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Sentiment analysis about airport ground access using social media

Análise de sentimentos sobre o acesso terrestre ao aeroporto utilizando mídias sociais

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ABSTRACT
An adequate airport ground access system is relevant for a good level of service, and it is essential to identify the user's perception of the available means of transport. Sentiment analysis techniques and machine learning have been identified as positive and negative sentences with user-generated content on the social network Twitter. From March 2018 to December 2019, we collected spontaneous opinions about the case study of GRU Airport (SBGR). The tweets surveyed were related to the terms: airport, Guarulhos, and means of transport: transport apps of urban mobility, bus, taxi, train, and private vehicles. Trains had a greater quantity of tweets, with the main reason for dissatisfaction related to the location of the airport station. In addition, the indicators positively evaluated were services availability, cost, and journey time. The Naïve Bayes machine learning technique showed an accuracy of 82.14% and a precision of 88.14% for classifying tweets into positive or negative perceptions. The results obtained can be valuable to government entities, influencing the level of service offered. The content generated on social media can be useful in several areas of knowledge, complementing field research and helping to develop new research methods and data analysis.

RESUMO
Um adequado sistema de acesso terrestre ao aeroporto é relevante para um bom nível de serviço e é essencial para identificar a percepção do usuário sobre os meios de transporte disponíveis. Para identificar as percepções positivas e negativas foram utilizadas as técnicas de análise de sentimentos e aprendizado de máquina com conteúdo gerado pelo usuário na rede social Twitter. De março de 2018 a dezembro de 2019 foram coletadas opiniões espontâneas sobre o acesso terrestre ao Aeroporto Internacional de São Paulo/Guarulhos (SBGR). Os *tweets* pesquisados referiram-se aos termos: aeroporto, Guarulhos e meios de transporte: aplicativos de transporte de mobilidade urbana, ônibus, táxi, trem e veículos privados. Os trens tiveram maior quantidade de *tweets*, sendo o principal motivo de insatisfação relacionado à localização da estação do aeroporto. Além disso, os indicadores avaliados positivamente foram disponibilidade dos serviços, custo e tempo de viagem. A técnica de aprendizado de máquina Naïve Bayes apresentou acurácia de 82,14% e precisão de 88,14% para classificar os *tweets* em percepções positivas ou negativas. Os resultados obtidos podem ser valiosos para as entidades governamentais, influenciando no nível de serviço oferecido. O conteúdo gerado nas redes sociais pode ser útil em diversas áreas do conhecimento, complementando a pesquisa de campo e ajudando no desenvolvimento de novos métodos de pesquisa e análise de dados.

1. INTRODUCTION

Airports with good ground access conditions can provide the users with a positive experience, which can influence the demand for air services (ALHUSSEIN, 2011). From this perspective, a fast and convenient access system to the airport can bring benefits for those choosing short air travel, when there is competition among operators of other means of ground transport if there are other airports in the region, and in the level of service for passengers (TSAMBOULAS & NIKOLERIS, 2008).

Therefore, it is relevant to understand the indicators that influence the perceptions of employees, passengers, companions, and visitors in their choices of ground access. Having such knowledge can help the distribution policies and management of some passenger terminal subsystems, such as curb sizing, capacity, offers and prices of parking spaces, development of infrastructure access, such as roads, railways, and subways, and the provision of public transport services (PSARAKI & ABACOUMKIN, 2002).

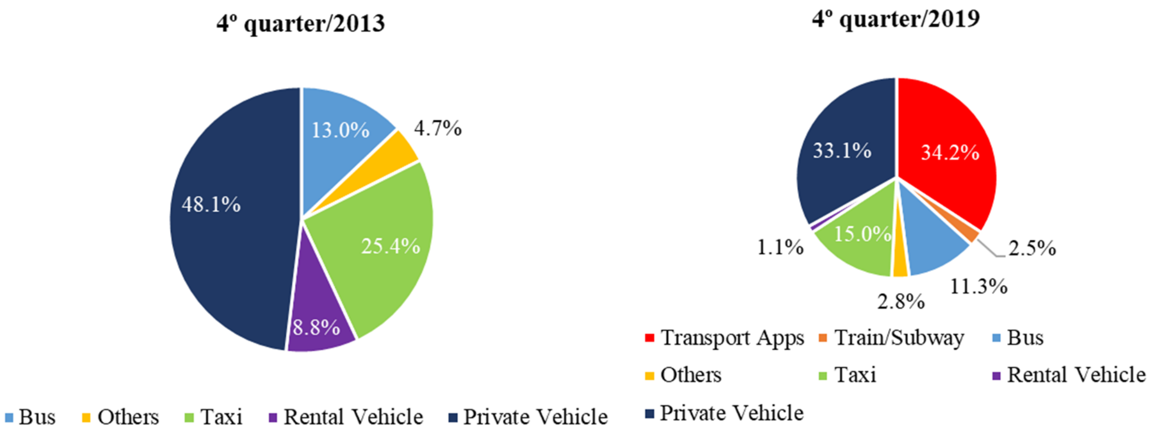

Figure 1. Average ground access airport percentage for SBGR in the fourth quarter of 2013 and 2019, respectively (MINISTRY OF INFRASTRUCTURE, 2020)

According to the National Civil Aviation Secretariat (SAC) Passenger Satisfaction Survey, the means of transport chosen by passengers to access the International Airport of São Paulo/Guarulhos – Governor André Franco Montoro (SBGR) have changed in recent years. As an example, there is a variation in the use of private vehicles. In the fourth quarter of 2013, it represented 48.1%, while in the fourth quarter of 2019, the option represented 33.1% of users who accessed the airport. Another interesting point is the inclusion of transport application services, which were not available in 2013 and represented 34.2% of the sample in 2019. Figure 1 shows the percentage of choices for the means of transport in the fourth quarter of 2013 and the fourth quarter of 2019, respectively (MINISTRY OF INFRASTRUCTURE, 2020).

