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Social discourse and reopening after COVID-19: A post-lockdown analysis of flickering emotions and trending stances in Italy

by Massimo Stella

Abstract

Although the COVID-19 pandemic has not been quenched yet, many countries lifted nationwide lockdowns to restart their economies, with citizens discussing the facets of reopening over social media. Investigating these online messages can open a window into people's minds, unveiling their overall perceptions, their fears and hopes about the reopening. This window is opened and explored here for Italy, the first European country to adopt and release lockdown, by extracting key ideas and emotions over time from 400k Italian tweets about #fase2 — the reopening. Cognitive networks highlighted dynamical patterns of positive emotional contagion and inequality denounce invisible to sentiment analysis, in addition to a behavioural tendency for users to retweet either joyous or fearful content. While trust, sadness and anger fluctuated around quarantine-related concepts over time, Italians perceived politics and the government with a polarised emotional perception, strongly dominated by trust but occasionally featuring also anger and fear.

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Introduction

Social media represents a valuable source of information for understanding how people perceive and discuss events. Internet discourse has given voice to millions of users, creating flows of information populated by many different viewpoints (Dodds, *et al.*, 2011; Stella, *et al.*, 2018; Ferrara, 2020). Identifying and understanding users' knowledge and emotional content poses a research challenge with crucial implications. Under a time of crisis like the current one, where the COVID-19 pandemic is revolutionising people's way of life all over the world, Internet discourse is key for understanding how large audiences are perceiving multiple aspects of the global emergency. With the right tools, online discourse can unlock perceptions of the pandemic, subsequent lockdowns and their aftermaths.

This study adopts cognitive networks, tools at the fringe of computer science and psycholinguistics (Siew, *et al.*, 2019), as a compass for exploring social discourse around post-lockdown reopening. Focus is given to unraveling the emotional dimensions of social discourse debating the multiple facets of reopening a whole country with the threat of a global pandemic.

Language as embedded in online messages is used to reconstruct how individuals perceived the reopening and emotionally coped with multiple aspects of it. The identified emotional trends and the tools highlighting them help understanding the key issues faced by people during a reopening, their fears but also their hopes, all data useful for achieving effective future policy-making. To test this aim and the powerfulness of the above techniques, Italy is selected as a case study.

Case study: Italy, COVID-19 and the lockdown

Italy was the first European country to release lockdown after being severly struck by the COVID-19 pandemic (Bonaccorsi, *et al.*, 2020). In this way, the social dynamics taking place among Italian users on social media anticipate the discourse of other countries about the reopening. The whole country was locked down one day earlier than COVID-19 being declared a global pandemic by WHO on 11 March 2020. Several studies investigated how Italians reacted to the sudden lockdown. Pepe and colleagues (2020) identified drastic drops of social mobility, which were confirmed also by other studies (*cf.*, Bonaccorsi, *et al.*, 2020). Stella and colleagues (2020) investigated the Italian Twittersphere in the first week of lockdown and found evidence for Italians expressing concern, fear and anger towards the economic repercussions of lockdown. These fears became reality, as the lockdown strongly amplified social and economic inequality across the country, as recently quantified by Bonaccorsi and colleagues (2020).

After two months of nationwide lockdown, the slow down of the COVID-19 contagion and the pressure of restarting the economy both motivated the Italian government to release the lockdown. On 4 May 2020, social mobility was almost completely restored. People could travel within their own regions, attend public places and enjoy a mostly normal lifestyle. All while the novel coronavirus still circulated within the population and hundreds of casualties were still registered.

This study investigates the emotions and ideas before, during and after the 4 May reopening.

Research questions

By adopting a cognitive network science approach, considering text as data representative of people’s mindsets as expressed in texts (Stella, *et al.*, 2019; Stella, 2020; Stella, *et al.*, 2020), this work explores and compares how different ways of reconstructing knowledge and emotions can address the following research questions:

> *RQ1*: Which were the main general emotions flowing in social media about the reopening?
> *RQ2*: Were there emotional shifts over time highlighted by some emotion models but neglected by others?
> *RQ3*: Which were the most prominent topics of social discourse around the reopening?
> *RQ4*: How did online users express their emotions about specific topics in social discourse?
> *RQ5*: Were messages expressing different emotions reshared in different ways?

The main contribution of this investigation is identifying the key topics of discussion around the reopening through a cognitive network science approach. Rather than focusing over COVID-19 or its specific hashtags, key ideas and their emotional perceptions are identified in language, within the social discourse taking place in Italy around the loose topical hashtag #fase2. This hashtag, which stood for a synonym of reopening in Italian news media, included a wide variety of topics of discussion, a constellation of facets of debate regarding the restart, each one associated with certain language, semantic frames and emotions. The investigation over time of these interconnected semantic frames/emotional perceptions is the main focus of this investigation. Key ideas and emotions in discourse are extracted through emotional profiling and sentiment analysis. These two approaches are compared in their ability to detect emotional fluctuations over time of the whole social discourse (*RQ1–2*), with emotional profiling highlighting more discussions of social debate than mere sentiment. Word frequency and cognitive networks are merged together in order to identify ideas of prominence for social discourse over time (*RQ3–4*). Emotional profiling around these prominent concepts outlines microscopic patterns of trust formation around the institutions and concern about the contagion that were not visible with the global-level emotional analysis. Behavioural trends towards messages containing different emotions are investigated and discussed in light of previous positive biases based on mere sentiment (*RQ5*).

Background and related literature

Stances in language. Identifying people's perceptions and opinions about something is a problem known as "stance detection" in computer science (Kalimeri, *et al.*, 2019) and "authorial stance" in psycholinguistics (Berman, *et al.*, 2002). The identification of a stance is crucial in every communication, in order to identify whether someone is in favour or against a given topic, *e.g.*, a person expressing support of the economic measures promoted by a government or giving voice to criticism about a given campaign of social distancing. Historically, stance detection has focused over speeches and written text, like books or pamphlets, and used language analysis in order to reconstruct a stance, *e.g.*, using positive words. This task was performed by linguists and required human coding (Berman, *et al.*, 2002).

Stances in social media. The advent of social media and the huge volumes of texts produced by online users made human coding impractical, motivating automatic approaches to stance detection with limited human intervention (*cf.*, Mohammad, *et al.*, 2016). The state-of-art in identifying (dis)agreeing stances in social media is represented by machine learning approaches (Hassani, *et al.*, 2020), which capture linguistic patterns from a training set of labelled texts, create an opaque representation of different stances and then use it for categorising previously unseen texts (Ferrara and Yang, 2015; Mohammad, *et al.*, 2016). This approach is powerful in detecting also additional features of stances like sentiment intensity (Kiritchenko, *et al.*, 2014; Hassani, *et al.*, 2020), *e.g.*, how positively or negatively a given stance is. The main limit of machine learning is that the reconstructed representation of different stances cannot be directly observed. This issue prevents access to how knowledge and sentiment were structured in different stances, *e.g.*, which concepts were associated with each other in a specific stance? To provide a transparent representation of knowledge and stances embedded in text, recent approaches have adopted cognitive network science (Siew, *et al.*, 2019; Stella, *et al.*, 2019).

Cognitive networks as windows into people's minds. Cognitive networks model how linguistic knowledge can be represented in the human mind (Aitchison, 2012). Recent approaches overwhelmingly showed that the structure of conceptual associations in language is not only predictive of several cognitive processes like early word learning or cognitive degradation (*cf.*, Siew, *et al.*, 2019) but is also useful for reconstructing different stances in social media discourse (Stella, *et al.*, 2018) or in educational settings (Rodrigues and Pietrocola, 2020; Stella and Zaytseva, 2020). Relying on these approaches, this manuscript adopts cognitive networks of syntactic associations between concepts for reconstructing the stances promoted by social discourse around specific aspects of the lockdown. Among many successful approaches building complex networks from text (Arruda, *et al.*, 2019; Brito, *et al.*, 2020; Rodrigues and Pietrocola, 2020), this work adopts the framework of *textual forma mentis* networks, representing syntactic and semantic knowledge in combination with valence and emotional aspects of words (Stella, 2020). Reminiscently of the networked linguistic repository used by people for understanding and producing language, *i.e.*, their *mental lexicon* (Aitchison, 2012), a forma mentis network opens a window onto people's minds (and mental lexica). This is achieved through forma mentis networks giving structure to language, reconstructing the conceptual and emotional links between words in a text. In this way, forma mentis networks reconstruct a collection of stances expressed in a discourse, *i.e.*, a mindset (in Latin *forma mentis*).

Combining networks and emotions. Coupling syntactic/semantic networks and emotional trends makes it possible to understand how individuals perceived and directed their emotions towards specific entities. For instance, Stella, *et al.* (2019) found that high school students directed anxiety and negative sentiment towards math, physics and related concepts but not towards science. As a comparison, STEM researchers directed mostly positive sentiment towards all these topics. The interconnectedness between specific knowledge and the emotions surrounding/targeting it is the main element enabling for forma mentis networks (FMNs) to better understand how people perceive events and topics.

Emotions in language. The emotional profile of a portion of language can be considered an extension of its sentiment. Whereas sentiment aims at reconstructing the valence of language, *i.e.*, understanding its pleasantness, emotional profiling contains other dimensions like arousal, *i.e.*, the excitement elicited by a given entity (Posner, *et al.*, 2005), but also projection into the future, desires and beliefs (Plutchik, 2003; Scherer and Ekman, 2014). In cognitive neuroscience, the circumplex model of arousal and valence is one of the most simple yet powerful model for reconstructing the emotions elicited by words in language through their combined pleasantness and excitement (for more details see Methods and Posner, *et al.*, 2005). The innovation brought by Big Data Analytics approaches to psycholinguistics opened the way also to alternate approaches mapping specific emotional states. The NRC Emotion Lexicon by Mohammad and colleagues identifies which words give rise to eight basic emotional states, like fear or trust among others (Mohammad and Turney, 2013). Relying on the theory of basic emotions from cognitive psychology (Plutchik, 2003; Scherer and Ekman, 2014), these eight states act as building blocks, whose combination can describe a wide range of emotions like elation, contempt or desperation.

Emotions and behavioral trends in social media. On social media, understanding the emotional perception of different topics can be insightful also for understanding how knowledge with different emotional profiles spreads. Ferrara and Yang (2015) showed how messages with different emotions can be re-shared in different ways on social platforms. The authors identified a positive bias on Twitter, where online users reshared more those messages with a stronger positive sentiment. Other studies identified that not only sentiment but also the semantic content of tweets can boost message diffusion. For instance, Brady and colleagues (2017) found that content eliciting moral ideas was shared more by online users during voting events, linking this phenomenon not only to the sentiment expressed in tweets but also to their emotions. The importance of measuring emotional trends in social media motivated approaches like the Hedonometer, built by Dodds and colleagues (2011) in order to gauge people’s happiness through real-world massive events.

Aim and manuscript outline. In the current study, investigating semantic networks, valence, arousal and emotions will wholly be aimed at understanding how online users waited for, perceived and discussed the lockdown release. The Italian Twittersphere is used as a case study. The element of novelty of this manuscript is providing a network of interconnected topics, mapping how individuals discussed a variety of concepts, as expressed in their tweets, when discussing the loose topical hashtag #fase2 about the reopening.

The Methods section outlines the novel methodological tools adopted to the above aim. The Results section investigates the individual research questions outlined above. Results are then combined together and commented in the Discussion section in view of the lockdown release. Current limitations and future research directions opened by this study are also outlined in that section. The Conclusions summarise the contributions of this work and its research questions.

Methodology

This part of the manuscript outlines the linguistic datasets and methods adopted and implemented in this work, referencing also previous relevant works and resources.

Twitter dataset. This work relied on a collection of 408,619 tweets in Italian, gathered by the author through Complex Science Consulting’s Twitter-authorised account (@ConsultComplex). The tweets were queried through the command ServiceConnect[] as implemented in Mathematica 11.3. Only tweets including the hashtag *#fase2* (phase 2) were considered. The flags “Recent” and “Popular” were both used in ServiceConnect in order to obtain either recent tweets produced on the same day of the query or trending tweets, produced on earlier dates but highly re-shared/liked. This combination led to a Twitter dataset including both: (i) large volumes of tweets produced by individuals and (ii) a small fraction of highly reshared/liked tweets. Almost 1.5 percent of the retrieved tweets received more than 100 retweets. These “popular” tweets received on average 286 retweets and 401 likes. Even though these numbers are considerably smaller than those in the Twittersphere of English speakers, they are still remarkable in a population as small as the Italian one (where only 2.85 percent of Internet users has an active Twitter account in 2020, *cf.*, https://gs.statcounter.com/social-media-stats/all/italy, last accessed 1 July 2020).

Tweets were gathered between 1 May and 20 May 2020 in order to evaluate how online users perceive the release of national lockdown before, during and after the actual end of the lockdown on 4 May 2020.

Tweets were ordered chronologically and categorised in each of the 20 considered days. Twitter IDs have been released on a OSF repository and are available for research purposes.

Language processing. Each single tweet was tokenised, *i.e.*, transformed into a series of words. Links and multimedia content were discarded from the analysis, which focused over linguistic content. Emojis and hashtags were translated in words. Emojis were translated by using Emojipedia (https://emojipedia.org/people/, last accessed 1 July 2020), which describes emoticons in terms of simple words, and appended to tweets. Hashtags were translated by using a simple overlap between the content of the hashtag without the \# symbol and Italian words (*e.g.*, #pandemia became "pandemia", Italian for pandemic). Words in tweets were then stemmed by using SnowballC as implemented in R 3.4.4, called in Mathematica through the RLink function. Word stemming is important for getting rid of linguistic suffixes in Italian describing the plural and gender of a noun (*e.g.*, "ministro" and "ministra" both indicate the concept of a minister) or the tense of verbs (*e.g.*, "andiamo" or "andate" both indicate the concept of going). Previous evidence from psycholinguistics indicates that appending different suffixes to the same stem does not alter the semantic representation attributed to them (Aitchison, 2012), which is rather dependent only on the stem itself (*e.g.*, ministro and ministra both elicit the same conceptual unit relative to minister). This flexibility of language in representing lexical units for denoting concepts has been shown to hold across multiple languages, including Italian (Aitchison, 2012). Stems and syntactic relationships between them were used in order to construct forma mentis networks.

