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HUMIDITY AND AIR TEMPERATURE PREDICT POST COUNT ON TWITTER IN 10 COUNTRIES: WEATHER CHANGES & LIWC PSYCHOLOGICAL CATEGORIES

Vlažnost i temperatura vazduha predviđaju broj objava na Tviteru u 10 zemalja – vremenske promene i LIWC psihološke kategorije

Abstract

There are many indications that weather conditions influence human life and well-being. Some of these indicators, such as the influence of weather on human health, have been explored in detail. On the other hand, the influence of daily fluctuations of different meteorological variables on the human psychological state still remains unknown. We apply combined methods from statistics, psychology, machine learning, and complex networks theory to explore the influence of weather parameters on different psychological categories of Twitter users in ten different countries. Our results show that the temperature, pressure, and humidity are highly correlated with Twitter users' activity, sense, and affect. Our comparative analysis for different countries shows that the strongest correlation was found for the USA, Italy, and Portugal, indicating differences between countries. However, our results show that the level of activity of Twitter users, described as Post Count, is strongly connected to changes in temperature and humidity in all countries. We use complex networks theory to explore these connections and differences between countries further. Our findings suggest that weather parameters can be used to predict Twitter users' activity and psychological manifestations, which can be beneficial to marketing and advertising.

Keywords: *Twitter, social media, weather, advertising, big data*

Sažetak

Postoje mnoge indikacije da vremenske prilike utiču na živote i dobrobit ljudi. Neki od ovih pokazatelja, kao što je uticaj vremena na zdravlje ljudi, detaljno su istraženi. S druge strane, uticaj dnevnih fluktuacija različitih meteoroloških varijabli na psihičko stanje čoveka i dalje ostaje nepoznat. U ovom radu primenjujemo kombinovane metode iz statistike, psihologije, mašinskog učenja i složene teorije mreža da bismo istražili uticaj vremenskih parametara na različite psihološke kategorije korisnika Tvitera u deset različitih zemalja. Rezultati pokazuju da su temperatura, pritisak i vlažnost u korelaciji sa aktivnošću, čulnim izražajima i afektom kod korisnika Tvitera. Komparativna analiza među zemljama pokazuje da su najjače korelacije pronađene za SAD, Italiju i Portugal, što ukazuje na razlike između zemalja. Međutim, rezultati pokazuju da je broj tvitova korisnika društvene mreže Tviter povezan sa promenama temperature i vlažnosti u svim zemljama. Koristimo kompleksnu teoriju mreža da dalje istražimo ove veze i razlike između zemalja. Nalazi sugerišu da se vremenski parametri mogu koristiti za predviđanje aktivnosti i psiholoških manifestacija korisnika Tvitera, što može biti korisno za marketing i oglašavanje.

Ključne reči: *Tviter, društvene mreže, vremenski parametri, oglašavanje, veliki podaci*

Introduction

Most of us feel sleepy while it's raining. Others react to sudden weather changes. People sometimes report feeling depressed, low in energy or uplifting, depending on the weather. The richest individuals move to places with a lot of sunshine. These statements could be considered anecdotal evidence, pointing towards potential weather-mood relationships. The question bears wider importance, because human mood may be related to cognitive flexibility, social connectedness, perceived social support, optimism, adaptive coping responses, quality of life and happiness [59], [44], [58], [14].