We considered it relevant to identify the users' perception about the means of transport and the infrastructure due to the changes in the users' choice profile to access the SBGR. One of the ways to identify these perceptions is through online user-generated content on digital platforms. Passengers have been connected to the internet since 2009 at airports (MARTIN-DOMINGO & MARTÍN, 2016), which means less time of interaction with employees (KALAKOU, PSARAKI-KALOUPTSIDI & MOURA, 2015). The internet can also be used by them to give their opinion about services on social media. This information can help us to understand users' preferences and demands (GREAVES *ET AL.*, 2013).

Among the options for the content generated on social media are blogs (GITTO & MANCUSO, 2017), Google reviews (LEE & YU, 2018), and the social network microblog Twitter (PUNEL & ERMAGUN, 2018; GITTO & MANCUSO, 2019; MARTIN-DOMINGO, MARTÍN & MANDSBERG, 2019; QI, COSTIN & JIA, 2020). This information available on social media can configure databases (GITTO & MANCUSO, 2017), which complement standard surveys and non-recognition of specific perceptions, which questionnaires have not addressed yet. There is also the possibility of developing new methods in different areas of knowledge, complementing conventional data analysis (MARTIN-DOMINGO, MARTÍN & MANDSBERG, 2019). In addition to its role in academic studies, the information contained on social media can be applicable for airport operators, governments, companies, and it can assist in decision-making of infrastructure projects and in improving the level of service offered at an airport (NASSEREDDINE & ESKANDARI, 2017).

Thus, the objective of this work is to verify a possibility to identify the user's perception of ground access to a Brazilian airport through content generated on social media, specifically analyzing the options: urban mobility transport applications, bus, taxi, train, and private vehicle. We propose to investigate the factors that influence positive and negative perceptions with the Sentiment Analysis technique. Furthermore, we propose the application of a machine-learning algorithm to optimize the process. In the future, it can be extended to a large volume of real-time data. Thus, an organization in this work presents a bibliographic review in session two, in session three the methodology, in session four the results and discussion, in session five as conclusions, in session six the acknowledgments, and in session seven the references.

2. BIBLIOGRAPHIC REVIEW

Good ground access and adequate parking for vehicles and buses are supportive for the quality of the airport service because of the diversity of geographic origins of airport users. One of the concerns of occasional airport users is the lack of familiarity with the system, which can lead to discomfort and irritation. In return, employees can bear high transportation and/or parking costs. It is necessary to identify airport traffic, costs, the performance of alternative systems, and users' preferences to find solutions to mitigate these problems (DE NEUFVILLE, 2013).

In this context, some studies addressed the choice factors and users' profiles for ground access to the airport. These factors are socioeconomic aspects, trip characteristics, and hypothetical scenarios. They concluded that time savings, the absence of transfers, and the storage of baggage favor the choice. On the other hand, the price is less impactful. Jou, Hensher, and Hsu (2011) investigated the impact of a new mass rapid transit system for ground access to Taiwan Taoyuan International Airport in Taiwan. The authors stated that improving public transport time could decrease the use of private vehicles and taxis.

Akar (2013) analyzed the factors of choice for alternative means to the private vehicle (bus, charter bus, taxi, and van) at Port Columbus International Airport. She concluded that business travelers, alone or with few companions, tend to use more alternative means. The factors indicated were, in descending order: reliability, travel time to the airport, flexibility in departure time, frequency, low cost, and space for baggage.

Gokasar and Gunay (2017) investigated whether transit catchment areas affect the choice of ground access to Atatürk International Airport in Istanbul, Turkey. They concluded that the influencing variables are: the distance to access the airport, the type of destination, access cost, presence of own car, employment, number of people traveling, origin and time difference between departure from origin and flight.

Zaidan and Abulibdeh (2018) analyzed the impact of inserting a metro on the choice of ground access to Hamad International Airport in Doha, Qatar. The study concluded that the private vehicle is still not surpassed. Metro use is discouraged because of the region's hot climate, the number of suitcases, large groups, and groups with children. On the other hand, the encouraging factors were convenience and competitive cost. In addition, the presence of Wi-Fi internet offer, complementary services, and payment facilities, such as tickets for families, can be positive factors for its use.

The aforementioned works used surveys with users in a face-to-face format at airports (JOU, HENSHER & HSU, 2011; AKAR, 2013; GOKASAR & GUNAY, 2017; ZAIDAN & ABULIBDEH, 2018), but recent works developed in the air sector have used generated content in social media (PUNEL & ERMAGUN, 2018 GITTO & MANCUSO, 2019; MARTIN-DOMINGO, MARTÍN & MANDSBERG, 2019). It is noteworthy that some topics covered were the quality of airport service (LEE & YU, 2018; MARTIN-DOMINGO, MARTÍN & MANDSBERG, 2019), the market segmentation of the airline industry (PUNEL & ERMAGUN, 2018), and the perception of users of the airports (GITTO & MANCUSO, 2019).