Forma mentis network. Textual forma mentis networks were introduced in Stella (2020) as a way of giving network structure to text. Forma mentis networks (FMNs) represent conceptual associations and emotional features of text as a complex network. In a FMN, nodes represent stemmed words. Links are multiplex (Stella, *et al.*, 2017) and can indicate either of the following conceptual associations: (i) syntactic dependencies (*e.g.*, in "Love is blissfulness" the meaning of "love" is linked to the meaning of "blissfulness" by the specifier auxiliary verb "is") or (ii) synonyms (*e.g.*, "blissfulness" and "happiness" overlapping in meaning in certain linguistic contexts). These links were built by using the TextStructure syntactic parser implemented in Mathematica 11.3 and the Italian translation of WordNet (Bond and Foster, 2013). Emotional features are attributed to individual words/nodes. Valence, arousal and emotional eliciting (*e.g.*, does a given word elicit fear?) were attributed according to external cognitive datasets. Notice that the approach adopted here was mostly "bottom-up", as the considered forma mentis network was built through the command TextStructure, which extracted syntactic relationships directly from text. However, FMNs used also semantic associations from WordNet, whose adoption for meaning attribution is considered a "top-down" approach in natural language processing. In this way, the combination of syntactic and semantic associations makes FMNs a hybrid or *multiplex* approach in capturing meaning from text (Stella, 2020).

Cognitive datasets. This study used two different datasets for emotional profiling, namely the Valence-Arousal-Dominance (VAD) dataset by Mohammad (2018), including 20,000 words, and the NRC Emotion lexicon by Mohammad and Turney (2013), including 14,000 words. Both the datasets were obtained through human assessment of individual words, like rating how positively/negatively/neutrally a given concept was perceived or if a given word elicited fear, trust etc. Combinations of valence and arousal can give rise to a 2D space known as the circumplex model of emotions (Posner, *et al.*, 2005), which has been successfully used for reconstructing the emotional states elicited by single words and combinations of them in text. In the circumplex model, emotions are attributed to words by passing through their locations in the 2D space (*e.g.*, high valence/arousal corresponds to excitement). The NRC Emotion Lexicon enables a more direct mapping, indicating the specific words that elicit an emotional state in large audiences of individuals (Mohammad and Turney, 2013). The dataset includes 6 basic emotions (Joy, Sadness, Fear, Disgust, Anger and Surprise) and two additional emotional states (Trust and Anticipation). Whereas the six basic emotions are self-explanatory and identified as building blocks of more nuanced emotions by Ekman's theory in cognitive psychology (Scherer and Ekman, 2014), trust and anticipation include more complex dimensions. Trust can come from a combination of mere affect towards an entity (*e.g.*, trusting a loved one) or rather from logic reasoning (*e.g.*, trusting a politician who behaves rationally), see also (Plutchik, 2003). Anticipation is a projection towards the future that can be either positive or negative, like looking forward to meeting new friends or dreading the day of an exam (Scherer and Ekman, 2014). For this analysis, emotions and emotional states are used interchangeably. Valence/arousal scores and direct emotions were attributed to words in Italian, which were then linked in the forma mentis network according to the language used by social media users.

Representing language as a network defines semantic frames and emotional auras. Representing social discourse as a complex network is advantageous. In fact, this representation conveniently enables the adoption of many network metrics to the aim of detecting text features. The simplest example is using conceptual associations to understand which emotions permeated discourse around specific concepts. For instance, Stella and Zaytseva (2020) found that students associated "collaboration" mainly with positive concepts and thus attributed to it a positive aura, *i.e.*, a positive perception, which was confirmed by independent feedback. This study uses a more general measure of conceptual aura combining emotions and semantic frames. In a FMN, the network neighbourhood of a concept C identifies which words were associated to C by online users through syntactic and semantic associations in messages.

According to *semantic frame theory* (Fillmore, 2006), these associations extracted from language bring contextual information which specifies how *C* was perceived, described and discussed by individuals. Checking the semantic content elicited by words in the network neighbourhood of *C* can, therefore, characterise the meaning attributed to *C* itself in social discourse. Hence, network neighbourhoods in a FMN represent the semantic frames attributed by individuals to concepts in language. Extracting semantic but also emotional information from these frames/neighbourhoods gives insights about people's perceptions and perspectives, *i.e.*, auras, as attributed to concepts.

Quantitative measuring of emotional auras. This study reconstructed the emotional aura or profile of a given concept by counting how many of its associates in the FMN eliticed a given emotion, analogously to past approaches (Mohammad and Turney, 2013; Stella, *et al.*, 2020). Words linked to a negation ("non", "nessun" and "senz" in Italian) were substituted with their antonyms as obtained from the Italian WordNet. This operation preserved the flipping in meaning as expressed in text when negating words. The computed emotional richness was then compared against random expectation preserving the same empirical number of emotion-eliciting associates to a word but also randomising their emotions. A collection of 1,000 random samplings was performed for every empirical richness value reported in the main text, with error bars indicating standard deviation. A z-score indicating emotional richness higher or lower than random expectation at a significance level of 0.05 was also plotted in order to provide a clear visual clue about how individual concepts were perceived in social discourse. These z-scores were organised according to a flower layout and referenced in text as emotional flowers, with the center being the rejection region $z < 1.96$ and petals representing emotional z-scores. Emotional flowers give an immediate visual impression of which emotions populate a given semantic frame more than random expectation. In fact, all the bars falling outside of the inner semi-transparent circle (*i.e.*, the rejection region) indicate an emotional richness stronger than the random baseline. Notice also that in emotional flowers every ring outside of the semi-transparent circle indicates a z-score unit after 2, *i.e.*, the first ring outside the flower centre is relative to a z-score of 3, etc., thus making it immediate to assess the strongest emotions in a semantic frame and attribute also a z-score to them.

An example of the FMN as extracted from online discourse around "govern" (governate/government) is reported in Figure 1. Figure 1 reports the network neighbourhood of "govern" (government/govern), *i.e.*, the frame of semantic/syntactic associations linked with "govern" in tweets. Nodes are stemmed words and links indicate syntactic or semantic relationships. Words are colored according to the emotion they elicit. In case one word elicits multiple emotions, the coloring is attributed according to the strongest emotion permeating a given semantic frame (like in Figure 1) or the whole social discourse (like in Tables 1A and 2A in the Appendix).

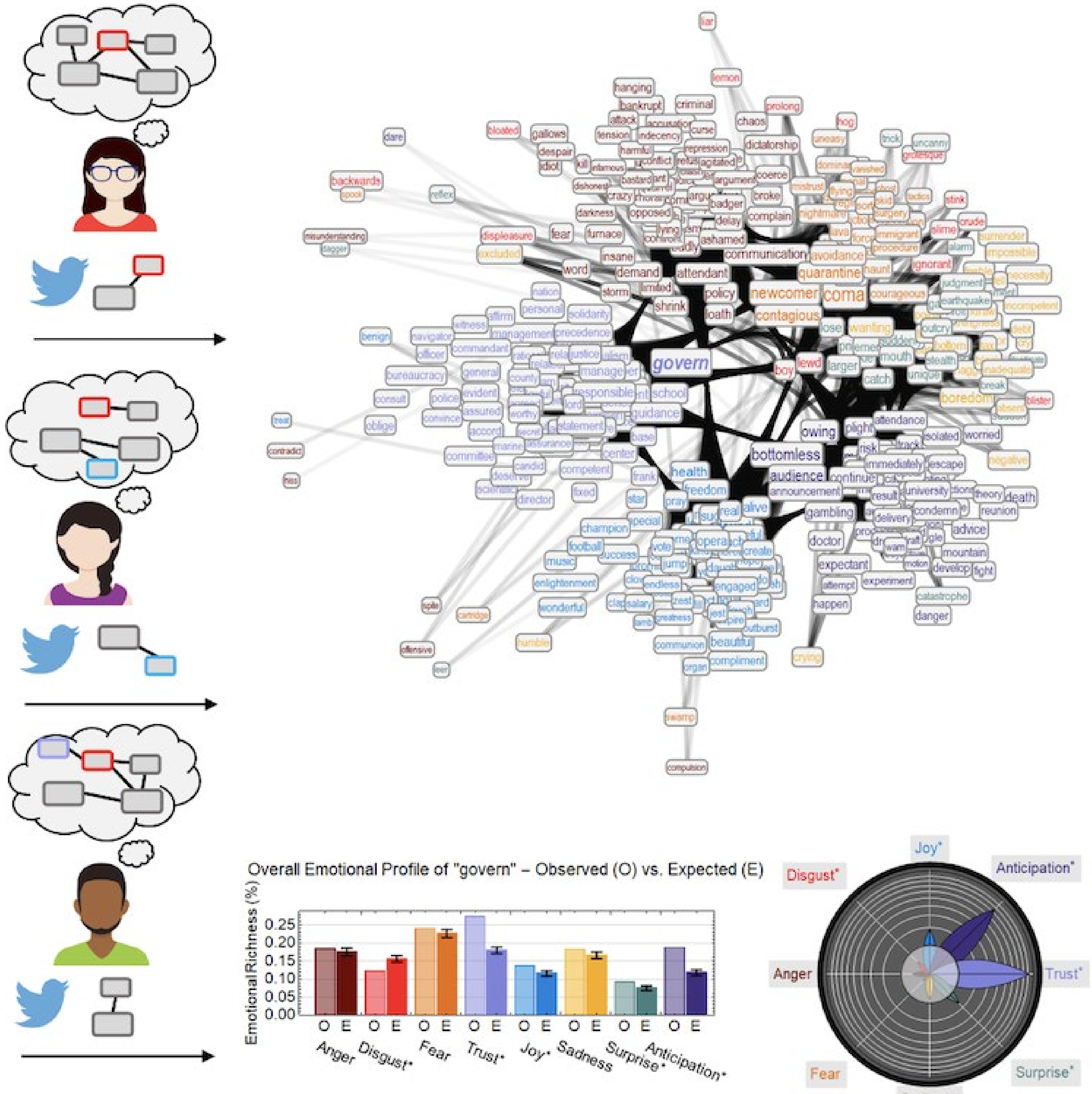


Figure 1: Users' language in tweets reflects their mental perceptions (left), reconstructed here as a forma mentis network outlining the emotions (bottom right) and semantic frame attributed to a concept, *e.g.*, "govern" (top right). Words are emotion-coloured (*cf.*, Methods).

The number of words eliciting different emotions is reported as "emotional richness". Z-scores between empirical and expected emotional richness are reported as an emotional flower (bottom right).

In the emotional flower in Figure 1, the bar of joy arrives up to the first ring outside of the semi-transparent circle, *i.e.*, joy is relative to a z-score of 3. Reading words in the network and considering those emotions stronger than random expectation, *i.e.*, with bars outside of the inner white circle in the emotional flower, make possible to assess that in all tweets between 1 May and 20 May, Italians discussed "govern" with more trust-, anticipation- and joy-eliciting words than expected. Also, jargon of different emotions co-existed together.

Figure 1 illustrates also the cognitive approach adopted by this study. As schematized in Figure 1 (left), each Twitter user produces messages according to their mental lexicon, *i.e.*, a cognitive system storing and processing linguistic knowledge and emotional perceptions about the world. Users communicate their knowledge and perceptions through language in tweets. Hence, Twitter messages contain conceptual associations and emotions. Extracting and aggregating these types of information enables the construction of a knowledge network representing social discourse, *i.e.*, a forma mentis network (Stella, 2020). Notice that words are clustered in network communities of tightly connected concepts as identified with Louvain (Blondel, *et al.*, 2008). Every network visualisation featured words translated from Italian to English. The translation process relied on the translations English-Italian provided already by the NRC Emotion Lexicon (*cf.*, Mohammad and Turney, 2013).

Beyond network neighbourhoods. FMNs make it possible to study social discourse also in terms of network centrality. In this study, frequency and closeness centrality were compared and used at the same time in order to identify prominent concepts in social discourse. Frequency is based on repeated tweets and indicates how many times single words appeared in the dataset on each day independently of other words. Closeness depends on the number of syntactic/semantic links connecting a word to all its neighbours (Siew, *et al.*, 2019). A lower number of these connections indicates that a word is more directly syntactically related/associated to other concepts, expressing prominence in the underlying discourse or texts. Stella (2020) showed that, on benchmark texts, high closeness centrality in FMNs was able to identify text topics by highlighting prominent concepts. In cognitive network science, syntactic/semantic distance and closeness have been shown to be highly predictive of word prominence also beyond topic detection, in contexts like early word learning (Stella, *et al.*, 2017).

Temporal analysis. Emotional profiling and forma mentis networks are applied in order to reconstruct the main emotions and ideas around lockdown release as discussed online, on each day between 1 May and 20 May, in a fashion similar to the Hedonometer by Dodds and colleagues (2011). The stream of tweets is processed chronologically. When emotions are profiled, single tweets are considered. This means considering temporal trajectories of 400k points, one for each emotional state (*e.g.*, fear, trust, anticipation, etc.), one for the total valence scores and one for total arousal scores of words in a tweet. These noisy trajectories were averaged over time. An exponentially weighted moving average was used in order to smooth noisy outliers over a short time window. The smoothing factor was chosen as an average over 10,000 different attempts of minimising the mean squared error of the 1-step-ahead forecasts using 10,000 tweets and starting from any random time between 00:00 1 May 2020 and 23.59 20 May 2020. An average of 0.00075 was identified for the smoothing factor of emotional time series, indicating the ability for the smoothed signal to detect shifts in emotions determined by an average of 1/0.00075 1,333 tweets. For valence and arousal, an average smoothing factor of 0.0006 was detected, corresponding to shifts including 1,667 tweets. This error minimisation technique was simple enough to preserve long-term changes and trends in the time series while also smoothing out short-term fluctuations.

Emotional fluctuations. Emotional deviations were operationalised by deviations from the interquartile range of all detected signals in a given time window. Notice that the filtered signals and the observed deviations from interquartile range were not used in order to make forecasts or attribute statistical significance but only in order to qualitatively highlight potential shifts in social discourse. These potential deviations were then cross-validated by a frequency analysis of words/retweeting counts of tweets/forma mentis emotional auras in the considered time windows.

