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Why are some social-media contents more popular than others? Opinion and association rules mining applied to virality patterns discovery

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ABSTRACT

Discovering the main features of virality patterns in Twitter is the focus of this research. Five trending topics related to the COVID-19 pandemic were selected for the study, with Spanish as the target language. To carry out the discovery of virality patterns, we applied opinion mining techniques that enable us to structure the information based on the polarity of the messages and the emotions they contain. After transforming the information from an unstructured textual representation to a structured one, data mining techniques were applied, specifically association rules mining. Message patterns with the highest virality (high shares and high likes), and at the same time the most relevant characteristics of the patterns with less impact were extracted. After an exhaustive analysis of the most relevant non-redundant rules, it can be concluded that messages with a high-negative polarity and a very high emotional charge, especially emotions that have intensified with the COVID-19 pandemic, such as fear, sadness, anger and surprise are more likely to go viral in social media. By contrast, messages with little news coverage in the media, few authors, and the absence of surprise are relevant features when it comes to seeing messages with very low dissemination in social media.

1. Introduction

In the context of the COVID-19 pandemic, a correlation can be drawn between how coronavirus and the social media content becomes viral. Just as SARS-CoV-2 spreads among organisms so is social media a tremendously powerful tool for spreading information instantaneously worldwide, irrespective of its veracity.

The number of likes and shares obtained in various social media channels is a key measure of virality. As demonstrated by Kim (2018) the message with high shares and high likes resulted in greater perception of message influence on others. Social networks such as Twitter, one of the most popular, had 353 million active users in January 2021.[1] Twitter's model of likes and tweet–retweet generates a cascade effect that allows any type of information to go viral without any type of control. But what triggers a piece of digital content to go viral? As indicated by several studies, the **network structure** plays a fundamental role in the diffusion of the message (Centola, 2010; Weng, Menczer, & Ahn, 2013), in addition to how **communities** are created and evolve over time (Backstrom, Huttenlocher, Kleinberg, & Lan, 2006). Weng et al. (2013) demonstrated that the future popularity of a meme (units of transmissible information) can be predicted by quantifying its early spreading pattern in terms of community concentration. The more communities a meme permeates, the more viral it is. Weng et al. (2013) presents a practical method to translate data about community structure into predictive knowledge about what information will spread widely.

Another main aspect of virality refers to the textual content of the message. According to different literature studies, **emotional aspects of content** impact shareability. According to Berger and Milkman (2012b), content that evokes high-arousal emotions like awe, anger or anxiety is more viral. However, sadness was flagged as not a good emotional vehicle for viral communication purposes. Berger and Milkman (2012a) took a psychological approach to understanding virality. Using a three-month period dataset of all the New York Times articles, they examined the relationship between integral affect (i.e., the emotion evoked) and whether content is highly shared. Specifically, they examined how content valence (i.e., whether an article is more positive or negative) as well as the specific emotions it evokes (anxiety, anger, awe, disgust, sadness) relate to whether content is highly shared. Their results suggest a strong relationship between emotion and virality: affect-laden content, regardless of whether it is positive or negative,

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[1] https://es.statista.com/estadisticas/600712/ranking-mundial-de-redes-sociales-por-numero-de-usuarios/.

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is more likely to make the most shared list. Further, positive content is more viral than negative content; however, this link is complex. While more awe-inspiring and more surprising content is more likely to make the most shared list, and sadness-inducing content is less viral, some negative emotions are positively associated with virality. More anxiety- and anger-inducing content are both more likely to make the most shared list. In fact, the most powerful predictor of virality in Berger's model (Berger & Milkman, 2012a) is how much anger an article evokes. There was no significant relationship between disgust and virality. Similar findings were provided in Heimbach and Hinz (2016). However, these results refer to the emotions involved in the interpretation of a news item and its shareability. But, nowadays there is also an increase in social media users and these platforms create a different context in terms of user willingness to respond from that which exists for newspaper readers. Furthermore, in the context of the COVID-19 pandemic, surveys conducted globally suggest that the lockdown and social distancing measures have generated new or heightened emotional states in the form of greater psychological distress in people's daily life (Brooks et al., 2020; Jahanshahi, Dinani, Madavani, Li, & Zhang, 2020; Qiu et al., 2020; Zhang, Wang, Rauch, & Wei, 2020), resulting in an increased sense of sadness and other negative emotions. Moreover, chronic stress related to COVID-19 and its emotional corollaries (anxiety, anger, fear of death) are particularly high in society (Droit-Volet et al., 2020). Very recent studies on Twitter posts during 2020 reveal that negative emotions, such as anger and sadness, were dominant during the peak of the COVID-19 pandemic crisis (Lwin et al., 2020).

Thus, given the continuing pandemic situation, more studies are necessary to extract the main features of virality patterns in social networks like Twitter. Discovering these patterns with accuracy can be highly informative in guiding public health communication strategies, for instance. These better informed communication strategies are more likely to be effective in constraining the viralization of malicious content that may even be harmful to people's health.

As for the literature on Twitter and virality, Hoang, Lim, Achananuparp, Jiang, and Zhu (2011) present a virality model to find viral tweets, viral users and viral topics. According to Hansen, Arvidsson, Nielsen, Colleoni, and Etter (2011), the basic measure of virality in Twitter is the probability of a retweet. For this purpose, they analyzed the dimensions of tweet content that is likely to lead to retweeting. They concluded that: "If you want to be cited: Sweet talk your friends or serve bad news to the public". In Jenders, Kasneci, and Naumann (2013), they propose using linear or probabilistic models to study the virality of a tweet. The models used weighted features of tweets or users and they estimate the weight of each feature from a general sigmoid activation function. The most impactful features are chosen to build a learning model that predicts viral tweets with high accuracy.

To the authors' knowledge, research in the literature regarding virality from a computational perspective has to date been mainly focused on extracting virality patterns from the context in which these messages go viral (network structure, communities, influential users, ...) rather than extracting patterns from the high semantic content that tends to be associated with messages that go viral. This means extracting patterns from not just keywords but also polarity or the emotions implied in the message. According to our review of the state of the art, we found evidence that negatively charged content tends to go viral; however, in this work we go one step further and look for the social behavior rules, on a sample set, that show how the social media content can go viral and/or reach the approval (Likes) of users.

The **main novelty** of our work is the application of data mining techniques on structured data, specifically association rule mining, but using textual Spanish content from Twitter as input. The aim is to extract what patterns are followed by tweets that go viral (high shares and high likes), as well as those patterns that have less impact (low shares and low likes). To extract these virality patterns, we propose the following research objectives:

- To transform the unstructured information from Twitter, by applying Natural Language Processing (NLP) techniques, and more specifically sentiment analysis and opinion mining techniques, and generate structured data from the objective and subjective information extracted.
- To extract patterns from the structured data that result in high virality (high likes and shares) or low virality (low shares and low likes) by applying Data Mining techniques using association rules.

Association rule mining is a technique that aims to extract frequent patterns and associations among sets of structured items, typically in consumer markets, telecommunication networks,etc. This study exploits the potential of this technique to determine patterns of viral content in social networks.

2. Background

Our approach is a hybrid one combining (1) opinion mining to extract both the valence or polarity of messages and the emotions contained in them; and (2) association rule mining to identify common patterns in the sentiment analysis of viral Twitter posts. Therefore, in this section, first, we present a review of the main research on opinion mining. Second, the literature regarding association rule mining is outlined as well as research that combines both opinion mining and association rule mining which is then compared to our proposal.

2.1. Opinion mining in social media

Mining social media is not a new endeavor. Graph theory is probably the main method of social network analysis developed in the early stages of the social network concept (Borgatti & Everett, 2006; Ghosh & Lerman, 2010; Tweet, 2006). This approach is applied to social network analysis in order to determine important features of the network.

As for textual content delivered in social media, different text mining techniques are also applied to discover various textual patterns from those messages in social networking sites (Irfan et al., 2015). The main goal of opinion mining is to automate extraction of sentiments expressed by users from unstructured texts. Two major definitions of opinion mining emerge from the literature. The first definition is proposed in Rushdi-Saleh, Martín-Valdivia, Ráez, and na López (2011), and describes opinion mining as "The automatic processing of documents to detect opinion expressed therein, as a unitary body of research". The second major definition states that opinion mining is extracting from the web and analyzing people's opinions, appraisals, attitudes, and emotions toward organizations, entities, people, issues, actions, topics and their attributes (Jeyapriya & Selvi, 2015; Liu, 2012; Liu & Zhang, 2012). One of these is sentiment analysis, but there are several more, such as opinion extraction and sentiment mining. Thus, sentiment analysis is probably one of the most important tasks within the whole opinion mining process. More specifically, opinion mining, and within it sentiment analysis, on social network sites is used to discover and recognize positive or negative expression on diverse subject matters of interest. The task's purpose is to model opinions and determine trends in society in various areas of interest, such as politics (Fernandez, Llopis, Gutierrez, Martinez-Barco and Diez, 2017; Sobkowicz, Kaschesky, & Bouchard, 2012), reviews (Wang, Xu, & Wan, 2013), marketing (Arrigo, 2016), and measuring customer satisfaction (Kang & Park, 2014; Mostafa, 2013). This highly valued information can be a determining factor in strategic decision making. Comprehensive reviews are presented in Hemmatian and Sohrabi (2019) and Pang and Lee (2008).

Opinion mining and sentiment analysis has been actively researched for the last fifteen years (Bakshi, Kaur, Kaur, & Kaur, 2016; Ravi, 2015; Zhang, Wang, & Liu, 2018). Opinion mining involves detecting, extracting and classifying opinions, sentiments and attitudes on different topics based on what social media users express in textual input. According to the literature, textual data is extracted from social media such as Twitter, and classified in different ways, for example, by extracting the stance of the message (D'Andrea, Ducange, Bechini, Renda, & Marcelloni, 2019), the polarity (Kauer & Moreira, 2016; Rao & Ravichandran, 2009) or the topics (Aguero-Torales, Vilares, & Lopez-Herrera, 2021). There were also several recurrent competitions regarding opinion mining and sentiment analysis using Twitter as input (Chatterjee, Narahari, Joshi, & Agrawal, 2019; Mohammad, Bravo-Marquez, Salameh, & Kiritchenko, 2018; Nakov, Ritter, Rosenthal, Sebastiani, & Stoyanov, 2016; Patwa et al., 2020; Rosenthal, Farra, & Nakov, 2017; Rosenthal, Ritter, Nakov, & Stoyanov, 2014).