Content generated on social media can help identify the user's opinion (SREENIVASAH, LEE & GOH, 2012), obtain their perception (DIJKMANS, KERKHOF & BEUKEBOOM, 2015), and recognize the behavior and profile of members (WIENEKE & LEHRER, 2016). Areas of study include stock market prediction (BOLLEN, MAO & ZENG, 2011), restaurant reviews (KANG, YOO & HAN, 2012), brand perception (GHIASSI, SKINNER & ZIMBRA, 2013), games of football (YU & WANG, 2015), opinions on resorts (PHILANDER & ZHONG, 2016), natural disasters (RUZ, HENRÍQUEZ & MASCAREÑO, 2020), public sentiments about COVID-19 vaccines (LIU & LIU, 2021), among others.

Regarding the airport sectors, Martin-Domingo, Martín, and Mandsberg (2019) investigated the quality of services at Heathrow Airport in London. The authors identified that ground access was the second most mentioned term on Twitter, with 13% of the sample of 23 categories analyzed, including waiting (18%), passport control (12%), gates (8%), and security (7%). The result can be an indicative of the relevance of ground access for users. Information on social media about the means of transport and infrastructure conditions can indicate the daily needs of users, irregular events, and opinions about the services provided (GAL-TZUR *ET AL*., 2014).

Given previous research, this study aims to fill the gap on the identification of the perception of users who access a Brazilian airport, specifying if their feelings are either positive or negative, for each means of transport used: urban mobility transport applications, bus, taxi, train, and private vehicle, using content generated on social media.

3. METHODOLOGY

Analyzes of users' preference for one or another means of ground access to the airport must be carried out individually by the airport, as the transfer of experiences or the use of Benchmarking techniques is not valid. It results from air traffic conditions, airport location, nearby urban areas, political, social, and economic conditions (PSARAKI & ABACOUMKIN, 2002).

The International Airport of São Paulo/Guarulhos – Governor André Franco Montoro (SBGR) was chosen as a case study, as it presented more mentions about the means of ground access on the Twitter social network. The available ground access options were: urban mobility transport apps, bus, taxi, train, and private vehicle.

3.1. Sentiment analysis

Sentiment Analysis is a technique that classifies the user's emotions through data mining on a given topic (WANG & WAN, 2011). The technique derives from natural language processing (NLP), information retrieval (IR), information extraction, and artificial intelligence (AI) (XIANG *ET AL.*, 2017). Feelings can be positive, negative, or neutral for the sentences analyzed at the document or sentence level (QUAN & REN, 2014).

Among the Sentiment Analysis techniques, there are symbolic and machine learning techniques. Symbolic techniques employ known rules and lexicons. On the other hand, machine learning techniques employ training databases for supervised or weakly supervised learning (BOIY & MOENS, 2009).

For the application of Sentiment Analysis, four steps recommend a collection of user-generated content; definition of the period and mode of data collection; data filtering and disposal process and statistical structuring of data (MARTIN-DOMINGO, MARTÍN & MANDSBERG, 2019).

For this work, the content generated by the user employed was from the social network Twitter, suitable for applying the technique at the sentence level with tweets (short texts). The investigation focused on users who accessed the SBGR using a means of transport: urban mobility transport apps, bus, taxi, train, or private vehicle.

For data collection, we used the Python Programming language. The search parameters have been used to refer to the keywords for each means of transport. Then, we defined the period and the maximum number of tweets captured. The result found returns the user ID and name, the content, and the post date (PYPI, 2020), according to the pseudocode below:

```
Start
    Var search_terms, user_id, username, tweet_content: character;
    Var start_date, end_date, tweet_date: date;
    Var all_tweets, tweet_quantity, i: integer;
Start of collection algorithm
    Type (“Enter search terms”);
    Read search_terms;
    Type (“Enter the search start date”);
    Read start_date;
    Type (“Enter the search end date”);
    Read end_date;
    all_tweets = search_function (search_terms, start_date, end_date)
    tweet_quantity <- length (all_tweets)
For i from 1 to tweet_quantity do {
    Print (“user ID”, user_id);
    Print ("username", username);
    Print (“tweet content”, tweet_content);
    Print (“tweet date”, tweet_date);
```

i++;

} end for

End algorithm

The end

The selected collection period was from March 31, 2018, to December 31, 2019. The inauguration of CPTM train services to SBGR (CPTM, 2018) motivated the period choice. That constitutes six official options for ground access, according to the airport's website (GRU AIRPORT, 2020).

The terms screened are related to the five means of transport in the case study. The keywords related to urban mobility transport applications were: “app”, “Uber”, and “99”. Then, the keywords related to buses were “bus” (in Portuguese and in English), “big bus” and the bus companies “Airport Bus Service”, “Guarupass”, “Lirabus”, “Litorânea”, “Pássaro Marron”, “Viação Cometa”, and the buses of the companies “Gol”, and “Latam”. For taxis, the keywords were “taxi” and the taxi company that operates at the airport “Guarucoop”. For trains, the keywords were “train”, “CPTM”, “Line 13”, “Line Jade”, “Line 13-Jade”, “Airport Express”, and “Connect”. Finally, for private vehicles, the terms “driving”, “parking”, “traffic”, “highway” and “road”.