Results

RQ1: Which were the main general emotions flowing in social media about the reopening?

Figure 2 reports the emotional profile of social discourse over time. Remember that the emotional profile corresponds to how rich in each emotion was the overall social discourse (emotional richness, see Methods). Importantly, non-zero signals of all emotions were found across all time windows. This means that social discourse about the reopening was never dominated by a single positive or negative emotion, like trust or fear. The reopening was rather perceived as a nuanced topic of discourse, where positive and negative emotional texts co-existed together, in agreement with other studies (Lima, *et al.*, 2020; Gozzi, *et al.*, 2020; Stella,*et al.*, 2020).

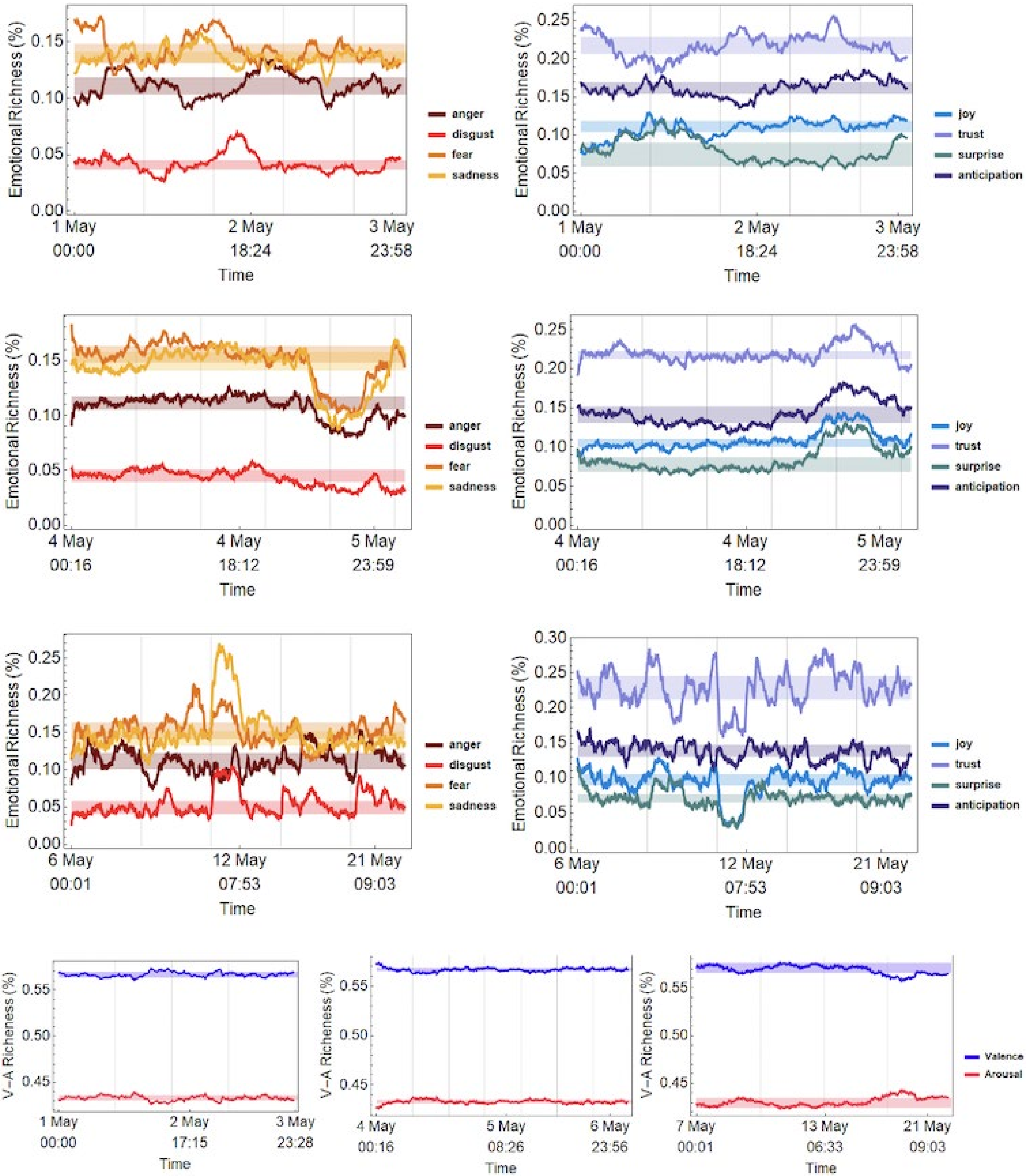


Figure 2: Emotional profiles of online discourse over time as measured with the NRC Emotion lexicon (top rows) and with the valence-arousal dataset (bottom row). Overlays indicate interquartile ranges.

Figure 2 indicates that sentiment mostly remains stationary over time whereas emotional richness shows more complicated dynamics, with peaks and deviations. This is the core of *RQ2*. Figure 2 focuses on individual, non-cyclic deviations from stationary behavior, like peaks or deviations featured on individual days.

Emotional fluctuations unveil social denounce, trust and joy. Several deviations from median emotional intensity are found in different time windows and for different emotions. Before the official reopening of 4 May, social discourse registered several fluctuations in terms of fear, anger, surprise and disgust. The morning of 2 May registered a progressive increase in anger co-occurring together with a spike of fear. According to Plutchik's (2003) theory of emotions, the alertness against a threat caused by fear can give rise to anger as a reaction mechanism so that the two emotions are not independent of each other. A closer investigation of the stream of tweets reveals the proliferation of highly retweeted tweets, in the morning of 2 May, mainly about: (i) political denounce of how the Italian government can use EU investments for reopening, expressing alarm about "vultures" preying on the misfortune of others, and (ii) gender gap denounce, criticising why only 20 percent of policy-makers enrolled by the Italian Government were women.

The afternoon of 2 May also registered a decrease in surprise and a spike of disgust. The most frequent words/most retweeted messages on that time window indicated the continuation of negative/criticising political debate together with messages protesting against the security measures for public businesses like restaurants, hairdressers and beauty centres. These negative trends did not impact the average joy measured on the day, which remained fairly constant over time and was expressed in several tweets expressing hope and excitement about the incoming reopening.

The observed decrease in surprise taking place on 2 May corresponded to the resharing of mass media articles, starting early in the morning and explaining the new measures concretely enabling the reopening, with jargon like "regol" (rules), "chiest" (ask), "intervist" (interview) and "espert" (expert). These articles explaining future events about the reopening also contributed to increasing anticipation, *i.e.*, an emotional projection into the future (Plutchik, 2003).

A delayed positive contagion. On 4 May, the day of the lockdown release all over Italy, emotional trends remained fairly constant over time. A drastic drop in negative emotions, co-occurring with a raise in positive ones, was found on 5 May, starting around 10 AM. A closer look at the stream of Twitter messages reveals that this massive change in global emotions was due to tweets of news reporting how the contagion slowed down in the three previous days. Messages expressing excitement about the reopening ("let's enjoy phase 2!") were the most retweeted ones on 5 May. Interestingly, positive messages included also: (i) desire for travelling, (ii) appreciation for the newfound freedom, and (iii) trustful instructions about how to use self-health sanitary tools, like facemasks, for living together with COVID-19. Hence, the emotional effects of the lockdown release were not observed on the same day of reopening, 4 May, but were rather delayed by one day and enhanced the overall flow of positive emotions on 5 May. Such delayed and drastic alteration in emotional profile provides evidence for a collective emotional contagion, indicating how the reopening was collectively perceived with mostly positive emotions by online users.

Peaks of sadness and social distancing. Emotional trends remained mostly constant in the aftermath of the reopening, with strong fluctuations present on 11 May and 12 May. The sudden spike in sadness and disgust registered in the afternoon of 11 May and early morning of 12 May is related to tweets of complaint. The most retweeted messages in this time window expressed concern and complaint about a lack of clear regulations about social behaviour, exposing critical issues like large crowds assembling in public spaces and a difficulty for restaurants to guarantee social distancing. The most frequent jargon in this time window was "misur" (measure), "distanz" (distance) and "tavolin" (table). At the same time, the Twitter stream also featured news of local COVID-19 outbreaks. A smaller peak in anger and disgust was featured on 20 May and mostly related to Twitter messages of political denouncement.

In order to better understand the above emotional shifts, in the next section the same Twitter stream is analysed with the valence-arousal circumplex model (see Methods). Results are compared against the above ones obtained with the NRC Emotion Lexicon.

RQ2: Were there emotional shifts over time highlighted by some emotion models but neglected by others?

The above emotional fluctuations indicate changes in the global perception of social discourse that were confirmed by a closer look at the Twitter stream, indicating the powerfulness of the NRC lexicon to identify emotional transitions over time. Figure 2 (bottom row) reports the richness in valence and arousal of words as embedded in tweets. Despite the plot range being the same as in Figure 2 (top row), both valence and arousal remained mostly constant over time, hiding the emotional peaks and fluctuations observed with the NRC Emotion Lexicon. Notice that no fluctuations were observed even by manually tuning the smoothing factor of the valence/arousal curve. The only stronger deviation observed with the valence-arousal circumplex model is on 20 May, where the drop in valence and the increase in arousal are compatible with negative/alarming emotions like anger, in agreement with what was found with the NRC Emotion Lexicon.

Reopening was a positive event but no "happy ending". The above results also indicate that the reopening after the lockdown was met with a positive emotional contagion over social media. The deluge of trust and joy, in combination with anticipation, indicate a positive and hopeful perception of restarting after a lockdown. The restart itself was not a happy ending, though. Negative emotions indicated a deluge of complaints and social denouncement about gender disparities, risks of inappropriate behaviour, difficulties to keep up with social distancing and political denouncement.

In order to better understand how social discourse was structured across days, conceptual prominence over time is investigated in the next section.

RQ3: Which were the most prominent topics of social discourse around the reopening?

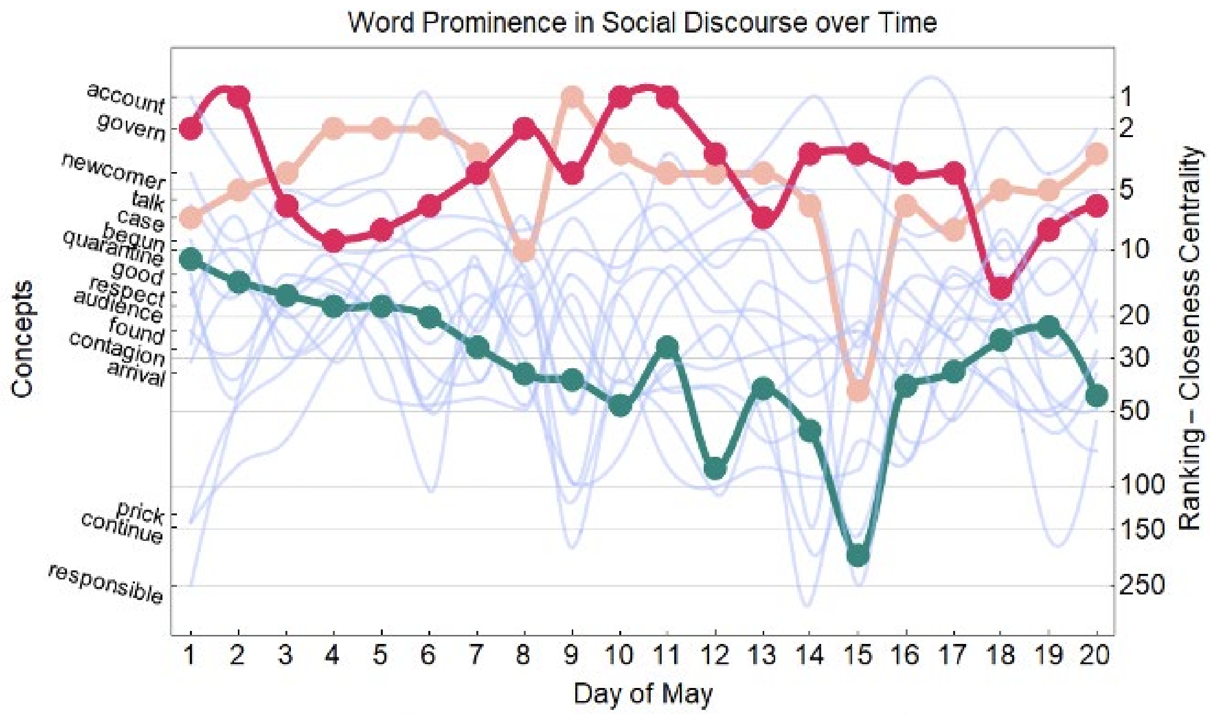
Prominent words combine fear and hopes about restarting. Tables 1A and 2A (*cf.*, Appendix) report the most frequent concepts and those words with the highest closeness centrality in FMNs, respectively, as extracted from daily social discourse around #fase2. Words are colored according to the emotion they elicit (see Methods). The negator "not" was consistently ranked first in all cases and was not reported for the sake of visualisation. Notice how on 3 May the most frequent word in social discourse was "doman" (tomorrow), indicating anticipation expressed by online users towards the reopening on 4 May. The concept of "govern" (government, to govern) was highly ranked by both frequency and closeness centrality across all days. This indicates that a substantial fraction of tweets was linked to the governmental indications and measures for the reopening, as identified also in emotional profiling. Jargon related to the COVID-19 pandemic like "cas" (case), "contag" (contagion) and "quaranten" (quarantine) remained highly central across the whole period, indicating that social discourse about the reopening was strongly interconnected with news about the contagion, as also indicated by Gozzi and colleagues (2020). Concepts like "nuov" and "mort" popped high in both frequency and closeness ranks on some days because of the reported news about local COVID-19 outbreaks. Inspirational jargon like "respons" (responsible), "affront" (to face), "entusiasm" (enthusiasm) and "sper" (hopeful) were prominent across the whole time period and with both measures. This quantitative evidence indicates that social discourse was strongly focused about a concretely positive attitude towards a responsible reopening.