Early studies

Both psychological and physiological studies have been conducted by early researchers of mood-weather relationship. Main characteristic of these attempts is small groups of research participants. Goldstein [24] correlated semantic mood ratings of 3 female and 4 male students with temperature, humidity, and pressure to conclude that reactivity depends from sex and belief in external control of reinforcement. Persinger [49] calculated correlations between 4 self-reported mood reports per day of 10 subjects and 10 meteorological variables during a 90 days period. Multiple regression analyses indicated that the weather could account for 35% of the mood. However, the conclusion was that lower moods were associated with fewer sunshine and higher humidity. Cunningham [15] conducted two field studies to conclude that generosity of the tip left in restaurant was related to sunshine, lunar phase, sex and age. Sanders & Brizzolara [55] had been conducting a poll every weekday morning to 30 college students for 5 weeks, while at the same time obtaining weather data from the National Weather Service. They found that vigor, social affection and elation correlate significantly with high humidity. Additionally, sunshine and temperature were related to the waitress's self-reported mood. In their research paper "A multidimensional approach to the relationship between mood and weather", Howarth & Hoffman [28] examine concentration, cooperation, anxiety, potency, aggression, depression, sleepiness, skepticism, control, and optimism in a study that included 24 male subjects over 11 consecutive days. They concluded humidity, temperature and hours of sunshine had the utmost effect on mood. Rising temperatures lowered anxiety and skepticism scores. Humidity was a significant predictor in regression and canonical correlation analysis. Research of Parrott & Sabini [48] established the relationship between mood and high levels of sunlight in 2 field quasi-experiments. Rind, B. [52] conducted two studies on sunshine and tipping. The first one was based on a food delivery to 266 hotel rooms, during which the delivery boy had been reporting actual sunshine conditions to guests, either sunny, partly sunny, cloudy or rainy. The conclusion was that the tip increased linearly from the worst to the best conditions. Kripke [35] had been conducting light therapy for nonseasonal depression, while measuring benefits of 12-35% within 1 week. He concluded that light produced faster antidepressant benefits than conventional treatment. Stain-Malmgren et al. [57] examined 11 patients with seasonal affective disorder (SAD) before and after light therapy that was applied in duration in 10 days, two hours per day. They found that 7 patients had a 50% reduction in CPRS scores, which was used to measure SAD. In their paper "Effect of Beliefs About Future Weather Conditions on Restaurant Tipping", Rind, B. & Strohmetz, D. [53] found that favorable weather is connected with increased tipping and that beliefs that weather is favorable can provoke higher tips.

Some authors attempted exploring the impact of weather on mood from a physiological perspective. Mood, behavior and affective disorders were examined by Lambert et al. [36] in relation to weather and seasonal changes. Authors took blood samples of study participants to measure concentration of serotonin. They found turnover of serotonin by the brain was lowest in winter, while its production was directly related to the duration of sunlight. Serotonin is related to feelings of happiness and fulfillment. Leppämäki at al. [38] divided 80 study participants into two groups, one exercising outdoors in bright light, while the other did that in normal indoor conditions. Authors concluded that the exercise was significantly effective at alleviating atypical depressive symptoms when combined with exposure to sunshine.

After earliest studies we register some more recent ones, with larger numbers of research participants. Watson [63] traced the daily mood reports of 498 students and found no important correlations between self reported mood and weather variables such as sunshine, barometric pressure, temperature and precipitation. In two studies of 605 participants, Keller et al. [31] discovered that hotter weather was associated with better mood, increased memory for the period of the spring, as time outside increased. Another study followed 497 adolescents during 30-day period matching responses with weather data [32]. Authors grouped participants into summer lovers, unaffected, summer hater and rain haters. They concluded that weather reactivity may run in the family. Finally, an online diary study of 1233 participants was conducted by Denissen et al. [17] to discover effects of temperature, wind power, and sunlight on negative affect.

There has been a special focus of researchers towards establishing a connection between current mood induced by the weather and life satisfaction. For example, women were more reactive than men to the weather, found Connolly [13]. Additionally, he establishes that life satisfaction decreases if it rains on the day of the interview. As research was done in a sunny climate during the summer it showed that low temperatures increase happiness and reduce tiredness and stress, while high temperatures reduce happiness. Li et al. [39] explored the influence of weather factors on 4 mood dimensions: Hostility-Anger, Depression-Dejection, Fatigue-Inertia and Sleepiness-Freshness. They concluded people tend to be happier as temperature becomes cooler, while they become a little bit negative after a small temperature increase. Researchers found strong relationships between negative mood and precipitation, while establishing influence of temperature on anger, snow depth and depression and high temperature leads and tiredness. In a robust study, self-reported life satisfaction was examined by Feddersen et al. [22] to conclude that day-to-day weather variation impacted self-reported life satisfaction. Another inquiry looked at 1 million US citizens over 5-year period to conclude that weather conditions were unrelated to life satisfaction judgments [40].