After data collection, it was applied the filtering of tweets, considering only those related to ground access to the airport. Similar tweets made by the same user on an even day were disregarded to prevent the database from being overcharged for an individual issue. However, tweets from the same user, but on different days were considered, because it is understood the problem persists. Finally, the tweets that exemplified a situation from the same user were grouped together. In cleaning, the tweets that contained perceptions about the transport service were “cleaned”, so that noise would not influence the later stages. At this stage, we removed the links, hashtags (#), and emoticon user names (QI, COSTIN & JIA, 2020).

3.2. Manual classification and categorization

Tweets about the perception of ground means of access to the airport were manually classified by two researchers independently. A third researcher was consulted when the classification diverged (MARTIN-DOMINGO, MARTÍN & MANDSBERG, 2019). The objective was to use them as training and testing databases in the machine learning stage. Tweets with favorable opinions, such as praise, were rated as positive. Those in which the service brought dissatisfaction, such as criticism, were classified as negative. In cases where there was no mention of any sentiment, they were classified as neutral. Opinions with ironies were classified following the interpretation of irony. Table 1 presents examples of positive, negative, and neutral tweets according to the manual sentiment analysis.

Table 1 – Examples of manually classified tweets

Manual Sentiment Analysis	Example tweet
Positive	*“Excellent news that puts sampa on the list of cities in the first world Soon and with business hours, we will be able to reach the most frequented airport in Latin America, Guarulhos, using CPTM!”*
Negative	*“The train connects the Tatuapé station to the city of Guarulhos and not to the airport. If you want to go to the airport, you'll have to walk or take a bus, carrying your bags. And yet the closest terminal is the annex”*
Neutral	*“Going by train to Guarulhos International Airport in São Paulo”*

3.3. Machine Learning

We choose the machine learning technique, Naïve Bayes, for automatic classification. The technique uses probability as a prediction. It is simple, fast, with good research results, and can develop in free programming languages. Moreover, as the Twitter contains a vocabulary which is unstructured, ungrammatical and not standardized, employing methods such as keyword dictionaries would be very complex, and could lead to loss of information if incompletely structured. Therefore, machine learning techniques are more efficient and accurate (QI, COSTIN & JIA, 2020).

To apply the technique, we applied the Python programming language. First, 80% of the training bank, chosen randomly, was used with the tweets and their polarities for training the algorithm. Then, we applied the test bank to verify the model. As a result, we have the sentence polarity, negative or positive (TEXTBLOB, 2020). For simplicity, the pseudocode below exemplifies the steps followed.

```
Start
        Var training_tweet, training_polarity, training_positive, training_negative, test_tw
        eet, test_polarity, model_polarity: character;
        Var training_quantity, i,
        test_quantity, true_positive, true_negative, false_positive, false_negative: integer;
        Var accuracy, precision, recall, f1: float;
Start of Naïve Bayes algorithm:
        Read (training_tweet);
        Read (training_polarity);
        training_quantity <- length(training_tweet);
For i from 1 to training_quantity do {
        If (training_polarity[i] = = positive)
                training_positive <- store(training_tweet[i]);
        else
                training_negative <- store(training_tweet[i])
        End if
        i++;
} end for
        Read (test_tweet);
        Read (test_polarity);
        test_quantity <- length(test_tweet)
For i from 1 to test_quantity do {
        If test_tweet[i] in training_positive do
                So model_polarity[i] <- positive;
                Write ("This sentence is character: ", model_polarity[i]);
        else
                model_polarity[i] <- negative;
                Write ("This sentence is character: ", model_polarity[i]);
        End if
        If (model_polarity[i] == test_polarity[i])
```

```
                If (model_polarity[i] = = positive)
                        then true_positive <- true_positive++;
                else
                        true_negative <- true_negative++;
                End if
        End if
        If (model_polarity[i]!= test_polarity[i])
                If (model_polarity[i] = = positive)
                        then false_positive <- false_positive++;
                Else
                        false_negative <- false_negative++;
                End if
        End if
        i++;
} end for
        accuracy <- (true_positive + true_negative) /
        (true_positive + true_negative + false_positive + false_negative);
                Write ("The accuracy of the prediction is: ", accuracy);
        precision <- (true_positive) / (true_positive + false_positive);
                Write ("The precision of the prediction is: ", precision);
        recall <- (true_positive) / (true_positive + false_negative);
                Write ("The recall of the prediction is: ", recall);
        f1 <- 2 * (precision * recall)/ (precision + recall);
                Type ("The F1 of the prediction is: ", f1);
End algorithm
The end
```

As the database showed inequality between positives and negatives, which can affect accuracy (MOUNTASSIR *ET AL.*, 2012), we used the oversampling technique, in which minority data are replicated (in the positive case). Neutral tweets, due to their small sample size, were not considered. After training, 20% of the sample was used for testing. We measured accuracy, precision, recall, and F1 to evaluate the model, according to Equations (1), (2), (3), and (4), respectively.

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \tag{1}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{2}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3}$$

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

With the definition of a well-trained algorithm, the application is planned for a greater database, making it possible to apply the technique with real-time data, and to infer perceptions about ground access, minimizing possible setbacks, and helping in planning and management.

4. RESULTS AND DISCUSSION

From March 31, 2018 to December 31, 2019, 2177 tweets were collected, 2148 of which dealt with ground access options for the SBGR: urban mobility transport applications, bus, taxi, train, and private vehicle. In descending order: 1798 tweets about trains (83.7%), 137 tweets about urban mobility transport apps (6.4%), 118 tweets about private vehicles (5.5%), 87 tweets regarding buses (4.1%), and 8 tweets about taxis (0.3%).