Frequency captures more negative jargon. As indicated by emotional profiling, these prominent and positive concepts coexisted with prominent but negative concepts, like "vergogn" (ashamed), "critica" (criticism) and swearing. These concepts were captured mostly by frequency rather than by closeness centrality, indicating the proliferation of negative messages repeating these concepts with fewer contextual richness when compared with positive concepts (which end up being more central in FMNs). An example of this trend is on 14 May, where frequency captures mostly blaming concepts whereas closeness identifies more general topics like "govern", "far" (do) and "misur" (measures). This difference calls for a more systematic comparison of frequency and closeness in identifying word prominence.

Closeness captures contextual diversity. Frequency and closeness correlated positively across the whole period, with a mean Kendall Tau of 0.67 ± 0.04 ($p<10^{-6}$) averaged over all 20 days. This value indicates that words ranked highly by closeness centrality tended to be ranked highly also by frequency. As an example, a scatter plot of log frequency and closeness centrality of individual words is reported in Figure 1A in the Appendix. The correlation between the two quantities is not perfect (*e.g.*, equal to 1). On the one hand, closeness better captures contextual richness (Stella, *et al.*, 2017), *i.e.*, the numbers of different semantic contexts and frames featuring a concept, an example being meaning modifiers commonly occurring in different contexts like "non" that tend to have high closeness. On the other hand, high frequency but lower closeness identifies words with very narrow semantic frames, appearing always within the same context and bearing the same meaning, *e.g.*, "shock" and "disordine" (disorder). Combining closeness and frequency can therefore highlight more nuances of the meanings attributed to words through a complex network approach.

Closeness highlights dynamics invisible to frequency. On top of this difference, Figure 3 (left and top) indicate that closeness and frequency highlight different time-evolving patterns for the same set of prominent words in social discourse. The figure reports ranks over time of the top-ranked words identified by closeness and frequency on 4 May.

While frequency outlines that concepts like "govern" (government/to govern), "cas" (case) and "quaranten" (quarantine) remained highly ranked between 1 May and 20 May, closeness identified a different dynamics for "quaranten". In the first half of May, "quarantine" became monotonously less central in the forma mentis networks of daily social discourse, registering a decrease of almost 200 positions in its ranks. This difference indicates that quarantine kept being a frequent concept in social discourse but it appeared in fewer and fewer contexts, gradually becoming more peripheral in the discussion. This decrease reached a halt and an inversion of tendency on 15 May, after which "quaranten" acquired a higher closeness. Investigating the Twitter stream reveals that the increase in rank of quarantine registered after 15 May is due to many tweets reporting the decision of the Italian government to accept tourists with no obligation for self-quarantine.



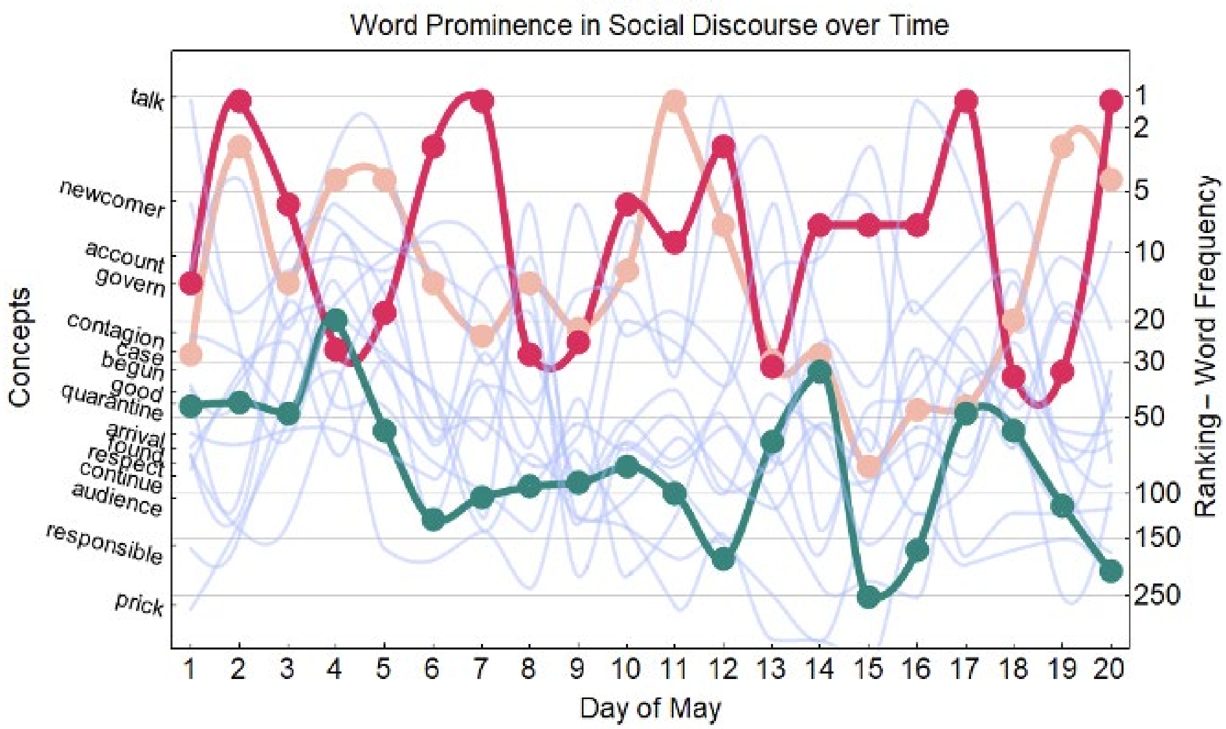


Figure 3: Closeness and frequency ranks over time of "govern" (magenta), "case" (pink) and "quarantine" (green) and other prominent concepts on 4 May.

RQ4: How did online users express their emotions about specific topics in social discourse?

The previous sections characterised social discourse across days. Instead, this section explores how online users described specific concepts on a single day.

What preoccupied online users on the vigil of reopening? The emotional profiles and semantic frame/FMN neighbourhood around "worried" ("preoccup") as extracted from the stream are reported in Figure 4. When talking about their preoccupations about #fase2, Italians displayed different emotional profiles between 3 May and 4 May. The day before the reopening, trust, anger and fear coexisted together (see also Figure 2A in the Appendix). The semantic content of the FMN contains information about the main concepts eliciting these emotions. Negative emotions mainly targeted/concentrated around the difficulties of reopening ("difficulties", "complain", "fear"), which were projected to/linked with "tomorrow". On the day of the reopening, 4 May, the anger of the previous day vanished and more hopeful words appeared (*e.g.*, "success" and "hope"). On 4 May, preoccupation was linked to the institutions, featuring fear and sadness for their "absence". The links involving "not" contrasted the negative meaning of "worried" with positive, rather than negative, associations like "opportunity", "alive" and "respect". The links between "worried", "commerce" and "plight" also indicate that even on the day of the reopening, social media expressed concern about the economic repercussions of the lockdown for commerce. Jargon related to the contagion ("coma", "case", "contagious") indicates a concern about the COVID-19 contagion present even on the day of the reopening.

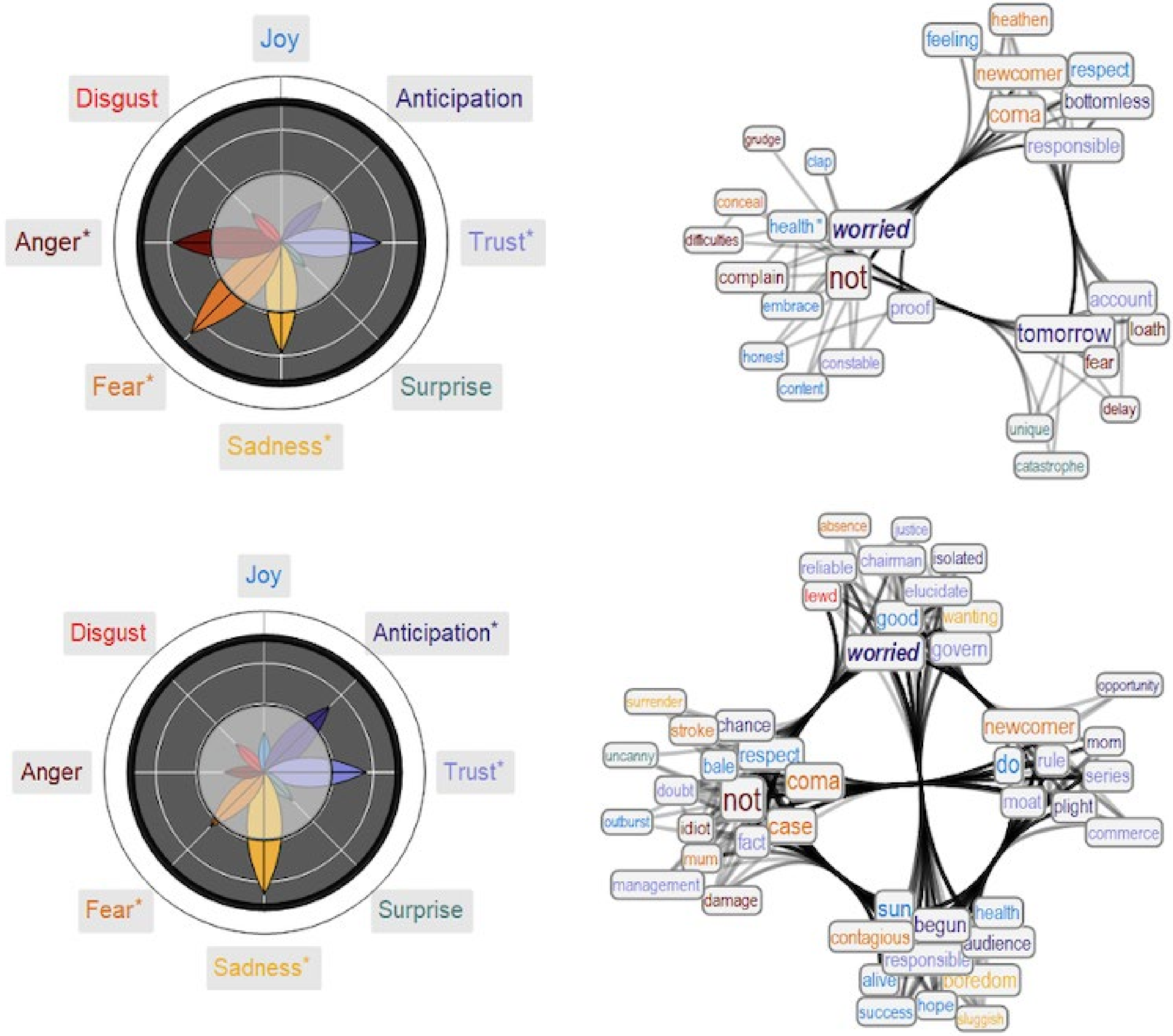


Figure 4: Emotional flowers with z-scores (left) and semantic frames (right) of “worried” (“preoccup”) on 3 May (top) and 4 May (bottom). Strong emotions (z > 1.96) fall outside of the semi-transparent circle in flowers. Words are emotion-coloured (*cf.*, Methods).

Ending the quarantine was not a “happy ending”. As reported above, the concept of the “quarantine” (“quarantin”) became less and less prominent in social discourse in terms of closeness centrality, *i.e.*, it became peripheral in the flow of social discourse by being presented in fewer and fewer different contexts. Did its emotional aura undergo also some transformation? Figure 5 compares the semantic-emotional frames of “quaranten” (quarantine) on 1 May (top) and 6 May (bottom). Before the reopening, social discourse around quarantine elicited trustful associations of anticipation towards the future, involving the government and celebrating the success of the quarantine in slowing down the contagion (“success”, “volunteer”, “gorgeous”). Traces of social denounce were present too, with links towards anger-related jargon like “ashamed”, “damage” and “rebel”. However, the registered emotional richness of anger around “quaranten” on 1 May was compatible with random expectation (see also Figure 3A in the Appendix). This positive perception of the quarantine did not last. Two days after the reopening, the threat of new cases of contagion was prominently featured in social discourse around the quarantine, as captured by the triad with "newcomer" and "contagion" and also by other negative associates like "isolated", "death", "coffin" and "long"-"forgotten". In a few days, positive emotions around the quarantine dissipated and were replaced by sadness. A closer check at the stream of tweets reveals that this flicker of sadness originated in news media announcements reporting local outbreaks of COVID-19. Reopening the country with the COVID-19 still circulating among the population disrupted the positive "happy ending" perception of the (end of the) quarantine.

