Burstiness in Emotions: A Case Study on Collective Affective Responses in Italian Soccer Fandoms

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Abstract. The bursty nature of emotions is rarely investigated outside cognitive and psychological studies. Therefore this work addresses a gap in the literature, investigating the phenomenon of emotional burstiness using tools from the analysis of complex systems, and considering as case-study soccer fans' affective responses on social media. We reconstruct collective reactions on Instagram posts from official accounts of 40 Italian football teams during the first round of the 2023-2024 season – 20 teams from Serie B (the second tier of Italian Football) and the 20 most followed teams in Serie C (the third tier). With this data, we build sequences of emotional signals for four types of emotions: joy, anger, sadness, and fear. Our analysis reveals trends of anti-burstiness in expressions of joy among users, reflecting fans' consistent support for teams, occasionally interspersed by bursts of anger and sadness, with no signals of fear. This preliminary investigation provides insights for the understanding of emotional dynamics in online discussions and team supporting in soccer leagues.

Keywords: burstiness · memory · time series · emotions

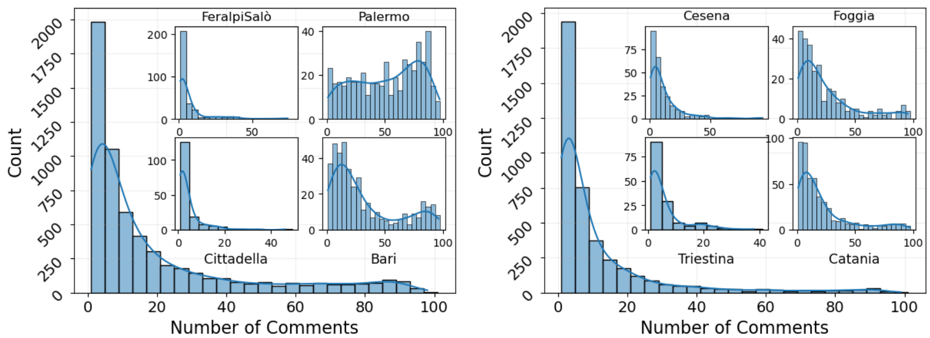
1 Introduction

Time-dependent activity patterns are ubiquitous in nature, from the burstiness of earthquakes [3] to the intermittency of rainfall [25]. Human behavior exhibits complex dynamics as well, shaped by selection mechanisms [5] and social interactions [27, 7], which result in bursty patterns across various activities such as email exchanges, financial transactions, phone calls, and online messages, among others [17]. Despite numerous contributions in uncovering these patterns within different domains [17], several aspects of human complexity still lack adequate attention. Among these, the dynamics of emotions are among the most challenging to represent and analyze [19, 11], due to the difficulty of directly mapping subjective experiences. Differently from recording when a mail is sent or a financial transactions is processed, emotions cannot be easily measured.

Various psychological studies have hinted to the bursty nature of emotions. Affect bursts [24] have been defined as brief expressions of affect, and measured in both face and voice variations in response to events of positive/negative valence [26]. Intense bursts of joy and positive emotions are characteristic of the manic phase of bipolar disorder [1], while violent outbursts of anger may indicate behavioral conditions like in the intermittent explosive disorder [1]. Emotional responses take place in social media as well, and being triggered by online content consumption can lead to hasty variations in users' emotional states [29]. Novel areas of research within social media analysis aim to quantify emotional variations from various perspectives, e.g., that of mental health online self-disclosure, by observing emotional shifts in online support communities over time [4], or by identifying early signals of suicidal ideation [16]. Other perspectives rely on the detection of hate speech and negative content [28], relating it to misinformation [8], to emotional persistence/instability [12], and to the dynamics of emotional shifts driven by recommender systems [15]. However, despite their bursty quality and the importance of understanding their stable or unstable nature, emotions have never been addressed through the quantitative tools offered by the science of complex systems. In other words, emotions have never been thought of as measurable time-dependent signals. The aim of this study is to follow Goh and Barabasi's milestone work about burstiness quantification [14] and apply it to build and measure sequences of emotional activity. Goh and Barabasi [14] have uncovered two main processes that characterize bursty activities within complex systems: a distribution of inter-event times that deviates significantly from Poissonian processes, and the memory between pairs of consecutive inter-event times.