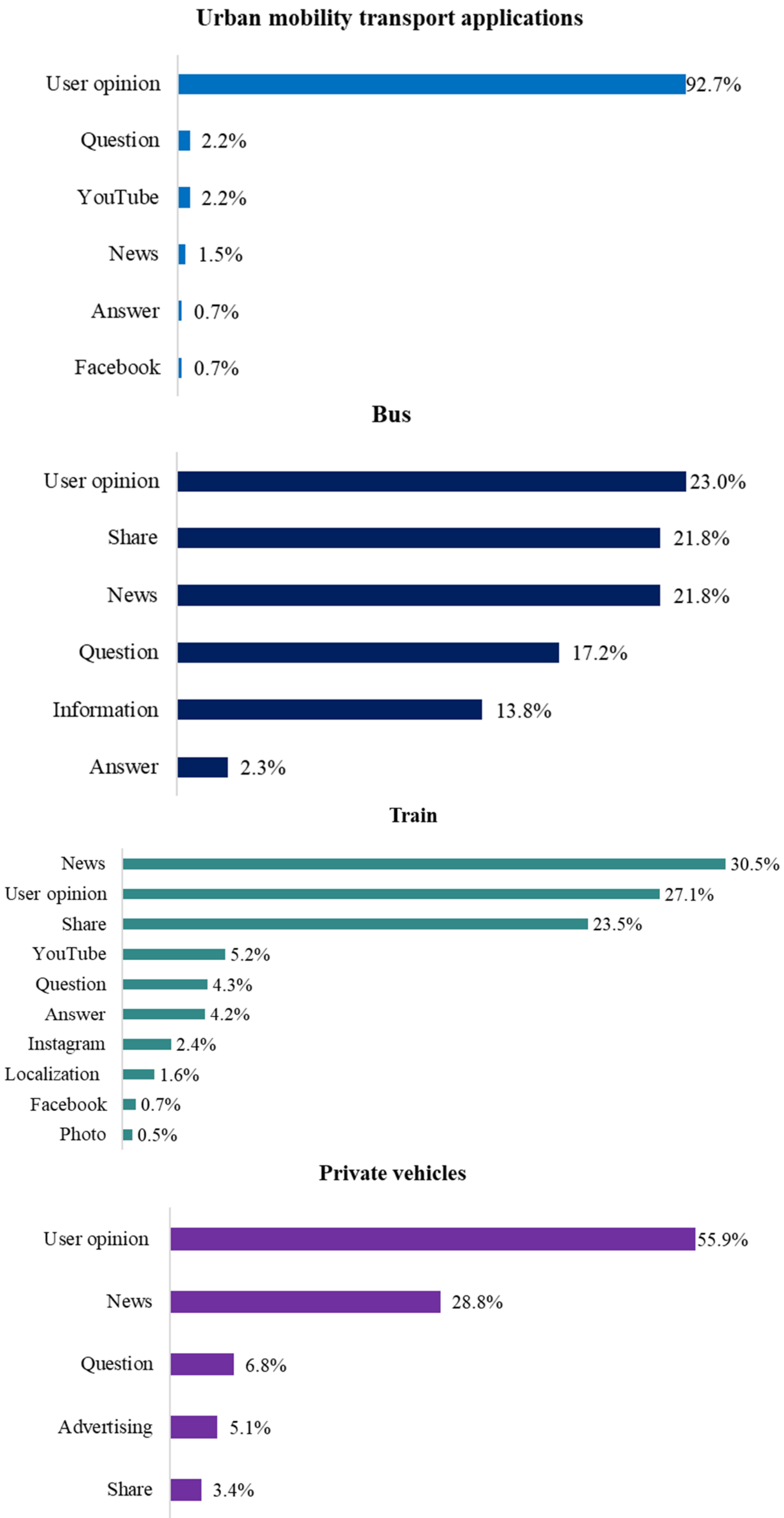

Figure 2. Tweet topics about ground access via urban mobility transport applications, bus, train, and private vehicle for the SBGR

