ΕΞ' ΑΠΟΣΤΑΣΕΩΣ ΜΕΤΑΠΤΥΧΙΑΚΟ ΠΡΟΓΡΑΜΜΑ ΣΤΟ ΨΗΦΙΑΚΟ ΜΑΡΚΕΤΙΝΓΚ

Title:

"The impact of Twitter posts on the performance of the airline: the case study of Lufthansa & Swiss International airlines."

Διατριβη η οποία υποβλήθηκε προς απόκτηση εξ αποστάσεως μεταπτυχιακού τίτλου σπουδών στο Ψηφιακό Μάρκετινγκ στο Πανεπιστήμιο Νεάπολις Πάφου.

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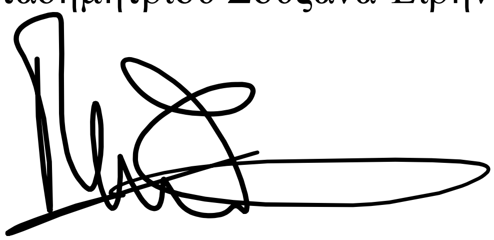
ΥΠΕΥΘΥΝΗ ΔΗΛΩΣΗ

Η Παπαδημητρίου Σουζάνα-Ειρήνη, γνωρίζοντας τις συνέπειες της λογοκλοπής, δηλώνω υπεύθυνα ότι η παρούσα εργασία με τίτλο « The impact of Twitter posts on the performance of the airline: the case study of Lufthansa & Swiss International airlines », αποτελεί προϊόν αυστηρά προσωπικής εργασίας και όλες οι πηγές που έχω χρησιμοποιήσει, έχουν δηλωθεί κατάλληλα στις βιβλιογραφικές παραπομπές και αναφορές. Τα σημεία όπου έχω χρησιμοποιήσει ιδέες, κείμενο ή/και πηγές άλλων συγγραφέων, αναφέρονται ευδιάκριτα στο κείμενο με την κατάλληλη παραπομπή και η σχετική αναφορά περιλαμβάνεται στο τμήμα των βιβλιογραφικών αναφορών με πλήρη περιγραφή.

Η Δηλούσα,

Παπαδημητρίου Σουζάνα-Ειρήνη.



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Abstract:

With the increasing importance of social media and online presence in digital marketing strategies, consumers of products and services have realized the power given to them by social media and online reviews. For this reason, it is in the great interest of companies to be able to quantify how specific reviews and their frequency can affect their business, and thus adjust their incident management strategies, and invent new methods of approaching dissatisfied customers.

This study aims to examine how passengers can influence an airline's performance through their online behavior and feedback, propagated via social media and specifically Twitter. The collected data were categorized based on their sentiment (positive, negative or neutral) using the sentence-level sentiment analysis method and determined their polarity score. Moreover, the temporal relationship for both airlines was studied in combination with the Pearson correlation metric, which was classified as "negligible association". In order to confirm the Pearson correlation findings, an attempt was made to fit a linear regression model and the R^2 scores to the data.

The final conclusion was that for both companies the linear regression model had no explanatory power over the relationship of the dimension under study. In both companies, the resulting lines have considerable distance from most of the data points of the sample, while the R^2 metric score hints that the polarity metric cannot explain a significant part of the revenue's variance.

Key words: social media, Twitter, customers, sentiment analysis, polarity score, Pearson correlation, linear regression.

Περίληψη:

Με την ολοένα αυξανόμενη σημαντικότητα των μέσων κοινωνικής δικτύωσης και την διαδικτυακή παρουσία στις στρατηγικές ψηφιακού μάρκετινγκ,οι καταναλωτές προϊόντων και υπηρεσιών έχουν συνειδητοποιήσει τη δύναμη που τους δίνουν τα μέσα κοινωνικής δικτύωσης και οι διαδικτυακές κριτικές. Για το λόγο αυτό, είναι προς το μεγάλο συμφέρον των επιχειρήσεων να μπορούν να ποσοτικοποιήσουν τον τρόπο με τον οποίο συγκεκριμένες κριτικές και η συχνότητά τους μπορούν να επηρεάσουν την επιχείρησή τους, και έτσι να προσαρμόσουν τις στρατηγικές διαχείρισης των περιστατικών τους και να εφεύρουν νέες μεθόδους προσέγγισης δυσαρεστημένων πελατών.

Η παρούσα μελέτη έχει ως στόχο να εξετάσει τον τρόπο με τον οποίο οι επιβάτες μπορούν να επηρεάσουν την απόδοση μιας αεροπορικής εταιρείας μέσω της διαδικτυακής τους συμπεριφοράς και των σχολίων τους, που διαδίδονται μέσω των μέσων κοινωνικής δικτύωσης και συγκεκριμένα του Twitter. Τα δεδομένα που συλλέχθηκαν κατηγοριοποιήθηκαν με βάση το συναίσθημά τους (θετικό, αρνητικό ή ουδέτερο) χρησιμοποιώντας τη μέθοδο ανάλυσης συναισθήματος σε επίπεδο πρότασης και προσδιορίστηκε το polarity score τους. Επιπλέον, μελετήθηκε η χρονική σχέση για τις δύο αεροπορικές εταιρείες σε συνδυασμό με τη μετρική συσχέτισης Pearson, η οποία χαρακτηρίστηκε ως "αμελητέα συσχέτιση". Προκειμένου να επιβεβαιωθούν τα ευρήματα της συσχέτισης Pearson, επιχειρήθηκε η προσαρμογή ενός μοντέλου γραμμικής παλινδρόμησης και των μετρικών R^2 στα δεδομένα.

Το τελικό συμπέρασμα ήταν ότι και για τις δύο εταιρείες το μοντέλο γραμμικής παλινδρόμησης δεν είχε καμία επεξηγηματική δύναμη πάνω στη σχέση της διάστασης υπό μελέτη. Και στις δύο εταιρείες, οι γραμμές που προκύπτουν έχουν σημαντική απόσταση από τα περισσότερα σημεία δεδομένων του δείγματος, ενώ η βαθμολογία της μετρικής R^2 υποδηλώνει ότι το polarity score δεν μπορεί να εξηγήσει σημαντικό μέρος της διακύμανσης των εσόδων.

Λέξεις κλειδιά: Μέσα κοινωνικής δικτύωσης, Twitter, καταναλωτές, ανάλυση συναισθήματος, συσχέτιση Pearson, γραμμική παλινδρόμηση.

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Introduction

There is no doubt that social networking tools have replaced traditional marketing tools and have led to the production of content generated by consumers (UGC) that enables businesses to draw conclusions about how they are perceived by their customers (Thelwall, M., et all, 2011). Twitter possesses one of the highest rankings amongst social media because users can easily express their opinions or problems and due to the character limitation, they get right to the point they wish to make (Agarwal, A., et all, 2011). Nowadays, consumers rely on the online reviews or comments about a company or a brand for information before they proceed with a purchase, which indicates that user generated content can actually affect the buying intentions of future customers.
Consequently, a brand’s reputation, the consumer’s brand perception and the process of decision-making are directly associated by what other people comment online (Ye et al., 2011).
Airline companies are dependent on their customer feedback, due to their need of continuously improving their services and optimizing the customer experience (Wan & Gao, 2015). However, we can argue that they can no longer rely on traditional methods to collect customer feedback, e.g questionnaires, due to the high probability that the responses might not reflect the true customer sentiment. The application of sentiment analysis is an alternative and up-to-date way of collecting data that truly reflect consumer opinions. In the past, other researchers have successfully investigated the usefulness of Twitter data. For instance, Asur and Huberman (2010) investigated the strength of social media into predicting the results of real-life issues. In particular, their intention was to predict box-office revenues for movies, taking into consideration the conversation around these movies on Twitter. They managed to collect 2.89 million tweets about 24 movies and they predetermined a critical period for each movie that was related to its cinema release. The researchers were able to measure how much attention each movie received, by the rate of tweet creation every hour. Eventually, they proved a correlation between the tweets and the box office revenue, which was demonstrated by the linear regression model they used. In conclusion the passengers’ opinion towards an airline, and the image it shapes for it through social media, is a crucial matter in the digital age and therefore needs further examination. The airlines, and other companies that use the social media channel can utilize and greatly benefit from a tool that can quantify the effect that customer reviews have in their future performance and use it in their everyday business.

Chapter 1. Social Media

1.1 Basic Meanings & Definitions of social media

Social networking has been a topic of great interest to both the general public and academia due to its dynamic development and widespread use (Albarran et al., 2020; Fuchs, 2017; Kaplan & Haenlein, 2010). Electronic social media, which are a direct product of Web 2.0, have transformed the traditional one-way communication of mass media into a more diverse and interactive dialogue. In this chapter, we aim to provide a conceptual understanding of social media terms frequently used in this paper through a literature review. To facilitate this understanding, we will begin with a brief historical overview of the Web 1.0 and 2.0 eras, which will help readers transition to the definitions of Social Networking, Social Network, and social media.

1.2 Social Networking

Throughout history, humans have been recognized as social beings, with an inherent need for social interaction and communication. Aristotle famously noted that humans are naturally social creatures. Wenger (1998) defines a community as a group of individuals who learn and interact together, building relationships that foster a sense of belonging and mutual commitment. In the digital age, social networking has emerged as an online activity that allows people to communicate and connect with others from anywhere, at any time (Misra et al., 2014). Social networking is defined as the practice of expanding knowledge through networking with individuals who share similar interests (Ellison et al., 2007). Social networking, facilitated through electronic social media, enables users to exchange ideas, opinions, and experiences, ultimately enriching their knowledge and social ties. Therefore, social networking tools act as a kind of social glue to electronic socialization, uniting individuals' lives in both good and bad ways (Christofides et al., 2009).

1.3 Social Network

In the present day, the term "social network" is often synonymous with the popular social media platform Facebook, due to its widespread use in our daily lives. However, social networks are not a new phenomenon. Interpersonal social networks existed prior to the advent of digital social media and have been extensively studied by sociologists (Lin, 2017).

Electronic social media have expanded upon human social networks, which have existed since ancient times. Barabasi (2002) notes the existence of social networks among early Christians, and various types of networks have emerged over time, including national, tribal, and commercial networks such as multinational companies.

Sociologists define social networks as a collection of personal contacts through which individuals maintain their social identity, receive emotional and material support, access information, and create new social connections (Lin, 2017). This definition encompasses a range of networks, including family networks, which are primarily made up of strong ties that hold members together with a common purpose and ideology.

Today, online social networks or social networking sites have emerged, with Boyd and Ellison (2007) defining them as web-based services that allow individuals to create public or semi-public profiles, build a list of connections, and view and share those connections with others in the system. Kwon and Wen (2010) provide a more recent definition, stating that social networks are websites that enable people to build relationships online, share information, and create groups based on similar interests.

The analysis of a social network is examining the ways in which network members interact and exchange information (Maranto & Barton, 2010). This analysis is also commonly used as a research tool for social media data analysis.

Overall, social networks have a long history, with digital social media platforms building upon existing human social networks. Their analysis remains a valuable tool for understanding social networks, both online and offline.

1.4 Social Media

Social media are online platforms that allow users to create, share, and exchange content through virtual communities and networks. These platforms are characterized by their user-generated content, interactivity, and ability to connect people with similar interests and backgrounds.

Boyd and Ellison (2007) define social media as "a web-based service that allows individuals to construct a public or semi-public profile within a bounded system, articulate a list of other users with whom they share a connection, and view and traverse their list of connections and those made by others within the system." This definition describes the key features of social media, which is the user's ability to create a public or semi-public profile, connect with others, and interact with their connections.

There are various types of social media platforms, such as social networking sites, microblogging sites, messaging apps, and photo and video sharing platforms. Although each type offers distinctive features and functions, their ultimate objective is to enable social interactions and communication among their users.

One study by Lui and Campbell (2019) explored the psychological effects of social media use and identified three key negative outcomes: fear of missing out (FoMO), social comparison anxiety, and loneliness. FoMO is the anxiety and distress that people experience when they feel they are missing out on social experiences or events that others are participating in. Social comparison anxiety occurs when people compare themselves to others on social media and feel inadequate or inferior as a result. Finally, a person can experience loneliness when social media usage eventually replaces face-to-face social interactions.

On the other hand, social media may have a positive impact on individuals and society. For example, social media can facilitate social connections and support among individuals, promote civic engagement and political participation, and provide access to important health and scientific information.

However, we have witnessed the misuse of social media for purposes like the spread of misinformation, the propagation of hate speech and harassment, and the threat on the privacy and security status of an individual. Liu, Chen, Han, and Zhang (2020) examined the correlation of social media use and privacy - security risks. In their study found that social media use is positively associated with both privacy concerns and security risks, suggesting that users need to be aware of these risks and take steps to protect their personal information.

Social media is a broad and complex phenomenon that contains a wide range of platforms and features. It is clear that these platforms can have positive and negative implications for individuals and society. Studies on social media have proved that social media assist in making social connections smoother among individuals (Lui & Campbell, 2019), promote community engagement and political participation (Kahne et al., 2018), and provide access to important health and scientific information (Bode & Vraga, 2020). On the other hand, as mentioned above , they can also pose risks and challenges such as the spread of misinformation (Bode & Vraga, 2020) and the propagation of hate speech and harassment (Ellison et al., 2020). As their involvement continues to shape our lives, it is important for researchers and users alike to consider the potential benefits and drawbacks of these platforms and to take steps to promote positive outcomes while mitigating negative effects.