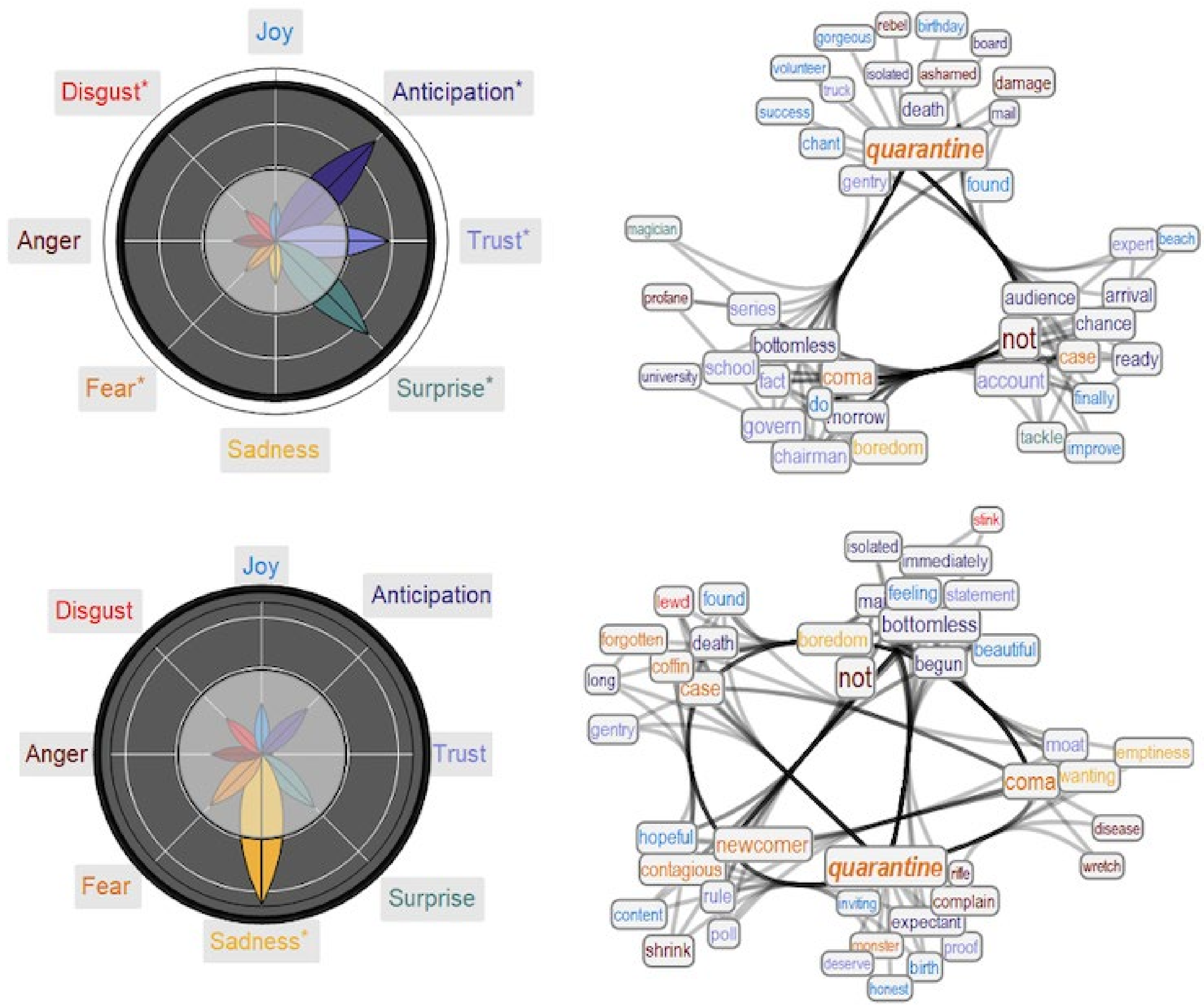


Figure 5: Emotional flowers with z-scores (left) and semantic frames (right) of "quarantine" ("quaranten") on 1 May (top) and 6 May (bottom). Strong emotions (z > 1.96) fall outside of the semi-transparent circle in flowers. Words are emotion-coloured (*cf.*, Methods).

An unwavering yet nuanced trust in politics. Different emotions can coexist not only in the global social discourse but also around specific concepts. An example is "politics" ("polit"), which consistently featured a trust in its semantic/emotional frame higher than random expectation consistently between 1 May and 20 May (z-scores higher than 1.96). As reported in Figure 6, trust in politics on 2 May was mainly focused around the government (“govern”), its crew of experts (“expert”) and its strategies for containing the contagion and countering the economic repercussions of the lockdown (see links with “launch”, “plan” and “economy”). Although persisting over time, trust co-existed also with other emotions surrounding “politics” (see also Figure 4A in the Appendix). For instance, on 11 May, “politics” featured several associations with anger-eliciting words, like “dictatorship”, “garbage”, “controversial” and “ashamed”, all concepts expressing political denouncement against controversial political measures of the lockdown. The FMN on 11 May also reports the source of this anger, as reported in those tweets registered during that time window, politics was considered to be “responsible” for and expected to find “money” for preventing small businesses from going “bankrupt”. This burst of anger (with z-score > 1.96, *cf.*, the emotional flower in Figure 6, bottom) is another example of flickering emotion. In this case, notice that anger and sadness co-existed with trust, indicating a persistent perception of trust in politics in online users’ discussions. It has to be underlined that, as reported in the emotional flower in Figure 1, also “govern” (to govern/government) featured a trustful emotional aura.

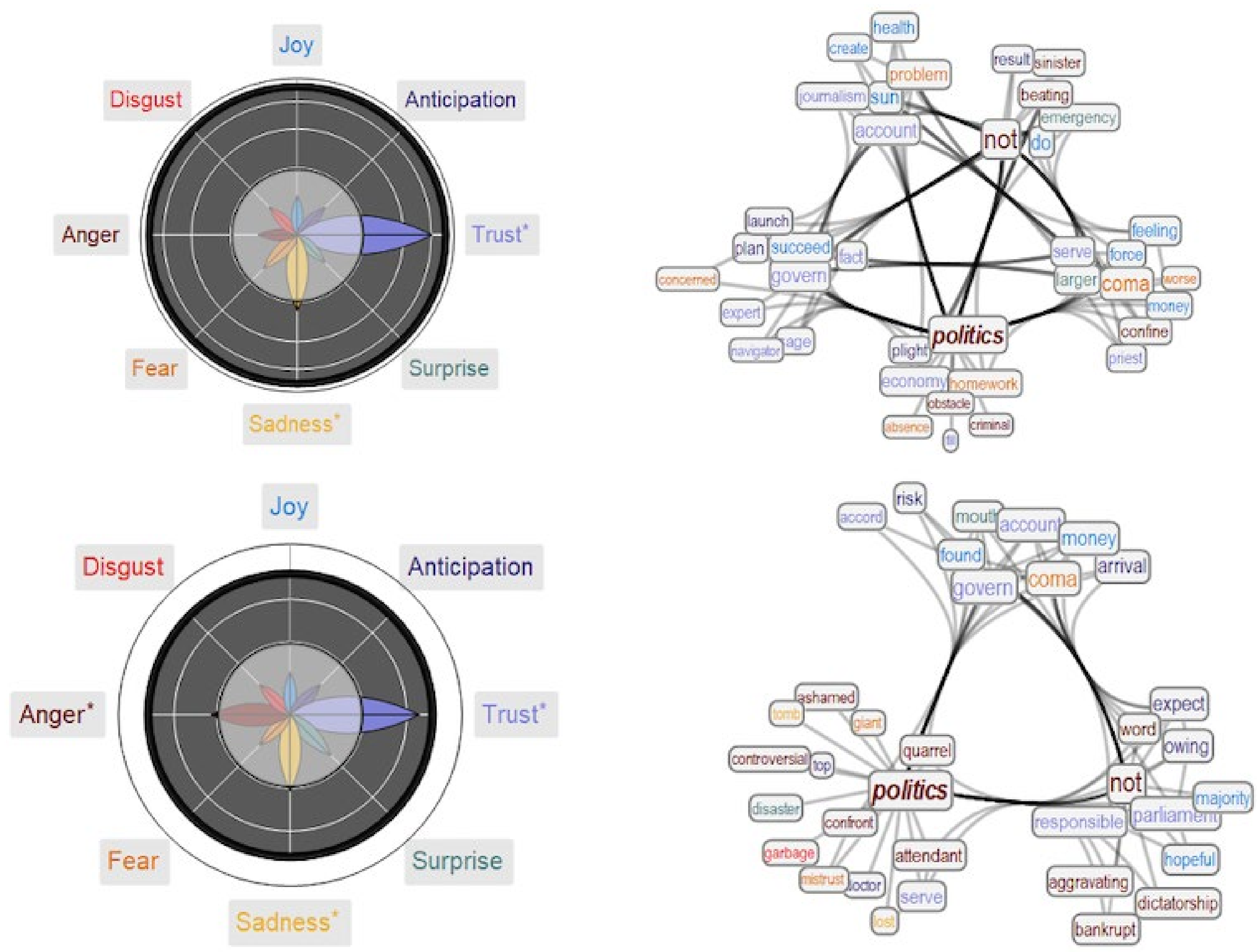


Figure 6: Emotional flowers with z-scores (left) and semantic frames (right) of “politics” (“polit”) on 2 May (top) and 11 May (bottom). Strong emotions (z > 1.96) fall outside of the semi-transparent circle in flowers. Words are emotion-coloured (*cf.*, Methods).

RQ5: Were messages expressing different emotions reshared in different ways?

Previous studies already established that valence can influence the extent to which tweets are re-shared by online users (Ferrara and Yang, 2015; Brady, *et al.*, 2017). In particular, Ferrara and Yang (2015) found a positive bias on Twitter, *i.e.*, a tendency for users to share messages with a positive sentiment/valence.

This section aims at testing whether differences in tweet sharing hold also beyond valence and across the whole spectrum of different emotions.

Considering the emotions of moderately and highly retweeted messages. Attention was given to the most retweeted messages and their emotional content. Distributing tweets according to their retweet count, focus was given to the top 98.5 percent percentile, which included 5,942 tweets with a median of 205 retweets, a minimum of 100 re-shares and a maximum of 2,822 retweets. Tweets above the median of 205 retweets were considered as highly retweeted (HR). Tweets below the median of 205 re-shares were considered as moderately retweeted (MR). Using the NRC lexicon, the emotional profile of each single HR and MR tweet was computed. For every emotion, the two distributions of emotional richness resulting from HR and MR tweets were compared.

With a statistical significance of 0.05, highly retweeted messages about the Italian reopening exhibited:

1. A lower emotional richness in anger than moderately retweeted messages (mean HR: 0.0452, mean MR: 0.0488, Mann-Whitney stat. $2.09 \cdot 10^6$, $p = 0.0124$);
2. A higher emotional richness in fear than MR messages (mean HR: 0.0874, mean MR: 0.0925, Mann-Whitney stat. $1.92 \cdot 10^6$, $p = 0.0225$);
3. A higher emotional richness in joy than moderately retweeted messages (mean HR: 0.0874, mean MR: 0.0925, Mann-Whitney stat. $1.91 \cdot 10^6$, $p = 0.0068$).

For all the other emotions, namely disgust, sadness, anticipation, surprise and trust, no statistically significant difference was found between highly and moderately retweeted messages.

Fear subverted the positive bias of resharing. In the current social discourse, tweets shared significantly more by online users elicited more joy, a higher fear and less anger. These results provide evidence confirming and extending the previous positive bias identified only over sentiment by Ferrara and Yang (2015). According to the circumplex model (Posner, *et al.*, 2005), joy is an emotion depending on positive sentiment whereas fear and anger live in the space of negative sentiment. Finding that people tended to reshare more tweets with higher joy and lower anger represents additional confirmation of the positive bias that people tend to re-share content richer in positive sentiment. However, this tendency does not hold across the whole spectrum of emotions. Fear subverted the positive bias: online users tended to re-share messages richer in fear, and thus in negative sentiment.

Discussion

The main take-home message of this investigation is that the post-COVID-19 reopening in Italy was not a “happy ending”, since social discourse highlighted a variety of semantic frames, centered around several issues of the restart and mixing both positive and negative emotions.

This rich semantic/emotional landscape emerges as the main novelty of this approach, which transparently links together emotions (rather than more simplistic sentiment patterns) with the specific semantic frames evoking them and extracted from the language of social discourse. This extraction relies on a fundamental assumption: text production and therefore social media both open a window into people’s minds (Aitchison, 2012; Ferrara and Yang, 2015). Under a time of crisis, like during a pandemic, being capable of seeing through such window is fundamental for understanding how large audiences are coping with the emergency (Bonaccorsi, *et al.*, 2020; Gallotti, *et al.*, 2020; Gozzi, *et al.*, 2020). This challenge requires tools that provide a transparent representation of knowledge and emotions as expressed in social discourse. This work used computational cognitive science for seeing through the window of people’s minds with the semantic/emotional analysis of tweets (Stella, *et al.*, 2020), without explicitly relying on machine learning. The analysis performed here on social discourse in 400k Italian tweets, including #fase2 (phase 2) and produced between 1 May to 20 May 2020, provides several important points for discussion.

The reopening was not a happy ending. As outlined within *RQs* 1, 3 and 4, emotional profiling provided evidence for a positive emotional contagion happening online after the day of the restart, with levels of trust, joy, happiness and anticipation all simultaneously higher than previously registered. This positive emotional contagion did not last and it did not feature the complete disappearance of negative emotions, like fear or anger, which rather co-existed with the others in social discourse. The coexistence of different types of emotional trends was found also in previous works about COVID-19 (Stella, *et al.*, 2020) and it is not surprising, given the unprecedented range of socio-economic repercussions that the pandemic brought not only over the health system but also over social mobility and the economy (*cf.*, Bonaccorsi, *et al.*, 2020; Pepe, *et al.*, 2020). What is more interesting is that such constellation of different positive, negative and neutral emotions cannot be focused only on the concept of "reopening" but it rather has to be distributed or scattered across circulating news or key topics of social discourse. This scattering creates a methodological challenge for understanding the targets and actors of these emotions.

News flows and politicians were found to be relevant in driving emotions like disgust (see *RQ1*), which were invisible to sentiment analysis (see *RQ2*). Enhancing standard frequency-based lexical analysis with closeness (*RQ3*) highlighted a plurality of key concepts, brought by news and users' messages, being discussed in different ways across days. The semantic frames reconstructing how online users perceived such prominent concepts revealed a set of flickering emotions (*RQ4*), which were assessed in detail thanks to forma mentis networks. Notice that this approach gave focus to the cognitive structure of the language used by online users and not to their identity. The flickering emotions/conceptual prominence reported here might be the effect of a "topic drift" promoted by a handful of influential users, who brought attention on specific aspects of the reopening by launching additional hashtags or by simply targeting specific users while creating flaming content or trolling. The latter scenario has been frequently unearthed in previous studies focusing on the Twittersphere (Zelenkauskaite and Niezgoda, 2017; Bessi and Ferrara, 2016; Stella, *et al.*, 2018; Ferrara, 2020), which showed how trolling and social bots might be capable of depicting political climate in ways rich of negative sentiment and anger-related emotions. The specific identification of the exact actors enabling emotional contagion and topic drift represents a very interesting research direction for future work.

The limits of valence/arousal in social discourse analysis. On a methodological side, the results in *RQs* 1 and 2 indicate that the NRC Emotion Lexicon (Mohammad and Turney, 2013) is considerably more powerful than the circumplex model in detecting spikes and shifts in social discourse. This difference can be explained with the observation that social discourse is different from a single text or a book. In social media multiple individuals can participate in a conversation, often reporting different angles, perspectives or stances about the same topic. Hence, whereas in a book a single author usually reports a stance with a predominant emotional tone (Berman, *et al.*, 2002), in social discourse multiple tones can co-exist together (Kalimeri, *et al.*, 2019) and they could average out when considering valence/arousal. For instance, anger in the circumplex model corresponds to high arousal (excitement) and negative valence (negativity) whereas trust corresponds to low arousal (calmness) and positive valence (positivity). The coexistence of anger and trust, as found in the current dataset with the NRC lexicon, would average out the opposing contributions of angry/trusting messages.