As for opinion mining applied to discover the viralization phenomenon, most of the research deals with the task as a classification problem. Dargahi Nobari, Sarraf, Neshati, and Erfanian Daneshvar (2021) use social network Telegram as the source, and applied statistical and word embedding approaches to detect viral messages by identifying their category and sentiment. Kumar and Sangwan (2018) proposed a framework that determines the likelihood of content going viral based on the strength of similar emotion across the tweets on a topic. They applied a hybrid approach combining natural language textual cues of emotions from different part-of-speech items and supervised learning techniques to detect viral information.

The novelty of our work in the context of the extant literature consists of not treating the problem as a classification problem but rather in extracting knowledge and converting it into structured data for exploring the phenomenon of virality using data mining techniques. This means not using just keywords or explicit content, but the high-level semantics implicit in the content, which is given by the degree of polarity and emotional tone of the text. Below is the background related to the data mining technique known as association rule mining that we apply in this work.

2.2. Association rule mining

The enormous amount of information that is posted on social networks and the importance of this information as one of the most widely used means of communication nowadays requires the use of data mining techniques to facilitate the reforming of unstructured data, and placing them within a systematic pattern (Injadat, Salo, & Nassif, 2016).

One of these data mining techniques is association rule mining. Association rule mining is a data mining technique proposed by Agrawal, Imieliński, and Swami (1993) and it enables pattern discovery in a structured dataset in the form of rules. These rules indicate which items or tags in the dataset are related, i.e. they appear together frequently. From these frequent datasets, quality measures of the rules are used to select those that appear more often, or to select those rules so that whenever one item appears, the other item also appears with a certain degree of confidence.

Regarding Twitter, association discovery has been used for the automatic generation of taxonomies from posted content or contextual features (Li, Guo, & Zhao, 2008). These automatic processes make it difficult carry out accurate sentiment or polarity analysis to ascertain, in line with set objectives, happiness, sadness, anger, etc and establish the content valence of a message, that is, whether it is positive or negative.

Cagliero and Fiori (2013a) applied association rule mining to hashtags in tweets to discover trends in dynamic rules and identify when different rules appear and disappear on Twitter, based on event changes. TweCoM (Tweet Context Miner) framework entails the mining of relevant recurrences from the content and extracts the most relevant keywords from the contents of tweets. The mechanism obtains patterns of the most recurrent keywords in tweets, that is, it extracts generalized association rules to discover high level recurrences (Cagliero & Fiori, 2013b).

2.3. Combining opinion mining in social networks with association rules

Since our approach combines opinion mining and association rule mining, a review of the research in the literature that combines both approaches has been conducted.

One of the areas where research has shown the benefits of combining opinion mining and association rules is in product reviews. For instance, Wang et al. (2013) adopts a set of complementary methods to mine association rules, allowing them to detect implicit features in product reviews, in order to use these implicit features in the opinion mining task. Also, Kim, Ryu, Kim, and Kim (2009) proposed a method for opinion mining of product reviews using association rules by firstly POS tagging each review sentence and extracting feature and opinion words in the form of transaction data. Secondly, by discovering from the transaction data association rules that, combined with review summarization, returned a summary of the advantages and disadvantages of product features

Association rules are also applied in recommendation systems, such as in the work of Tewari and Barman (2017) where a recommendation system was proposed that generates item recommendations to users with the help of dynamic content based filtering, collaborative filtering, association rules and opinion mining. The approach uses association rule mining for the analysis of current market trends. It generates association rules only from those items that are liked by the users, allowing the measurement of an item's popularity.

In addition to the consumer market sector, other domains have been researched by adopting this hybrid combination. In the health domain, for instance, Mittal, Kaur, Pandey, Verma, and Goyal (2019) presented a framework for real-time twitter feeds which are used to discover highly occurring ailments and applies the association rules for finding the correlation between Epidemic symptoms, and discovering the terms most frequently used by people when posting tweets. In the educational domain, Rashid, Asif, Butt, and Ashraf (2013) combines data mining with NLP to extract the knowledge from a student feedback dataset in textual free format about faculty evaluation. Mined rules are applied on testing files to extract frequent features and opinion words.

Association rules mining has been also applied using inferential models for discovering emotional or polarity patterns to predict different scenarios. Bing, Chan, and Ou (2014)'s proposal consisted of using a data mining algorithm to determine whether stock markets movements can be predicted by 15 million records of tweets (i.e., Twitter messages). They extract ambiguous textual tweet data through NLP techniques to define public sentiment and make use of a data mining technique to discover patterns between public sentiment and real stock price movements. The authors propose an approach using non-parametric techniques (Chi-square) to find relationships between attributes and then propose a measure of estimation of the variance of the association from a maximum likelihood method in the association of any pair of attributes.

Our study also adopts a hybrid approach, working with structured data obtained by using opinion mining techniques to characterize the type of content and then apply data mining with association rules.

The main difference between the previously mentioned research and the approach adopted in our study is that in our case opinion mining is not the end but the means by which viral behavior of social media content can be modeled. Furthermore, to the best of our knowledge, none of the previous work has studied virality as an end in itself using association rules. The timeliness of understanding virality patterns in the context of the COVID-19 pandemic cannot be underestimated, given the likelihood of distortion from strong emotions and polarity persisting in social media communication.

In the following section, we detail how opinion mining is performed to obtain a structured dataset that will allow us to generate association rules and thus extract virality patterns of Twitter content.

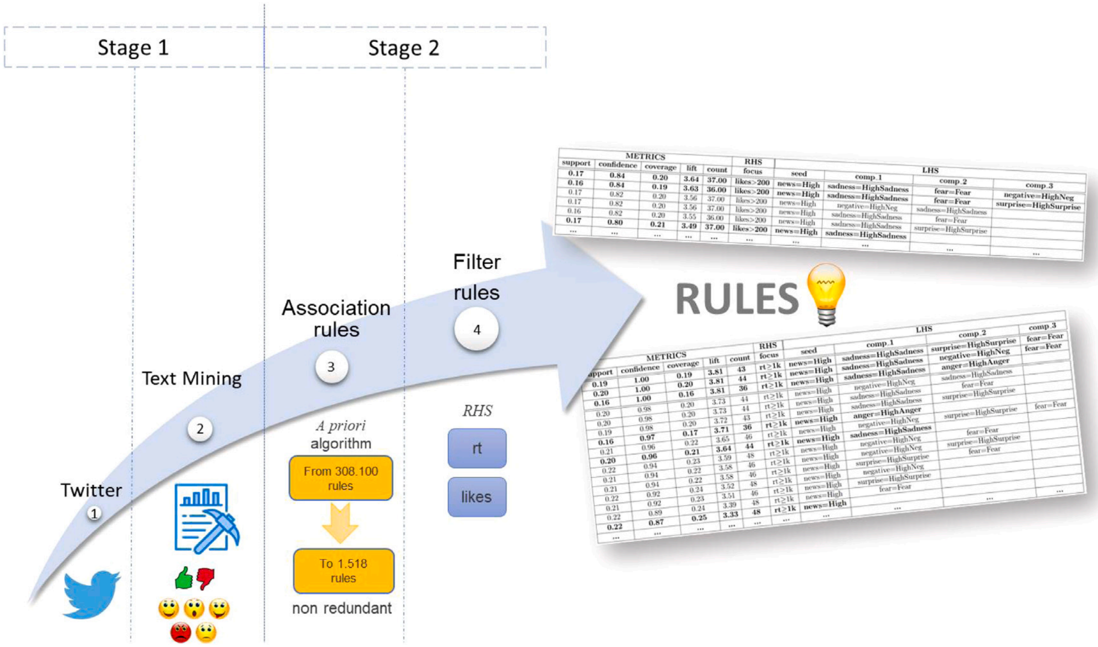

Fig. 1. Text mining and association rules discovery framework.

3. Text mining and association rules discovery framework

Measuring opinions and emotions of social media users is important in relation to the COVID-19 pandemic given that such a global health crisis makes it necessary to know the types of messages that are going viral on social media. Highly viral malicious content can lead to serious public health problems worldwide. In this context, NLP and opinion mining techniques can be extremely useful, enabling the detection of social media content types that have the potential to be highly shareable on social media. In addition, knowing in advance the patterns that make messages go viral on these networks is also a very powerful tool that can be used by public health information services to better inform and guide their external communication strategies. Therefore, the aim of this work is to create a framework that enables the discovery of pattern-types that go viral on social networks. For this purpose, we focused on the following five trending topics related to the pandemic and collected information on them over a period of 45 consecutive days between 01/01/2021–14/02/2021:

- COVID-19 vaccine
- COVID-19 origins
- COVID-19 consequences
- COVID-19 lockdown
- COVID-19 cures and remedies

As Fig. 1 shows, this unstructured textual information was first processed and analyzed using NLP techniques such as sentiment and polarity analysis. Then, viral content patterns were obtained using association rules mining from the structured data generated. The two stages of the framework are presented in depth in the next subsections.

3.1. From unstructured to structured data

The web application "GPLSI Social Analytics" system provides real-time monitoring of entities in social networks and obtains reputation measurements of certain parameterizable concepts from the number of positive and negative opinions received, as well as the emotions triggered. The assessment is determined from a series of formulas that consider the positivity and negativity aspects of the mentions, as well as the influence of the groups that make them (Fernandez, Llopis, Martinez-Barco, Gutierrez and Diez, 2017).