Some examples of commonly used terms today, regardless of one's education, socio-economic background, or profession, include TikTok, Snapchat, LinkedIn, and Reddit. The prevalence of these social media platforms is continuously growing on a global scale, indicating that they have become a multicultural and widespread phenomenon that still has room for growth and development (Wirtz, J. et al., 2011). For instance, a survey conducted by J. Clement found that approximately 4.66 billion individuals worldwide actively used social media as of October 2020, which equates to 59 percent of the global population (J. Clement, 2020).

1.5 Historical Evolution of social media

Social media has progressed a lot since its inception in the early 2000s. Starting with platforms like Friendster and MySpace, social media evolved into a complex and universal phenomenon. Some key milestones in the evolution of social media include the launch of Facebook in 2004, the introduction of Twitter in 2006, the rise of Instagram in 2010 and the launch of Tik Tok in 2016.

The factors that played a key role in the evolution of social media are the major technological advancements, the changes in the users' behavior and the changes in society in general. As users increasingly turn to social media for communication, entertainment, and information, researchers have sought to understand its effects on individuals and society as a whole.

The paper from Tufekci and Wilson (2012), examines the footprint of social media on social movements. The authors argue that social media has altered the way social movements are organized and sustained, allowing for greater participation and coordination among individuals with diverse backgrounds and beliefs.

Boyd and Ellison (2018) discuss the different types of social media platforms that have emerged over time and in which ways they have been used by individuals and businesses.

In general the evolution of social media has been shaped by various factors, and it continues to evolve at a rapid pace. As researchers continue to explore its impact on society, it is likely that social media will continue to be a subject of ongoing research and analysis.

1.6 Basic Characteristics of social media

Social media is characterized by several key features. First, social media platforms encourage user participation and feedback, enabling two-way communication between customers and businesses unlike traditional media which broadcast content to an audience (Alalwan et al., 2017; Kaplan & Haenlein, 2010; Kietzmann et al., 2011). Most social media services are easy to access, in most cases there is no financial requirement for the user (Kaplan & Haenlein, 2010). Furthermore, social media offer the possibility of creation of online communities of individuals with similar interests and goals, such as the love for a particular TV show etc., (Alalwan et al., 2017). Lastly, a big part of the online platforms rely on links to other wedsites, resources, and people to create a sense of coherence and connectedness (Kaplan & Haenlein, 2010).

1.7 Categorization of social media

Social media has become an integral part of our daily lives. As technology advances, the social media platforms are constantly evolving, providing new features and functionalities. It is important to categorize them, as their amount keeps increasing, according to their primary purpose and functionality.

Social Networking Sites (SNS)

Social networking sites are platforms that allow users to create profiles, connect with friends, and share content such as photos, videos, and messages. SNSs are one of the most popular types of social media, with over 3.6 billion users worldwide. Examples of SNSs include Facebook, Twitter, LinkedIn, and Instagram. According to a recent study by Statista, Facebook remains the most popular social network worldwide, with over 2.8 billion monthly active users (J. Clement, 2021).

SNSs are used for many purposes, including social interaction, information sharing, self-expression and professional purposes. Zhang et all, in 2021, confirmed that SNSs are used for both social and professional purposes, with users primarily utilizing them to maintain existing relationships and connect with new people.

Microblogging Platforms

These platforms allow users to share short-form content such as text, images, and videos and they are often used for real-time updates, news, and trends. The most popular microblogging platform is Twitter, which has over 330 million monthly active users. Zhan et all (2020) concluded that Twitter is primarily used for news consumption and is very popular for political communication. Other examples of microblogging platforms include Tumblr and Reddit.

Media Sharing Networks

Media sharing networks are social media platforms that focus on sharing multimedia content such as photos, videos, and music. Examples of media sharing networks include YouTube, TikTok, and Pinterest. According to a recent study by Hootsuite, YouTube remains the most popular media sharing network, with over 2 billion monthly active users. These networks have multiple purposes including entertainment, education, and self-expression. Kim, K. et al, (2021) explored user behaviors on TikTok and found that it is primarily used for entertainment and self-expression purposes, mostly by Gen-Z.

Discussion Forums

Discussion forums are social media platforms that allow users to participate in online discussions on a variety of topics, such as Reddit and Quora and mainly used for information seeking, social support and entertainment.

Blogging Platforms

Blogging platforms allow users to create and share blog posts such as WordPress and Blogger. According to a study by Statista, WordPress powers over 40% of all websites on the internet.

Research has shown that blogging platforms are used for a variety of purposes, including self-expression, professional development, and community building. This is confirmed from a study conducted by Wu and colleagues (2021), in which they found that blogging platforms are primarily used for self-expression and community building.

1.8 Twitter

Twitter is a popular microblogging and social networking service that enables users to distribute short messages, known as "tweets," among groups of recipients via personal computers or mobile phones.

Four people are responsible for the launch of Twitter in 2006, Jack Dorsey, Noah Glass, Biz Stone and Evan Williams. This platform is consisted of multiple elements of social networks and blogs, but with noteworthy differences (Javaid, F., et al., 2021).

Like other social media, Twitter users can “follow” other users and see their posts but the other user can decide if they will follow back. Unlike blogs, Twitter users can not comment on individual posts, the profiles are quite modest and public but there is the option to tweet publicly or within the user’s network.

The account holders are restricted to using 280 characters for their tweets, but they have come up with other practices in order to add structure to their posts. As an example, users began using the *“@user”* syntax, to address other users (e.g., @evangelospapadopoulos). This feature has multiple purposes in Twitter, including the direct messaging to specific people (the @reply)(Li, Y., et al., 2022).

According to Honeycutt and Herring (2009), the @user function is basically addressing a person or indicating the recipients of the messages that are posted, in order to start a conversation. In addition, they mention that this function is mainly intended to seek attention and notify the tagged person that their name is addressed in the platform (Li, Y., et al., 2022).

In general, Twitter remains a very popular platform these days, for spreading information and opinion exchange and has managed to keep its own unique features and conventions. Understanding these features and how they are used can help users make the most of the platform's potential

1.9 Twitter Chronology

The origins of Twitter can be traced back to a meeting of the board members of Odeo, a podcasting company. In 2006, Jack Dorsey, came up with the idea of using SMS so that a person can communicate with a small group. The code name for this service was twttr, which was inspired by the five-digit length of American SMS short codes and the photo-sharing website, Flickr. The original name for Twitter was twitter.com, but the company had to buy the domain name since it was already taken. The name was later changed to Twitter.

The first prototype of Twitter was developed by Dorsey and contractor Florian Weber and was used as an in-house service for Odeo employees. The full version of Twitter became public on the 15th of July, 2006. In October 2006, Biz Stone, Evan Williams, Dorsey, and other members of Odeo became founders of the Obvious Corporation, which acquired Odeo.com and Twitter.com. Twitter became its own company in April 2007.

The milestone for Twitter's popularity was the 2007 South by Southwest Interactive (SXSWi) conference. During the event, Twitter usage increased from 20,000 tweets per day to 60,000.

Twitter has made several acquisitions over the years to expand its offerings. In February 2015, Twitter acquired Niche, an advertising network for social media stars, for $50 million. A month later, in March 2015, Twitter announced the acquisition of Periscope, an application that allows live video streaming. In the same year, Twitter acquired TellApart, an advertising technology company, for $532 million. In June

2016, Twitter acquired Magic Pony Technology, an artificial intelligence technology company, for $150 million (wikipedia.com).

1.10 Social media and the correlation with a company's revenue

Nowadays, social media are a separate and respected part of the marketing mix for businesses across various industries. Most of the companies now use these platforms for customer engagement, build brand awareness, and increase sales. As a result, researchers have explored the correlation between social media use and a company's revenue.

Willemsen, Neijens, and Bronner (2020) examined the footprint of advertising in social media platforms on consumer behavior & brand loyalty and found that social media advertising positively influences brand loyalty and purchase intention, which can ultimately lead to increased revenue for companies.

Xie & Xie (2020) investigated the relationship between social media and brand performance. They argue that social media can be a beneficial tool for business, as it gives them the opportunity to connect with customers and gather their feedback, which eventually leads to product improvement and the overall performance.

Additionally, a study by Huang and Benyoucef (2019) investigated the correlation between social media marketing and the company's performance. What they found confirmed the positive effectiveness of social media marketing to a company's financial performance, especially for those with high levels of customer engagement.

These studies suggest that social media can have a positive impact on a company's revenue and performance. By engaging with customers and leveraging social media platforms for marketing and advertising, businesses can improve brand loyalty, increase sales, and ultimately boost their bottom line.

Chapter 2. Sentiment Analysis

2.1 Introduction

Sentiment analysis has its roots in the analysis of public opinion, dating back to the early 20th century, and the analysis of subjectivity in text in the 1990s (Wiebe, Wilson, & Cardie, 2005). Recently, a growing interest has emerged towards emotion analysis, especially with the high volume of available online comments on the internet and social media platforms (Pang & Lee, 2008).

Opinion, sentiment, and the related concepts, such as evaluation, appraisal, attitude, and emotion demonstrate a key role to human psychology and are key influencers of behavior (Scherer, 2001). People's opinions are influenced to a great extent by how others see and perceive it. Therefore, individuals' perceptions of reality and their decision making are conditioned to a certain extent by how others view the world (Rosenthal, 2019).

When it comes to the application part, it is only natural that individuals and organizations wish to gather different points of view and feelings from strangers on the subjects that are considered popular, in the eyes of the public, which makes them the focus of the sentiment analysis. The distinction between emotion analysis and knowledge mining is not always clear, and their meanings are often interchangeable (Liu, 2012).

The interest in other people's knowledge can be traced back to the first organized societies. Leaders have always sought to maintain or increase their popularity, and one tool that can be used for this purpose is to collect information regarding the opinion of their subordinates. Voting to determine common desires was first used in the 5th century BC, while the first trend-setting questionnaires appeared in the early 20th century (Rosenthal, 2019).

The first academic studies to determine public opinion were conducted during World War II for political purposes. In the middle of the last decade, the primary purpose of sentiment analysis was to evaluate and upgrade online products and services. The technology that has developed on the internet, the rise of new techniques for shaping web content by users, and social networking have led to the expansion of the use of emotion analysis for other purposes, such as predicting the possible future direction of financial markets, public acceptance of products or services, anticipation of reactions to abrupt situations, and political and social changes (Mäntylä, Graziotin, & Kuutila, 2017).

In the past few years, there have been many challenges when it comes to emotion analysis, for example the detection of more complex emotions, the metaphorical use of words and the adaptation of different languages.

Other researches have investigated plenty of applications of sentiment & emotion analysis. For example, Pitsilis et al., (2021), identified online hate speech, while Lopez et al., (2021) worked on predicting the emotional states of individuals. Johansson & Nygren (2019) used sentiment analysis to explore and analyze the sentiment of political tweets. Researchers have also explored the potential of incorporating physiological signals and facial expressions into emotion analysis (Shin et al., 2019; Vukovic et al., 2021).

Sentiment analysis and emotion analysis have a long history and have evolved significantly in recent years due to the fact that there are more and more available subjective texts online. These analyses have significant impact in many fields like marketing, politics, psychology etc. While challenges remain in detecting more complex emotions and adapting to multi-lingual sources, researchers continue to develop new methods and explore innovative applications for sentiment and emotion analysis.

2.2 Description & Definitions

Sentiment analysis, also known as opinion mining, is a field of natural language processing that includes identifying and extracting information from written language, including individual opinions, attitudes and emotions. With the development of social media networks and the amounts of data that are available, sentiment analysis has become an essential tool. The methods of applying this tool expands beyond computer science into other fields, as mentioned above, due to its significance for society and businesses (Pak & Paroubek, 2010).

According to Liu (2012), sentiment is a quintuple that includes an entity (e), an aspect of the entity (a), the sentiment on the aspect of the entity (s), the opinion holder (h), and the time when the opinion is expressed by the holder (t). The sentiment can be positive, negative, or neutral and may be expressed using a numeric rating system (e.g., 1-5 stars), such as in review sites like Google and Amazon. The entity can be a product, service, topic organization, or event.

Emotion analysis is a composition of methods that identify, measure and utilize attitudes, opinions and emotions from online data (Grimes, 2008). The terms “sentiment analysis” and “opinion mining” are often used as alternatives for one another, but “opinion mining” specifically seeks to determine an individual’s attitude for a specific object.

In recent years, sentiment analysis has been applied in various industries, including finance, healthcare, and politics, among others (Hutto & Gilbert, 2014). Its usefulness extends beyond identifying public sentiment towards brands and products but also in identifying and managing mental health conditions (Cohan et al., 2021).

2.3 Different Levels of analysis

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

2.3.1 Document Level

Sentiment analysis in a document level involves analyzing an entire document as a single entity, assuming that the text contains only one opinion and carries a single emotion. The primary objective of this method is to identify and quantify the overall emotion conveyed by the text, such as a product or film review. However, this approach has certain limitations as it fails to capture multiple opinions expressed in the same text. For instance, in a movie review, the critic may appreciate the actors' performances but criticize the direction and script, leading to mixed opinions. As a result, the negative aspects might overshadow the positive ones, resulting in a negative rating for the film (Kokkinis, G., Papadimitriou S.E., 2021).