Hence, the current results provide strong evidence for the necessity of adopting emotion specific tools for the analysis of social discourse beyond valence/sentiment. While extremely useful in single-author texts, the valence-arousal circumplex model of emotions might not be suitable for the investigation of highly nuanced emotional profiles in social discourse, where multiple positive or negative emotions might co-exist together. Exploring the eight basic emotional dimensions of Twitter discourse, in terms of fear, anger, disgust, anticipation, joy, surprise, trust and sadness (Mohammad and Turney, 2013), highlighted spikes in social and political denounce of gender and economic inequality or outbreaks of news media announcements about the COVID-10 pandemic. These phenomena went unnoticed when considering the valence and arousal of social discourse (Posner, *et al.*, 2005), underlining the necessity to move from general sentiment/arousal intensity approaches to more comprehensive emotional profiling investigations of social discourse.

Cognitive networks and stance detection. This whole study revolves around giving structure to social discourse through complex networks. This procedure enabled a quantitative understanding of people's perceptions and stances toward various aspects of the nationwide reopening. To this aim, textual forma mentis networks were used, reconstructing syntactic, semantic and emotional associations between concepts as embedded in text by individuals (Stella, *et al.*, 2019; Stella and Zaytseva, 2020; Stella, 2020). As explored within *RQ3*, closeness centrality in networks built from social discourse on each day consistently identified as central positive concepts, related to the government, the willingness of restarting and the necessity of establishing measures for rebooting economy and social places, but also negative words, related to attention about the contagion and new cases. Word frequency captured analogous prominent concepts but also tended to highlight more negative words, expressing political and social denounce. Closeness, based on conceptual distance, and frequency, based on word counts, did not perfectly correlate with each other and even offered different information about how conceptual prominence evolved over time. An example is "quarantine", which became progressively used in fewer and fewer different contexts, mainly related to local COVID-19 outbreaks and the decreasing epidemic curve, while remaining consistently highly frequent in discourse over time.

Indeed, frequency neglects the structure of language used for communicating ideas and emotions, so that it is expected for frequency to provide different results when compared to closeness. Consider the simple example of a collection of 100 tweets, with 80 of them being the repetition of "I hate coronavirus" and the remaining 20 linking "coronavirus" with medical jargon in different ways (*e.g.*, "One of the symptoms of the novel coronavirus affliction is cough", "The novel coronavirus is a pathogen originated in animals and transmitted to man", etc.). Keeping into account only frequency would identify social discourse as dominated by "hate" and "coronavirus" but it would miss the constellation of less frequent words giving meaning and characterising "coronavirus" itself through medical links and contextual associations, which are rather captured by closeness itself. The empirical and methodological aspects outlined above underline the necessity of considering not only frequency but also other structural measures of language, like network closeness, in order to better assess opinion dynamics and online public perceptions over social media.

Flickering emotions surrounded specific facets of the reopening. As reported within *RQ4*, forma mentis networks also highlighted how people's perceptions of specific aspects of the reopening changed over time. On the day of lockdown release, the main preoccupations of Italians focused about the economy but were strongly contrasted with hopeful messages, semantically framing the reopening as a fresh new start for getting back to normality. Hope did not embrace all aspects of the reopening. Announcements of local COVID-19 outbreaks altered the perception of "quaranten" (quarantine), which was previously perceived as successful in reducing contagion. Trust vanished and was replaced with a sad perception of quarantine, related to sudden, local outbreaks (see also Gozzi, *et al.*, 2020). Italians displayed also an unwavering trust in politics and the government across the whole considered time window. Notice that a persistent trust in politics and governments can be beneficial in guiding a whole nation towards successfully reopening after a nationwide lockdown (Massaro, 2020; Lima, *et al.*, 2020). However, trust co-existed with other negative emotions on some days, indicating a nuanced perception portrayed in social discourse, combining trust in the institutions with political denounce, anger and sadness about delays or lack of clarity. The microscopic patterns observed in *RQ4* indicate that the general analysis of social discourse in terms of emotional profiling is not enough for understanding the complex landscape of public perception in social media. A complex network approach, structuring concepts and emotions around specific events, represents a promising direction for future research understanding social media perception and dynamics (see also Arruda, *et al.*, 2019; Brito, *et al.*, 2020; Stella, 2020).

Resharing behaviours and fear. As reported in *RQ5*, this study also investigated user behaviour in sharing content with certain emotional profiles. Tweets richer in joyful concepts were found to be more frequently re-shared to users, while the opposite was registered for anger. Retweeting more joyful and less angry tweets is compatible with the positive bias for users to retweet tweets with positive sentiment found by Ferrara and Yang (2015). However, this bias was subverted by fear, as in the current analysis online users were found to re-share more those messages richer in negative, fearful jargon. This tendency might be due to the strong affinity of the considered tweets with the COVID-19 contagion, a phenomenon met with fear and panic over social media (Stella, *et al.*, 2020; Lima, *et al.*, 2020). The observed pattern might therefore be a symptom of panic-induced information spreading (Scherer and Ekman, 2014). These distinct behavioural patterns mark a sharp contrast in the way that different emotions work over social media. Future research should investigate not only the amount of retweets but also the depth of content spreading in order to better understand how different emotions pervaded the Twittersphere.

Limitations of this study

The current analysis presents mainly four limitations which are accounted for and discussed in view of potential future research work.

Accounting for cross-linguistic variations in emotions. This study investigated tweets in Italian by considering cognitive datasets, like the NRC Emotion Lexicon and the VAD Lexicon, which were not built specifically from native Italian speakers. In fact, these datasets were obtained in mega-studies with English speakers and then translated across different languages (*cf.*, Mohammad and Turney, 2013; Mohammad, 2018). From a psycholinguistic perspective, translation might not account for cross-linguistic differences in the ways specific concepts are perceived and rated (Aitchison, 2012). In absence of large-scale resources mapping words to emotions directly from Italian native speakers, the above translations represent a valuable alternative, successfully adopted also in other studies (Stella, *et al.*, 2020). With the advent of Mechanical Turk and other platforms for realising psycholinguistic mega-studies, future research should be devoted in order to obtain emotional lexica specifically tailored for Italian and other languages different from English.

Focusing over user replies. The considered dataset mapped only tweets incorporating the *#fase2* (phase 2) hashtag and did not consider user replies without that hashtag. This limitation means that the social discourse investigated here was mostly generated by individual users and was not the outcome of a user reply. As a consequence, by construction, the considered dataset is more focused on reporting the plurality of individual perceptions about the reopening, without considering trolling or debates spawning from post flaming (Stella, *et al.*, 2020) or from malicious social bots (Ferrara, 2020). Notice also that the dataset included retweets and user mentions, which contributed to discussions between users. Future studies might focus more on the conceptual/emotional profiling of users storylines and discussions.

Combining networks and natural language processing. From a language processing perspective, this study focused on extracting the network structure of syntactic and semantic relationships, it included word negation and reported also meaning modifiers. However, the current analysis did not amplify or reduce emotional richness according to other features of language like punctuation or adverbs (*e.g.*, distinguishing between “molto gioioso”/very happy and “gioioso”/happy), like it was done in other studies (Stella, *et al.*, 2018). Despite this lack of fine structure, the emotional profiles built and analysed here were still capable of highlighting events in the stream of tweets like the proliferation of messages about social/political denounce or strong fluctuations in the perception of specific aspects of the reopening as promoted by news media, *e.g.*, local outbreaks of COVID-19 cases or quarantine-less tourism. More advanced methodologies combining the network approach and natural language processing (*cf.*, Vankrunkelsven, *et al.*, 2018) would constitute an exciting development for a more nuanced understanding of emotions in social discourse.

Profiling the emotions of different discourse dimensions. Another limitation of the study is that it does not explicitly relate emotions and concepts to specific aspects of social discourse like knowledge transmission, conflict expression or support. The coexistence of hopeful, angry and fearful patterns highlighted in this study indicate an overlap of these different dimensions of conversation in social discourse. A promising approach for uncovering these dimensions and identifying the emotions at work behind conflict, knowledge sharing and support for the reopening would be the application of recent approaches to text analysis relying on deep learning (*cf.*, Choi, *et al.*, 2020).

Conclusions

This study reconstructed a richly nuanced perception of the reopening after national lockdown in Italy. The Italian Twittersphere was dominated by positive emotions like joy and trust on the day after the lockdown release (*RQ1*), in an emotional contagion dominated by hopeful concepts about restarting. It was not a happy ending (*RQ3*). Emotions like anger, fear and sadness persisted and targeted different aspects of the reopening, like sudden raises in the contagion curve, economic repercussions and political denouncement, even fluctuating from day to day (*RQ4*). User’s behaviour in content sharing was found to promote the diffusion of messages featuring stronger joy and lower anger but also expressing more fearful ideas (*RQ5*).

This complex picture was obtained by giving structure to language with cognitive network science (Stella, 2020) and emotional datasets (Mohammad and Turney, 2013). Whereas the valence/arousal model of emotions was unable to detect emotional shifts (Mohammad, 2018), the NRC Emotion Lexicon and its eight emotional states coloured a richly detailed landscape of global and microscopic networked stances and perceptions (*RQ2*).

Reconstructing and investigating the conceptual and emotional dimensions of social discourse is key to understanding how people live through times of transitioning. This work opens a simple quantitative way for accessing and exploring these dimensions, ultimately giving a structured, coherent voice to online users perceptions. Listening to this voice represents a valuable cornerstone for future participatory policy-making, using social media knowledge as a valid tool for facing difficult times.

About the author

Massimo Stella is a lecturer in computer science at the University of Exeter and a scientific consultant and founder of Complex Science Consulting. His research interests include cognitive network science and knowledge extraction models for understanding cognition, language and emotions. He published 33 peer-reviewed papers and has a Ph.D. in complex systems simulation from the University of Southampton (U.K.).
E-mail: massimo [dot] stella [at] inbox [dot] com

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References

J. Aitchison, 2012. *Words in the mind: An introduction to the mental lexicon*. Fourth edition. Malden, Mass.: Wiley-Blackwell.

H.F. de Arruda, V.Q. Marinho, L. da F. Costa and D.R. Amancio, 2019. "Paragraph-based representation of texts: A complex networks approach," *Information Processing & Management*, volume 56, number 3, pp. 479–494.
doi: https://doi.org/10.1016/j.ipm.2018.12.008, accessed 7 July 2020.

R.A. Berman, H. Ragnarsdóttir and S. Strömqvist, 2002. "Discourse stance: Written and spoken language," *Written Language & Literacy*, volume 5, number 2, pp. 255–289.
doi: https://doi.org/10.1075/wll.5.2.06ber, accessed 7 July 2020.

V.D. Blondel, J.-L. Guillaume, R. Lambiotte and E. Lefebvre, 2008. "Fast unfolding of communities in large networks," *Journal of Statistical Mechanics: Theory and Experiment*, number 10, P10008, at https://iopscience.iop.org/article/10.1088/1742-5468/2008/10/P10008/meta, accessed 17 July 2020.

A. Bessi and E. Ferrara, 2016. "Social bots distort the 2016 U.S. Presidential election online discussion," *First Monday*, volume 21, number 11, at https://firstmonday.org/article/view/7090/5653, accessed 17 July 2020.
doi: https://doi.org/10.5210/fm.v21i11.7090, accessed 17 July 2020.

G. Bonaccorsi, F. Pierri, M. Cinelli, A. Flori, A. Galeazzi, F. Porcelli, A.L. Schmidt, C.M. Valensise, A. Scala, W. Quattrociocchi and F. Pammolli (2020). "Economic and social consequences of human mobility restrictions under COVID-19," *Proceedings of the National Academy of Sciences*, volume 117, number 27 (7 July), pp. 15,530–15,535.
doi: https://doi.org/10.1073/pnas.2007658117, accessed 7 July 2020.

F. Bond and R. Foster, 2013. "Linking and extending an open multilingual wordnet," *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics*, pp. 1,352–1,362, and at https://www.aclweb.org/anthology/P13-1133.pdf, accessed 7 July 2020.

W.J. Brady, J.A. Wills, J.T. Jost, J.A. Tucker and J.J. Van Bavel, 2017. "Emotion shapes the diffusion of moralized content in social network," *Proceedings of the National Academy of Sciences*, volume 114, number 28 (11 July), pp. 7,313–7,318.
doi: https://doi.org/10.1073/pnas.1618923114, accessed 7 July 2020.

A.C.M. Brito, F.N. Silva and D.R. Amancio, 2020. "A complex network approach to political analysis: Application to the Brazilian Chamber of Deputies," *PloS ONE*, volume 15, number 3, e0229928.
doi: https://doi.org/10.1371/journal.pone.0229928, accessed 7 July 2020.

M. Choi, L. M. Aiello, K. Z. Varga and D. Quercia, 2020. "Ten social dimensions of conversations and relationships," *WWW '20: Proceedings of the Web Conference 2020*, pp. 1,514–1,525.
doi: https://doi.org/10.1145/3366423.3380224, accessed 7 July 2020.

P.S. Dodds, K.D. Harris, I.M. Kloumann, C.A. Bliss and C.M. Danforth, 2011. "Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter," *PloS ONE*, volume 6, number 12, e26752.
doi: https://doi.org/10.1371/journal.pone.0026752, accessed 7 July 2020.

E. Ferrara, 2020. "What types of COVID-19 conspiracies are populated by Twitter bots," *First Monday*, volume 25, number 6, at https://firstmonday.org/article/view/10633/9548, accessed 7 July 2020.
doi: https://doi.org/10.5210/fm.v25i6.10633, accessed 7 July 2020.

E. Ferrara and Z. Yang, 2015. "Quantifying the effect of sentiment on information diffusion in social media," *PeerJ Computer Science*, volume 1, e26.
doi: https://doi.org/10.7717/peerj-cs.26, accessed 7 July 2020.