As a domain of analysis, we choose soccer fans' affective responses on social media. We reconstruct the emotional collective responses of soccer fans commenting Instagram posts of the 20 official football teams' accounts during the first round of the Italian 2023-24 Serie B, and the first round of the 20 teams with the highest number of Instagram followers among the three Groups of the 2023-24 Serie C. The rationale behind the choice of the soccer domain lies in the investigation of emotional dynamics in a context where emotions unfold collectively [13] as well as emotional outbursts. We focus on lower soccer leagues as they provide the opportunity to analyze genuine and local fandoms [20], without the overexposure of international fans present in major leagues. We choose Instagram because it offers a simpler way to distinguish between the collective sentiment of each fandom by leveraging the posting activity sequence of each team account, as opposed to using hashtags or conversations on Twitter [9, 22] or communities on Reddit [6], where discussions and comments are more mixed.

The paper proceeds as follows. Section 2 introduces the measures used to describe the bursty properties of complex systems together with the dataset constructed for this analysis. Section 3 highlights the main results on both leagues. Section 4 discusses the results and concludes the work towards future research directions.



(a) Serie B

(b) Serie C

Fig. 1: Distribution of the total number of users' comments from all Serie B teams' accounts (a) and the chosen 20 teams from Serie C (b) for the selected temporal activity window. For both leagues, the plots within show 4 (out of 20) individual distributions.

2 Materials and Methods

This section introduces the data collection and pre-processing (Section 2.1). Subsequently, it presents the measures used to describe burstiness and memory in generic activity sequences (Section 2.2), following Goh and Barabasi's work [14].

2.1 Data Collection and Pre-processing

We characterize the emotional engagement of fandoms examining teams' activity on Instagram. This includes posts such as halftime and full-time scores, highlights, squad lists, etc... We build a dataset from user comments on Instagram posts from the 20 official Italian accounts of the teams participating at the 2023-24 Serie B[5], the second-highest division in the Italian football league system, and from the 20 most followed accounts on Instagram among the three Groups of the 2023-24 Serie C[6]. Regarding Serie C, out of the 20 chosen teams, 10 belong to Group C, which is the one where teams from the South of Italy participate, 5 are from Group B (Center Italy: Cesena, Entella, Olbia, Perugia, and Pescara) and other 5 are from Group A (North Italy: Alessandria, Padova, Pro Vercelli, Triestina, and SPAL). To ensure that every team played exactly once against every other team, users' comments on posts were extracted using the official Instagram APIs between August 15, 2023, and December 27, 2023, for Serie B, and between August 31, 2023, and December 24, 2023, for Serie C, i.e. the day before the first match and the day after the last match of the first round of the two leagues.

[5] https://en.wikipedia.org/wiki/2023-24_Serie_B
[6] https://en.wikipedia.org/wiki/2023-24_Serie_C

We perform a task of emotion classification using *feel-it*[7], a python library tailored for emotion classification in Italian [2]. This tool allows us to predict the emotional content of a given text, categorizing it into one of four types of emotions: joy, anger, sadness, and fear. Considering that the detection of an emotional event may not be significant if a post contain one or a very few number of comments, we have developed a tailored labeling strategy. We label each Instagram post indicating either the absence/non significant presence (0) or maximal presence (1) of an emotion, for each emotion. The maximal presence of an emotion represent the collective sentiment generated by a post. Moreover, this aggregation guarantees the privacy of individual users. Formally, being E the set of emotions considered, and n_e the number of comments on a post p classified with the emotion $e \in E$, the label l of each post is calculated as $l = argmax_{e \in E}\ n_e$. Thus, if a post contained 20 comments, with 18 of them classified as anger, the post would be labeled as conveying anger (1 for anger, 0 for other emotions).