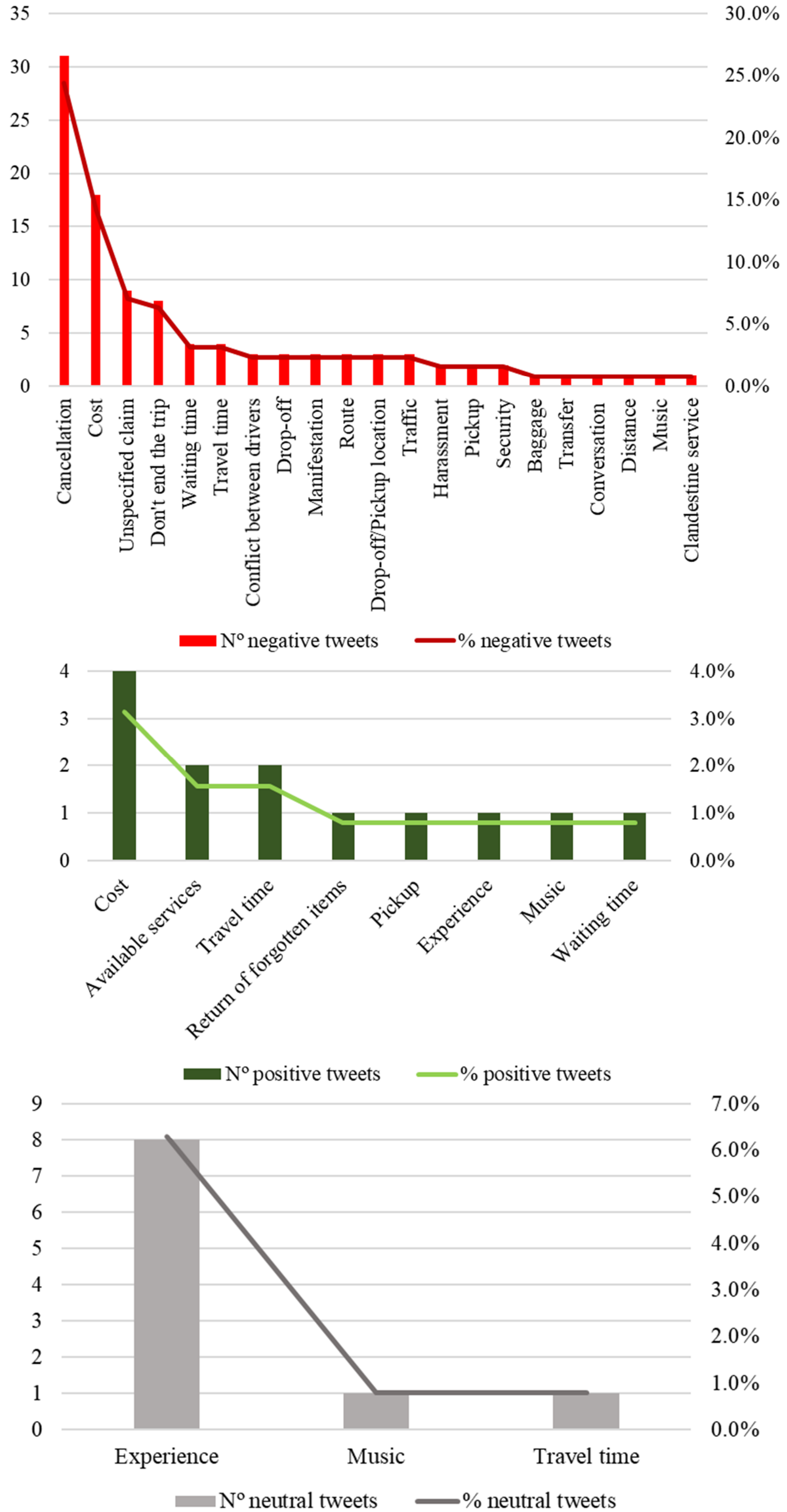

Figure 3. Categories of negative, positive, and neutral tweets about ground access via urban mobility transport applications for SBGR

137 tweets about the use of urban mobility transport applications dealt, in descending order, with user opinions, questions, YouTube (video sharing site), news, answers, and Facebook (social network). 87 tweets about the use of buses dealt, in descending order, with user opinion, share, news, question, information, and answer. There were 8 tweets with user opinions regarding taxis. The 1798 tweets regarding trains dealt, in descending order, with news, user opinions share, YouTube, question, answer, Instagram (photo and video social network), location, Facebook, and photo. Finally, 118 tweets about the use of private vehicles were divided between user opinion, news, questions, advertisement, and share. Figure 2 shows the previous results obtained by manual categorization.

Of the users' opinions about transport apps, 127 tweets split between 104 negative tweets (81.9%), 13 positive tweets (10.2%), and 10 neutral tweets (7.9%), according to manual classification. The point that generated the greatest dissatisfaction was the cancellation of the requested races. That fact can hinder or make them unfeasible, discouraging their use. Then there is the cost, unspecified complaints, non-completion of trips at the end of the races, among others. Cost appears, to a lesser extent, among the positive tweets as well. Some points mentioned as positive were the competitive price concerning companies in the same and other sectors, and promotional coupons with discounts. It is possible that the socioeconomic profile influences this aspect. Also, there is the availability of the service, which influences usage (GOKASAR & GUNAY, 2017). Neutral tweets addressed experience, music, and travel time. Figure 3 presents categories of negative, positive, and neutral perceptions for transport applications.