C.J. Fillmore, 2006. "Frame semantics," In: D. Geeraerts (editor). *Cognitive linguistics: Basic readings*. Berlin: Mouton de Gruyter, pp. 373–400.
doi: https://doi.org/10.1515/9783110199901, accessed 7 July 2020.

R. Gallotti, F. Valle, N. Castaldo, P. Sacco and M. De Domenico, 2020. "Assessing the risks of 'infodemics' in response to COVID-19 epidemics," *medRxiv* (16 April).
doi: https://doi.org/10.1101/2020.04.08.20057968, accessed 7 July 2020.

N. Gozzi, M. Tizzani, M. Starnini, F. Ciulla, D. Paolotti, A. Panisson and N. Perra, 2020. "Collective response to the media coverage of COVID-19 pandemic on Reddit and Wikipedia," *arXiv*:2006.06446, at https://arxiv.org/abs/2006.06446, accessed 7 July 2020.

H. Hassani, C. Beneki, S. Unger, M.T. Mazinani and M.R. Yeganegi, 2020. "Text mining in big data analytics," *Big Data and Cognitive Computing*, volume 4, number 1, article 1.
doi: https://doi.org/10.3390/bdcc4010001, accessed 7 July 2020.

K.G. Kalimeri, M. Beiró, A. Urbinati, A. Bonanomi, A. Rosina and C. Cattuto, 2019. "Human values and attitudes towards vaccination in social media," *WWW '19: Companion Proceedings of The 2019 World Wide Web Conference*, pp. 248–254.
doi: https://doi.org/10.1145/3308560.3316489, accessed 7 July 2020.

S. Kiritchenko, X. Zhu and S.M. Mohammad, 2014. "Sentiment analysis of short informal texts," *Journal of Artificial Intelligence Research*, volume 50, pp. 723–762.
doi: https://doi.org/10.1613/jair.4272, accessed 7 July 2020.

C.K.T. Lima, P.M. de Medeiros Carvalho, I.D.A.S. Lima, J.V.A. de Oliveira Nunes, J.S. Saraiva, R.I. de Souza, C.G. Lima da Silva and M.L.R. Neto, 2020. "The emotional impact of coronavirus 2019-nCoV (new coronavirus disease)," *Psychiatry Research*, volume 287, 112915.
doi: https://doi.org/10.1016/j.psychres.2020.112915, accessed 7 July 2020.

S. Massaro, 2020. "The organizational neuroscience of emotions," In: L.-Q. Yang, R. Cropanzano, C.S. Daus and V. Martnez-Tur (editors). *Cambridge Handbook of Workplace Affect*. Cambridge: Cambridge University Press, pp. 15–36.
doi: https://doi.org/10.1017/9781108573887.003, accessed 7 July 2020.

S. Mohammad, 2018. "Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 English words," *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, Volume 1: Long Papers*, pp. 174–184.
doi: http://dx.doi.org/10.18653/v1/P18-1017, accessed 7 July 2020.

S.M. Mohammad and P.D. Turney, 2013. "Crowdsourcing a wordemotion association lexicon," *Computational Intelligence*, volume 29, number 3, pp. 436–465.
doi: https://doi.org/10.1111/j.1467-8640.2012.00460.x, accessed 7 July 2020.

S.M. Mohammad, S. Kiritchenko, P. Sobhani, X. Zhu and C. Cherry, 2016. "Semeval-2016 task 6: Detecting stance in tweets," *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, pp. 31–41.
doi: http://dx.doi.org/10.18653/v1/S16-1003, accessed 7 July 2020.

E. Pepe, P. Bajardi, L. Gauvin, F. Privitera, B. Lake, C. Cattuto and M. Tizzoni, 2020. "COVID-19 outbreak response: A first assessment of mobility changes in Italy following national lockdown," *Scientific Data*, volume 7, article number 230.
doi: https://doi.org/10.1038/s41597-020-00575-2, accessed 20 August 2020.

R. Plutchik, 2003. *Emotions and life: Perspectives from psychology, biology, and evolution*. Washington, D.C.: American Psychological Association.

J. Posner, J.A. Russell and B.S. Peterson, 2005. "The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology," *Development and Psychopathology*, volume 17, number 3, pp. 715–734.
doi: https://dx.doi.org/10.1017%2FS0954579405050340, accessed 7 July 2020.

E. Rodrigues and M. Pietrocola, 2020. "Between social and semantic networks: A case study on classroom complexity," *Education Sciences*, volume 10, number 2, article 30.
doi: https://doi.org/10.3390/educsci10020030, accessed 7 July 2020.

K.R. Scherer and P. Ekman (editors), 2014. *Approaches to emotion*. New York: Psychology Press.
doi: https://doi.org/10.4324/9781315798806, accessed 7 July 2020.

C.S. Siew, D.U. Wulff, N.M. Beckage and Y.N. Kenett, 2019. "Cognitive network science: A review of research on cognition through the lens of network representations, processes, and dynamics," *Complexity*, volume 2019, article ID 2108423.
doi: https://doi.org/10.1155/2019/2108423, accessed 7 July 2020.

M. Stella, 2020. "Text-mining forma mentis networks reconstruct public perception of the STEM gender gap in social media," *PeerJ Computer Science*, volume 6, e295.
doi: https://doi.org/10.7717/peerj-cs.295, accessed 12 October 2020.

M. Stella and A. Zaytseva, 2020. "Forma mentis networks map how nursing and engineering students enhance their mindsets about innovation and health during professional growth,," *PeerJ Computer Science*, volume 6, e255.
doi: https://doi.org/10.7717/peerj-cs.255, accessed 7 July 2020.

M. Stella, V. Restocchi and S. De Deyne, 2020. "*#lockdown*: Network-enhanced emotional profiling at the time of COVID-19," *Big Data and Cognitive Computing*, volume 4, number 2, number 14.
doi: https://doi.org/10.3390/bdcc4020014, accessed 7 July 2020.

M. Stella, E. Ferrara and M. De Domenico, 2018. "Bots increase exposure to negative and inflammatory content in online social systems," *Proceedings of the National Academy of Sciences*, volume 115, number 49 (4 December), pp. 12,435–12,440.
doi: https://doi.org/10.1073/pnas.1803470115, accessed 7 July 2020.

M. Stella, N.M. Beckage and M. Brede, 2017. "Multiplex lexical networks reveal patterns in early word acquisition in children," *Scientific Reports*, volume 7, article number 46730.
doi: https://doi.org/10.1038/srep46730, accessed 7 July 2020.

M. Stella, S. de Nigris, A. Aloric and C.S.Q. Siew, 2019. "Forma mentis networks quantify crucial differences in STEM perception between students and experts," *PloS ONE*, volume 14, number 10, e0222870.
doi: https://doi.org/10.1371/journal.pone.0222870, accessed 7 July 2020.

H. Vankrunkelsven, S. Verheyen, G. Storms and S. De Deyne, 2018. "Predicting lexical norms: A comparison between a word association model and text-based word co-occurrence model," *Journal of Cognition*, volume 1, number 1, number 45.
doi: http://doi.org/10.5334/joc.50, accessed 7 July 2020.

A. Zelenkauskaite and B. Niezgoda, 2017. "'Stop Kremlin trolls:' Ideological trolling as calling out, rebuttal, and reactions on online news portal commenting," *First Monday*, volume 22, number 5, at https://firstmonday.org/article/view/7795/6225, accessed 17 July 2020.
doi: https://doi.org/10.5210/fm.v22i5.7795, accessed 17 July 2020.

Appendix

This Appendix gathers tables and supporting information of relevance for the results reported in the main text.

Day/Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
May 1	talk	sun	coma	newcomer	bottomless	fact	tomorrow	account	govern	feeling	money	death	daily	do	contagion
May 2	govern	case	account	fact	coma	explain	badly	baby	ready	boy	deserve	newcomer	sun	bottomless	do
May 3	tomorrow	do	coma	govern	sun	begun	fact	newcomer	case	good	found	expect	respect	account	buddy
May 4	coma	good	case	account	begun	responsible	newcomer	do	contagion	sun	talk	respect	quarantine	bottomless	moat
May 5	coma	good	case	sun	do	account	talk	newcomer	continue	begun	bottomless	govern	outcry	sluggish	react
May 6	coma	govern	sun	fact	newcomer	talk	do	account	case	sluggish	react	serve	immediately	sincere	bottomless
May 7	govern	coma	accord	freely	guess	newcomer	do	bottomless	contagion	sun	account	fact	death	testament	case
May 8	bottomless	coma	real	responsible	risk	rational	respect	sun	case	contagion	chance	talk	disaster	commerce	combat
May 9	coffin	do	real	arrival	sun	coma	fact	communication	policy	account	shrink	elucidate	boredom	case	risk
May 10	coffin	rule	coma	govern	begun	regiment	eagle	case	fact	account	bottomless	do	newcomer	feat	arrival
May 11	case	boredom	measure	plight	coma	govern	helper	coffin	safe	evident	bottomless	arrival	do	policy	bankrupt
May 12	begun	govern	mouth	account	case	weary	coma	do	owing	manage	series	boredom	measure	plight	bottomless
May 13	coma	account	sun	respect	do	owing	inability	newcomer	mouth	bottomless	guidance	lines	begun	manage	series
May 14	insult	coma	sun	base	govern	contagion	newcomer	do	ashamed	danger	generous	enthusiasm	account	fact	faithless
May 15	coma	newcomer	sun	contagion	govern	communication	do	coffin	nothingness	believed	demand	money	holiday	base	faithless
May 16	criticism	fort	unpaid	crap	govern	sun	coma	hopeful	do	series	talk	newcomer	bottomless	boredom	succeed
May 17	govern	tomorrow	account	do	coma	sun	newcomer	fort	criticism	bottomless	crap	good	restriction	arrival	expect
May 18	coma	sun	coffin	newcomer	do	bottomless	mistress	good	begun	shopkeeper	general	retain	case	account	deserted
May 19	coma	case	sun	management	system	reliable	account	owing	do	heathen	talk	found	newcomer	socialism	immediately
May 20	govern	coma	case	do	management	newcomer	law	bottomless	sun	mouth	fact	mistrust	die	account	buddy

Table 1a: Daily top-ranked concepts according to frequency. Higher frequency indicates higher occurrence in tweets. Words eliciting negative (positive) emotions are in warm (cold) colors (see also Figure 1 in the main text).

Day/Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
May 1	account	govern	sun	newcomer	do	talk	case	fact	begun	bottomless	quarantine	owing	good	policy	respect
May 2	govern	sun	do	account	case	bottomless	contagion	buddy	newcomer	audience	fact	elucidate	talk	quarantine	arrival
May 3	coma	sun	do	case	begun	govern	newcomer	account	buddy	fact	owing	boredom	responsible	bottomless	found
May 4	sun	case	do	bottomless	newcomer	begun	fact	owing	govern	account	good	respect	boredom	found	responsible
May 5	sun	case	do	newcomer	begun	fact	bottomless	govern	talk	account	owing	contagion	boredom	respect	health
May 6	newcomer	case	bottomless	sun	do	govern	account	boredom	health	talk	contagion	fact	economy	responsible	begun
May 7	do	sun	case	govern	newcomer	bottomless	account	talk	fact	leisure	audience	begun	owing	feat	boredom
May 8	sun	govern	do	health	bottomless	owing	contagion	account	fact	case	respect	talk	responsible	newcomer	continue
May 9	case	do	sun	govern	boredom	account	newcomer	rule	leisure	begun	series	owing	prick	freedom	testament
May 10	govern	sun	case	account	bottomless	do	fact	economy	talk	boredom	serve	begun	chance	newcomer	audience
May 11	govern	do	newcomer	case	sun	talk	bottomless	begun	coffin	account	fact	arrival	audience	chance	health
May 12	sun	do	govern	case	bottomless	newcomer	account	policy	owing	contagion	coffin	talk	fact	begun	rule
May 13	sun	bottomless	newcomer	case	account	do	govern	talk	contagion	fact	measure	buddy	economy	audience	rule
May 14	newcomer	sun	govern	do	account	case	bottomless	rule	measure	feat	owing	fact	health	talk	coffin
May 15	sun	do	govern	newcomer	coffin	feat	change	contagion	bottomless	leisure	serve	talk	communication	rule	boredom
May 16	coma	sun	do	govern	bottomless	case	succeed	newcomer	responsible	fact	boredom	risk	finally	begun	prick
May 17	account	tomorrow	sun	govern	do	bottomless	newcomer	case	boredom	owing	fact	arrival	contagion	leisure	begun
May 18	sun	newcomer	do	coffin	case	bottomless	owing	talk	good	rule	account	boredom	begun	leisure	govern
May 19	coma	do	bottomless	newcomer	case	account	contagion	govern	coffin	owing	audience	fact	risk	change	rule
May 20	do	newcomer	case	sun	contagion	govern	fact	talk	respect	account	health	helper	real	bottomless	change

Table 2a: Daily top-ranked concepts according to frequency. Higher frequency indicates higher richness of different contexts in tweets. Words eliciting negative (positive) emotions are in warm (cold) colors (see also Figure 1 in the main text).