As presented above, early studies have harvested opposite conclusions by researchers, which made the debate about the psychology of weather confusing and long-lasting, with lots of open questions. In most cases, traditional research methods have been surveys, self reports, quasi experiments and field studies. The main drawbacks of this kind of approach have been subjectivity of responses, limited datasets and the fact that these were usually one-time surveys, without continuity. However, some of the newer inquiries consider social media data.

Analyzing social media

The appearance of new kinds of data sources such as social media made it possible to make large and long-lasting quantitative inquiries in this direction. On one side, we have social media with posts published each day by their users. Social media users tend to express their emotions, attitudes and values through social media platforms, such as Facebook, Twitter, Instagram, TikTok and others, which is valuable for researchers. Social media therefore surpass traditional polls, because of the quantity of data from many users and chronological aspect, as well. Another useful source of data in this realm is weather API, with live weather parameters, which are at easy disposal to researchers. Important characteristic of both social media and weather data is their non-expensiveness. Researchers are able to access these data for free.

These possibilities have been used by Li et al. [39]. They acquired Twitter posts data, contrary to traditional means, that have been used before in similar "weather – mood" research inquiries. By analyzing 10% of all posts, in duration of two years, from 17 US cities to establish correlations between multiple dimensional structure of human mood with meteorological effects Li at al. did a comprehensive study. They confirmed some longstanding hypotheses, such as people tend to be angrier at high temperatures, snow increases depression and suicide rates or Seasonal Affective Disorder. Using artificial intelligence on the Twitter data, correlated with the weather, at the time and geo-location of the tweets, Hannak et al. [25] found that when the humidity increases, the predicted sentiment decreases for all values of temperature. Coviello et al. [14] measured emotional contagion provoked by rainfall on Facebook data of millions users across the US to establish that rainfall influences the emotional content of status messages published by persons experiencing rainfall, but also friends of those persons in areas without the rain, at that moment. Dzogang et al. [20] analyzed logs of Wikipedia pages and Twitter in the UK over a period of four years using LIWC to conclude that subjects search for Seasonal Affective Disorder at the time when indicator in Twitter content is increasing. Additionally, authors compared Twitter mood indicators with weather data, finding that negative affect can be partially explained in terms of the climatic temperature and photoperiod. Sadness can be partially explained by the photoperiod, while anxiety is partially explained by the level of precipitation. Baylis et al. [5] encompassed both Twitter and Facebook data from the 75 most populated metropolitan areas in the US to compare them with temperature, precipitation, humidity, and cloud cover. Their analysis used LIWC dictionaries to measure expressions of sentiment finding that positive expressions increase up to maximum temperatures of 20°C and decline past 30°C, precipitation worsens expressed sentiment and finally levels of relative humidity exceeding 80% decrease positive expressions. Additionally, Baylis, P. [4] analyzed more than a billion Twitter posts from seven English speaking countries with natural language processing. He found significant declines in expressed sentiment related to both hot and cold temperatures. Similar results were acquired in four countries, while results in the other two differed. Purpose of Baylis's analysis is to estimate how climate change affects the economy.

Some of the recent research inquiries also take into account weather changes and social media sentiment. Molina et al. [43] found that people's mood on social media platforms such as Twitter is influenced by weather conditions. Another research demonstrates the effectiveness of including external contextual features such as weather, location, and time in sentiment analysis on social media, and that they can improve performance by 3% compared to transformer-based language models [29]. This study by Dzyuban et al. [21] examined the relationships between weather and social media sentiment on Twitter, demonstrating the viability of Twitter data as an indicator of periods of higher heat experienced by the public and greater negative sentiment towards the weather. Finally, the study by Stevens et al. [60] investigated the relationship between temperature and both offline assault and online anger on Twitter, finding that while assaults increased with hot weather, angry tweets decreased, suggesting that online anger is an inverse predictor of assault.