To compute the sentiment and emotional analysis metrics, GPLSI Social Analytics applies the algorithm developed by Fernández, Gutiérrez, Tomás, Gómez, and Martínez-Barco (2015) which in general terms follows the following procedural steps:

1. Term extraction: This task begins by normalizing single terms to lowercase, removing user nicks and URLs, and deleting repeated characters that deform words. Next, these single terms are used to generate skip-gram terms as context representation for each text line.
2. Scoring skipgram terms with polarity scores: Skipgram terms are scored according to the relevance with which they appear in phrases annotated as Positive, Negative, or Neutral. This relevance to a given category is obtained by applying the scoring procedure described at Fernández et al. (2015). The same procedure is applied for scoring the emotional categories.
3. Language Modeling: In this step, to build the sentiment classification model, it is necessary to construct a feature matrix where each polarity is considered as a feature, and each text as a training instance. For example, in the case of categorizing into positive, negative or neutral (three categories), there will be three features by instance (i.e. text), called positiveFeatureScores, negativeFeatureScores, and neutralFeatureScores respectively, and a fourth that represents the target to be predicted (i.e. the category). The values for these features is the sum of the scores in relation to the skipgram occurrences in the text (i.e.,skipgram scores). This produces a value (i.e. the sum of the skipgram scores) and the mathematical formula is detailed at Fernández et al. (2015). At the end of this step, a computational model is generated. When modeling emotions, the features considered would be configured according to the emotional categories previously mentioned, and the feature matrix construction process would also follow the same strategy applied to the polarities. However, in the case of emotions, we are using emotional instead of polarity corpora. The machine learning algorithm applied to generate this model was Support Vector Machines (SVM) by employing the library LibSVM (Chang & Lin, 2011) and with the default implementation recommended by the library (*linear kernel*, $C = 1$, $\epsilon = 0.1$). LIBSVM is a widely extended machine learning library for support vector classification

(C-SVC, nu-SVC), regression (epsilon-SVR, nu-SVR) and distribution estimation (one-class SVM). The choice of SVM was due to its good performance in text categorization tasks (Sebastiani, 2002) and previous works (Fernández et al., 2013).
4. Text classification: To predict the polarity and emotions of new texts, each input text is pre-processed by extracting features, as previously mentioned. Then, based on these features, the model predicts probability scores to each polarity category, for example: Positive: 0.8; Negative: 0.05; Neutral: 0.15 ; as well as the six Ekman emotions (Ekman, 1992), for example: Fear: 0.1; Happy: 0.6; Sadness: 0.0; Surprise: 0.2; Angry: 0.1; Disgust: 0.0. In Table 1, some examples of tweets classified with emotions are presented. More details about the overall procedure can be found at Fernández et al. (2015).

The quality of both, sentiment polarity and emotion procedures has been evaluated. Regarding the sentiment polarity classification, as can be seen in the results reported by the challenge TASS 2015 (Villena-Román et al., 2015), the top accuracy reported for the polarity classification task at global level was 0.672. However, under the same circumstances (i.e. corpora, task and evaluation metrics), the algorithm used by the GPLSI Social Analytics system reports a highly competitive accuracy of 0.863 (Fernández et al., 2015). With respect to the emotion classification, this algorithm was set up and trained by using the corpus provided by Alm (2010). Given that its evaluation has not been published yet on shared events, we performed an internal evaluation by using the corpus.[2] Our evaluation over this corpus, obtained an accuracy of 0.897. In comparison with the state of the art reported by Saravia et al. (2018), the best accuracy reported was around 0.810, thus 0.08 lower than our internal evaluation score. It is important to remark that we opted to classify with emotion categories only those texts that obtained a very high score in line with each emotional category. Consequently, from the global evaluation corpus few texts were classified, reaching only a recall of 0.268. This implies that few texts can be classified with an emotion, although the predictions obtained are highly competitive and robust.

The overall monitoring system operates as follows. First, it downloads messages and comments from Twitter, then it extracts useful information (text, author, polarity, etc.) and finally, it stores it to generate a report in real time. The system is divided into three main modules:

1. **"listening"** module,[3] messages from the social network are periodically downloaded and temporarily stored in the "Entities" database. The Twitter API allows this download in streaming;
2. **"processing"**,[4] data extraction, detection and sentiment analysis of the messages retrieved through the "listening" module are performed. In this module, the polarity of the texts is also extracted from the hybrid approach described in the previous paragraph; and,
3. **"presentation"**[5] allows access to all the system data: number of mentions of each entity; potential message audience; reputation; polarity; etc. (Fernandez, Llopis, Martinez-Barco et al., 2017).

Subsequently, the information is stored in three databases as part of a fourth module, only intended for **data persistence**[6]:

1. in **"Entities"** the key terms necessary to retrieve the conversations around the subjects are stored as the objects to study (that is, the five subjects about COVID19). In this work, as will be seen, the terms listed next are selected as keywords;
2. in **"Repository"** messages and comments obtained on Twitter are temporarily stored. Once processed, this information is eliminated and only the metadata obtained persists;
3. in **"Index"**, the metadata and fragments of messages and Twitter comments are indexed in a way that allows analysis and statistics to be carried out efficiently (Fernandez, Llopis, Martinez-Barco et al., 2017).

Table 1
Real examples for each type of emotion extracted from the dataset.

Emotion	Examples
Fear	*Tweet: "Soy esa persona que tiene miedo a que le pongan la vacuna del Covid-19 porque soy alérgica a medicamentos".* (I am that person who is afraid of getting the Covid-19 vaccine because I am allergic to medication.) *Tweet: "Le tengo más miedo a la vacuna, que a la enfermedad."* (I am more afraid of the vaccine than I am of the disease.)
Happiness	*Tweet: "Después de 2 meses que alegría, se levantan las restricciones frente al COVID-19 en: Algete, Arroyomolinos, CampoReal."* (After 2 months what a joy, COVID-19 restrictions are lifted in: Algete, Arroyomolinos, CampoReal.) *Tweet: "Que alegría, no perdamos la esperanza. En años pasados han habido pandemias y se han superado."* (What a joy, let us not lose hope. There have been pandemics in the past and they have been overcome.)
Sadness	*Tweet: "Estoy triste de no poder ver a mi amiga en su cumpleaños. Estoy harta de este confinamiento. Estoy harta del covid."* (I am sad that I can't see my friend on her birthday. I am sick of this lockdown. I am sick of covid.) *Tweet: "Tanta muerte y sin esperanza de una vacuna confíable para Venezuela. QEPD Con dolor lamento informar el fallecimiento del Dr. EDDY RAMIREZ."* (So much death and no hope of a reliable vaccine for Venezuela. QEPD With sorrow I regret to inform of the death of Dr. EDDY RAMIREZ.)
Anger	*Tweet: "Que rabia la gente que se pasa las restricciones por donde yo me sé y luego quiere que se acabe el covid."* (It's so annoying to see people who ignore restrictions and then want covid to end.)
Disgust	*Tweet: "Si, estamos cansados del virus Covid, del virus del Gobierno, y de todos los parásitos periodistas palmeros, que es... Estamos muy cansados. Llevamos cerca de un año con restricciones muy duras."* (Yes, we are tired of the Covid virus, of the government virus, and of all the parasitic journalist cronies, which is... We are very tired. We've been under severe restrictions for about a year now.)
Surprise	*Tweet: "Una cosa que siempre me ha sorprendido desde que estamos con covid y tuvimos que desarrollar una vacuna para la enfermedad."* (One thing that has always surprised me since we have lived with covid and had to develop a vaccine for the disease.)

As can be seen, this platform provides subjective information from tweets, i.e. sentiment polarities and emotions; and also the following factual information: Tweet author; who is being mentioned in tweets; retweets; likes; number of author followers, which directly affects the potential tweet audience; and, news published in Twitter.

3.1.1. Listening set-up

The aim of this study is to monitor the five previously mentioned trending topics related to the COVID-19 crisis in Spain. Due to the fact that large volumes of data can be obtained in a short time-frame, the starting point is to discover if there are any rules that manage the information chaos created by the enormous quantity of social media content. For instance, discovering the features of trending topics that are expected to become viral in order to establish the queries in the listening process.

[2] https://huggingface.co/datasets/emotion provided by Saravia, Liu, Huang, Wu, and Chen (2018).
[3] http://rua.ua.es/dspace/handle/10045/74075.
[4] http://rua.ua.es/dspace/handle/10045/74074.
[5] http://rua.ua.es/dspace/handle/10045/74073.
[6] http://rua.ua.es/dspace/handle/10045/74072.

Query terms:

The period of time studied was from **January 1st to February 14th, 2021**. The target language is Spanish and the subjects to monitor were queried as follows[7]:

- **COVID-19 vaccine**:
  Query: ((Vacuna covid19) OR (vacuna covid-19) OR (vacuna covid-19 5G) OR (vacuna covid19 5G))
- **COVID-19 origins**:
  Query:((origen covid19 laboratorio Wuhan) OR (origen covid-19 Bill Gates) OR (origen covid19 Bill Gates) OR (origen covid19 5G) OR (origen covid-19 epidemias que se repiten) OR (origen covid-19 laboratorio Wuhan) OR (origen covid19 fabricación *y* venta del virus) OR (origen covid19 epidemias que se repiten) OR (covid-19 paciente cero) OR (origen covid-19 epidemia repite) OR (origen del covid-19 5G) OR (origen del virus covid-19) OR (origen covid19 venta del virus) OR (origen covid19 fabricación))
- **COVID-19 consequences**:
  Query: ((consecuencias del covid-19) OR (covid19 falsa indicación) OR (covid19 falso medico) OR (covid19 qué es falso) OR (covid19 vacuna consecuencia) OR (covid19 cantidad afectados) OR (covid19 solución falsa) OR (covid19 politica) OR (covid19 numero afectados) OR (covid19 medidas falsas))
- **COVID-19 lockdown**:
  Query: ((restricciones covid) OR (restricciones covid19) OR (restricciones covid-19) OR (confinamiento covid19) OR (confinamiento covid-19) OR (Confinamiento covid))
- **COVID-19 cures and remedies**:
  Query:((covid19 eucalipto) OR (covid19 lejía) OR (covid19 aguantar la respiración 10 segundos) OR (clorito de sodio covid19) OR (remedios para covid-19) OR (covid19 curas ilegales) OR (alimento contra el coronavirus (café o eucalipto)) OR (café contra covid19) OR (curas covid-19) OR (recomendaciones para detectar covid19) OR (prevenir covid19 no maquillarse) OR (covid19 plata coloidal) OR (covid19 salvaslip) OR (garganta húmeda covid19) OR (recomendaciones para detectar el coronavirus))

As result, a total of **96,694** tweets were obtained, with an average of **2149** tweets per day. They were split into batches per day by considering a set of structured variables that can be measured. In Table 2, all the structured variables used in the study, with their description, are presented. Besides, the two objective variables on which the study is focused are indicated in the table (Objective type).