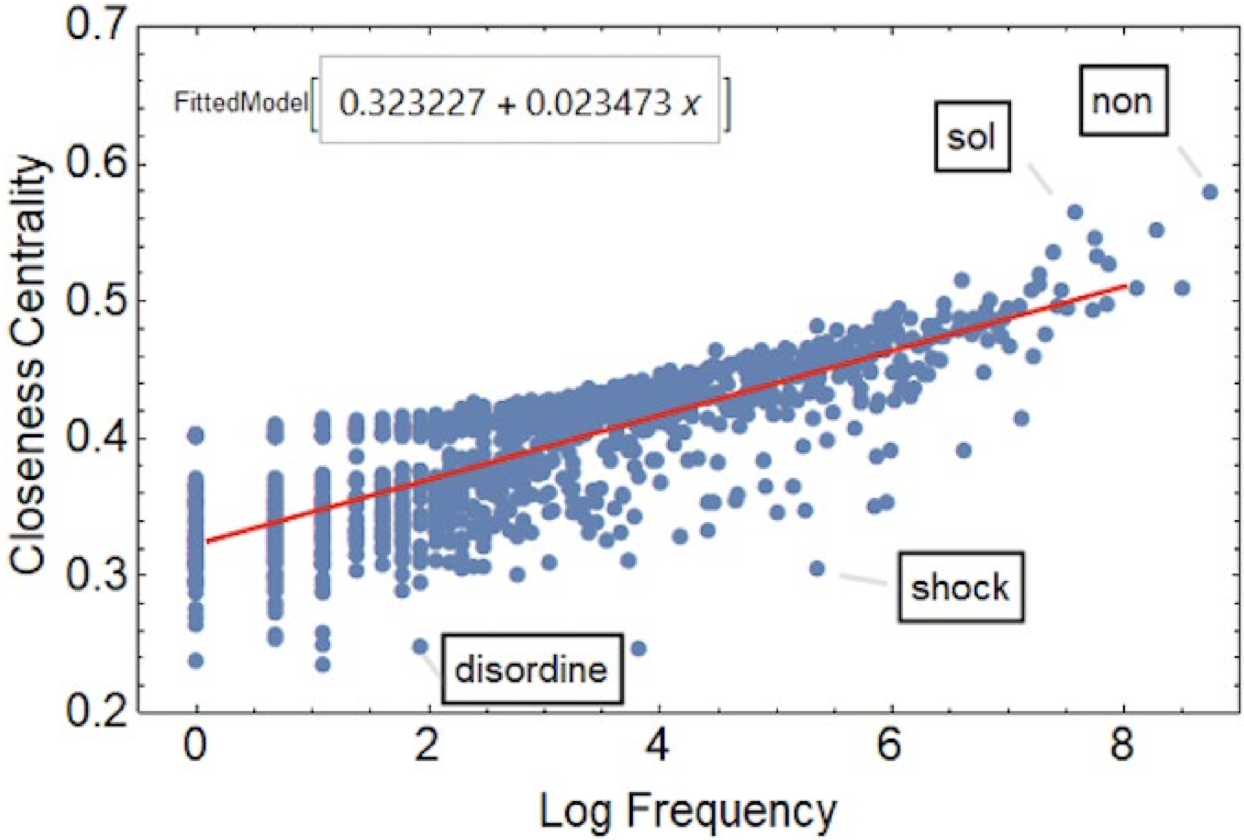

Figure 1a: Log frequency vs. closeness scatter plot of words on 4 May.

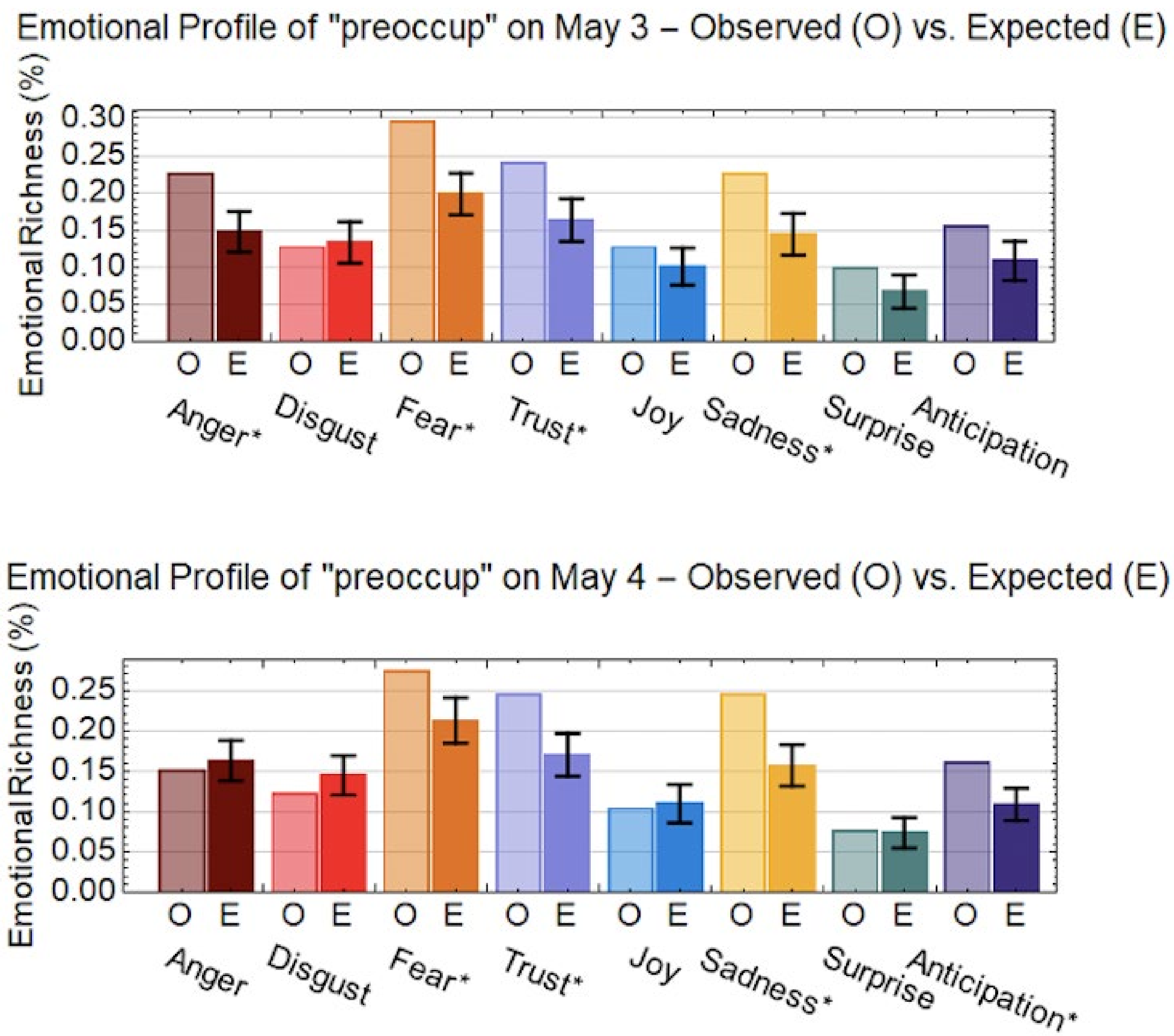

Figure 2a: Emotional richness of 'preoccup' (worried) on 3 May (top) and 4 May (bottom). Words are colored according to their emotions.

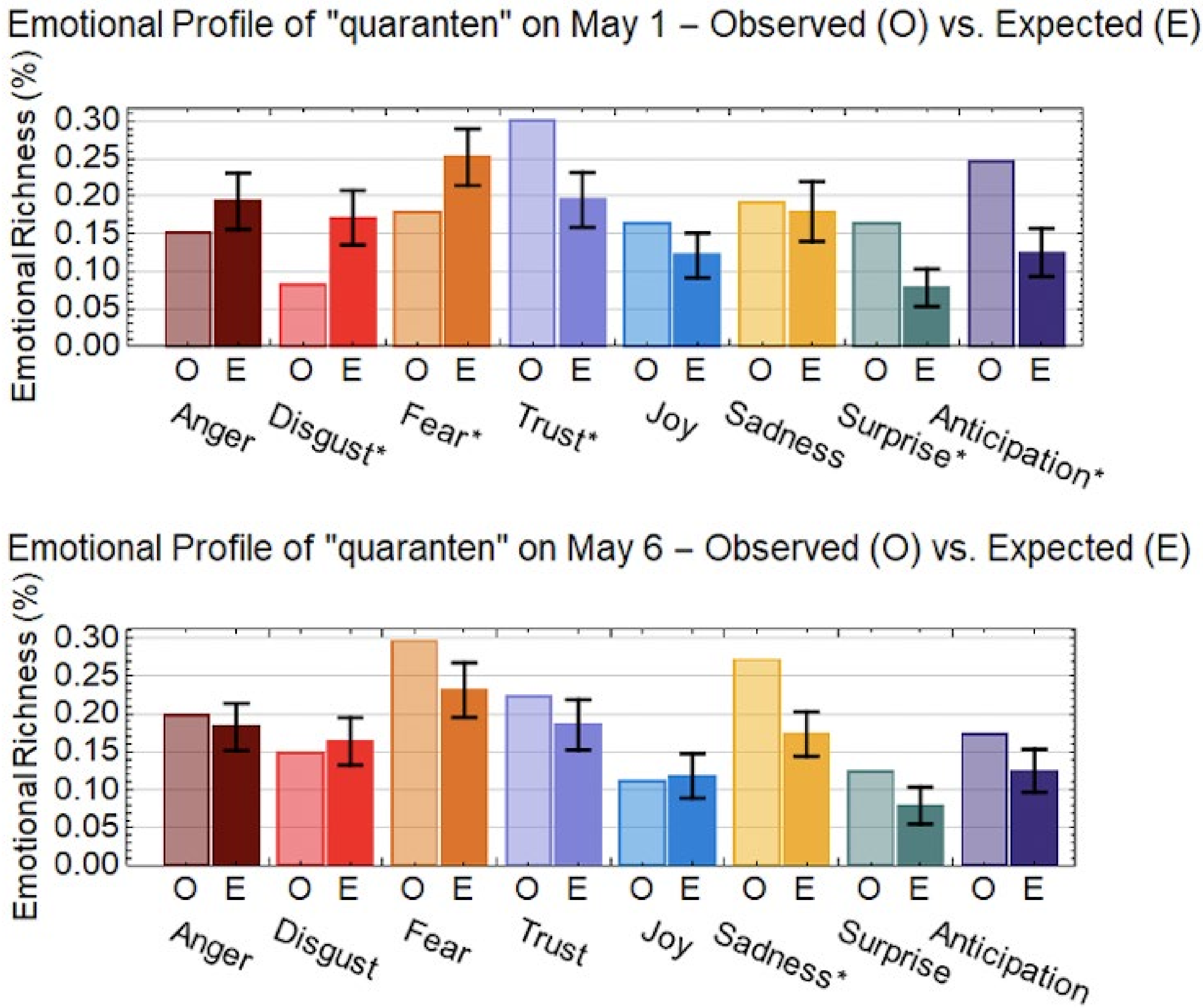

Figure 3a: Emotional richness of 'quaranten' (quarantine) on 1 May (top) and 6 May (bottom). Words are colored according to their emotions.

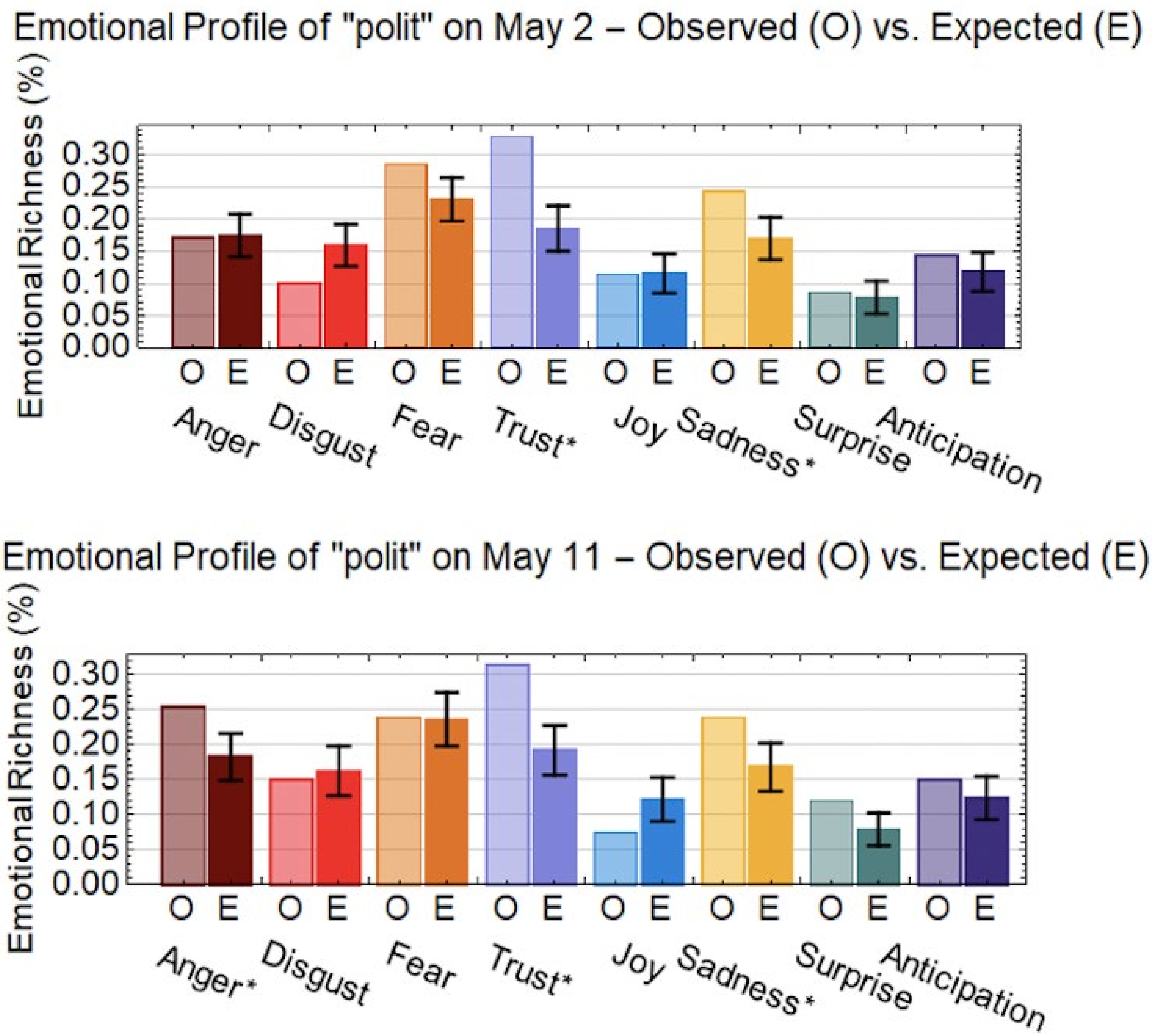

Figure 4a: Emotional richness of 'polit' (politics) on 2 May (top) and 11 May (bottom). Words are colored according to their emotions.

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