To sum it up, previous research inquiries considered few parameters such as positive and negative expressions. Locations that have been examined in the past included one, or in one case four, English speaking countries. Some authors explored multiple locations within one country. Also, previous investigations have found conflicting results in regard to the relationship between weather and mood.

Based on the literature review above we seek to explore the following questions:

RQ1: First of all, are other psychological parameters correlated to weather changes, except positive emotions, negative emotions, anger, sadness and fear?

RQ2: Secondly, are there some weather parameters correlated in the same way with psychological categories detected in Twitter posts in different countries?

By understanding the link between weather and Twitter users' activity, marketers and advertisers can use this information to better target their campaigns. For example, they could launch campaigns during times when Twitter users are most active and receptive to messages, or when their sentiment is most favorable. Knowing the weather conditions and their correlations with human psychology, marketers can apply this knowledge to create targeted advertising campaigns or targeted discounts for customers in different countries, considering the local weather conditions. Through the link between weather and Twitter users' activity, marketers and advertisers can create more effective campaigns and consequently generate higher returns on investment.

Materials and methods

Source of data

We chose Twitter as the most suitable source of data for this kind of analysis. After getting posts from Twitter users, the next step was to analyze them by LIWC software. This helped us get the desired stats then imported to SPSS software, for basic correlation analysis. Finally, we wanted to examine findings further by applying the generalized cross-correlation measure and tools from complex networks theory.

Twitter is social media that empowers its users to publish short textual posts since its inception in 2006. The Twitter content is usually public, but mainly seen by followers of a profile that publishes these short texts, usually called tweets. Tweets are limited to 280 characters. Twitter users don't post their demographic data, except the location they post from and nickname they use. Since its inception in 2006, Twitter has become one of the most popular social media online. As of the year 2021, Twitter had 206 million daily active users worldwide and 500 million tweets per day.

This platform offers access to massive amounts of data through two kinds of API protocols, which are used for research and other purposes. These are Streaming and Rest APIs. First one is chosen for our analysis, as it provides live data, rather than the second one, which provides data in batches. Streaming API is capable of getting public posts of twitter users from chosen locations for free, thus being more suitable for research purposes. There are two downfalls however. First of all, the free version of API provides up to 1 percent of data [50]. As we decided to ask Twitter for a live stream of posts from at least 10.000 of users per each location, this enabled us to have more than sufficient number of posts per location for analysis. Also, when compared to Rest API, getting data from Streaming API is a slow process, as Twitter provides live data this way. This meant we had been collecting data from 11th May of 2019 until 5th January of 2020. This is 7 months and 25 days in total. Additionally, the choice to use the Streaming API from Twitter came as this social network offered clear contracts to users of its API, which lists scientific research as legitimate purpose of use. Other social media have much more limited API protocols, as they usually have lots of private profiles. This is not the case with Twitter.

Another important reason to choose Twitter as source of data was their highly precise offering of geolocated tweets. This means that users of Twitter API could set geo coordinates of desired points and get all tweets published in diameter around it, which is also set by API users. Specifications we sent to Twitter included locations in centers of major cities, in countries that were chosen for analysis, and diameters of just 20 km around these points. These cities were London in the UK, Paris in France, Moscow in Russia, Lisbon in Portugal, San Francisco in the US, Belgrade in Serbia, Berlin in Germany, Amsterdam in the Netherlands, Rome in Italy and Madrid in Spain. The reason why we chose noted countries was because we were limited to LIWC dictionaries that we had. We took the most prominent locations representing the languages that we were limited to.

To get more precise results, profiles that tweeted more than 20 posts per day were kicked out from the analysis, as these usually were not private profiles. Additionally, we excluded re-tweets to only consider straightforward content generated by users.