After defining the structured variables, the dataset's main features are presented in Table 3.

As observed in Table 3, the topic from which most posts were extracted in the set period was "Vaccines". In addition, the table includes the following information: the predominant polarity of the posts (positive, negative or neutral) and the number of associated tweets; the predominant emotion and the number of associated tweets; and, the number of tweets classified at the same time with the predominant polarity and predominant emotion.

In addition to the prevalent polarity and emotion presented in Table 3, Fig. 2 shows the total distribution of polarity by subject and for the five topics together as a whole. In this work, we consider as neutral the ones without a positive or negative charge.

Similarly, for all those tweets that have been classified with an emotion, Fig. 3 includes the distribution by emotion for each topic and for the five topics as a whole. As can be observed, Surprise, Fear and Sadness are the dominant emotions.

Finally, Fig. 4 presents the percentage of tweets in the following contexts: when only polarity is classified without being assigned an emotion (blue positive-yellow negative); and, when there is an intersection between polarity and an emotion (red and green). The four values are provided for each topic, and for all the topics together.

[7] Since Spanish is the target language, original queries in this language are indicated.

Table 2
Variables included for study.

Variable	Description	Type
From newspaper's perspective		
news	Total number of news published in Twitter each day about the subject	Participant
From Twitter's perspective		
rt	Total number of ReTweets talking about the subject on Twitter each day	**Objective**
likes	Total number of likes of Tweets that talk about the subject on each day	**Objective**
authors	Total number of Twitter accounts talking about the subject on each day	Participant
post	Total number of Tweets talking about the subject on each day	Participant
audience	Total number followers that potentially received Tweets talking about the subject on each day	Participant
maxAudience	Largest number of Twitter accounts have received Tweets talking about the subject on Twitter each day	Participant
positive	Total number of positive Tweets talking about the subject on each day	Participant
negative	Total number of negative Tweets talking about the subject on each day	Participant
happiness	Total number of Tweets talking about the subject on each day that express happiness emotion	Participant
sadness	Total number of Tweets talking about the subject on each day that express sadness emotion	Participant
anger	Total number of Tweets talking about the subject on each day that express anger emotion	Participant
disgust	Total number of Tweets talking about the subject on each day that express disgust emotion	Participant
surprise	Total number of Tweets talking about the subject on each day that express surprise emotion	Participant
fear	Total number of Tweets talking about the subject on each day that express fear emotion	Participant

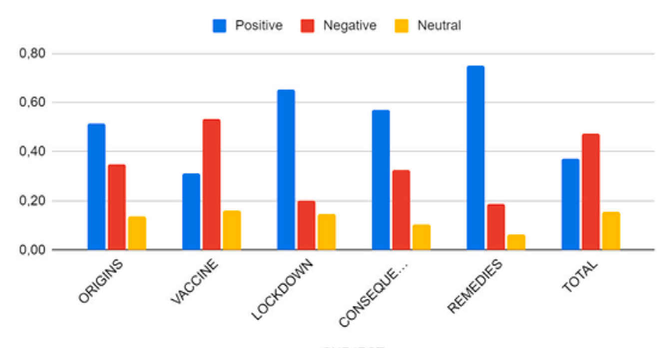

Fig. 2. Polarity distribution from the structured dataset by subject.

3.2. Association rules applied to discover social media viralization patterns

Association rules are an intuitive mechanism for finding patterns in structured data. They have the form of a statement: If A then B, where A is the antecedent or left-hand-side (lhs) and B is the consequent or right-hand-side (rhs), and where A and B is an individual item or set of items (itemset). This technique is very useful in shopping cart analysis to identify items that are purchased together on web page searches to identify patterns, among others.

Table 3
Figures obtained from the dataset by topic.

COVID-19 subject	Total Tweets	Tweets per day (Av.)	Total audience	Average audience per day	Dominant polarity	Tweets Dom. polarity	Dominant emotion	Tweets Dom. emotion	Tweets Dom. polarity + Dom. emotion
Lockdown	13,956	310.13	4908×10^6	109×10^6	Positive	9,135	Fear	218	139
Conseq.	2,365	52.55	827×10^6	18×10^6	Positive	1,353	Surprise	54	27
Origins	543	12.07	576×10^6	13×10^6	Positive	280	Surprise	19	10
Remedies	701	15.58	234×10^6	5×10^6	Positive	525	Surprise	25	16
Vaccine	79,129	1758.42	$27,507 \times 10^6$	611×10^6	Negative	42,092	Sadness	1128	691

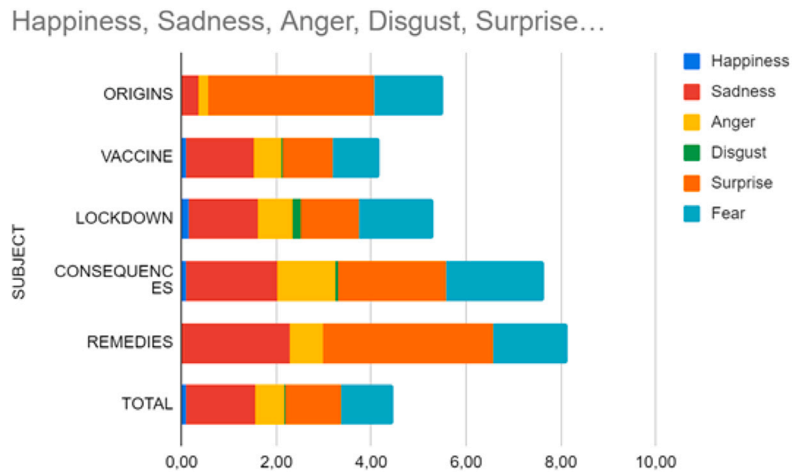

Fig. 3. Percentage of tweets of the structured dataset classified with emotions by subject.

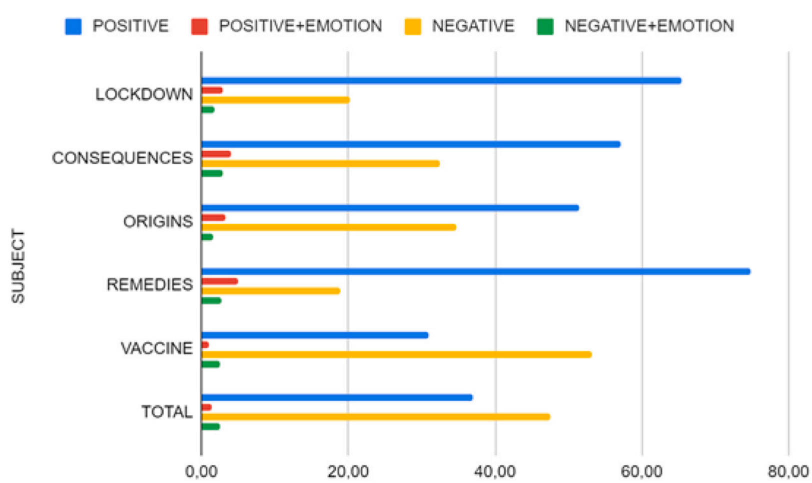

Fig. 4. Percentage of tweets by subject (with polarity and with polarity plus emotions) from the structured dataset.

There are several metrics to measure the quality of an association rule such as support, confidence, coverage and lift.

Let D be the dataset, A and B items from the dataset, and $A \Longrightarrow B$ an association rule.

- Count: It is the number of times that the antecedent A (lhs) appears in the dataset D.

$$count(A \Longrightarrow B) = |A|$$

- Coverage: It is the proportion of times that the antecedent A (lhs) appears in the dataset D.

$$coverage(A \Longrightarrow B) = \frac{|A|}{|D|}$$

- Support: The proportion of times the antecedent (lhs) and consequent (rhs) appears in the dataset. The support of a rule is a measure of how frequently A and B together appear in the dataset.

$$supp(A \Longrightarrow B) = \frac{|A \cap B|}{|D|}$$

- Confidence: The proportion of times the antecedent (lhs) and consequent (rhs) appear in the subset where the antecedent (lhs) already appears. Then, confidence $conf(A \Longrightarrow B)$ is a measure of how frequently the association rule is true in the A itemset.

$$conf(A \Longrightarrow B) = \frac{|A \cap B|}{|A|}$$

- Lift: Compares the observed frequency of a rule with the frequency expected simply by chance (if the rule does not actually exist) (Brin, Motwani, Ullman, & Tsur, 1997). When the lift is close to 1, it is more likely that the rule is by chance, i.e., lhs and rhs are independent. And when lift < 1 there is a NEGATIVE association. It is important to bear in mind that the lift does not understand cause and effect, it only studies the mutual relationship; it is analogous to a correlation.

$$lift(A \Longrightarrow B) = \frac{|A \cap B|}{|A| \times |B|}$$

We used A priori algorithm (Agrawal & Srikant, 1994), an unsupervised machine learning algorithm for extracting association rules from frequent itemsets. A priori is an easily understandable frequent itemset mining algorithm. It is the oldest algorithm and the most widely used. The A priori algorithm uses an iterative process that involves the following four steps:

1. Calculate the support for itemsets of size 1 (only one label).
2. Discard items whose support is lower than the predefined support (by default the minimum support is 0.1).
3. Repeat the process with itemsets of size 2 and so on, successively building up the set of frequent itemsets.
4. Generate all possible association rules from the frequent itemsets whose confidence is higher than the minimum predefined confidence (by default the minimum confidence is 0.8).