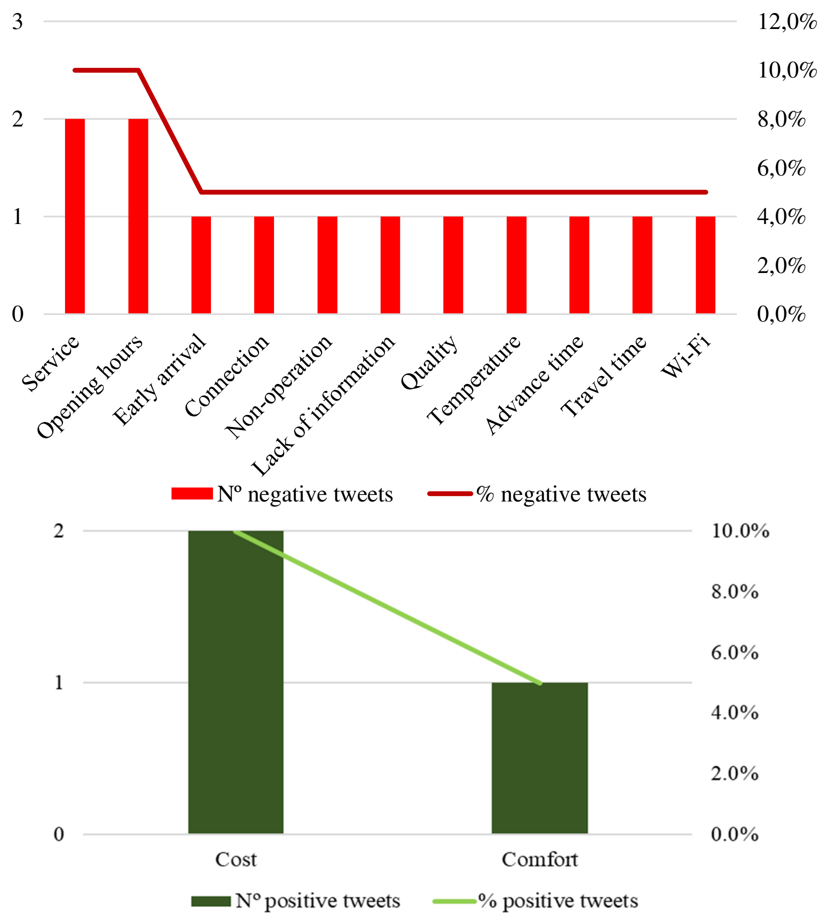

Figure 4. Categories of negative and positive tweets about ground access via bus to SBGR

The 20 tweets of users' opinions about buses were divided into 13 negative tweets (65%), 3 positive tweets (15%), and 4 neutral tweets (20%), according to the manual classification. Dissatisfaction has been caused by service, opening hours, early arrival, connection, non-operation, lack of information, quality, temperature, advance time, travel time, and Wi-Fi. Positive opinions dealt with cost and comfort, while the neutral category reported on the experience. Figure 4 presents categories of negative and positive perceptions for buses.

Regarding taxis, the sample contains 8 tweets, 7 of which had negative opinions. Dissatisfactions were related to cost, parking, and waiting time, according to manual categorization. The positive opinion reported the return of forgotten items. Figure 5 shows the percentage of negative tweets for taxis.

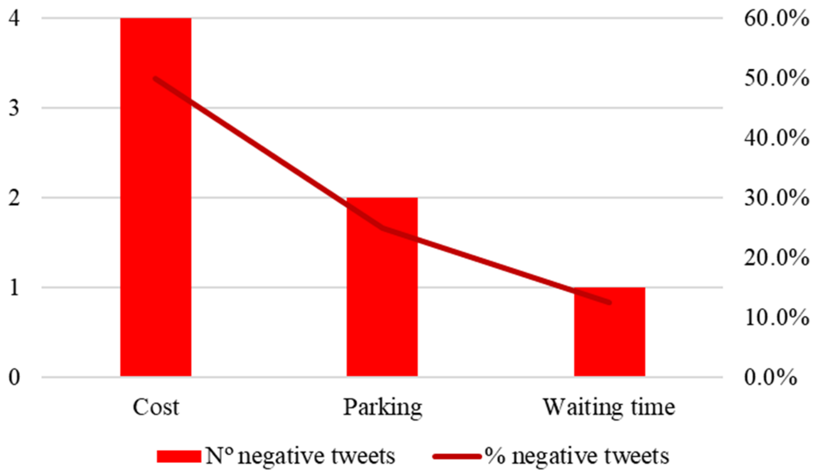

Figure 5. Categories of negative tweets about ground access via taxi to SBGR

Regarding the users' opinions about trains, the 489 tweets were divided, according to manual classification, into 116 positive (23.72%), 354 negative (72.39%), and 19 neutral (3.89%), according to Figure 6. The 19 neutral tweets were about the experience, inauguration, travel time, and connection bus, without expressing any feelings about the facts.

In the analysis of positive tweets, cost, available services, and travel time were the most present terms. A fact that collaborates with Gokasar and Gunay (2017), in which the greater availability of services positively influences the choice of means of public transport. Regarding negative tweets, the location of the station is the majority complaint, mainly because it is located 500 m from Terminal 1, 1.5 km from Terminal 2, and 2.0 km from Terminal 3 (SÃO PAULO STATE GOVERNMENT, 2019). Because of the transfer, the airport offers a free shuttle for transfers (GRU AIRPORT, 2020), but transfers discourage use (JOU, HENSHER & HSU, 2011). This fact can justify the low adherence to the use of trains, verified in the survey by the Ministry of Infrastructure (2020).

In addition, the delay in the work and the lack of better service for other neighborhoods in the city are points of dissatisfaction. There is also the presence of faulty accessibility equipment, such as escalators and elevators, which can discourage their use by passengers with luggage (ZAIDAN & ABULIBDEH, 2018). Other suggestions desired by users are more available hours, better publicity, and less need for transfers. Improvement measures, such as those mentioned above, in service and infrastructure, can cause a higher level of user satisfaction (NASSEREDDINE & ESKANDARI, 2017).

Figura 6. Categories of positive, negative, and neutral tweets about ground access via train to SBGR

The opinion of users of private vehicles was present in 59 negative tweets (89.4%), 1 positive tweet (1.5%), and 6 neutral tweets (9.1%). The most cited point among the negative tweets was traffic, which generates an increase in travel time, the need to leave with more time in advance, insecurity, and irritability (DE NEUFVILLE, 2013). Then there is parking, with complaints related to cost, safety, and conditions. Neutral tweets were about experience and travel time. The only positive tweet about traffic. Figure 7 shows the manual classification for negative, and neutral tweets, respectively.

