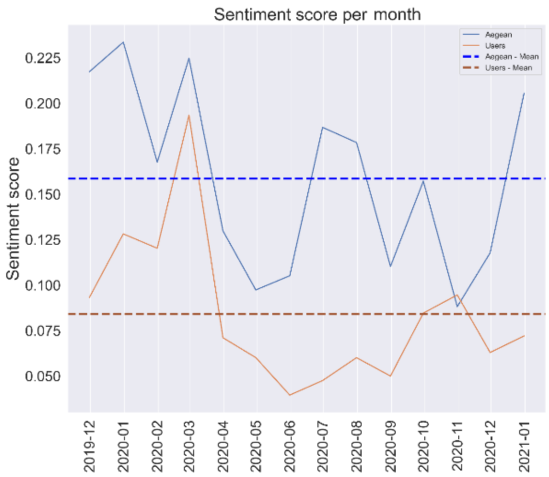

Figure 10: Sentiment breakedown per month (Aegean & Users)

giving vouchers for previous flight cancellations, and promoting good news for the company to reverse the negative eWoM affecting the company's reputation.

Figure 11 shows how the compound sentiment is distributed worldwide. Considering that most of the tweets originate from Europe, we also present a clear image of the sentiment in this continent (Figure 24). The positive sentiments are colored in green, while the red sentiments are colored in red. The color scale between these 2 is dynamic, and it depicts with high accuracy the total sentiment of each country towards Aegean. For example, in the first map, in USA and Africa, the dark green indicates strong positive sentiment. As for the second map, the dark red in Malta provides us with negative sentiment.

Figure 11. Sentiment Worlwide

In order to conduct a deeper investigation of the sentiments, we also present three more word clouds divided in categories depending on their sentiment category. In figure 12a we present the word cloud regarding the positive sentiment, in figure 12b the negative and figure 12c depicts the neutral tweets. The contribution of these word clouds is that not only they visualize the most frequent words, but also, they help us better understand what might have caused them.

Regarding the positive sentiment, the most popular words are: “refund”, “cancelled”, “booking”, “flights”, “ticket” etc. The size of the words determines their frequency in the sample. When observing these words in positive tweets, we could safely assume that passengers were satisfied with the company regarding their refund policy, flight schedule, and services. In addition, regarding the complaints from which these words stem, we assume that there was swift correspondence from the company.

In Figure 12b, the words represent certain demands or complains of the passengers, and in addition, it shows in which areas the company should focus its customer service on. For once more we should emphasize that the major COVID-19 outbreak, left the airline exposed to negative feedback.

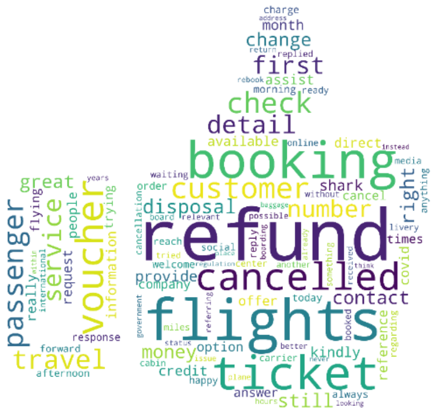

Figure 12a: Positive Sentiments

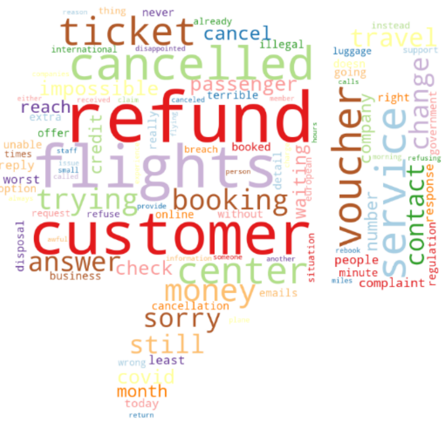

Figure 12b: Positive Sentiments

Issues that are present in both categories abo, “refund”, “cancelled”, “flights”, “ticket”, “booking” etc. appear in both word clouds but, their context is different. Specifically, in figure 12a their effect is positive but in figure 12b is clearly negative, depending on the service provided by the airline or the reassurance that any complication will be managed. It is vital for a company to manage any issues immediately, and further adapt to new circumstances while receiving the least negative feedback.