Despite its limitations, document-level sentiment analysis is relatively simple to implement, requiring modeling of only a few properties. Recent academic studies have also highlighted the significance of document-level sentiment analysis for various applications, including political analysis, social media sentiment analysis, and stock market prediction (Cui et al., 2021; Li et al., 2020; Zhang et al., 2021).

2.3.2 Sentence Level

In this level of analysis, the focus is on identifying the emotion expressed in each sentence and associating it with the relevant entity or topic. Unlike document-level analysis, this approach allows a more detailed examination of the text and the recognition of multiple opinions and emotions within a single document.

The sentence-level is associated with the problem of identifying the subjectivity, which involves determining whether a sentence expresses an opinion or a fact. By identifying subjective sentences, sentiment analysis can be performed only on the relevant parts of the text. Aiming on evaluating whether a sentence is objective, e.g whether it simply records an event ("The sea is blue") or if it contains an opinion ("The new iPhone is beautiful").

Studies from Chen et al. (2021), Li et al. (2020), and Zhang et al. (2021) examine different techniques for sentence-level sentiment analysis and subjectivity detection.

These studies examine methods such as neural networks, machine learning algorithms, and lexicon-based approaches to improve the accuracy and efficiency of sentiment analysis at the sentence level.

2.3.3 Aspect Based Level

The aspect-based level is considered the most difficult for the reason that in the previous two levels of analysis, researchers make some assumptions, like how many opinions a text contains in order to simplify the problem. This level though, conflicts with indirect references and similar mentions of different aspects, making accurate identification difficult.

Research has addressed these challenges by developing novel techniques for entity and aspect identification. Deep learning-based methods have been shown to improve performance in identifying entities and their associated aspects (Zhang et al., 2020). Researchers have also used domain-specific models to improve the accuracy when they apply aspect extraction (Wang et al., 2021). Additionally, methods such as co-reference resolution and semantic role labeling have been used to improve the accuracy of identifying entities and their associated aspects (Bian et al., 2021).

2.4 Sentiment Analysis Approaches

In this section we will explore the different approaches to sentiment analysis. The approaches are categorized based on the methodologies in use. Important criterion in the clustering of the approaches is how they manage features of natural language modeling. Figure X shows the hierarchy of the various techniques. These can be divided into Machine learning (supervised and unsupervised) and Semantic Orientation (unsupervised).

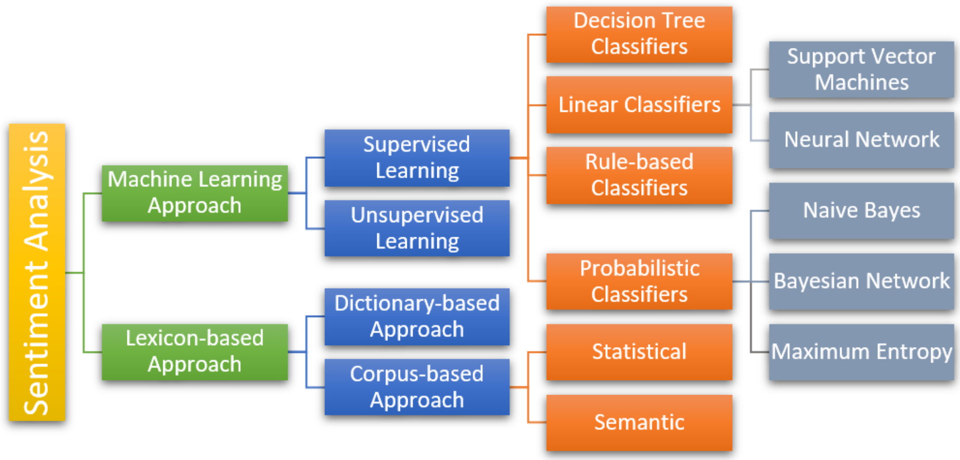


Figure 1. Different Approaches of Sentiment Analysis

2.4.1 Machine Learning

The goal of machine learning is the development of algorithms that allow machines to learn tasks through data, without depending on specific programmed instructions. This can be achieved by creating statistical models based on data features. Features are properties of entities that are measurable, and the goal is to select or extract representative features that can be used to recognize patterns in the data.

The research in the field of machine learning has developed innovative techniques for feature selection and extraction, such as deep learning-based methods and ensemble methods. Deep learning-based approaches have been shown to improve performance in various machine learning tasks (Goodfellow et al., 2016). Ensemble methods, which combine the results of multiple machine learning models, have also demonstrated improved performance in various domains (Zhou et al., 2021). Additionally, researchers have explored novel feature engineering techniques, such as autoencoders and generative adversarial networks, to extract informative and meaningful features from complex data (Wang et al., 2021).

The techniques of machine learning are divided into three main subcategories, the supervised, unsupervised and reinforcement learning techniques. In the first subcategory, the examples in the data (the result or its class) is known, for example which number is displayed in the image, whether an email is spam or not etc.). Based on this information, in combination with the features, the result is a corresponding statistical model. In contrast to unsupervised learning techniques, the goal is to discover structures and patterns in the data (e.g. clustering), without knowing how many there are or if they exist. Additionally, reinforcement learning is in a sense unsupervised learning, in the sense that no 'labels' are given to the model. In this case, a reward function is created that gives a positive or negative reward to the algorithm agent, depending on the action it takes in each state in the environment. Through repetition, the agent understands the corresponding patterns while trying to maximize its total reward.

These techniques have had their application with sentiment analysis, with each focusing on solving different sub-problems (Kokkinis, G., Papadimitriou S.E., 2021).

For instance, when there is a text classification problem based on emotional orientation (positive, neutral, or negative) the supervised learning techniques are usually preferred. In supervised learning, sets of documents, sentences and single words are used, for which their orientation is known. The model learns to recognize the emotions of new texts, based on the patterns found in the previous materials.

For problems such as the production of summaries of opinions expressed on a text, unsupervised learning techniques are used (e.g., customer segmentation). This is because in these types of problems, it is difficult to produce recorded data (Pang et al. 2002; Hu M. & Liu, B., 2004; Zhuang et al., 2006).

2.4.2 Semantic Orientation

Semantic orientation assumes that the sentiment of a text (positive, neutral, or negative) is ascertained by the combination of the sentiment of individual words/phrases within the text. It involves the procedure of deciding the sentiment orientation of each term in the text. Once the sentiment of each term is known, they are combined to determine the overall sentiment orientation of the whole text, whether it is a sentence, document, or phrase.

This sentiment analysis process can be clustered in two groups: (1) corpus-based, which is based on a large corpus of text and uses statistical methods to identify sentiment patterns, and (2) lexicon/dictionary-based, which involves predefined lists of words with associated sentiment values.

Sentiment analysis papers have explored the success of deep learning models (neural networks, recurrent neural networks) in an attempt to improve the accuracy of sentiment analysis (e.g., Wang et al., 2021; Zhang et al., 2021). These studies concluded that deep learning models can outperform traditional machine learning algorithms in sentiment analysis tasks.

2.4.2.1 Corpus Based

The corpus/text based approach to sentiment analysis is based on the assumption that when a word co-appears, more often with more positively oriented words (e.g., beautiful), its value tends to be positive as well. The same applies with the negative oriented words (e.g., ugly).

In this approach, a set of words, for which the researchers already know the orientation, is selected, which belongs to one of the two classes (positive or negative). However, we need a significant amount of text data to ensure the reliability of the statistics and to identify the sentiment orientation of each word.

One additional issue with the text-based method is the assumption that the orientation of a word is one-dimensional. Basically, it means that the orientation for a word is fixed, regardless of the context that is used. In reality, however, this does not happen because the positiveness or negativeness of a word, changes depending on the conceptual context and the domain it refers to. For example the word “cheap” can have a positive orientation when it is used to describe a low budget product and a negative orientation when used to describe a low-quality product.

Chen et al., (2021) and Liu et al., (2021) have explored new ways of improving the accuracy of sentiment analysis by using more advanced machine learning techniques like deep neural networks. In their work, they proved that deep learning models can indeed capture different relationships among the words (and their sentiment) and consequently can have better results compared to the traditional machine learning algorithms.

2.4.2.2 Lexicon Based

In this approach, pre-made dictionaries are used, in which for each word we are aware of its semantic orientation. Such dictionaries are, for example WordNet, SenticNet, TextBlob etc. The dictionaries use a pre-defined list of words and their sentiment polarity in order to analyze the sentiment of a text as well as its intensity. The sentiment polarity values in TextBlob are either positive, negative, or neutral. Unlike the text-based approach, the dictionary-based approach relies on the pre-existing values assigned to each word in the dictionary (Mohammad et al., 2013; Bradley and Lang, 2007; Warriner et al., 2013).

One problem with the lexicon-based approach is the need for a dictionary that covers multiple fields. The solution to this is the combination of individual dictionaries from different domains or the creation of a dictionary specifically designed for a certain purpose, using machine learning techniques (Balamurali and Dhanalakshmi, 2021; Agarwal et al., 2021).

The advantage of these techniques is that they do not require the creation of a statistical or machine learning model. These days there are many open-source lexicons available to the public, which makes sentiment analysis more accessible. Some people may argue that it is relatively easy to utilize and implement these approaches. T

However, semantic orientation approaches have been "accused" of being biased towards the "positive" direction. The main reason for that is because people tend to use more positive words when they wish to express themselves (Kokkinis G., Papadimitriou S.E., 2021). Exceptions might include reviews related to customer satisfaction, in many cases in the form of Tweets, because customers are more likely to express negative sentiment towards a product or service that did not satisfy them enough, but to express a possible positive sentiment experienced by the use of the product.

Chapter 3. Lufthansa & Swiss International Airlines

Lufthansa is a German airline holding company that is based in Cologne, Germany. From a European perspective, it is the largest airline, in terms of the number of passengers carried and fleet size. The Lufthansa group is composed of the following airlines: Lufthansa, Swiss International Airlines, Austrian Airlines, Eurowings and Brussels Airlines.

The Lufthansa Group has been recognized for its leadership in the aviation industry, as evidenced by its ranking as the world's seventh largest airline by revenue, and its recent inclusion in the Dow Jones Sustainability Index for the 18th consecutive year. Lufthansa's strong brand reputation has also been recognized by Forbes, which ranked it as the ninth most valuable airline brand in the world in 2021.

In terms of financial performance, Lufthansa Group has faced challenges due to the COVID-19 pandemic, which led to a significant decline in demand for air travel. In 2020, the Lufthansa Group reported a net loss of €6.7 billion, in comparison to 2019's €1.2 billion profit. However, the company has been taking measures to recover from the pandemic, such as reducing its costs, renegotiating contracts with suppliers, and expanding its cargo business.

One of the key strengths of Lufthansa Group is its focus on sustainability. The company has set a goal of becoming climate-neutral by 2050 and has been working on several initiatives to reduce its carbon footprint. For example, they have been investing in more fuel-efficient aircraft, using sustainable aviation fuels, and implementing measures to reduce energy consumption and waste generation.

In terms of organizational structure, Lufthansa Group has a decentralized structure, with each of its subsidiaries having a level of autonomy. This has allowed the company to tailor its operations to the specific needs of each market and improve its customer service.

On the other hand, this structure also poses challenges in terms of coordination and cost management. According to the paper by Frenzel and Koens (2017), the company's focus on cost-cutting measures had a negative impact on its service quality and customer satisfaction. Another study by Hu and Zhang (2020) pointed out the challenges of managing a decentralized organization and the need for effective communication and coordination. The Lufthansa Group is a major player in the global aviation industry, with a strong brand reputation and a focus on sustainability.

Swiss International Airlines

Swiss International Airlines, or Swiss, is the national airline carrier of Switzerland. The company was established in 2002, after the bankruptcy of Swissair, and it is a subsidiary of the Lufthansa Group.

It operates a global network of flights to over 100 destinations in around 50 countries. It is primarily based at Zurich Airport, it is mostly known for its high level of service and reliability, and it is awarded multiple times for its customer satisfaction and operational excellence.

The company operates a fleet of around 90 aircraft, consisting of Airbus A220, A320, A330, and A340 aircraft. It also has codeshare agreements with several other airlines, including Lufthansa, United Airlines, and Singapore Airlines, allowing the passengers to connect with a wide range of destinations around the world.

Swiss Airlines has made a commitment to sustainability and reducing its environmental impact. Like Lufthansa, the company has implemented several measures to reduce carbon emissions and promote sustainability, including investing in new, more fuel-efficient aircraft, optimizing flight routes and operations to minimize fuel consumption, and implementing waste reduction and recycling programs. Swiss is a member of the IATA's (International Air Transport Association) Carbon Offset program, which offers the passengers the chance to offset the carbon emissions of their flights by supporting sustainable projects.

Chapter 4. Pearson's correlation - R Squared - Linear Regression

In this study we will use Pearson correlation in an attempt to quantify the relationship between the tweets for the two airlines and their revenue for the same time period.