We have recognized various factors that could affect mood swings within major populations, such as negative news, the ones related to crime, pandemics, disasters and death of celebrities. Because of that, the so-called algorithmic pre-analysis was used to detect any major public event that could change the mood parameters of the public. In case when this kind of event is detected, the posts wouldn't be considered.

Further, exactly the same geo locations were sent to a free weather API [46], to get daily weather parameters that included barometric pressure, humidity. wind speed, cloudiness, rain volume, snow volume and air temperature. We match meteorological variables in a location to the tweets from the same places and dates.

We have gathered 29.347.201 tweets from 135.258 Twitter profiles in 10 locations during 240 days, after application of all above mentioned filtering techniques. Similar number of tweets were collected each day.

Digital footprints

Digital footprints are potentially useful for research of mass behavior, group sentiment and psychological patterns. The following studies attempted to establish a firm connection between psychological indicators found in online data and people expressing them. In that regard, Settanni and Marengo [56] validate online sources for studies in the domain of social psychology. They found people suffering from depression, anxiety and stress used to express negative emotions through emotion-related-textual indicators more frequently. On the other hand, use of positive emoticons correlated negatively with stress level. Twitter research has been shown as sensitive at detecting psychological patterns [18] and real-life events in various fields including health [62], economics and stock market [51], political events [45], [37]. Extracting public sentiment has been a challenge for researchers starting from blogs [42], Twitter [47], Facebook and other social media. By extracting 46 billion words and 4.6 billion expressions published during 33 months by 63 million Twitter users, Dodds et al. [19] established a text-based hedonometer. Additionally, Kramer [33] validated metrics of Gross National Happiness, previously launched by Facebook. He showed that positive and negative words from status updates on Facebook correlated with self reported satisfaction with life. Emotions can be spread to others through emotional contagion, making people experience the same emotions, without being aware of that [34].

Primary analysis

Primary analysis of data included application of natural language processing (NLP). This is a technique used to translate unstructured text into the quantitative data [41]. We wanted to focus on sentiment analysis, so choosing one of more than 60 publicly available algorithms for that purpose was the next step. Because we wanted to examine the relationship of weather with as many parameters that could be registered in text beyond just positive and negative sentiment, we chose to use the Linguistic Inquiry Word Count (LIWC).

LIWC dictionaries were first introduced in 1992. They have been in development ever since, with many scientific inquiries confirming their capability to accurately identify emotions in texts [3], [30], [61], [10], [26]. The dictionaries were available in dozens of languages, but we had access to 9 of them: English, Spanish, German, Italian, French, Russian, Portuguese, Dutch, and Serbian. They measure the following linguistic categories: standard linguistic dimensions, psychological categories, personal concerns, and spoken categories. We decided to use psychological categories, personal concerns, while omitting standard linguistic dimensions and spoken categories as this would be relevant for examination of our research questions. Within psychological processes we covered: social, affective, cognitive, perceptual biological processes and relativity. Additionally, beyond LIWC psychological categories, we took number of posts published per day as another parameter in the analysis. We called this Post Count.

Procedure to use LIWC dictionaries included examination of all the words from raw corpus of downloaded tweets to check how many of them belong to any of the noted categories. Stats were grouped by day and location. Of course, different LIWC dictionaries were used to analyze text depending on the language that was used in a particular country. At the end of the day we had separate tables for each location, showing stats for LIWC categories and Post Count per day.

Secondary analysis

The next step was to use SPSS software to perform the data analysis [9]. Pearson correlations were calculated to inspect significance and strength of relationships. If r is lower than 0.2 we considered this as a weak correlation. Additionally, when r was between 0.2 and 0.5, this would be judged as moderate correlation [54]. Following this, multiple regressions were calculated only for strongest correlations to draw solid conclusions.

We decided to further examine data by implementing methods from complex networks theory by applying the community structure analysis to our datasets.