Fig. 1 depicts the distributions of the number of comments on each post in the two leagues. The maximum number of comments is limited to 100 for computational feasibility. The distribution of comments displays a peaked long-tail pattern, indicating that most posts receive a small number of comments, while a few posts attract a high number of comments. Notably, the distribution is not uniform across all teams. For instance, as reported in the highlights of Fig. 1(a), the comment distribution for Cittadella and FeralpiSalò mirrors the overall pattern, i.e., a consistent presence of posts with only one comment. Conversely, other comment distributions can exhibit either bimodal patterns (Bari) or a more uniform distribution (Palermo). Similarly, as illustrated in Fig. 1(b), there is a degree of variability among teams in Serie C, too, albeit less pronounced. Moreover, there is a difference among the two leagues in terms of volumes during the analyzed time frame, with Serie B accumulating 115552 comments, and Serie C, 47613.

Taking into account the observed heterogeneity in the distributions of the number of comments across the different accounts, we opt for individual thresholds (rather than a global one) to select the retained posts: we consider only posts having at least a number of comments equal to the median of the distribution of the individual account. E.g., for FeralpiSalò we keep posts having at least 2 comments, and for Palermo, at least 28.

Fig. 2 shows the relative frequency of each emotion for each fandom over Serie B's 2023-2024 first round. Similarly, Fig. 3 highlights the same for the selected teams from Serie C. These frequencies are used to retrieve the most frequent emotion and build the binary sequences of 0s and 1s. In Serie B, Parma's joy sequence will be full of joy emotional events (labeled as 1), whilst Bari's joy sequence will lack of events (labeled as 0). Similarly, Olbia and SPAL represent opposite extremes in Serie C, with Olbia's fans mostly conveying joy and SPAL's fans mostly conveying anger.

[7] `https://github.com/MilaNLProc/feel-it`

2.2 Measures

Let τ be the inter-event time between two consecutive events. First, we aim to quantify whether the distribution of the inter-event times $P(\tau)$ deviate from the random activity pattern characterized by the exponential distribution. In our cases, $P(\tau)$ is the distribution of the waiting time τ that elapses before a target emotion appears again in the emotional sequence. We use the mean value of the distribution, $\mu_\tau = \frac{1}{n_\tau}\sum_{i=1}^{n_\tau}\tau_i$, where n_τ is the length of the sequence, and the standard deviation, $\sigma_\tau = \sqrt{\frac{\sum_{i=1}^{n_\tau}(\tau_i-\mu_\tau)^2}{n_\tau}}$, to measure the coefficient of variation r as follows:

$$r = \frac{\sigma_\tau}{\mu_\tau} \tag{1}$$

The variation r is a measure of the dispersion of a distribution compared to its mean. Goh and Barabasi [14] use r to introduce the burstiness parameter B as follows:

$$B = \frac{\sigma_\tau - \mu_\tau}{\sigma_\tau + \mu_\tau} = \frac{r-1}{r+1} \tag{2}$$

Burstiness B ranges from -1 and 1, where 1 indicates the bursty time series (σ_τ much higher than μ_τ), -1 the periodic one, and 0 indicates the random activity pattern.

Being B affected by the finite number of events in the time series, Kim and Jo [18] propose a variation of B for finite event sequences of size n as follows:

$$B_n = \frac{\sqrt{n+1}\cdot r - \sqrt{n-1}}{(\sqrt{n+1}-2)r + \sqrt{n-1}} \tag{3}$$

This modification allows to analyze time series with a relatively small number of events, which can be the case of low posting activity of a team account. In the experiments, we will use the quantity B_n described in Eq. 3 to measure burstiness.

Second, Goh and Barabasi [14] suggest that the burstiness parameter is not the unique mechanisms describing the dynamics of non-random activities. They focus also on the role of memory, described by the memory parameter M [14] as follows:

$$M = \frac{1}{n-1}\sum_{i=1}^{n-1}\frac{(\tau_i-\mu_1)(\tau_{i+1}-\mu_2)}{\sigma_1\sigma_2}, \tag{4}$$

where μ_1 and μ_2, and σ_1 and σ_2 are sample mean and sample standard deviation of τ_i's values and τ_{i+1}'s values, with $(i = 1, ..., n_\tau - 1)$. The memory coefficient M is similar to the autocorrelation of a time series at lag=1. Schleiss and Smith [25] suggest extending M to a generic lag k, replacing 1 in $n_\tau - 1$ with k, and letting calculate the correlation between two inter-event times τ and τ'