Scatter plot is a tool for identifying the relationship between two variables and is mainly used for examining the dependency of two variables and non-linear regression for a dataset (Dastmard B., 2013)

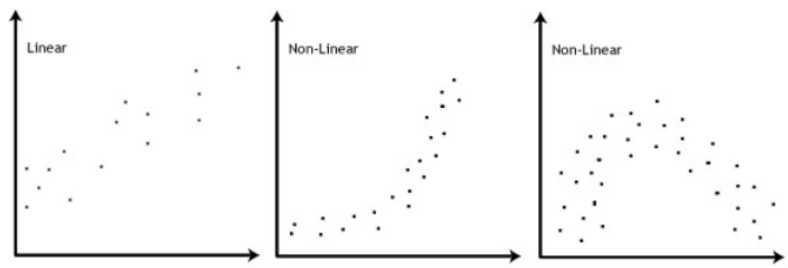


Image 1. Scatter plots of different dependencies

Different scatter plots are illustrated in image 1 and the linear relationship can be quantified by using Pearson's correlation under certain assumptions.

Pearson's correlation is a statistical measure of linear dependence between two variables X and Y. The coefficient p has a range between -1≤ ρ ≤ +1 for the true population. Perfect positive on negative linear coefficient equals 1 or -1, which means that the data should align exactly on the line. Pearson correlation has the following properties and makes these assumptions about the variables X and Y (Dastmard, 2013).

$$\rho_{X,Y} = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}$$

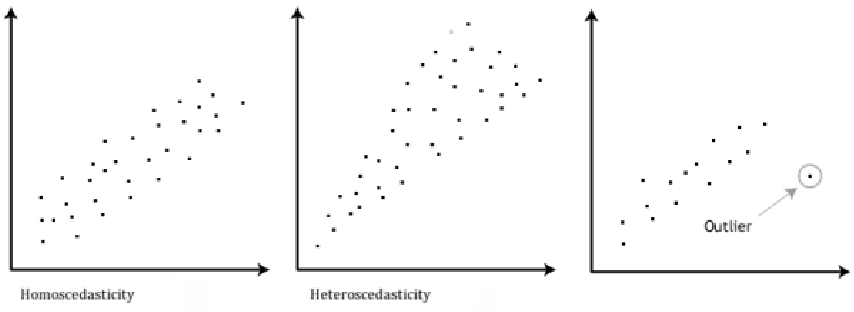


Image 2. Illustration of homoscedasticity and outlier in scatter plots

- X and Y show homoscedasticity which can be observed in figure x. The variances along the line of best fit remain similar as we move along the line. In other words, it is invariant under strictly increasing transformation. $\rho(aX + b, Y) = \rho(X, Y)$ if $a > 0$ and $\rho(aX + b, Y) = -\rho(X, Y)$ if $a < 0$
- If X and Y are independent, this implies $\rho(X, Y) = 0$ but not the converse.

Regression is a statistical model that is used to assess the relationship between variables and to predict scores on a variable given scores on other variables (Mantzaris, A., 2017).

Linear regression can handle only one independent variable X and a dependent variable Y, which is expressed as a linear function of X.

The value yi of variable Y, for every value xi of variable X, is given by the following equation:

$yi = \alpha + \beta xi + i$

Parameters α and β express the linear dependence of the dependent variable Y from the independent variable X in the best way possible. Every pair of values α,β determines a different and separate linear relationship geometrically expressed by a straight line and the parameters of the equation are defined as follows:

• The constant term α has the value of y for x = 0.

• The factor β of x is the slope of the straight line, in other words the regression coefficient. It expresses the change of variable Y when variable X changes by one.

• The random variable i represents the regression error and is defined as the difference between the actual value of Y and the predicted value of Y (Mantzaris, A., 2017).

R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of multiple determinations for multiple regression or as the coefficient of determination. It is the percentage of the response variable variation that is explained by a linear model. R − squared = Explained variation Total variation R-squared is always between 0 and 100%. 0% means the model explains none of the variability of the response data around its mean. 100% indicates that the model explains all the variability of the response data around its mean. Generally, the higher the R-squared, the better the model fits the data (Frost, 2013)

Chapter 5. Application of Sentiment Analysis on Twitter posts

5.1.1. Data Collection

For this paper, we have collected data from Twitter via a text scraping library in Python, called snscrape. This library provides the functions necessary to collect data from a variety of social media, including Twitter. The library provides the flexibility to adjust the scraping procedure by selecting between three different scanning options: keyword search, username search, and hashtag search. In this work, we have opted for selecting the first method, using the Twitter username of each airline as a filter criterion. By customizing our search parameters to use the username, we are able to include the remaining two search categories at the same time, as the whole text is scanned, including hashtags and handles.

The reasoning behind selecting Twitter amongst the various social media that are currently in use, is the large volume of text data being published every day, in contrast with the majority of social media, in which the posts are centered around multimedia, such as video content. Moreover, the 280 character limit set by the platform, combined with the spontaneous publishing of Tweets, when users encounter a situation, have formed the basis of having high volumes of information-rich content available for analysis Furthermore, Twitter data are easily accessible via the company's API (Application Programming Interface), and in parallel, many scraping and downloading frameworks have been developed over the past years.

5.1.2 Description of the initial data sample

As described above, we have used a text scraping library in python to collect data from Twitter, by using the official username of the two companies as a search term. For reference, the official accounts of the two airlines can be identified by the following handles: @lufthansa for Lufthansa (LH), and @FlySwiss for Swiss (LX) airlines.

The total number of Tweets sampled, before the basic cleaning is conducted, is 799.744 non distinct Tweets, spanning in the years 2018, 2019 and 2022.

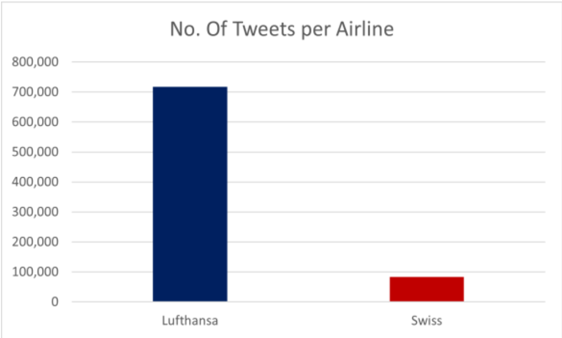


Figure 2. No. of Tweets per Airline before cleaning

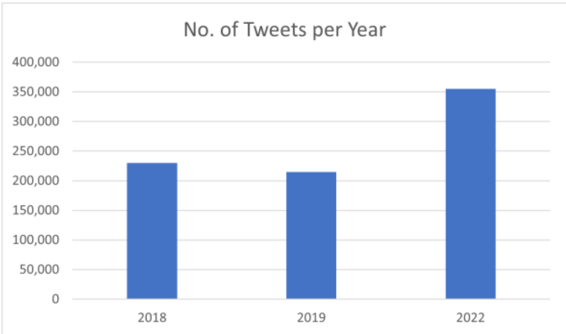


Figure 3. No. of tweets per year before cleaning

The initial pieces of information that can be extracted from the above figures, is that the majority of tweets (approximately 90%) are related to the Lufthansa account, while the tweets referring to Swiss airlines comprise only the remaining 10% of the sample.

This large difference is expected, since Lufthansa possesses a larger fleet of aircrafts, operates more flights with a larger number of passengers, and to a wider range of destinations. Therefore, a higher volume of tweets is expected, as its client base is larger than the one of Swiss airlines.

In the yearly distribution presented on Figure 3, we can notice that approximately half the sample concerns 2022 data. A possible justification would be that airlines are still encountering many challenges while recovering from the Covid-19 crises, which might prompt users to complain by using Twitter. Furthermore, as the Covid-19 restrictions have mostly ceased to exist worldwide, customers might be trying to compensate for the time they have spent under lockdowns, and thus using the airline services to travel.

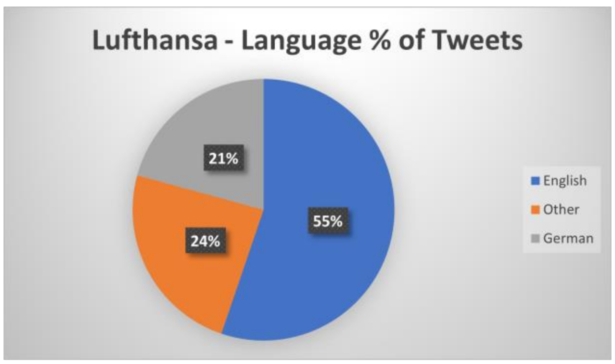


Figure 4. Language Distribution-LH

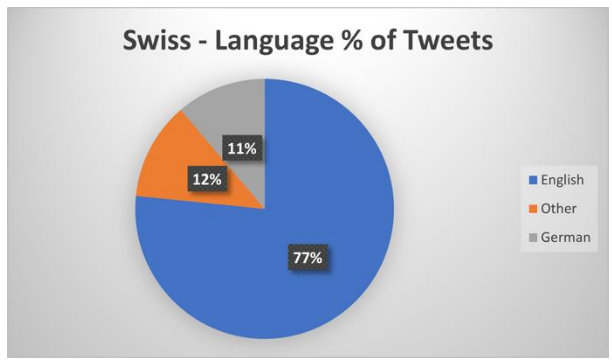


Figure 5. Language Distribution - LX

Regarding the language distributions presented above, English language tweets are predominant in both samples, while the ones written in the German language are following in the second place. Those observations can be rationalized by the fact that English is the universal language of communication, while on the other hand both airlines are the flagship carriers of two German-speaking countries. Specifically, as shown in figures 4 and 5, 55% of Lufthansa's tweets were in English, 21% were in German and the remaining 24% were in other languages. For Swiss airlines, we observe that 77% of the tweets were in English, 11% in German and 12% in other languages.

5.1.3 Data Cleaning

The cleaning procedure applied in the data can be summarized by the list of actions outlined below:

- Deduplication of the dataset by using two main dimensions: the Twitter ID, which is also used as a primary key of the database and the text of each tweet.
- Removal of tweets that contain only emojis, links, pictures or mentioning usernames.
- Removal of all the Tweets that are written in a language different than English and German.

- Removal of irrelevant tweets, that happened to include the specific keywords but are referring to a different subject (e.g., Swiss cheese).

In addition to the above, we applied the following cleaning procedure to the text of the remaining tweets in order to have a more concrete result in the sentiment analysis:

- Removal of hyperlinks.
- Removal of the hashtag symbol and its corresponding text
- Removal of mentions, special characters, numbers, and punctuation.
- Conversion of the text to lowercase.

The reasoning behind including only English and German tweets in the analysis, is that as those are two of the most popular languages, it is guaranteed that accurate lexicons and libraries can be found for analyzing them. Moreover, as they comprise 77,2% of the sample, we are able to still retain most of the information.

5.1.4 Data exploration and descriptive results

After applying the cleaning methodology described in the previous chapter, 617.413 clean and distinct tweets remain for analysis, written either in the English or in the German language.

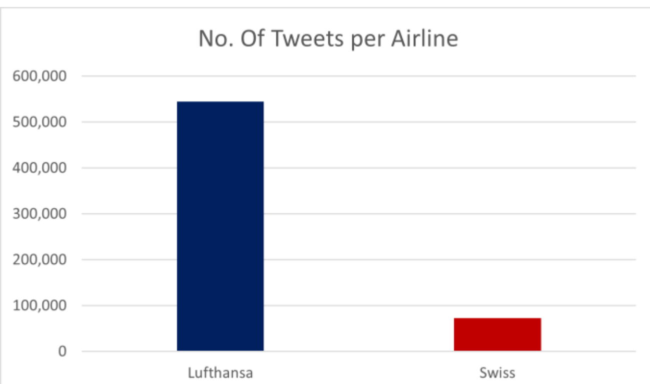


Figure 6. Number of Tweets per Airline after cleaning

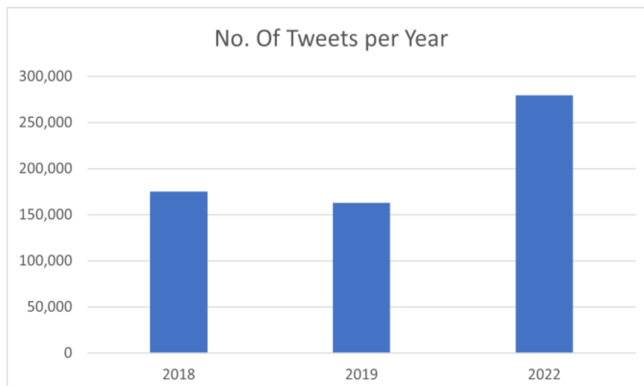


Figure 7. Number of Tweets per Year after cleaning

While a considerable proportion of the initial sample has been removed, the remaining data are still following the same distributions, against the airline and year dimensions.