Although there are other algorithms such as ECLAT or FP-Growth with high performance in time and memory usage, A priori is an equally valid algorithm given its ease of use and importantly, for the same parameters the same results are obtained. In our case, the execution time was almost instantaneous (<0.1 s) and, therefore, it was not necessary to implement any improvement and there is no noticeable difference in performance or memory usage on this dataset. This, together with the advantage of being one of the most widely used algorithms in association rule analysis, has led to its selection for this experiment.

Moreover, our approach does not employ an inference method. The algorithm A priori simply counts the number of times two attributes appear together. Thus, accuracy is inherent to our approach and thereby, the emergent patterns described have the benefit of certainty. Our goal is not to predict but to describe the observed data.

Data preparation: Once the Twitter posts were processed to obtain the structured data, we analyzed them using association rules to find common patterns. Since 4 of the 5 selected topics of study had a very scarce amount of data, all the data collected from the 5 topics were considered as a consolidated dataset. The dataset is a two-dimensional table that depicts rows representing the 45 days per topic, and the columns are the variables indicated in Table 2.

We established categories for the numerical variables to identify low, medium and high values for each input variable (Table 4). Depending on the range observed in each variable, 2, 3 or 4 categories were established. Statistical measures were used to balance the categories, using quantiles for each category, and then adjusted to logical measures for each variable by approximation, to make the rules intuitive and useful. For example, for maxAudience we considered four categories given the extent of the observed range (between 0 and 20 million): less than 100k, between 100k and 999k between 1M and 20M greater than 20M. For Tweet authors, we consider only 3 categories, less than 20, between 20 and 200 and more than 200 authors. For fear we used only two categories, Zero or Fear when appearing in the post.

Algorithm settings: We used *A priori* algorithm implemented in R by the $arules$ packages (Hahsler, Gruen, & Hornik, 2005). We set the following parameters: minimum support of 0.1, minimum confidence of 0.8, maximum of 10 items (maxlen), and a maximal time for subset checking of 5 s (maxtime). Increasing the minimum support reduces the number of rules because it discovers fewer frequent items. Increasing the minimum confidence also causes the same behavior, by requiring the discovered pattern to be more frequent. We obtained a vast number of rules (308,100).

For pruning the results we eliminated redundant rules. A rule is redundant if a more general rule with the same or a higher confidence exists. Finally, we obtained 1518 non-redundant rules. The maximum number of elements in the antecedent was set to 10 which is the default value in the A priori algorithm implemented in the "arules" package in R. But did not obtain any rule exceeding 4 antecedents that met the minimum support and confidence requirements and was not redundant.

We then filtered the rules with the consequent (rhs) objective of the study, i.e. retweet, likes, considering as possible antecedents (lhs) the participant variables shown in Table 2. Therefore, we could find all the rules whose result directly affects the objective.

4. Virality patterns

The focus of this work is to establish high-level semantic patterns of viral messages (high shares and likes) in a given day in Twitter COVID-19 context posts. Hence, the study is framed in line with the following benchmarks. First, the patterns of messages about the same topic that generate high shares in a given day are extracted. Secondly, the patterns of messages about the same topic with low shares in a given day are obtained. As indicated in Section 1 Twitter's model of tweet–retweet sharing generates the cascade effect in which virality is based. Based on this fact, the defined variable "rt" (retweets) is used as the consequent or right-hand-side of the rule (RHS), considering the consequent $rt \geq 1k$ for high shares and the consequent $rt \leq 100$ for low shares. Likewise, high and low-likes content about the same topic in a given day are studied, considering those rules whose consequent is the "likes" variable, being the consequent $likes > 200$ for high likes and the consequent $likes < 20$ and $20 \leq likes \leq 200$ for low likes.

The methodology used to explain the results is explained hereafter. In order to classify and study the association rules obtained, first, all those rules with the focused consequent were selected. Then, from those, the rules that are not redundant and with a high confidence value – confidence greater than 0.80 – and with lift greater that 1 – indicating that the rule is not the result of chance – were chosen. Finally, we determined as seed the characteristic that is common to the whole set of maximum confidence rules, and grouped together the rules by the seeds. All the rules containing the seed in the antecedent (LHS) are presented together. The seed combined with the different LHS complements (comp_x) generates different patterns whose metric values are compared and analyzed.

Although when applying the association rules in other areas, such as in the market basket analysis, the value of confidence 1 is not always interesting, since it may indicate trivial rules. However, in our case, as we intend to extract those content patterns that imply a specific consequent, such as high share, higher confidence rules (close to 1) will be a value to look for, as long as the lift is as high as possible and always greater than 1, as explained previously. This is mainly because there are no previous related studies and therefore, there is less information on the subject, whereas for market basket analysis trivial rules should be avoided given their prior knowledge (Agrawal et al., 1993).

As previously mentioned, the purpose of this study is to determine what type of content (polarity, emotional charge, etc.) causes a higher and lower virality. The following subsections present the association rules extracted for each benchmark and a discussion of the results.

For the analysis, the metrics support, confidence, coverage, lift and count, defined in Section 3.2, are presented in the following tables for each relevant rule. All patterns represented in the tables are in descending order by confidence value.

To draw conclusions from the analysis, we will give priority to those rules that maximize the confidence measure as this is the main metric to ensure the usefulness of the rule. However, we will also pay attention to

Table 4
Categories of variables.

Variable	Categories			
News	Zero	1–9	>9	
rt	<100	100–1000	>1000	
likes	<20	20–200	>200	
authors	<20	20–200	>200	
post	<20	20–200	>200	
audience	<10k	10k–100k	100k–1M	>1M
maxAudience	<100k	100k–999k	1M–20M	>20M
positive	Zero	LowPositive (1–5)	MidPositive (5–50)	HighPositive (>50)
negative	Zero	LowNegative (1–5)	MidNegative (5–50)	HighNegative (>50)
happiness	Zero	LowHappy (only 1)	MidHappy (2–3)	HighHappy (4)
sadness	Zero	LowSadness (1–5)	HighSadness (>50)	
anger	Zero	LowAnger (1–5)	HighAnger (>50)	
disgust	Zero	LowDisgust (1–5)	HighDisgust (>50)	
surprise	Zero	LowSurprise (1–5)	HighSurprise (>50)	
fear	Zero	Fear (>0)		

Table 5
High-share patterns with high news dissemination (news=High).

METRICS					RHS	LHS			
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2	comp_3
0.19	**1.00**	**0.19**	**3.81**	**43**	**rt≥1k**	**news=High**	**sadness=HighSadness**	**surprise=HighSurprise**	**fear=Fear**
0.20	**1.00**	**0.20**	**3.81**	**44**	**rt≥1k**	**news=High**	**sadness=HighSadness**	**negative=HighNeg**	**fear=Fear**
0.16	**1.00**	**0.16**	**3.81**	**36**	**rt≥1k**	**news=High**	sadness=HighSadness	**anger=HighAnger**	
0.20	0.98	0.20	3.73	44	rt≥1k	news=High	negative=HighNeg	sadness=HighSadness	
0,20	0.98	0.20	3.73	44	rt≥1k	news=High	sadness=HighSadness	fear=Fear	
0.19	0.98	0.20	3.72	43	rt≥1k	news=High	sadness=HighSadness	surprise=HighSurprise	
0.16	**0.97**	**0.17**	**3.71**	**36**	**rt≥1k**	**news=High**	**anger=HighAnger**		
0.21	0.96	0.22	3.65	46	rt≥1k	news=High	negative=HighNeg	surprise=HighSurprise	fear=Fear
0.20	**0.96**	**0.21**	**3.64**	**44**	**rt≥1k**	**news=High**	sadness=HighSadness		
0.22	0.94	0.23	3.59	48	rt≥1k	news=High	negative=HighNeg	fear=Fear	
0.21	0.94	0.22	3.58	46	rt≥1k	news=High	negative=HighNeg	surprise=HighSurprise	
0.21	0.94	0.22	3.58	46	rt≥1k	news=High	surprise=HighSurprise	fear=Fear	
0.22	0.92	0.24	3.52	48	rt≥1k	news=High	negative=HighNeg		
0.21	0.92	0.23	3.51	46	rt≥1k	news=High	surprise=HighSurprise		
0.22	0.89	0.24	3.39	48	rt≥1k	news=High	fear=Fear		
0.22	**0.87**	**0.25**	**3.33**	**48**	**rt≥1k**	**news=High**			

the support and coverage metrics since they will indicate whether the rule is relevant to the dataset as a whole. In this sense, a rule with high confidence but low support or coverage would be discarded as it is not representative of a general behavior in viralization processes. Likewise, we will also take into account the rules that maximize the lift metric, because they will guarantee that the rule is not obtained by chance, but because it obeys actual social media content behavior.

4.1. High-share patterns

According to the categories established for the numerical variables defined, based on our dataset and according to the statistical criteria exposed in Section 3.2, a high-share behavior is considered when “rt” is greater than 1000 per day, so the rules whose consequent is $rt \geq 1k$ have been extracted.

4.1.1. High news dissemination on social media

First, the seed from the newspaper’s perspective, $news = High$, is presented in Table 5. $news = High$ means that the total number of news items published in Twitter about the subject for the day on which the analyzed tweet was posted is greater than 9. Table 5 represents the patterns extracted on a given day. Starting from the seed, the different elements combined with this seed are presented in the table. The same procedure is performed with all the seeds detected for the high-share content behavior.

As observed in Table 5, the basic rule[8] that uses the seed is described as follows: “If $news = High$ then $rt \geq 1k$”. With this rule a 0.87 of confidence of having $rt \geq 1k$ is achieved, with a relatively high support (0.22) and coverage values (0.25). Support and coverage remain steady for all relevant patterns relating to high shares.