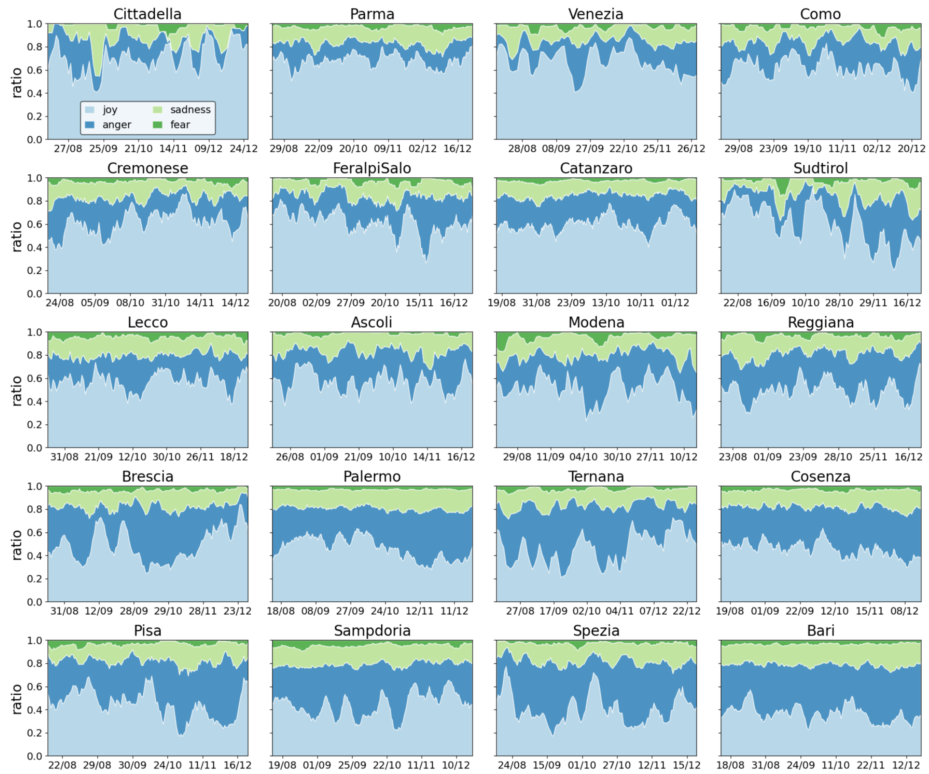


Fig. 2: Ratio of emotional levels of each fandom for the selected temporal activity window (from 15/08/2023 to 26/12/2023) ranked for the median value of joy: Cittadella's fandom manifests the highest levels of joy (in median), and Bari's fandom, the lowest one.

separated by k events (instead of 1 event) to better capture long-range correlations. Memory M ranges from -1 and 1, where 1 indicates short/long inter-event times followed by short/long ones, -1 indicates short/long inter-event times followed by long/short ones, and 0 indicates no correlation. In the experiments, we will use the quantity M described in Eq. 4 to measure the memory parameter, being coherent with [14], even if different values of k could enable further explorations into how different lags affect the correlation between inter-event times.

3 Results

We quantify the degree of both burstiness and memory in our datasets. Specifically, we investigate whether: *i)* emotional temporal sequences manifest bursty characters, *ii)* different emotions can be described by different mechanisms of