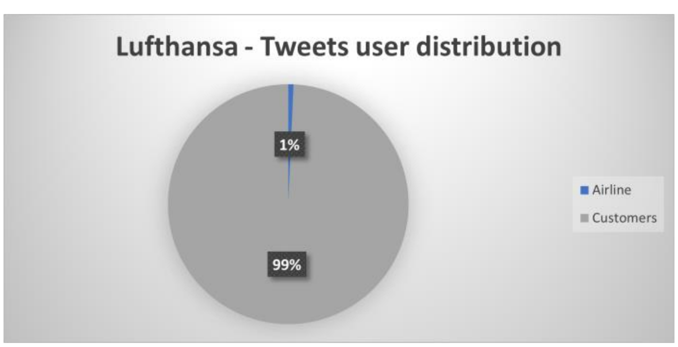


Figure 8. LH-Tweets-User distribution

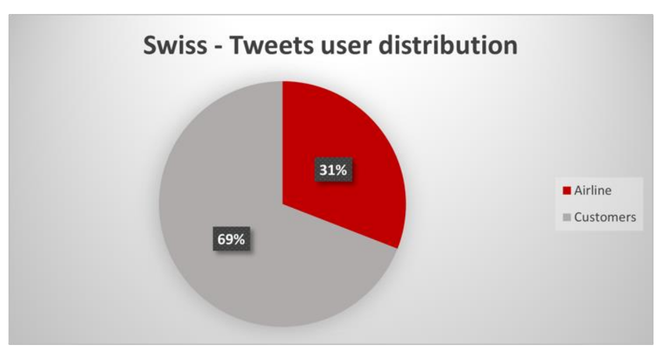
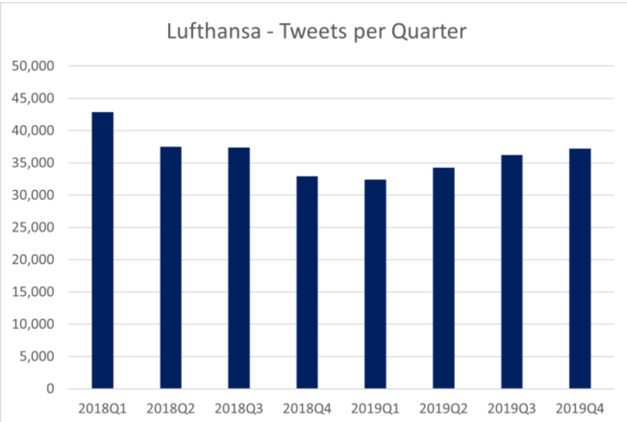


Figure 9. LX-Tweets-User Distribution

Concerning the user distribution of the tweets, Figures 8 and 9 showcase that 99% of Lufthansa's tweets come from the users while for Swiss the percentage of user tweets is 69%. A hypothesis that could justify such a large discrepancy between the two airlines, is that Swiss airlines have a more active Twitter account that could be used for performing activities related to customer satisfaction, such as managing complaints, assisting with possible issues, etc. - when necessary- or for marketing purposes. Regarding the minimal participation of Lufthansa's account in the total tweets, we could also assume that as their customer base is far larger, an analogous volume of tweets is to be expected.



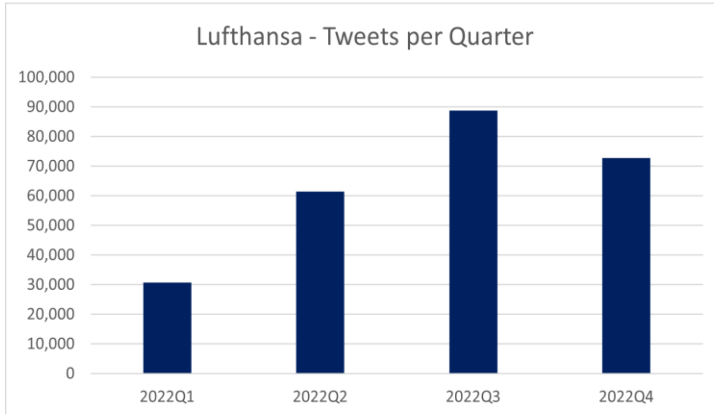


Figure 10b. LH-Tweets per Quarter 2022

Figure 10a. LH-Tweets per Quarter 2018 & 2019

Figure 10 depicts the quarterly distribution of Lufthansa related tweets. The general trend that we can observe is that the volume of tweets is highly seasonal, with the largest proportion of tweets being predominantly in the second and third quarters of every year, with the exceptions of Q1 2018 and Q4 2019.

Given the fact that the airline sector is characterized by high seasonality, especially centered around the summer months, the volume of tweets on Q1 2018 was unexpected.

What might have played a role in the number of tweets for that quarter, is the expansion of the airline's fleet and the addition of new destinations that Lufthansa announced at that time. Concerning the fourth quarter of 2019, which also presented a high volume of tweets, the fact that during that time the company faced some labor disputes with its employees, leading to flight cancellations and disruptions, could be a possible justification. Those events might have caused a decline in customer satisfaction, which could have been expressed on Twitter. As for 2022, the behavior on Twitter in terms of quarterly tweets, was expected. The world was still recovering from Covid-19, and that would explain the low number of tweets for Q1. The third quarter holds the most tweets due to the summer period.

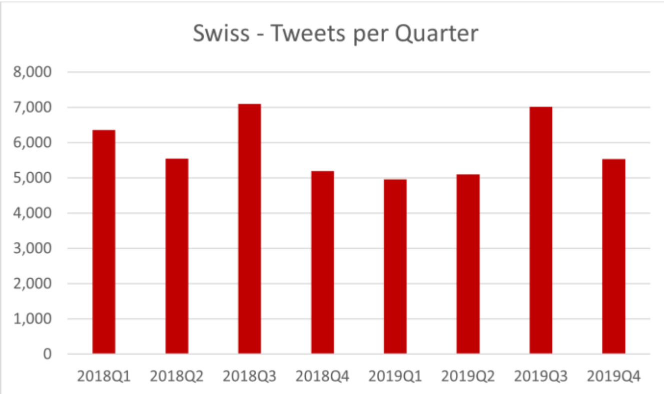


Figure 11a. LX - Tweets per Quarter 2018 & 2019

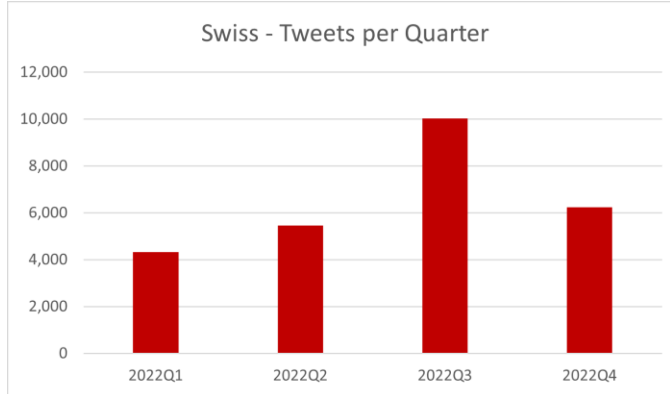


Figure 11b. LX Tweets per Quarter 2022

In Figure 11, the quarterly tweet volume for Swiss International Airlines is presented. We observe that for all the years (2018, 2019 & 2022), Q3 has the highest number of tweets, while together with the rest of the quarters, they follow a similar seasonal trend with Lufthansa’s volumes. Specifically for 2018, the company expanded its fleet in Q3 (https://www.planespotters.net/airline/Swiss) and won Europe's Leading Airline - Economy Class 2018 (https://www.worldtravelawards.com/award-europes-leading-airline-economy-class-2018) which could explain the number of tweet posts.

5.2 Sentiment Analysis

5.2.1 High-level aggregates

In this work, we have performed sentiment analysis on a sentence level, on the Twitter data described in the chapters above. To calculate the polarity of each tweet, we have used a lexicon-based approach, in which a pre-defined sentiment lexicon is used to calculate the polarity score of a sentence, by aggregating the sentiment score of its components. Specifically, we used the very popular and open-source Lexicon Textblob, which offers both English and German versions.

Moving forward, we are going to present the most important results obtained from the sentiment analysis of the data, such as the percentage of the three sentiment categories (positive, negative and neutral), and the percentages of those categories in the customer and airline subsets. Moreover, we will present the quarterly polarity score for both companies. Finally, we will continue with presenting the polarity scores and sentiment category distributions for both airlines, while excluding all neutral sentiment tweets, as well as those posted by the airline’s account, in order to achieve a more accurate estimate of customer opinion.

Regarding the sentiment categories outlines in the charts below, the classification has been conducted as follows:

- Positive: Polarity > 0
- Negative: Polarity < 0
- Neutral: Polarity = 0

Figure 12 shows the aggregated sentiment from the whole Lufthansa sample. The dominant sentiment is

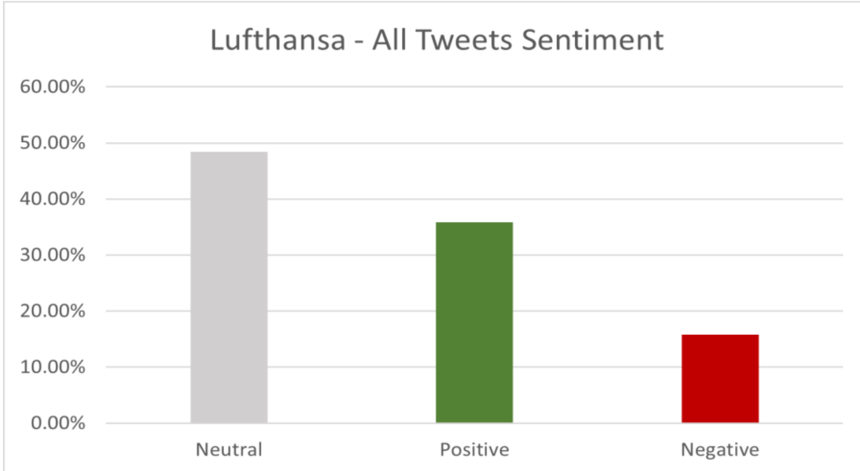


Figure 12. LH Sentiment Percentage of all Tweets

neutral, which means that most tweets either do not contain any sentiment and mostly refer to facts, or the net polarity score sums to zero. The positive sentiment comes second with a difference of approximately 12,5%, while the negative category is last with a participation of 15,8%.

In Figures 13a and 13b, we observe the sentiment percentage for Lufthansa divided by the users' sentiment (13a) and the sentiment percentages from the airline's Twitter account (13b). For Figure 13a, almost half of the sentiment is composed by neutral tweets (48,5%), followed by positive sentiment (35,8%) while the negative sentiment is last (15,65%). Although the neutral category is dominant, the difference between the positive and the negative sentiment is quite sizable, which is an important observation, especially because it refers to customer tweets. This observation leads us to the conclusion, that the company maintains a relatively good reputation among Twitter users.

In Figure 13b, the sentiment is extracted from tweets exclusively originating from Lufthansa's account. It is no surprise that the prevalent sentiment is positive (46%), while the negative sentiment comes second, comprising 32,2% of tweets. Finally, the neutral sentiment comes last with 21,6%. While observing tweets with a negative polarity originating from the airline's account is not expected, it can be explained by analyzing the available data. For example, there were cases that the company was referring to events with a negative meaning, such as flight delays, or replied to customer's tweets to apologize for an inconvenience, such as a flight cancellation or lost luggage.

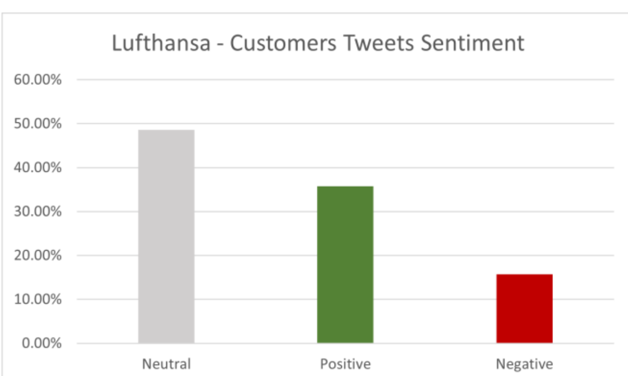


Figure 13a. LH Sentiment Percentage-Users

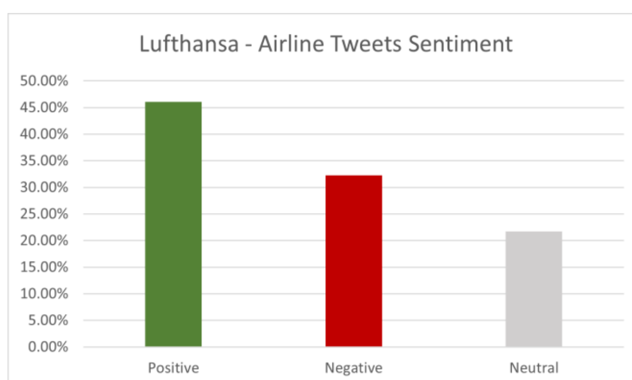


Figure 13b. LH Sentiment Percentage-Airline

In figure 14, we examine the sentiment percentage from Swiss users and the company's Twitter account. In this case, the positive category dominates with 52%, followed by neutral with 30% and the negative with only 18%. The predominant positive sentiment can hint that the company maintains a good relationship with its followers and that the company strives to have positive communication on the platform.