We have a N time series for each country dataset showing the number of tweets, average daily weather parameters, and the value of different LWIC categories in tweets for each day. To calculate the similarity between time series, we use the generalized cross-correlation GCC [2]. The GCC measure compares the determinant of the correlation matrix calculated for time lags until a time lag k of the bivariate vector with the correlation determinants of the two univariate vectors. By calculating GCC measures for each pair of time series in the dataset, we obtain the similarity matrix for a given dataset.

We determine the similarity matrix for each country and for time lags k={8,9,…,15}. The similarity matrix is then mapped onto a weighted undirected complex network [7]. The nodes in a weighted undirected network represent measured variables. A link between two nodes shows the similarity between two variables. The link weight equals the value of the similarity coefficient between two variables. Since the similarity matrix can be viewed as a fully connected weighted graph that would map onto the fully connected network, we need to remove several links. We use a threshold method for this [64] to filter out the similarity matrix. All elements in the similarity matrix smaller than a threshold are disregarded in this method, while those higher than the threshold are mapped onto network links. We obtain a network for each country and each time lag k.

To explore how different time lags influence the network structure, we compare the structure of networks obtained for different values of k within one country dataset. We focus on links since the number of nodes in networks for each country is fixed. We use the Jaccard correlation coefficient to compare the sets of links between networks obtained for different k. We also analyze how the link density is changing with lag k. Link density is a ratio between the number of existing links L and the number of possible links in the network 0.5*N(N-1). This analysis reveals the robustness of network structure regarding the lag k and its most suitable value.

After determining the most suitable choice of lag based on the analysis described in the previous paragraph, we analyze the structure of obtained networks. We are primarily interested in the possible formation of groups of different variables and their content. For this, we use the community detection approach [23]. To detect communities in weighted undirected networks, we use the Louvain algorithm. The Louvain algorithm finds communities in the network by maximizing the modularity function [6]. Modularity is a function that measures the density of links inside communities compared to links between communities. The maximum possible modularity value for a given network corresponds to the best possible grouping of the nodes in that network. We apply the Louvain method to each network and analyze the content of the groups found using this algorithm to find similarities between networks representing different countries.

Advantage of this methodology is escaping subjectivity of survey respondents. Aggregated analysis can surpass data errors because of the significant volume of population encompassed in this kind of analysis. Differences in age, gender and personality traits are thus leveled out, because of the high number of research participants, as concluded by Hopkins & King [27] and O'Connor et al. [45]. Also, other studies came to similar conclusions, confirming validity of Twitter data for the purpose of social sciences, especially in terms of flexibility, robustness and sensitivity [18], [19].

Limiting factors of this kind of LIWC analysis on Twitter may be about the context of posts. For example, to individually determine which post expresses a positive mood can be a daunting task. If we have a dictionary with positive and negative words, which are further recognized in the text, this will produce a certain number of mistakes because it wouldn't take context into account. Although this kind of analysis could give us an overview of underlying emotional states in chosen locations despite described limits, it may be important to note that this analysis is focused on all LIWC categories and Post Count, which is much more than just sentiment.

Results

Correlations

Numbers of correlations between weather parameters and measured categories, sorted by locations were 68 for US, 58 for Portugal, 54 for Italy, 50 for UK, 44 for Serbia, 38 for France, 37 for Spain, 31 for Germany, 27 for Netherlands and 24 for Russia. Numbers of correlations, sorted by weather parameters, listed as: temperature (123), pressure (80), humidity (70), wind speed (43), wind direction (41), cloudiness (37), rain volume (27) and snow volume (10). Correlations sorted by measured categories were Post Count (49), senses (26), affect (24), see (22), space (22), spiritual (21), achievement (20), hear (20), money (20), motion (20), social (20), humans (18), negative emotions (18), positive emotions (18), feel (16), leisure (15), work (14), sex (14), taste (11), friends (10), health (10), relative (9), family (8) and home (6). As for strength of correlations between weather parameters and measured categories 9 were found to be strong, 170 were found to be moderate and 252 were to be weak. Total number of significant correlations found was 431.