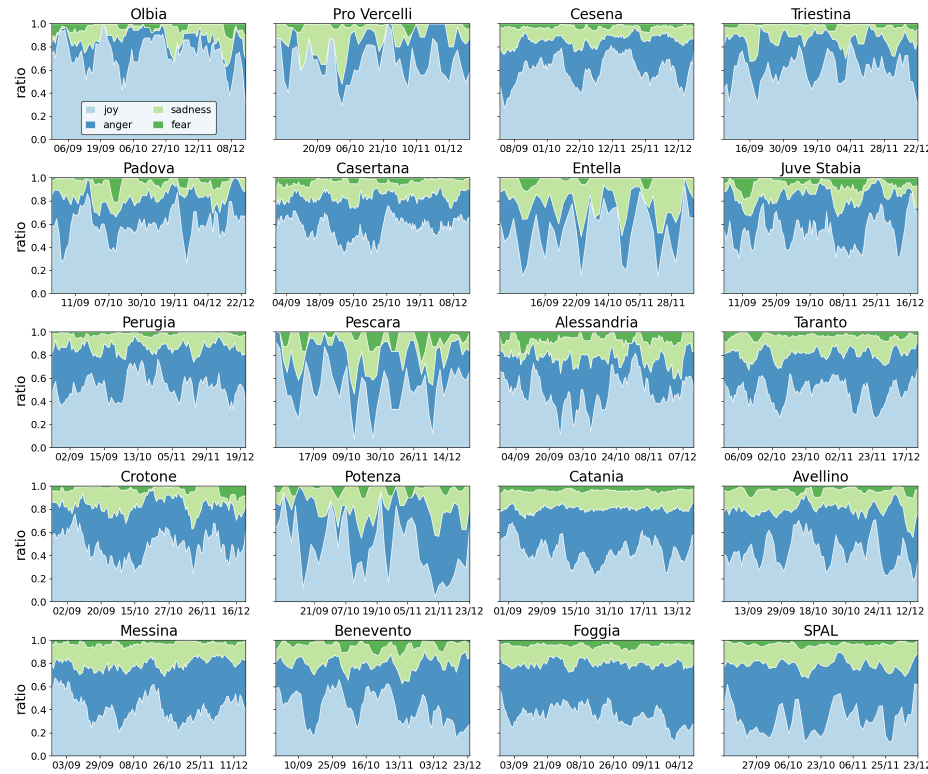


Fig. 3: Ratio of emotional levels of each fandom for the selected temporal activity window (from 31/08/2023 to 24/12/2023) ranked for the median value of joy: Olbia's fandom manifests the highest levels of joy (in median), and SPAL's fandom, the lowest one.

non-random dynamics, among burstiness and memory, and *iii)* similarities emerge from the two different leagues.

First of all, we decided to exclude the emotion *Fear* from this analysis, since it is never the most frequent emotional response on posts (see Fig. 2 and Fig. 3), and therefore it does not generate any significant time series to analyze.

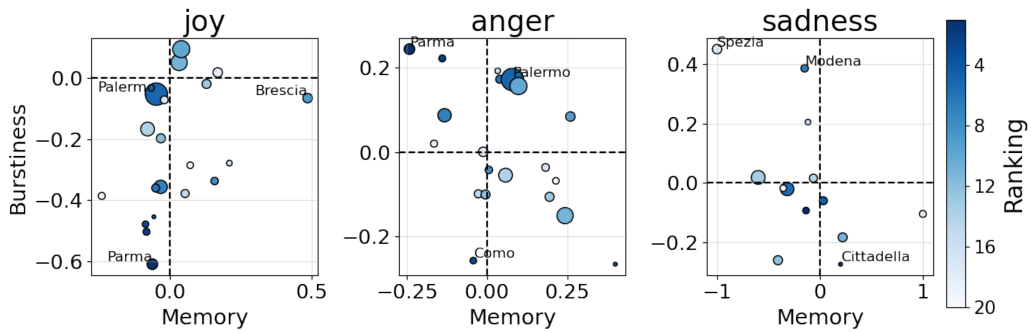
Fig. 4 shows the M-B diagrams for Serie B's teams, for each of the three remaining emotions. The color of each point, representing each team, is associated with the ranking at the end of the first round: the darker the point, the highest the ranking. The three emotions manifest different dynamics. Joy rarely exhibits a bursty character. It mostly comes as an anti-bursty emotional pattern within most fandoms. These anti-bursty, and regular, patterns indicate a consistent support for the respective teams. Moreover, joy patterns of teams in top positions are the most regular ones, as in the case of Parma's fans, the team in first place in the ranking, highlighted in Fig. 4(b). Some exceptions are represented by teams like Palermo, whose fandom does not exhibit the anti-bursty behavior expressed by other teams in top positions. To understand this behavior, it is necessary to analyze the burstiness value in light of fans' initial expectations for the championship. A reasonable proxy for the team's perceived potential can be the market value of the rosters of the team at the season's outset, indicating investments in key players. The market value considers factors such as team performance, player values, financial successes, brand, reputation, and the wisdom of its community, thus can change during the season. A more comprehensive perspective is provided by the Pearson correlations between the joy burstiness and the two features, market value and ranking, as reported in Table 1. As depicted in Fig. 4 (b), the memory shows a less powerful descriptive power: except for Brescia, all of the other teams memory value lies in a small interval (between -0.2 and 0.2). A plausible explanation for Brescia's performance can be its performance within the considered period: a long series of consecutive wins followed by a long series of draws and another one of consecutive loses[8].