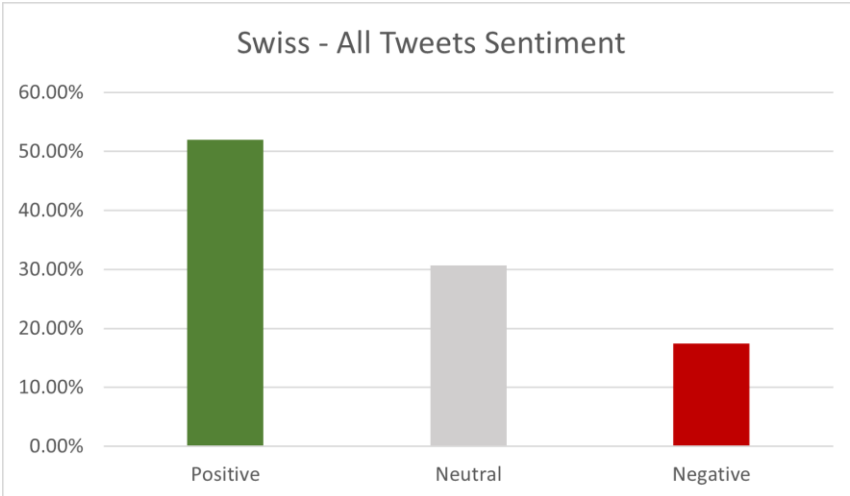


Figure 14. LX Sentiment Percentage of all Tweets

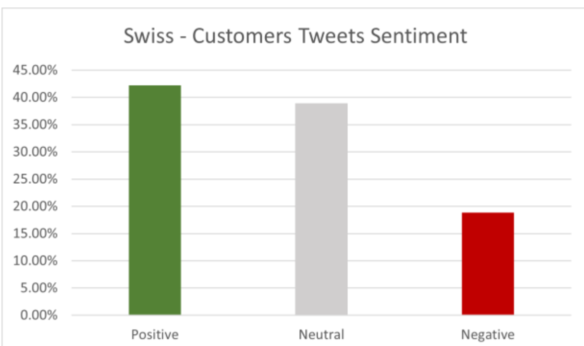


Figure 15a. LX Sentiment Percentage-Users

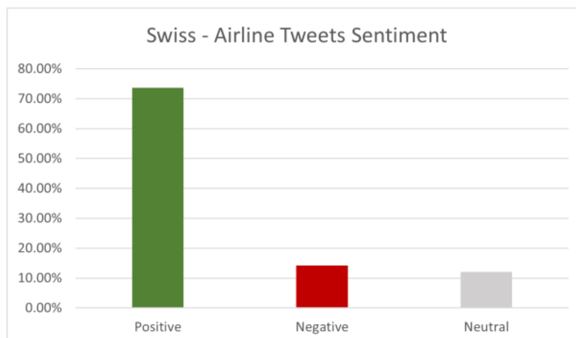


Figure 15b. LX-Sentiment Percentage-Airline

In the above figures we present the sentiment percentage of the users and the company separately. Specifically, in Figure 15a, which refers to customer sentiment, the positive sentiment ranks first with 42,2%, while the neutral category ranks second with 38,9% and the negative is last with 18,9%. The sentiment category distribution shown in the chart, confirms the main observation outlined in figure 16, concerning the good relationship of the company with its customer base.

Regarding the sentiment calculated from the airline related tweets in Figure 15b, it is no surprise that the positive tweets comprise the vast majority of the sample. Specifically, the positive tweets constitute approximately 74% of the total, while the negative and neutral categories follow with 14,2% and 12,1% respectively. If we compare the results for the two airlines, we can draw two conclusions. First, Swiss might have a more positive response to a user's tweet, with less negative words. Second, as the two companies differ in fleet and network size, and as a result, Lufthansa has a vastly larger passenger base, it makes it more susceptible to receive customer feedback on Twitter.

5.2.2 Temporal evolution

The main focus of this work is to attempt to create a quantitative relation between the polarity scores, and revenue figures of each airline. In order to achieve this, it is of paramount importance to analyze the temporal evolution of polarity scores. In Figures 16a & 16b, and 17a & 17b, we present the polarity score for both airlines in the years 2018, 2019 and 2022, broken down by quarter.

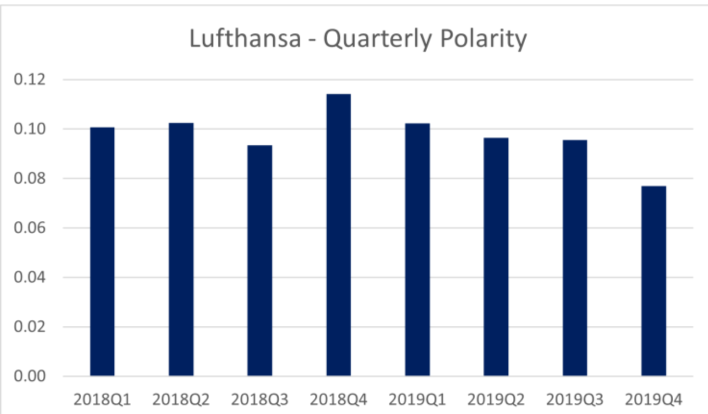


Figure 16a. LH-Polarity per Quarter 2018 &2019

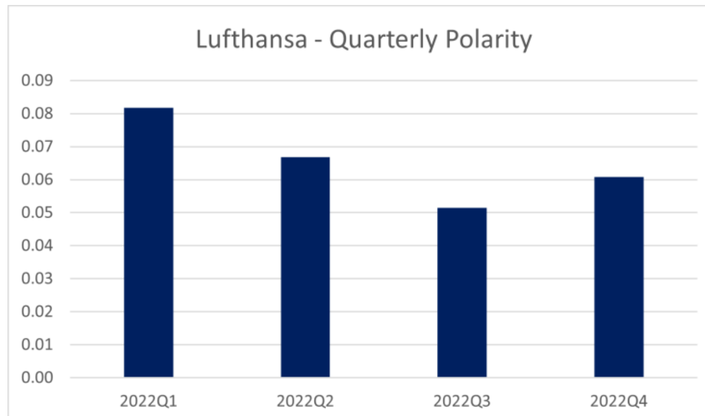


Figure 16b. LH-Polarity per Quarter 2022

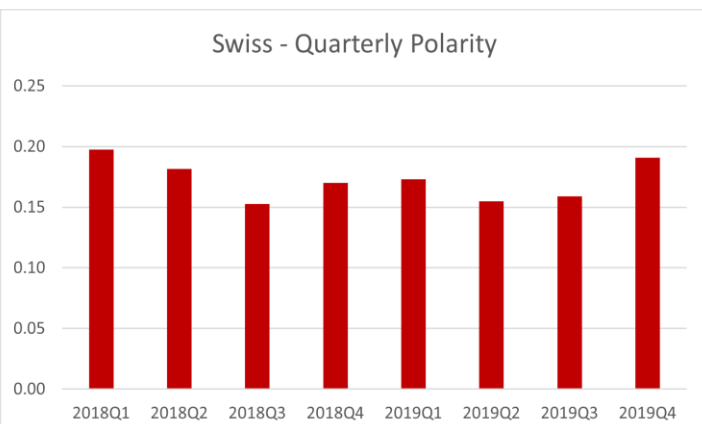


Figure 17a. LX-Polarity per Quarter 2018 &2019

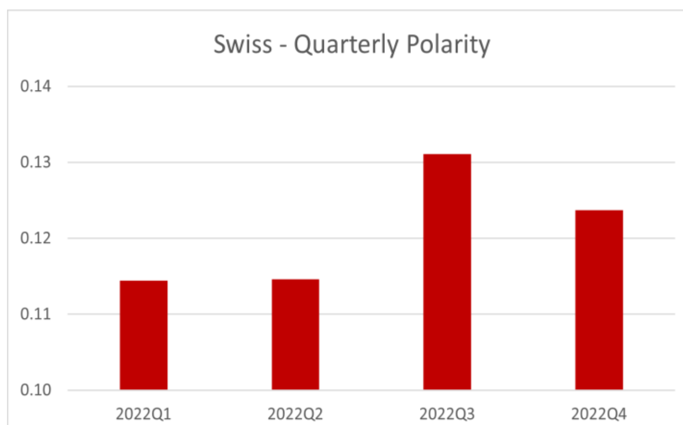


Figure 17b. LX-Polarity per Quarter 2022

The main observations extracted by the above charts can be summarized by the below statements:

- The polarity score for all quarters, and both companies, is positive but very close to zero. This means that while a 'mildly positive' score is observed, having a score range that close to neutral means that the net result of any positive or negative opinion is almost 0, which hints that events with very strong and lasting effect are needed to affect it.

- The variation between quarters is very small, if examined in absolute numbers, and it does not follow a strict seasonal trend.

For example, in Figure 16a, Q4 of 2018 has the biggest polarity score of that year (0,11) followed by Q1 of 2019 with 0,10. As for 2022, in Figure 16b, Q1 has the highest score (0,8) compared with the other quarters of that year.

Regarding Swiss airlines, in Figure 17a, Q1 of 2018 seems to be the most successful with a polarity score equal to 0.20 and Q4 for 2019 with a score of 0,19. For 2022, (Figure 17b) Q3 scored the highest with 0,13, followed by Q4 with 0,12, while Q1 and Q2 scored the same (0,11).

In an attempt to dive deeper in the dynamics of the data, the decision was made to exclude the neutral tweets as well as the tweets posted by the official accounts of both airlines. The reason for excluding the airline accounts from the data is because we assume that the airlines attempt to maintain a positive sentiment towards their followers and therefore, we would like to keep the general sentiment as positive as possible. Moreover, for the neutral tweets, their polarity equals zero and therefore they offer no additional value to the sample, while at the same time centering the quarterly averages towards zero.

The sample remaining after the removal of the above-mentioned tweets, is described below.

From the figures presented below we observe that there is no significant change to the quarterly distribution of tweets, for both airlines.

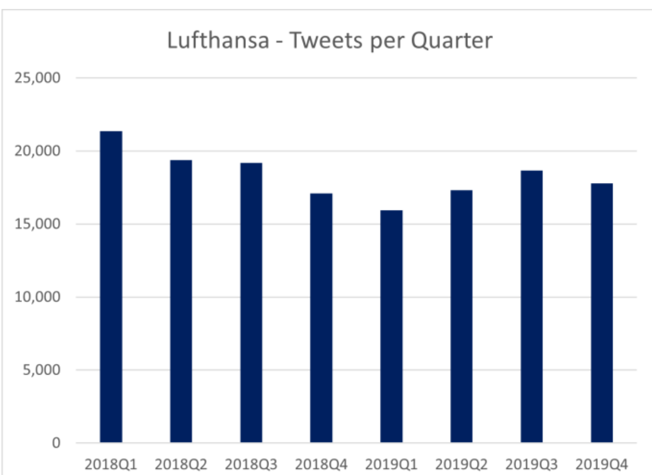


Figure 18a. LH- Tweets per Quarter (excl. neutral & Airline's) 2018 &2019

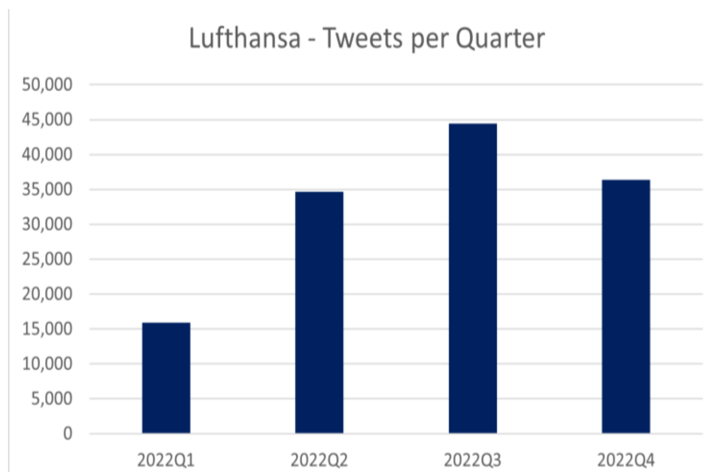


Figure 18b. LH- Tweets per Quarter (excl. neutral & Airline's) 2022

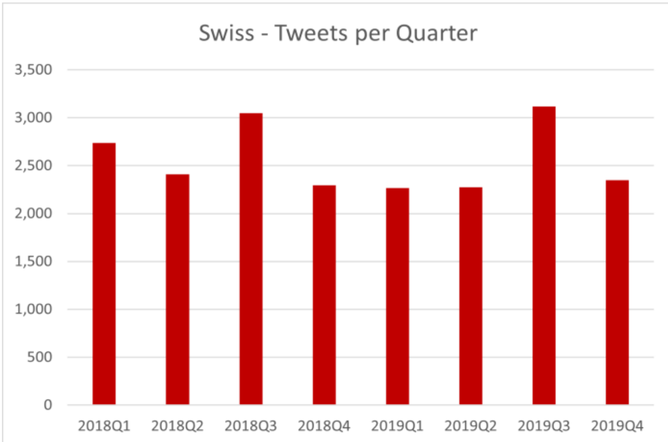


Figure 19a. LX-Tweets per Quarter (excl. neutral & Airline's) 2018 & 2019

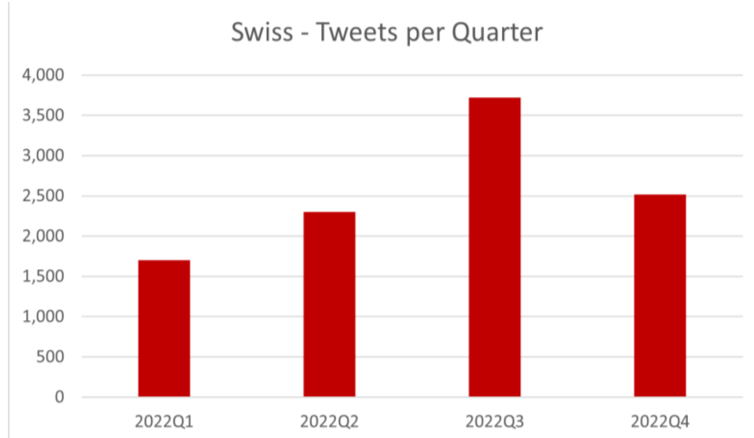


Figure 19b. LX-Tweets per Quarter (excl. neutral & Airline's) 2022

Regarding the new polarity scores, we can observe that there is no difference in the Lufthansa distributions, while for Swiss airlines a difference in the trend can be observed for year 2022, in which the polarity score has significantly decreased for the third and fourth quarter, signifying that the airline was contributing to the polarity score a lot with positive posts.