When combining the seed with a high level of emotions like sadness or anger separately, confidence is increased to 0.96 and 0.97 respectively. However, the maximum value of confidence is achieved when these two emotions (High sadness and high anger) are combined together with a high diffusion of related news in the media (news=High).

Furthermore, if there is a high dissemination of news, combined with fear and high sadness, maximum confidence value (1.00) is also achieved when adding high surprise or high negative polarity content to the post.

4.1.2. High level of polarity and emotions

In this subsection, the seeds from Twitter’s perspective were studied. When considering high negative and high sadness as seeds only rules with three items in the left-hand side were obtained. In Table 6, the seed is $negative = HighNeg$. This means that the number of negative tweets talking about the subject on a given day are more than 50. The basic rule that uses the seed is described as follows: “If $negative = HighNeg$ and $fear = Fear$ then $rt \geq 1k$” with a support of 0.25, a confidence of 0.80 and a high lift value.

According to the figures presented in Table 6, adding sadness to a high negative with fear content increases the confidence to 0.91. However, the highest confidence value is obtained if a high load of surprise is added to the post content, raising the confidence to 0.94, and a 0.54 increase in lift.

Table 7 represents the patterns extracted on a given day, using $sadness = HighSadness$ as seed. This means that the total number of

[8] The basic rule contains the seed and its confidence value is the lowest above the minimum threshold value (0.80).

Table 6
High-share patterns with a high level of negative polarity (negative=HighNeg).

METRICS					RHS	LHS		
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2
0.23	**0.94**	**0.24**	**3.59**	**50**	**rt≥1k**	**negative=HighNeg**	**surprise=HighSurprise**	**fear=Fear**
0.23	0.93	0.24	3.53	50	rt≥1k	negative=HighNeg	surprise=HighSurprise	
0.23	**0.91**	**0.25**	**3.46**	**50**	**rt≥1k**	**negative=HighNeg**	**sadness=HighSadness**	**fear=Fear**
0.23	0.89	0.25	3.40	50	rt≥1k	negative=HighNeg	sadness=HighSadness	
0.25	**0.80**	**0.32**	**3.05**	**56**	**rt≥1k**	**negative=HighNeg**	**fear=Fear**	

Table 7
High-share patterns with a high level of sadness (sadness=HighSadness).

METRICS					RHS	LHS		
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2
0.21	**0.98**	**0.21**	**3.73**	**46**	**rt≥1k**	**sadness=HighSadness**	**surprise=HighSurprise**	**fear=Fear**
0.16	**0.97**	**0.17**	**3.71**	**36**	**rt≥1k**	**sadness=HighSadness**	**anger=HighAnger**	
0.21	**0.96**	**0.22**	**3.65**	**46**	**rt≥1k**	**sadness=HighSadness**	**surprise=HighSurprise**	
0.23	0.91	0.25	3.46	50	rt≥1k	sadness=HighSadness	negative=HighNeg	fear=Fear
0.23	0.89	0.26	3.41	51	rt≥1k	sadness=HighSadness	fear=Fear	
0.23	0.89	0.25	3.40	50	rt≥1k	sadness=HighSadness	negative=HighNeg	
0.23	**0.88**	**0.26**	**3.35**	**51**	**rt≥1k**	**sadness=HighSadness**		

Table 8
High-share patterns with high level of surprise (surprise=HighSurprise).

METRICS					RHS	LHS		
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2
0.21	**0.98**	**0.21**	**3.73**	**46**	**rt≥1k**	**surprise=HighSurprise**	**sadness=HighSadness**	**fear=Fear**
0.21	**0.96**	**0.22**	**3.65**	**46**	**rt≥1k**	**surprise=HighSurprise**	**sadness=HighSadness**	
0.23	0.94	0.24	3.59	50	rt≥1k	surprise=HighSurprise	negative=HighNeg	fear=Fear
0.23	0.93	0.24	3.53	50	rt≥1k	surprise=HighSurprise	negative=HighNeg	
0.23	0.91	0.25	3.46	50	rt≥1k	surprise=HighSurprise	fear=Fear	
0.23	**0.89**	**0.25**	**3.40**	**50**	**rt≥1k**	**surprise=HighSurprise**		

tweets referring to the subject with a sadness emotion is more than 5 in a day. The basic rule that uses the seed is described as follows: "If $sadness = HighSadness$ then $rt \geq 1k$" with a support of 0.23 and a confidence of 0.88.

When high sadness is combined with fear or high negative polarity, confidence barely increases to 0.89. More remarkable, however, is the increase in confidence that occurs when combining high sadness with high anger or high surprise, where confidence reaches values of 0.97 and 0.96, respectively. Nevertheless, in this case, the highest confidence and lift values are obtained by combining high sadness with high surprise and fear, which increases confidence to 0.98 and a lift increase of 0.38.

Finally, Table 8 represents the patterns extracted on a given day, and the seed is $surprise = HighSurprise$. This means that the total number of tweets referring to the subject with a surprise emotion is more than 5 in a day. The basic rule that uses the seed is described as follows: "If $surprise = HighSurprise$ then $rt \geq 1k$" with a support of 0.23 and a confidence of 0.89.

According to Table 8, when adding high sadness to the seed considerably increases confidence to 0.96, but the highest confidence (0.98) is achieved when combining the seed with high sadness and fear, in comparison to having the seed with only fear (confidence = 0.91)

4.1.3. Key features of high-share patterns. A microscopic view

From the experiments, we observed that:

- Regarding polarity of the content in a given day, combining high-negative, with high-surprise and fear content delivers the highest confidence score in terms of being high-shared content.
- Regarding the emotional charge, combining high-sadness and high-anger in a content for a given day leads to high virality. Furthermore, posts that combine high-surprise and high-sadness for a given day also tend to go viral, with virality being more prevalent in combination with a fear-based message. Adding the factor of a high dissemination of news increases the significance of both previous patterns.
- Worthy of mention is that content tends to show viral behavior,on a given day, when highly related media coverage occurs alongside messages containing a high emotional and subjective charge that tends towards negativity and high-sadness and fear.

4.2. Low-share patterns

Considering low-share content behavior as those posts with less than 100 retweets, according to the criteria established in Section 3.2, the association rules with antecedent $rt \leq 100$ were extracted from input data, and then the relevant seeds were extracted. The rules are grouped together per seed.

4.2.1. Absence of news on social media

First, the seed from the newspaper's perspective is studied. Table 9 represents patterns extracted from the content on a given day and the seed is $news = Zero$, this means that there is no news published in Twitter about the subject that day, i.e. the day on which the analyzed tweet was posted. The basic rule that uses the seed is described as follows: "If $news = Zero$ then $rt \leq 100$" with a support of 0.41 and a confidence of 0.83.

Under $news = Zero$ seed, the addition of other emotional antecedents such as the absence of happiness, the absence of anger, the absence of fear, or the absence of sadness slightly raises confidence. However, for all of them, the emotion that makes the biggest difference is the absence of surprise, raising the confidence score to 0.92.

Indeed, the concurrence of polarity antecedents, the absence of news on social media (seed), and the scarcity of posts or authors is what especially determines a significant increase in the confidence score. The absence of polarity, either positive or negative, raises confidence up to 0.97, and even the maximum confidence (1.00) can be obtained when low positivity is combined with absence of surprise. In the same

Table 9
Low-share patterns with absence of news (news=Zero).

METRICS					RHS	LHS			
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2	comp_3
0.14	**1.00**	**0.14**	**2.03**	**31**	**rt≤100**	**news=Zero**	positive=LowPositive	**surprise=Zero**	
0.23	0.98	0.23	1.99	50	rt≤100	news=Zero	sadness=Zero	surprise=Zero	
0.22	0.98	0.22	1.99	48	rt≤100	news=Zero	post≤20	surprise=Zero	
0.18	0.98	0.19	1.98	40	rt≤100	news=Zero	negative=LowNegative	surprise=Zero	
0.32	**0.97**	**0.33**	**1.97**	**70**	**rt≤100**	**news=Zero**	**post≤20**		
0.29	0.97	0.30	1.97	65	rt≤100	news=Zero	authors≤20	sadness=Zero	
0.28	**0.97**	**0.29**	**1.96**	**62**	**rt≤100**	**news=Zero**	**negative=LowNegative**		
0.16	**0.97**	**0.16**	**1.97**	**35**	**rt≤100**	**news=Zero**	**positive=LowPositive**		
0.33	**0.96**	**0.35**	**1.95**	**74**	**rt≤100**	**news=Zero**	**authors≤20**		
0.24	0.96	0.24	1.95	52	rt≤100	news=Zero	authors≤20	surprise=Zero	
0.21	0.94	0.23	1.91	47	rt≤100	news=Zero	surprise=Zero	fear=Zero	
0.24	0.93	0.26	1.89	54	rt≤100	news=Zero	anger=Zero	surprise=Zero	
0.23	0.93	0.25	1.88	51	rt≤100	news=Zero	sadness=Zero	anger=Zero	fear=Zero
0.27	**0.92**	**0.29**	**1.87**	**59**	**rt≤100**	**news=Zero**	**surprise=Zero**		
0.31	0.92	0.34	1.87	69	rt≤100	news=Zero	sadness=Zero	anger=Zero	
0.25	0.92	0.27	1.86	55	rt≤100	news=Zero	sadness=Zero	fear=Zero	
0.28	0.91	0.31	1.85	62	rt≤100	news=Zero	anger=Zero	fear=Zero	
0.31	0.91	0.34	1.84	69	rt≤100	news=Zero	fear=Zero		
0.33	0.90	0.37	1.83	74	rt≤100	news=Zero	sadness=Zero		
0.36	0.87	0.42	1.76	80	rt≤100	news=Zero	happiness=Zero	anger=Zero	
0.37	0.86	0.43	1.75	81	rt≤100	news=Zero	anger=Zero		
0.40	0.84	0.48	1.70	89	rt≤100	news=Zero	happiness=Zero		
0.41	**0.83**	**0.49**	**1.67**	**90**	**rt≤100**	**news=Zero**			

Table 10
Low-share patterns with shortage of contributors (authors≤20).