Anger can exhibit both bursty and anti-bursty patterns, with memory playing a more relevant descriptive role. Interestingly, Parma's fans display bursty anger dynamics compared to their strongly regular joy. Similarly, Palermo's fans exhibit bursty patterns of anger. Examining the sequences highlighted in Fig. 4(b), we can explain the bursty anger behaviour observed in Palermo's fans as a gradual accumulation over time leading to an eventual outburst (indicated by positive memory values). In contrast, the behavior of Parma's fans appears to be more closely linked to individual matches, with a sudden decay in emotional intensity following each match (indicated by negative memory values). Thus, contrary to joy, where Pearson correlation between burstiness and ranking is positive, the correlation between anger burstiness and ranking is negative (Table 1): fandoms of teams in top positions seem to manifest a burstier character of anger.

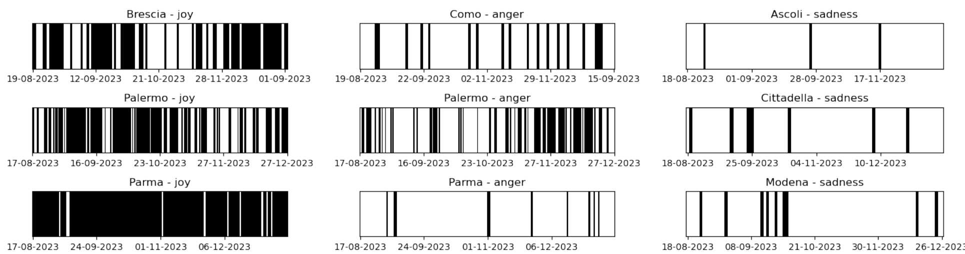
			Ranking (26/12/23)	Market Value (start season)
Serie B	Memory	Joy	0.17	-0.10
		Anger	0.18	-0.35
	Burstiness	Joy	0.44	0.00
		Anger	-0.20	0.45
Serie C	Memory	Joy	//	0.03
		Anger		-0.30
	Burstiness	Joy		0.28
		Anger		-0.10

Table 1: Pearson correlations between memory/burstiness in joy/anger and team ranking/market values. Ranking for Serie C are not measured due to the selection from the three different Groups.

[8] `https://en.wikipedia.org/wiki/2023-24_Brescia_Calcio_season`



(a)



(b)

Fig. 4: M-B diagrams for different emotions, focus on teams from Serie B only. Points represent memory and burstiness values describing the collective emotional reactions to the posting sequences of teams' accounts. Colors represent ranking at 26/12/2023. Sizes represent the total number of comments under the posts of a team. (a); Focus on some selected emotional sequences (b).

Finally, sadness dynamics are the burstiest ones. However, sadness is the only emotion where some outliers manifest, e.g., fandoms lying in the extreme ranges of the memory measure. These could be the only non-significative points in the dataset, see Ascoli's sequence of sadness (Fig. 4(b)), characterized by very few events that do not allow the two measures to properly capture a description of the signal. Outliers can be explained by the fact that sadness rarely manifests as a collective signal in this dataset, cf. Fig. 2. Also the absence of some points (e.g., Palermo) signifies that sadness does not manifest collectively, i.e., no time series to analyze.

Interestingly, all the patterns identified in Serie B teams are manifest in Serie C. Fig. 5 reports the M-B diagrams of the three emotions including both leagues. Overall such findings suggest that joy predominantly exhibits an anti-bursty property, while anger and sadness display more heterogeneous behaviors, including bursty patterns.