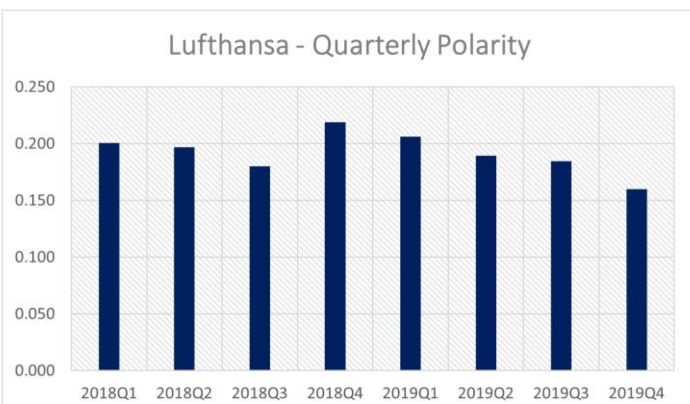


Figure 20a. LH Polarity per Quarter 2018 & 2019 (excl. neutral & Airline's

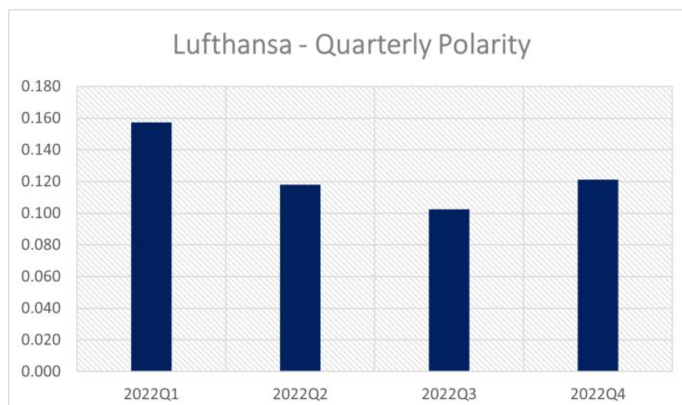


Figure 20b. LH Polarity per Quarter 2022 (excl. neutral & Airline's)

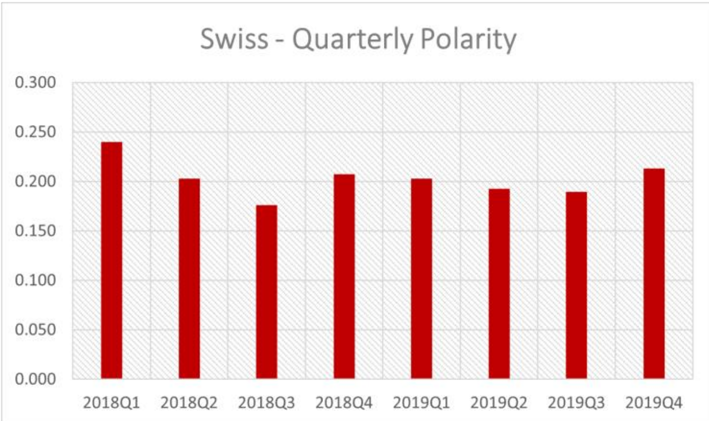


Figure 21a. LX Polarity per Quarter 2018 & 2019 (excl. neutral & Airline's)

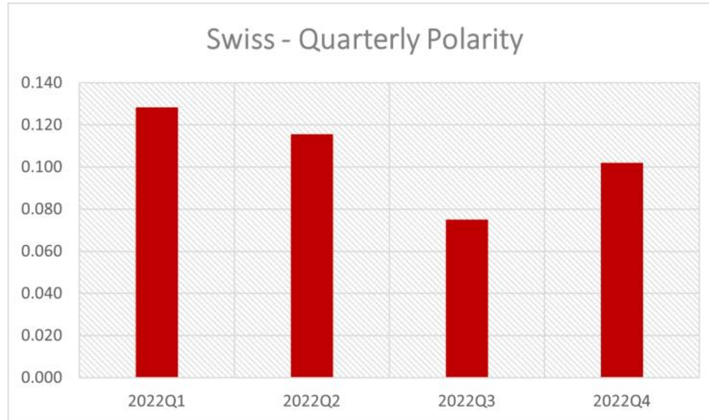


Figure 21b. LX Polarity per Quarter 2022 (excl. neutral & Airline's)

Chapter 6. Airline Financial data

In our attempt to quantify the effect of online customer opinions on the performance of the airlines, we also had to collect financial data. Specifically, we have extracted the quarterly revenue, number of passengers and number of flights, from the official quarterly reports published in the airline's official websites, for the years 2018, 2019 and 2022 (Lufthansa Group, 2023, Financial Reports, Investor-Relations). The data are summarized in table 1 below.

Year	Quarter	Revenue LH (mln)	Revenue LX (mln)	Passengers LH (thousands)	Passengers LX (thousands)	Flights LH	Flights LX
2018	Q1	3,340	1,061	14,757	4,106	131,063	37,370
2018	Q2	4,154	1,242	18,669	5,442	149,897	45,570
2018	Q3	4,457	1,376	19,899	5,992	154,963	46,695
2018	Q4	3,966	1,218	16,783	4,876	146,740	41,913
2019	Q1	3,385	1,109	14,977	4,347	129,589	36,694
2019	Q2	4,373	1,338	19,364	5,747	146,755	44,124
2019	Q3	4,569	1,452	20,283	6,401	148,185	46,950
2019	Q4	3,792	1,245	16,683	5,096	136,981	39,351
2022	Q1	1,759	746	7,193	2,151	72,158	20,509
2022	Q2	3,499	1,190	15,077	4,018	116,070	33,138
2022	Q3	4,153	1,531	15,877	4,894	113,495	36,937
2022	Q4	3,762	1,338	13,637	3,987	106,696	32,534

Table 1. Quarterly Airline Data (Revenue – Passengers- Flights) 2018, 2019 & 2022

Figures 22 and 23 depict the quarterly revenue of the two airlines. The first observation that can be extracted, is that the revenue follows a yearly seasonal trend, in which quarters three and two have significantly higher revenue than Q1 and Q4.

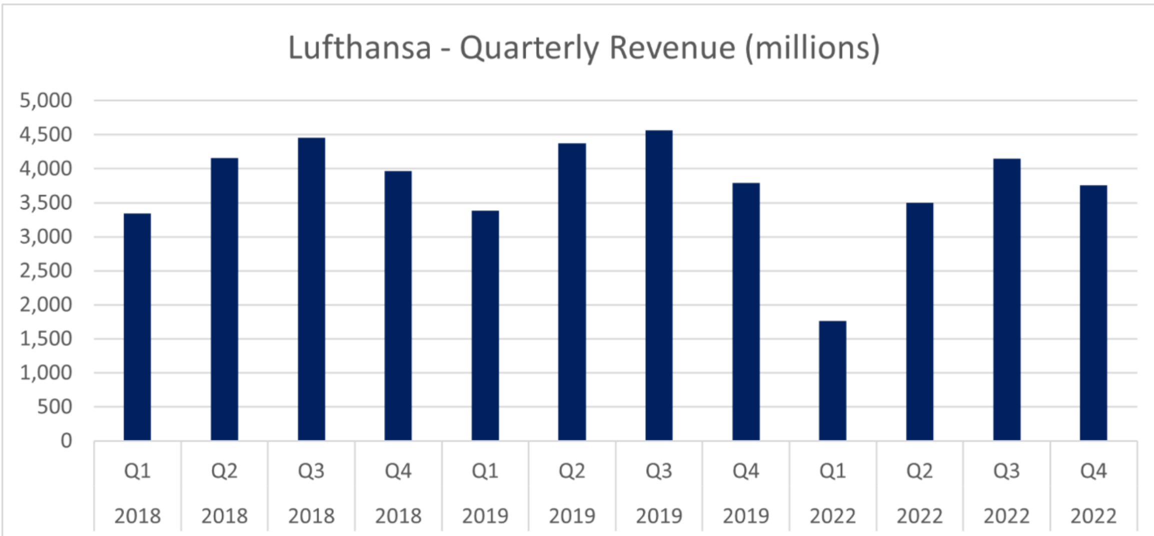


Figure 22. LH Quarterly Revenue – Years 2018, 2019 & 2022

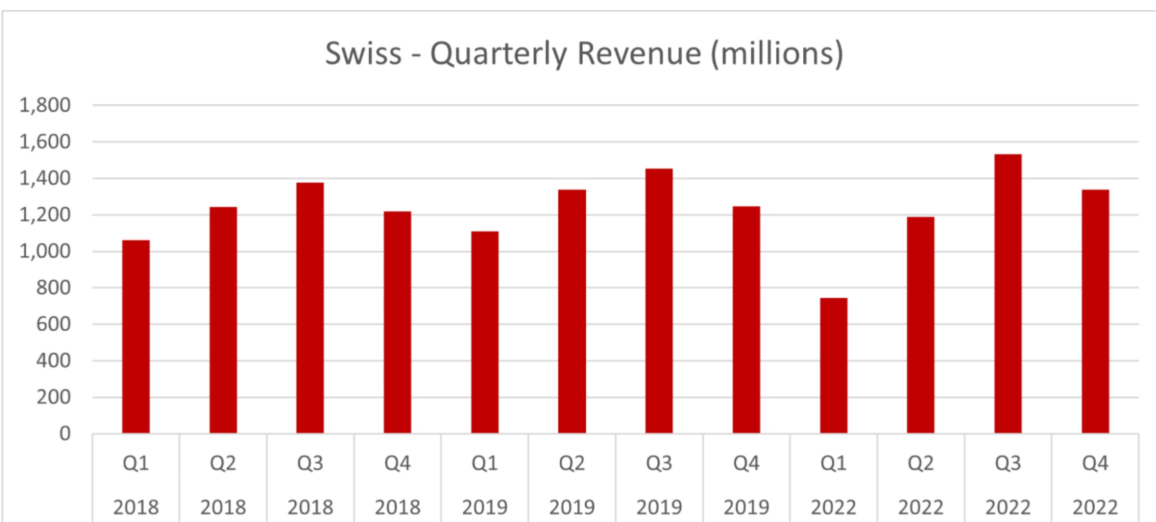


Figure 23. LX Quarterly Revenue – Years 2018, 2019 & 2022

Expanding on the above observation, we can define seasonality in the airline industry as the difference between the customer demand and the flight availability throughout the year (Merkert, R., & Webber, T., 2018). During the year, some seasons have higher demand for flights while some others have lower demand. There are several factors that contribute to this phenomenon.

First of all, the airline industry is the primary source of transportation for tourists. Travel behavior is influenced by public holidays, school vacations, weather conditions etc. In general, peak travel seasons mostly agree with what we call "popular vacation periods" where large numbers of people have some time off and they will probably travel. Moreover, another very important factor is the weather of the desired destination. For instance, certain destinations in Europe are more popular in the summer period (e.g Greece, Cyprus, Malta etc) due to their warm or "tropical" climate, and can attract a huge amount of tourists, something that would increase the demand of air travel. Finally, the airline companies anticipate the demand and therefore adjust their flight schedules accordingly. This adjustment leads to seasonal variations in flight availability and frequency (Kokkinis, G., Papadimitriou S.E., 2021).

Based on that, in both airlines we notice that the revenue in Q1 is relatively low and as we move to Q2 and Q3, it becomes higher. Furthermore, Q3 has the highest amount of revenue in all years. This confirms the seasonality factor that we discussed above especially after in Q4 the revenue in both companies is lower than Q3.

Chapter 7. Quantitative Relationship

In the previous chapters we have conducted a descriptive analysis of the data under study which has set the ground for expanding the analysis in order to study whether a quantitative relationship exists between the two main variables, namely the polarity score and the airline revenue. In order to understand if the above relationship exists, we must first study their temporal evolution in parallel and try to assess whether any level of correlation exists.

In Figures 24 and 25 we are presenting this temporal relationship for both airlines, using the sample of the data that does not include the airline account and neutral sentiment tweets.