METRICS					RHS	LHS		
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2
0.29	**0.97**	**0.30**	**1.97**	**65**	**rt≤100**	**authors≤20**	**news=Zero**	**sadness=Zero**
0.15	**0.97**	**0.15**	**1.97**	**33**	**rt≤100**	**authors≤20**	**positive=MidPositive**	**sadness=Zero**
0.14	**0.97**	**0.15**	**1.97**	**32**	**rt≤100**	**authors≤20**	**audience≥1M**	**surprise=Zero**
0.33	**0.96**	**0.35**	**1.95**	**74**	**rt≤100**	**authors≤20**	**news=Zero**	
0.33	**0.96**	**0.34**	**1.95**	**72**	**rt≤100**	**authors≤20**	**sadness=Zero**	
0.24	0.96	0.24	1.95	52	rt≤100	authors≤20	news=Zero	surprise=Zero
0.11	0.96	0.12	1.95	25	rt≤100	authors≤20	audience≥1M	positive=MidPositive
0.19	0.96	0.20	1.94	43	rt≤100	authors≤20	audience≥1M	
0.10	0.96	0.11	1.94	23	rt≤100	authors≤20	surprise=LowSurprise	
0.37	**0.95**	**0.39**	**1.93**	**82**	**rt≤100**	**authors≤20**		

way, the scarcity of posts or authors contributing to the social network during that day on that topic manages to raise the confidence of the rule to 0.97 and 0.96, respectively.

4.2.2. Shortage of contributors to social media

Secondly, the seeds from Twitter's perspective are studied. In Table 10, the seed is $authors \leq 20$, which means that less than 20 Twitter accounts talked about the topic on a given day.

The basic rule that uses the seed is described as follows: "If $authors \leq 20$ then $rt \leq 100$" with a support of 0.37 and a confidence of 0.95.

The resulting table shows that the scarcity of authors contributing to the dissemination of information on Twitter is absolutely decisive in obtaining a low level of retweets. Although this may seem an intuitively logical finding, the study quantitatively demonstrates it and shows it to be true with a confidence score of 0.95. It also shows how the combination of this seed with other antecedents hardly increases the confidence of the rule, reaching at most, maximum values of 0.97 and always at the cost of lower support and coverage.

4.2.3. Shortage of contributions to social media

Finally, Table 11 shows the result of seed $post \leq 20$, which indicates that less than 20 tweets talked about the subject on a given day. The scarcity of posts during a day should apparently affect the number of shares generated. Again, although this is a truism, we seek to quantify it with this study. In this case, we observe that the application of this feature alone is sufficient to generate a confidence of 0.96 with a very high support value (0.35). However, it should be noted that this value can still be slightly increased by accompanying the features already evaluated as significant in previous studies, such as the absence of news and the absence of surprise. In the case of both occurring, a confidence score of 0.98 was achieved.

As expected, the findings in Table 11 are related to those in Table 10, as similar content-sharing behavior is visualized.

4.2.4. Key features of low-share patterns. A microscopic view

From the experiments, we observed that:

- The absence of news on Twitter during a given day causes a significant drop in retweets, which becomes more significant when the message lacks a marked polarity, whether positive or negative.
- The scarcity of authors or posts broadcasting information on a given content during a day causes a significant drop in sharing without the need for other additional factors to concur.
- Of all the emotional features analyzed as a complement to the seeds studied, the absence of surprise in the message has become one of the most relevant elements for increasing confidence in the rule.

4.3. High-likes patterns

Considering high-likes content, those posts with more than 200 likes, according to the criteria established in Section 3.2, the association rules with antecedent $likes > 200$ are extracted from the input data. Then, the relevant seeds are obtained and the rules are grouped together per seed.

Table 11
Low-share patterns with shortage of posts (post≤20).

METRICS					RHS	LHS		
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2
0.22	**0.98**	**0.22**	**1.99**	**48**	**rt≤100**	**post≤20**	**news=Zero**	**surprise=Zero**
0.32	**0.97**	**0.33**	**1.97**	**70**	**rt≤100**	**post≤20**	**news=Zero**	
0.16	**0.97**	**0.17**	**1.97**	**36**	**rt≤100**	**post≤20**	**positive=MidPositive**	
0.13	0.97	0.13	1.96	28	rt≤100	post≤20	audience≥1M	surprise=Zero
0.35	**0.96**	**0.36**	**1.95**	**77**	**rt≤100**	**post≤20**		
0.24	0.96	0.25	1.96	54	rt≤100	post≤20	surprise=Zero	

Table 12
High-Likes patterns with high news dissemination.

METRICS					RHS	LHS			
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2	comp_3
0.17	**0.84**	**0.20**	**3.64**	**37.00**	**likes>200**	**news=High**	**sadness=HighSadness**	**fear=Fear**	**negative=HighNeg**
0.16	**0.84**	**0.19**	**3.63**	**36.00**	**likes>200**	**news=High**	**sadness=HighSadness**	**fear=Fear**	**surprise=HighSurprise**
0.17	0.82	0.20	3.56	37.00	likes> 200	news=High	negative=HighNeg	sadness=HighSadness	
0.17	0.82	0.20	3.56	37.00	likes> 200	news=High	sadness=HighSadness	fear=Fear	
0.16	0.82	0.20	3.55	36.00	likes> 200	news=High	sadness=HighSadness	surprise=HighSurprise	
0.17	**0.80**	**0.21**	**3.49**	**37.00**	**likes>200**	**news=High**	**sadness=HighSadness**		

Table 13
High-Likes patterns with high anger.

METRICS					RHS	LHS	
support	confidence	coverage	lift	count	focus	seed	comp_1
0.14	**0.86**	**0.17**	**3.75**	**32.00**	**likes>200**	**anger=HighAnger**	**sadness=HighSadness**
0.14	0.84	0.17	3.65	32.00	likes>200	anger=HighAnger	

4.3.1. High news dissemination on social media

Table 12 represents patterns extracted in a given day and $news = High$ is fixed as seed. $news = High$ means that the total number of news published in Twitter that day about the subject is more than 9. Starting from this seed, the basic rule that uses the seed is described as follows: "If $news = High$ and $sadness = Highsadness$ then $likes \geq 200$" with a support of 0.17 and a confidence of 0.80. In Table 12, the rules that include the seed are analyzed to see how they influence the impact of a post through the number of likes this post achieves.

By analyzing the relevant association rules obtained that contain the seed $news = High$, we detected that none of the rules containing only this seed have a sufficient confidence score to be considered relevant – confidence greater than 0.80 – and at least. It was necessary to combine high dissemination in news with high sadness to reach the 0.80 confidence value. Furthermore, combining $news = High$, high-sadness and fear with high-negative content or high-surprise content obtains the greatest confidence value (0.84), which occurs 20% of the times in the dataset.

4.3.2. High load of emotional content

When extracting the relevant rules regarding the seeds from Twitter's perspective, rules involving high-sadness and high-anger were extracted, using high-anger as seed, since it is the common element for all the relevant rules extracted.

Table 13 represents the patterns extracted on a given day. The basic rule is described as follows: "If $anger = HighAnger$ then $likes \geq 200$" with a support of 0.14 and a confidence of 0.84. In this case, given a content on a given day, the one that combines a high load of the two emotions (anger and sadness) achieves the highest confidence score.

4.3.3. Key features of high-likes patterns. A microscopic view

From the experiments, we observed that:

- A high dissemination of news on Twitter in a given day by itself does not determine a high-likes content.
- Fear and high-sadness emotions combined with a high dissemination of news and high-negative polarity obtain a remarkable confidence score in terms of high-likes for a given content during a day. In this case, exchanging the high-negative content for a content with high-surprise load indicates a significant pattern.
- High-anger and high-sadness together in a given COVID content during a day imply a considerable confidence score for high likes. Given that liking a post means that you agree with and support its content, the fact that we see this pattern indicates that Twitter users are likely to support content that spreads these types of emotions.

4.4. Low-likes patterns

Considering low-likes posts, those with less than 20 likes ($likes < 20$), only one relevant associated rule was extracted, shown in Table 14.

Table 14 represents the patterns extracted on a given day and the basic rule is described as follows: "If $maxAudience \leq 100k$ then $likes \leq 20$" with a support of 0.10 and a confidence of 0.82. This means that it is not possible to establish clear patterns when it comes to posts that get a low number of likes.

Nevertheless, an analysis of content with a medium number of likes – posts with likes between 20 and 200 – was done since more association rules with this consequent were extracted and grouped together per seed.

4.4.1. Shortage of news on social media

Considering a shortage of news on social media, all the rules containing the seed $news = Low$ are extracted and presented in Table 15 to show their contribution towards obtaining a moderate volume of likes ($20 \leq likes \leq 200$). The seed $news = Low$ means that the total number of news published in Twitter in a given day about the subject is between 1 and 9. The basic rule that uses the seed is described as follows: "If $news = Low$ and $fear = Fear$ then $20 \leq likes \leq 200$" with a support of 0.14 and a confidence of 0.81.

In this case, there is no relevant rule containing only the seed, and the combination between low dissemination of news and fear obtains the lowest confidence value. However, combining low news with low-anger content increases confidence to 0.88. Furthermore, including to both these two elements low-surprise or absence of happiness increases confidence score to 0.92 in both cases.

Table 14
Low-likes patterns with low maxAudience.

METRICS					RHS	LHS
support	confidence	coverage	lift	count	focus	seed
0.10	0.82	0.13	2.75	23.00	likes<20	maxAudience<100k

Table 15
Medium-Likes content with scarcity of news.