Fig. 6 offers a new perspective on Serie B dynamics, presenting two ternary plots that analyze the relationship between burstiness parameters of joy and

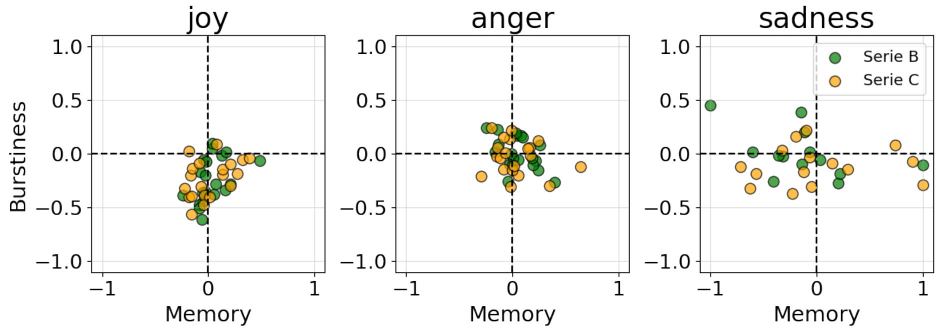


Fig. 5: M-B diagrams for different emotions including teams from both Serie B and Serie C. Points represent memory and burstiness values describing the collective emotional reactions to the posting sequences of teams' accounts

anger and what we can identify as fans' "Expectations versus Reality". Expectation is proxied by teams' market values at the beginning of the season, whilst Reality is represented by the ranking at the end of the first round of the championships. In other words, we aim to observe the eventual contrast between what fandoms hope will happen and what actually happens at the end of the first round. Fig. 6(a) compares the two dimensions of expectations and reality to the burstiness in joy. In the bottom left corner of the triangle we observe high valuable teams meeting expectations, thus displaying regular joy over time. Parma, Venezia, Como, and Cremonese, indeed, occupy this area. Moving towards the center of the triangle, we find Spezia, a high valuable team that does not meet fans' expectations but fans still demonstrate consistent support. Palermo's and Sampdoria's fans, being their teams other two high valuable clubs not meeting their expectations, fail to exhibit regular joy. This explains better the strong heterogeneity observed among fandoms. Similarly, Fig. 6(b) compares the dimensions of "expectations versus reality" of the anger's burstiness. It is worth noting that anger is burstier when teams occupy top positions in the ranking, with some differences, e.g., Como and Cittadella, making it difficult to observe completely predictable patterns of emotional signals (cf. next Discussion and Conclusion).

4 Discussion and Conclusion

The results describing the time-dependent sequences of collective emotions in Italian soccer fandoms lead us to conclude that their emotional patterns display complex dynamics. We have observed heterogeneous emotional patterns, from anti-bursty reactions of joy to heterogeneous expressions of anger and sadness. The emotional patterns are similar across the two different Italian leagues. This indicates perhaps a pattern that is independent from the level of the league and