The most consistent and strongest correlations were found between air temperature and humidity, on one side, and Post Count on the other side, in all countries. Among these 20 correlations, some of them were strong (9), others were moderate (11) and none of them were weak. Direction of noted correlations was negative for temperature and positive for humidity in most countries: France, US, Serbia, Germany, Netherlands, Italy and Spain. On the other hand, the direction of correlations was positive for temperature and negative for humidity for the following countries: UK, Russia and Portugal.

Correlations between air temperature and Post Count were: .824** for UK, -.362**for France, .650**for Russia, .431** for Portugal, -.233**for US, -.402**for Serbia, -.622**for Germany, -.651**for Netherlands, -.656** for Italy, and -.531**for Spain. Additionally, correlations between humidity and Post Count were: -.549**for UK, .239**for France, -.494** for Russia, -.450**for Portugal, .270**for US, .562**for Serbia, .448**for Germany, .339**for Netherlands, .387**for Italy, and .506**for Spain.

Taken as a set, the predictors air temperature and humidity account for the following percentages of the variance in Post Count: 69.6% for UK, 13.1% for France, 39.7% for Germany, 51.7% for Russia, 24.7 for Portugal, 47.2% for Netherlands, 44.7 for Italy, 8.6% for US, 31.2% for Spain and 33.7% for Serbia.

Complex networks theory

Furthermore, the relations between the time series of meteorological variables and LIWC categories obtained from the Tweets for one country are studied using tools and methods from complex networks theory. For each country, a network was created. In these networks, nodes represented time series, for instance, number of tweets per day, average values of meteorological variables per day, and values of LIWC categories per day. Time series of the number of tweets, average daily temperature, and LWIC category "feel" could be seen in Figure 1. The network links represent similarities between time series. To calculate the similarity between two different time series, we used the generalized cross-correlation function introduced by Alonso & Peña [1]. The generalized cross-correlation measure (GCC) compared the correlation matrix's determinant, until some lag k, the bivariate vector, with those of the two univariate time series.

The generalized cross-correlation coefficients for each country for several values of the time lag k were calculated. Figure 2 shows distribution of GCC, calculated for k=8 and k=15, corresponding to one-week and two-week time lags, respectively for UK and Spain. All GCC coefficients were non-negative. The bulk of the coefficients, with more than 50% of them, were smaller than 0.1.

We have calculated GCC for each country for time lags k={8,..,15}. Based on calculated GCC, we created a network for each country and each k, by only considering correlations GCC>0.1. This way, we created a network, where the link's weight equals the GCC value between two time series. First, we wanted to inspect the difference between two networks obtained for the same country and different values of k. First, we checked the similarity of networks when it comes to the retained links. For this, we used the Jaccard index to compare the set of links in networks obtained for different time lags. The overlap between networks' links decreased as we increased the time lag difference (Figure 3), where the overall overlap is smaller for USA networks. On average, networks obtained for Portugal had higher overlap, while other countries fell somewhere in between these two extremes. The link density had been growing with time lag k, which was expected (Figure 4).

Community structure analysis

Finally, community structure analysis *is performed* (*Fortunato, 2010*) for networks obtained for the time lag k=8. We consider networks to be weighted and undirected. Link weights were equal to the generalized correlation coefficient between two nodes representing time series. The largest connected component had four communities for the most countries, except Spain with five, and the USA and France with three communities. However, the structure of communities differed. Figure 5 showed the networks and their community structure for the first group consisting of Serbia, Netherlands, and Germany. In these countries, the Post Count variable belonged to the weather variable community, and it was only connected to variables belonging to this community, indicating a strong dependence of Post Count on the weather variables. The second group, depicted in Figure 6, contained the group of countries in which Post Count was connected to weather and LIWC variables. In Spain and Russia, the Post Count variable belonged to the weather community, while in the case of the UK, it belonged to one of the communities containing LIWC variables. Group 3 shown in Figure 7, depicted the countries where the Post Count variable belonged to one of the LIWC communities, while not being connected to temperature.