METRICS					RHS	LHS		
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2
0.11	**0.92**	**0.12**	**1.96**	**24**	**20≤likes≤200**	**news=Low**	**anger=LowAnger**	**happiness=Zero**
0.10	**0.92**	**0.11**	**1.96**	**23**	**20≤likes≤200**	**news=Low**	**anger=LowAnger**	**surprise=LowSurprise**
0.11	0.89	0.13	1.90	25	20≤likes≤200	news=Low	anger=LowAnger	fear=Fear
0.13	**0.88**	**0.15**	**1.87**	**29**	**20≤likes≤200**	**news=Low**	**anger=LowAnger**	
0.11	0.83	0.14	1.77	25	20≤likes≤200	news=Low	positive=MidPositive	
0.11	0.83	0.14	1.77	25	20≤likes≤200	news=Low	happiness=Zero	surprise=LowSurprise
0.13	0.83	0.16	1.76	29	20≤likes≤200	news=Low	surprise=LowSurprise	
0.11	0.83	0.13	1.76	24	20≤likes≤200	news=Low	happiness=Zero	fear=Fear
0.14	**0.81**	**0.17**	**1.72**	**30**	**20≤likes≤200**	**news=Low**	**fear=Fear**	

Table 16
Medium-Likes content with low-anger emotion.

METRICS					RHS	LHS		
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2
0.11	**0.93**	**0.12**	**1.97**	**25**	**20≤likes≤200**	**anger=LowAnger**	**surprise=LowSurprise**	**fear=Fear**
0.11	**0.89**	**0.13**	**1.90**	**25**	**20≤likes≤200**	**anger=LowAnger**	**negative=MidNegative**	
0.14	0.86	0.16	1.82	30	20≤likes≤200	anger=LowAnger	happiness=Zero	fear=Fear
0.10	0.85	0.12	1.81	23	20≤likes≤200	anger=LowAnger	happiness=Zero	sadness=LowSadness
0.14	0.84	0.17	1.78	31	20≤likes≤200	anger=LowAnger	surprise=LowSurprise	
0.12	0.84	0.14	1.79	27	20≤likes≤200	anger=LowAnger	happiness=Zero	surprise=LowSurprise
0.12	0.84	0.14	1.79	27	20≤likes≤200	anger=LowAnger	sadness=LowSadness	
0.18	0.81	0.22	1.73	39	20≤likes≤200	anger=LowAnger	happiness=Zero	

Table 17
Medium-Likes content with absence of happiness emotion.

METRICS					RHS	LHS		
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2
0.14	**0.86**	**0.16**	**1.82**	**30**	**20≤likes≤200**	**happiness=Zero**	**anger=LowAnger**	**fear=Fear**
0.10	0.85	0.12	1.81	23	20≤likes≤200	happiness=Zero	sadness=LowSadness	anger=LowAnger
0.12	0.84	0.14	1.79	27	20≤likes≤200	happiness=Zero	anger=LowAnger	surprise=LowSurprise
0.18	**0.81**	**0.22**	**1.73**	**39**	**20≤likes≤200**	**happiness=Zero**	**anger=LowAnger**	

4.4.2. Polarity and emotional content

This section analyses how the emotional and polarity features of the content affect the achievement of a mid-sized volume of likes. Table 16 represent patterns extracted in a given day for the low-anger seed. The basic rule using the seed is described as follows: "If $anger = LowAnger$ and $happiness = Zero$ then $20 \leq likes \leq 200$" with a support of 0.18 and a confidence of 0.81. In this case, we can see how the scarcity of anger emotion contributes to generate a medium volume of likes, but always accompanied by other emotional characteristics such as low-surprise, the absence of happiness or the incorporation of a medium degree of negativity. Specifically, the maximum value of trust is obtained by combining low-anger, low-surprise and a feeling of fear.

Table 17 represents the patterns extracted on a given day and the basic rule that uses the seed is described as follows: "If $happiness = Zero$ and $anger = LowAnger$ then $20 \leq likes \leq 200$" with a support of 0.18 and a confidence of 0.81. Table 17 shows how the absence of happiness affects the likes, and again there is a significant relationship of consequence, although again, always accompanied by other emotions. In this case, the low-anger emotion is always present, reaching the highest confidence score when combined with the feeling of fear.

Table 18 shows the impact of polarity on the achievement of an intermediate level of likes. The basic rule that uses the seed is described as follows: "If $negative = MidNegative$ then $20 \leq likes \leq 200$" with a support of 0.22 and a confidence of 0.80. In this case, the negative polarity of the messages, when occurring in a moderate way, also contributes to a moderate number of likes. This impact is even greater when combined with other emotions such as low-anger which generates the highest confidence value for the rule (0.89).

Finally, Table 19 presents the impact of the emotion sadness on the achievement of a moderate level of likes. The basic rule is described as follows: "If $sadness = LowSadness$ and $fear = Fear$ then $20 \leq likes \leq 200$" with a support of 0.14 and a confidence of 0.82. This emotion does not obtain significant values on its own, but its combination with other emotional markers such as low anger or absence of happiness contributes to a moderate generation of likes with high confidence values.

4.4.3. Key features of low-likes patterns. A microscopic view

From the experiments, we observed that:

- For the sample of data collected, it is not possible to establish a clear pattern for those contents that do not get likes during a given day.
- The shortage of news on Twitter in a given day is not a relevant element when analyzing a moderate level of likes on the post. Only when this feature is combined with a fear-based message does the rule become relevant. However, the shortage of news becomes more significant when the message has low-anger and low-surprise or low-anger and a shortage of happiness contents.
- Some emotional features have a significant impact on obtaining a moderate level of likes (between 20 and 200) on the message.

Table 18
Medium-Likes content with medium negative polarity.

METRICS					RHS	LHS	
support	confidence	coverage	lift	count	focus	seed	comp_1
0.11	**0.89**	**0.13**	**1.90**	**25**	**20≤likes≤200**	**negative=MidNegative**	**anger=LowAnger**
0.14	0.82	0.17	1.73	31	20≤likes≤200	negative=MidNegative	fear=Fear
0.15	0.80	0.19	1.71	33	20≤likes≤200	negative=MidNegative	surprise=LowSurprise
0.22	**0.80**	**0.28**	**1.71**	**49**	**20≤likes≤200**	**negative=MidNegative**	

Table 19
Medium-Likes content with low sadness.

METRICS					RHS	LHS		
support	confidence	coverage	lift	count	focus	seed	comp_1	comp_2
0.10	**0.85**	**0.12**	**1.81**	**23**	**20≤likes≤200**	**sadness=LowSadness**	**happiness=Zero**	**anger=LowAnger**
0.12	**0.84**	**0.14**	**1.79**	**27**	**20≤likes≤200**	**sadness=LowSadness**	**anger=LowAnger**	
0.14	0.82	0.17	1.73	31	20≤likes≤200	sadness=LowSadness	fear=Fear	

Among them, the absence of happiness, a low level of anger, a low level of sadness or a medium negative polarity have been shown to be particularly relevant.

5. Conclusions and further work

This work consists of extracting the high-level semantics – polarity and emotions – of Twitter posts in Spanish to discover, through association rule mining, the content patterns that can be associated with tweets going viral. Since association rule mining is a technique that uses structured information as input, and the content of social networks is highly chaotic and unstructured, opinion mining techniques will be used to extract the emotional content and polarity of the messages creating a structured dataset. In this research, five topics related to the COVID-19 crisis in Spain are monitored from January 1st to February 14th, 2021, with the COVID-19 vaccine topic being the most posted topic.

Considering that the focus of this work is to establish the patterns of viral messages (shares and likes), the study is framed in terms of high and low-share patterns and high and low-likes patterns for tweets of the five topics selected about the COVID-19 pandemic.

From the analysis of the extracted patterns regarding high virality, it can be concluded that the presence of news items related to the subject in the media is significantly relevant to sharing a post, as well as a content that evokes high-arousal emotions, as corroborated in the literature (Berger & Milkman, 2012a; Brooks et al., 2020; Lwin et al., 2020). More specifically, the emotions that play a key role in the case of this study are fear, a high surprise load, a high sadness load, a high anger load and a high negative polarity load. Different combinations of these elements denote a high virality in the messages in a given day. However, emotions like happiness or disgust, as well as positive content, do not play a major role in high virality in our study.

Regarding low virality patterns, the conclusion is that some circumstances contribute to a low level of sharing. Among them, the absence of news, the scarcity of authors and contributions, and some emotional characteristics such as the absence of surprise have proven to be particularly relevant. On the other hand, no significant features have been found that result in little or no volume of likes from a message, but those that generate a moderate volume of likes have been detected. These include lack of happiness, low levels of anger or sadness and medium negative polarity.

Importantly, the rules which allow the mining of high-share and low-share patterns obtain higher confidence values – including patterns with a confidence value of 1 – while for the rules obtained from high likes and low likes, high confidence values have been obtained but these are less than 1.

Although this work has not evaluated to what extent the patterns are generalizable to other languages, we consider that the semantic information on which we base the patterns (polarity and emotions) is something that is implicit in all languages, although there may be socio-cultural variations. For instance, the same text in different cultures or social situations may generate different emotions. However, the patterns depicting the emotions discovered in this study may also be applicable to other languages as susceptibility of certain types of emotion to virality is something expected and has been studied from a psychological perspective, as referenced in the introduction. In addition, the methodology is generalizable only by adapting the sentiment and emotion detection tool to the target language, so the study can easily be applied to different languages and socio-cultural situations, as well as to different domains. This experimentation is envisaged as further work.

Furthermore, in future work we propose to extend the study to include not only the information on emotions and polarity in social media content but also to mark the information as true or false after fact checking, and use this data to explore differences in the extracted patterns. In addition, we will study whether the geographical location from which a post is made influences its virality, extracting similar information on a topic from different territories. Furthermore, following the same methodology in different domains would be interesting to detect whether the viral content of different domains follows different behavior patterns.

CRediT authorship contribution statement

Estela Saquete: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Jose Zubcoff:** Methodology, Software, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization. **Yoan Gutiérrez:** Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Patricio Martínez-Barco:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Javi Fernández:** Software, Validation, Resources, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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