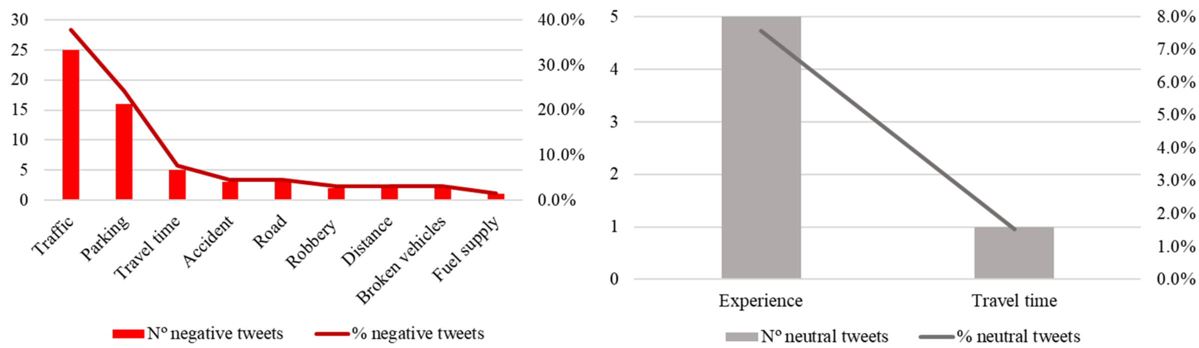

Figure 7. Categories of negative, and neutral tweets about ground access via private vehicle to SBGR

4.1. Machine Learning

In the application of the Naïve Bayes machine learning technique, we used 80% of the sample of negatives and positives on the trains, chosen randomly, for the training bank. The choice of trains was motivated because the database was consistent with the literature. Neutrals have been excluded as the sample was too small and would need to be replicated many times for balance. For balance, it replicated the positive tweets three times. The remaining 20% of the data has been used for the test bank.

The Naïve Bayes technique resulted in an accuracy of 82.14%, a precision of 88.14%, recall of 74.28%, and F1 of 80.62% for the Sentiment Analysis technique. For better visualization of the results, it constructed the confusion matrix presented in Table 2. The positive and negative tweets classified correctly, as well as positive and negative tweets classified erroneously, are present in Table 3.

Table 2 – Confusion Matrix

		Predicted Values	
		Negative	Positive
Actual values	**Negative**	63	7
	Positive	18	52

Table 3 – Examples of classified tweets

Diagnosis	***Tweet***
True positive	*“In love with the guarulhos airport train station”*
True negative	*“from the series: brazil is not for amateurs cptm's airport-guarulhos station does not actually go to the airport. to get to cumbica you still need to take a bus to one of the terminals”*
False positive	*“So cool the train that takes you to Guarulhos airport, but not on Sunday. Interval of trains is half an hour. It took me longer from Guarulhos to the south zone than from BH to SP”*
False negative	*“Wow!!! Train to Guarulhos Airport starts operating every day from this Monday”*

5. CONCLUSIONS

We verified that it is possible to identify the user's perception who accesses the SBGR using different means of transport from content generated on social media. The social network Twitter has been used to express dissatisfaction, satisfaction, questions, doubts, among others. Such information can complement traditional surveys while providing spontaneous opinions, on a variety of topics, issued from different locations with the possibility of a historical database. During the process, we verified some difficulties related to the collection tools, choice of keywords, and verification of the user's veracity.

For the analyzed sample, urban mobility transport applications presented complaints regarding cancellations, costs, and unspecified specifications. The cost is present in both negative and positive points, while service availability and travel time are positive. Concerning buses, service and opening hours discourage use. For taxis, the cost generated greater dissatisfaction.

The most cited means of public transport was the train, possibly due to the social, political, and economic interests involved. The most frequent complaint was about the location of the Airport station, as it is far from the Passenger Terminal, generating the need for transfers, which makes accessibility difficult and discourages use (ZAIDAN & ABULIBDEH, 2018). This indication of improvement can be done with the insertion of a new connection element or an increase in transfer bus frequencies. The inauguration of lines, especially those related to direct services, made a positive impression on users, as availability encourages use (GOKASAR & GUNAY, 2017). However, there are still complaints about the lack of service in other neighborhoods in the city of Guarulhos.

Finally, an important incentive point would be to expand the dissemination of available services, schedules, and travel times to favor the use (TAM, LAM & LO, 2011). Regarding private vehicles, issues related to congested traffic and parking received criticism. Traffic with inappropriate conditions can increase travel time, generate insecurity, and irritability (DE NEUFVILLE, 2013). Such perceptions can help to improve existing services, as well as influence future infrastructure constructions and public transport provision.

The content generated on social media provided a database with user perceptions, which can be generated for other areas of knowledge with the development of new analysis techniques. The analysis of feelings by the machine learning method showed an accuracy of 82.14%, precision of 88.14%, recall of 74.28%, F1 of 80.62%, consistent with the literature (QI, COSTIN & JIA, 2020). The application of automation techniques can reduce the time spent on analysis and allow the use of real-time analysis of large volumes of data.

Suggestions for future work include preliminary research to identify search terms, broaden the scope to understand how individuals act and react on social networks, as well as their trends and positions. Expand the automation steps, identify error points, comparing with other techniques. Also, add profile identification, profile group hypotheses, along user perception. Furthermore, the automation of categorization based on keywords would help to identify the relationship between category and perception. Furthermore, expansion of the collection period to determine if there is a change in perception with changes in ground access.

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