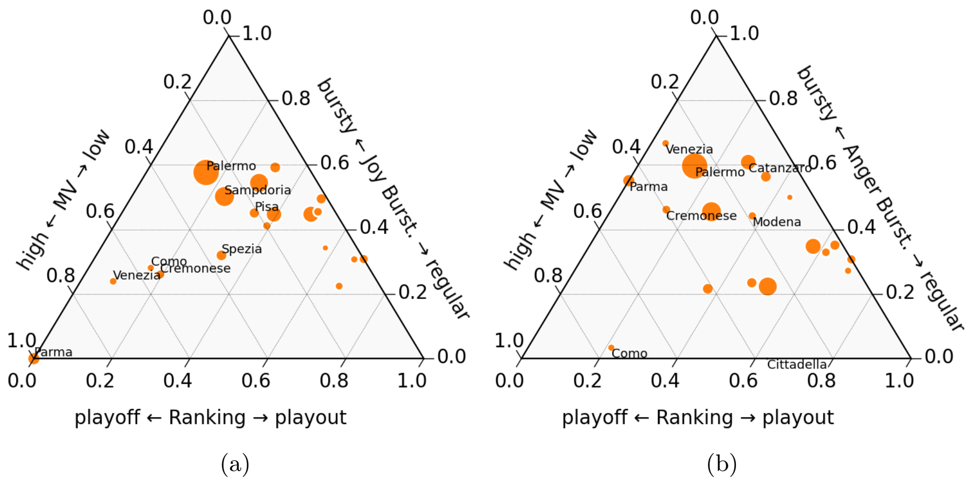


Fig. 6: Ternary plots highlighting ranking at 26/12/2023, market values at 15/08/2023, and burstiness of joy (a) and anger (b). The labeled teams are the top-8 richest in terms of market values (a) and the top-8 in the ranking at 26/12/2023 (b). The size of the points represents the total number of comments under the posts of a team.

its geographical origin that could be empirically investigated across different leagues in future research.

Analyzing collective emotions through the lens of complex systems may provide insights into the role of emotional burstinesses as signals, or triggers, of emerging collective/coordinated behaviors [21]. This preliminary work on soccer fans and users' affective response to social media posts is indeed rooted in the theory of collective emotions [13]. Understanding the significance of burstiness and memory in this domain is key for further extending the analysis to other domains. Regarding the burstiness parameter, anti-bursty patterns of joy in affective responses to own team's activities clearly reflect a constant support for the team. Moreover, correlating joy and anger burstiness with market values and ranking, a proxy for the "expectations versus reality", revealed interesting patterns. High market value teams like Parma, Cremonese, and Venezia in Serie B consistently showed regular joy and bursty anger when meeting expectations and holding top positions. Predictable patterns remain hard to disentangle. Initial season expectations from fandoms could provide valuable emotional signals for future investigations. However, it is crucial to interpret fandoms on a case-by-case basis, especially in this context. Burstiness exhibits a diverse range of behaviors associated with different scenarios, from fans with high expectations facing disappointment (Palermo, Sampdoria) to teams exceeding performance expectations (Catanzaro).

The interpretation of the memory parameter is not as straightforward as burstiness, yet it remains useful for describing the non-random dynamics of collective emotions among fans (e.g., see patterns of joy in Brescia). Using a memory parameter $k > 1$ would extend the scope of our analysis, enabling us to explore patterns over a longer time frame. This approach would permit to analyze long-range correlations of emotions beyond consecutive events, providing insight into their persistence over broader temporal scales.

Among the limitations, we first recognize the heterogeneous volume of posts and comments across teams' accounts. Soccer teams manage their accounts differently, resulting in varying levels of posting activity, users' engagement and thus users' emotional sequence sizes. On average, in our Serie B dataset, accounts' posting sequences are long 302 posts with a standard deviation of 129. Catanzaro exhibits the highest posting activity, with 702 posts within the analyzed time frame, while Venezia has the lowest, with only 145 posts. Comparable comment distributions are also evident in Serie C.

As shown in Fig. 1, the variation in the number of comments on posts is crucial for identifying emotionally significant sequences, assuming that posts with more comments would improve the quantification of the collective emotion. Finally, the quality of our results inevitably depends on the emotion classifier we used, which is based on the *feel-it* corpus for Italian [2]. In the original study [2], it is showed that a BERT-like emotion classifier trained on the *feel-it* corpus outperforms models trained on other corpora. The *feel-it* corpus, based on social media data, aligns well with the content of our dataset.

Our analysis reveals an interesting trend in the median joy ranking of Serie C teams, as depicted in Fig. 3. Teams from Group A and Group B generally exhibit higher median joy levels compared to those from Group C, with exceptions noted for Juve Stabia and Casertana, which performed well in the initial round considered. Further investigation is needed to determine if this geographical disparity persists, alongside exploring correlations with socio-economic and geographical indicators.

In conclusion, we believe that this preliminary study offers insights into emotional dynamics in social media and team support, suggesting potential research avenues in other leagues and domains, also involving user-oriented approaches [12], network interactions, or integration with soccer data [23].

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Authors Contribution

S.C. conceptualized the research, conducted the experiments, made the plots, wrote the code and the paper. G.M. conceptualized the research, supervised the experiments and wrote the paper. E.F. supervised the research and wrote the paper.

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