Finally, a word cloud with the neutral sentiment is presented. Although we were not able to classify these tweets as positive or negative, we are still able to receive feedback regarding the main concerns about the company. Figure 27 undoubtably shows that the words “refund” and “flights” monopolize the tweets of users and Aegean.

Figure 12c: Neutral Sentiment

In Figure 13, we attempt to give a network representation of the eWoM spread regarding Aegean. The purpose of this, is to better understand the eWoM dynamics from the data available. The central node represents Aegean, and the light blue nodes show the top 20 users that posted about the company, while the grey nodes represent their own followers. The green color of the edges suggests the spread of positive eWoM from the specific user, while the red one, a negative spread. We can observe a much greater number of followers is exposed to positive sentiment, compared to the negative one. Moreover, eWoM, passes to from user to user, and their own followers respectively, proving that the spread of eWoM starting from a single person, can greatly affect the reputation of the company. In addition, it is realized how important is for the company to manage and have a good relationship with people that are considered 'influencers' of the respective product or service, as they can greatly affect their reputation in the public.

IV. Conclusions

In this work, we attempted to investigate the sentiment of Twitter users regarding Aegean airlines. The data used also include a brief timeframe before the COVID-19 outbreak to include a benchmark period of normal activity on Twitter. Moreover, the word clouds played a key role into concluding that Twitter is used as a distribution channel

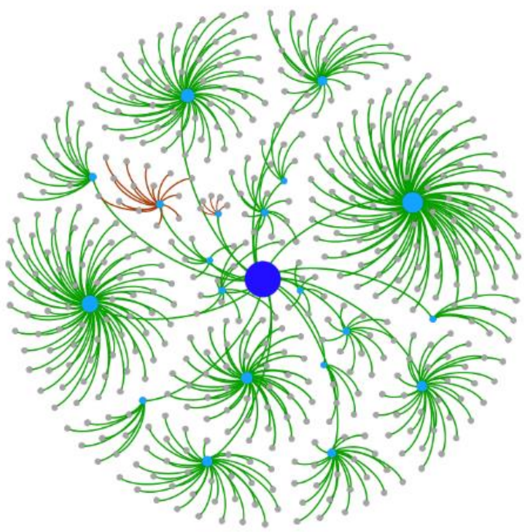

Figure 13. Network of Electronic Word of Mouth

because the positive and the negative word clouds included the same words but in a different context. This can be translated as an attempt from the company to manage and satisfy their passenger's needs or in many cases, users who for instance got a refund and happily tweeted about it.

During this work, we further tracked some important events that affected the company's activity on Twitter such as the purchase of a new type of aircraft, the ease of travel restrictions and the summer season of 2020. Despite the pandemic, many people travelled for summer holidays with all the necessary precautions taken. The extreme circumstances definitely had a negative effect on Aegean causing frustration and uncertainty amongst a percentage of its passengers.

After performing sentiment analysis on the tweets text, we observed that the positive sentiment dominates over the negative and based on polarity and subjectivity scores we conclude that the positive sentiment not only excels in quantity but also in the quality of the content. In other words, more tweets were posted with positive sentiment and more importantly, the positive sentiment is "stronger" than the negative.

By examining the sentiment score, we have observed many fluctuations. This variance represents the electronic Word of Mouth for each post. Additionally, the fact that there is a decent level of variance, can be considered to have a positive effect on Aegean's brand name. It shows that, despite the sentiment, the company increases its popularity, which in the future can act as a positive factor for expanding its clientele.

Finally, to present a clear image regarding the eWoM effect, we created a network which vividly illustrates the spread of positive and negative comments for the airline. The network shows the central hubs, which are the top twenty users by post volume, that communicate the sentiment in their own followers. Naturally, the positive eWoM is reproduced by the followers of the hubs and so on. The same stands for the negative Word of Mouth. Consequently, given the fact that the positive electronic Word of Mouth overpowers the negative one, it is safe to say that Word of Mouth operates as a useful tool for the company's brand in general.

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