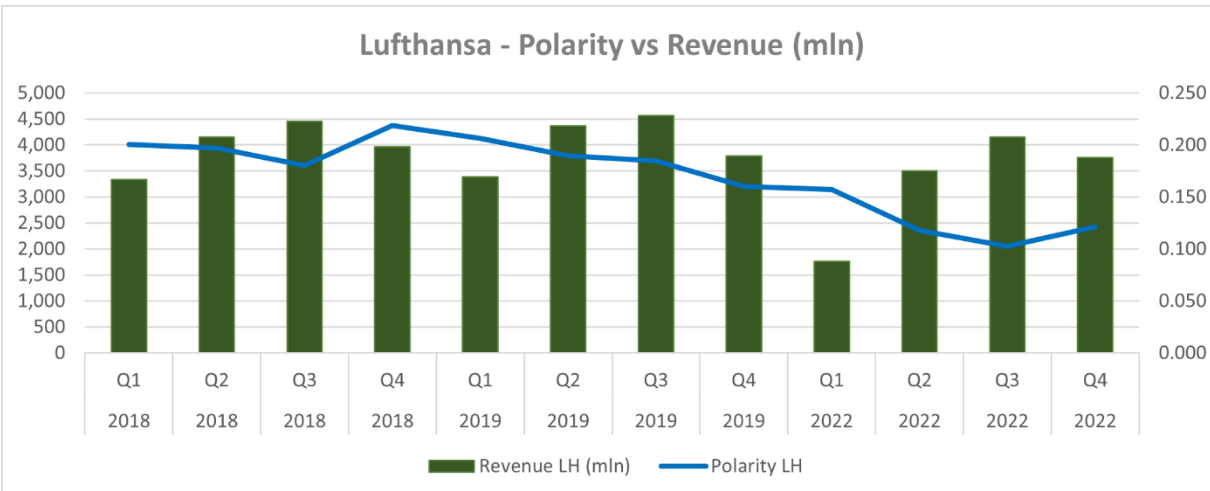


Figure 24. LH Polarity VS Revenue

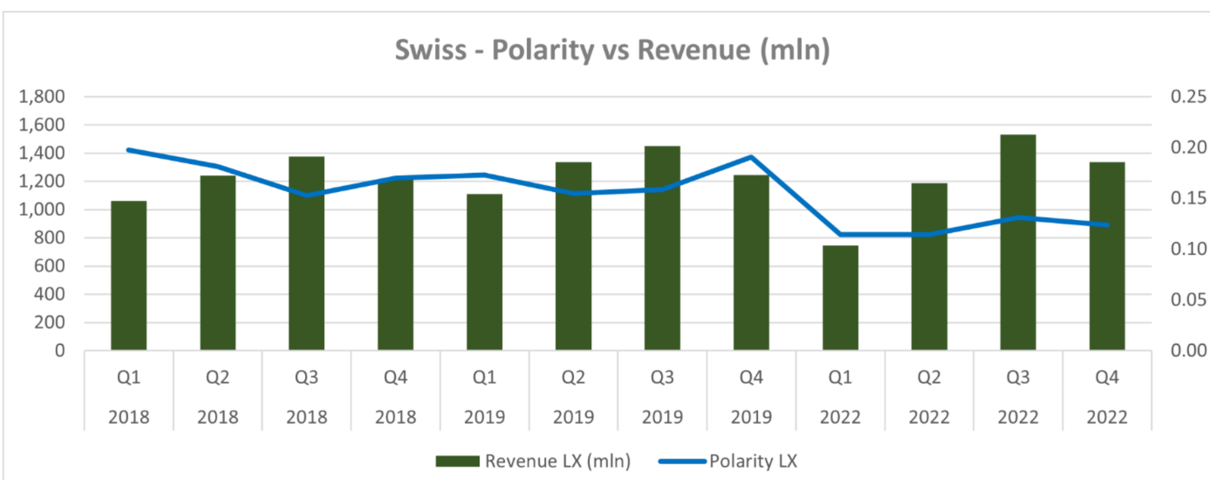


Figure 25. LX Polarity VS Revenue

While studying the figures above, the observation that there is not a strong temporal relationship can already be made, as the polarity score does not follow the same seasonal pattern as airline revenue.

In order to further investigate whether a quantitative relationship exists between the two dimensions, we have calculated the Pearson correlation metric and have also attempted to fit a linear regression model.

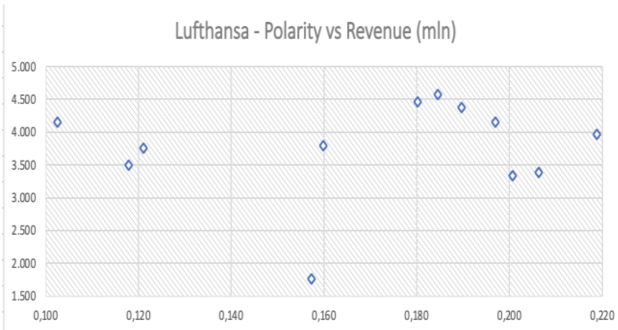


Figure 26. LH Scatterplot

Lufthansa Pearson r: 0,12

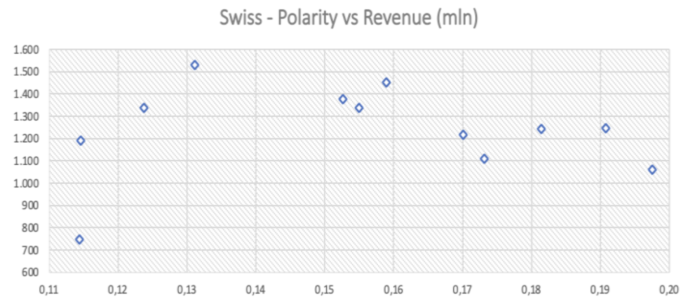


Figure 27. LX Scatterplot

Swiss Pearson r: 0,04

Observing the Pearson correlation outcome, in combination with the respective scatterplots, leads us to the conclusion that there is no quantitative linear relationship between the two dimensions. The Pearson scores can be both classified as ‘negligible association’, while at the same time the scatterplots suggest that it will be very unlikely that a linear regression will be able to accurately quantify the relationship under study.

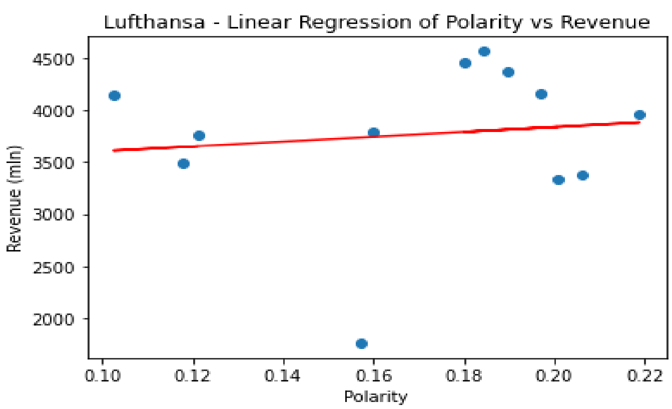


Figure 28. LH- Linear Regression

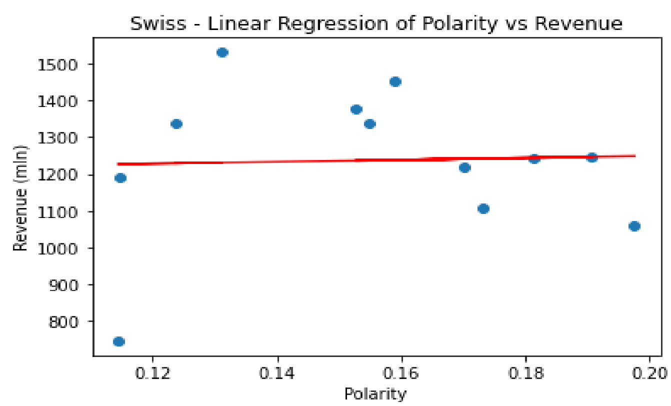


Figure 29. LX – Linear Regression

Expanding on our efforts to identify a quantitative relationship, we have attempted to fit a linear regression model to the data points described above. The linear equations, together with the R^2 evaluation metric, are outlined in Table 2 below.

Table 2. Linear Equations

Airline	Lufthansa	Swiss
Equation	Revenue = 2329.4 * Polarity + 3372.2	Revenue = 269.7 * Polarity + 1195.3
R^2	0,014	0,001

As it is evident from the regression charts, and the R^2 scores, the resulting linear regression models have no explanatory power over the relationship of the dimension under study. Both the resulting lines have a considerable distance from most of the data points of the sample, while at the same time the R^2 metric score hints that the polarity metric cannot explain a significant part of the revenue's variance.

The above results lead us to the conclusion, that at least for the two airlines, and periods under study, the polarity dimension is not a strong predictor of an airline's revenue. This can be attributed to the fact that airline revenue showcases an extremely strong seasonal trend, while at the same time it's a necessary service and its demand is apparently not very elastic to customer opinion.

Chapter 8. Conclusions and future research

In this work we attempted to quantify the effect between online customer opinions on the social media platform Twitter on the performance of Lufthansa and Swiss Airlines. For this purpose, we collected Twitter data utilizing a text scraping library in Python, using keyword search method, specifically the Twitter username of each airline as a filter criterion.

The choice of Twitter was made due to its capacity to publish large volumes of data on a daily basis in combination with its 280-character limitation on tweets and spontaneous user posting. The official accounts of the two airlines under study are @lufthansa for Lufthansa and @FlySwiss for Swiss Airlines. Before the basic cleaning of the data, our sample summed up to 799.744 no distinct Tweets, spanning in the years 2018, 2019 and 2022. The majority of the sample originates from the Lufthansa account (90%), while the tweets referring to Swiss were only 10%. At this point, this large difference in the volume of tweets was expected, since Lufthansa provides its services to a higher number of customers. Moreover, we noticed that the year 2022 contained almost half of the data sample. A possible explanation could be that the airlines were still facing challenges from the Covid-19 pandemic, which might prompt users to complain by using Twitter. Another explanation could be the passengers' desire for flying after the pandemic, in order to make up for the time spent in quarantine.

An interesting observation was that 99% of Lufthansa's sample were originating from the users while this percentage in Swiss was 69%. A possible justification can include the hypothesis that Swiss might hold a more active Twitter account than Lufthansa, which is used for managing customer complaints or for marketing-related topics.

Furthermore, regarding the quarterly spread of tweets for both companies, we noticed that their volume is highly seasonal with the largest proportion of tweets being predominantly in the second and third quarters of each year.

After we performed the sentiment analysis on a sentence level, we presented the most important results, such as the three sentiment categories (positive, negative and neutral), and their percentages. Additionally, we presented the quarterly polarity score for both companies and continued with the sentiment category distributions for both airlines, while excluding all neutral sentiment tweets, as well as those posted by the airline's account, in order to achieve a more accurate estimate of customer opinion.

Furthermore, we noticed that the dominant category of sentiments is neutral for Lufthansa's tweets and positive for Swiss airlines. Lufthansa's customer tweets noted a sizable difference between the positive and the negative sentiment which can lead to the conclusion that the company maintains a positive reputation among Twitter users. Swiss's customer sentiment was aligned with the general sentiment, confirming the good relationship of the company with its customer base.

In our attempt to create a quantitative relationship between the polarity scores and revenue figures for each company, we analyzed the temporal evolution of polarity scores. Our findings included a mildly positive score for both airlines and a small variation between the quarters which, if examined in absolute numbers, does not follow a strict seasonal trend. After that, we made the decision to exclude the neutral tweets as well as the tweets posted by the official accounts of both airlines, in order to dive deeper into the data and keep the general sentiment as positive as possible. We observed that after the exclusion, there were no significant changes to the quarterly distribution of tweets, for both airlines.

For the purposes of this work, we collected financial data from the airlines under study, specifically quarterly revenue, number of passengers and number of flights. We noticed that the revenue follows a yearly seasonal trend, in which quarters two and three have significantly higher revenue than Q1 and Q4.

In the last chapter of the analysis, we presented the temporal relationship for both airlines, the Pearson correlation metric, with the respective scatterplots, and the linear regression model. While studying the temporal relationship we observed that the polarity score did not follow the seasonal pattern as the airline revenue. Additionally, the Pearson correlation outcome can be classified as "negligible association" while the scatterplots indicate that there is no quantitative linear relationship between the two dimensions.

Finally, we attempted to fit a linear regression model and the R^2 scores to the data and we confirmed that the model has no explanatory power over the relationship of the dimension under study. In both companies, the resulting lines have considerable distance from most of the data points of the sample, while the R^2 metric score hints that the polarity metric cannot explain a significant part of the revenue's variance.

Chapter 9. Future Research

Due to limited time, we decided to investigate the effect between online customer opinions on Twitter by utilizing the sentence-based sentiment analysis method. Follow-up research could investigate other possible variables that might associate with Lufthansa or Swiss International Airlines revenue.

- **Investigate different social media platforms:** Companies like Lufthansa and Swiss International Airlines use several social media platforms like Facebook, Instagram, YouTube etc., to stay connected with their client base. Therefore, it is recommended that future research shall include these channels to get a clearer picture of the sentiment that exists towards those companies.
- **Investigating different metrics:** in this work we explored the relationship between the online feedback and the company's revenue and the results indicated that there is no correlation among them. A future suggestion can include the relationship of the online customer feedback and the company's stock price.
- **Changing the sentiment analysis technique:** For this paper a lexicon-based sentiment analysis approach was used to identify the sentiment percentage of tweets for each airline. However, a recommendation for the future could be the use of a machine learning technique to examine the same relationship or/ and include the airlines' stock prices. It would be interesting to see how the result might vary if all the languages of the sample are taken into consideration.
- **Change the companies under study:** the companies that were under study, both belong to the same industry, that is characterized by high seasonality. For future research, it would be interesting to investigate companies that seasonality is not one of their main characteristics. For example, companies that belong to the automotive industry, or the food industry.

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