Figure 1: Time series of different variables

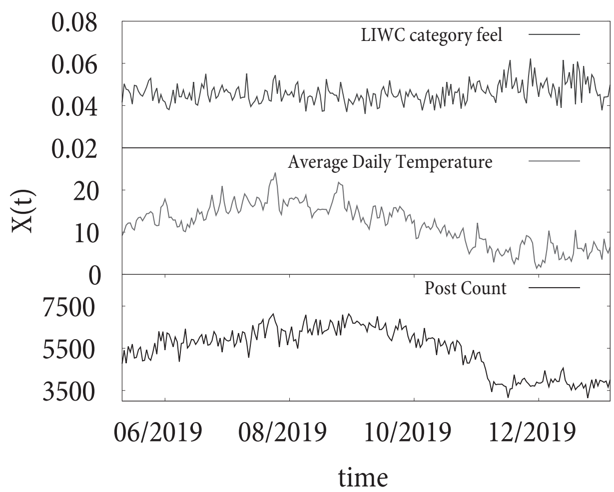


Figure 2: Probability density distribution of the value of GCC for UK and Spain and time lags k=8 and k=15

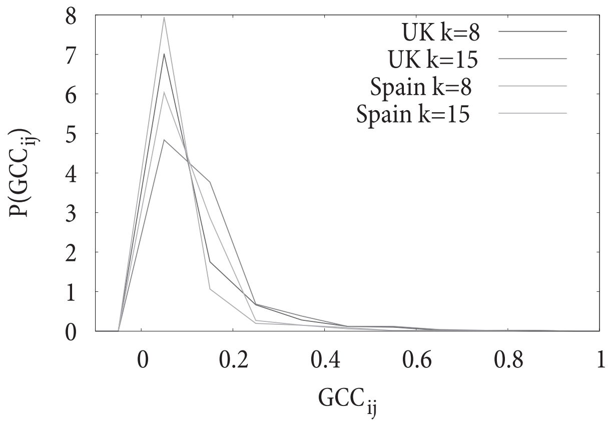


Figure 3: The dependence of Jaccard index calculated for the sets of links between two different networks on the difference of their time lags k

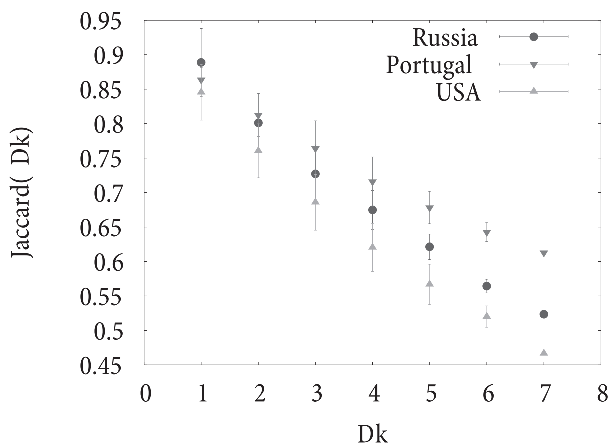


Figure 4: The link density dependence on time lag k average over all countries

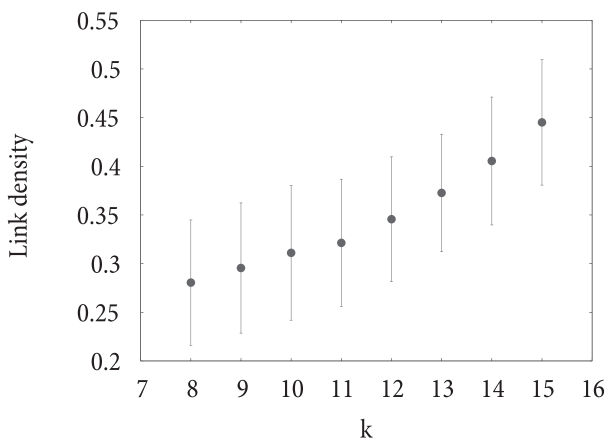


Figure 5: An example of network and community structure of countries belonging to Group 1

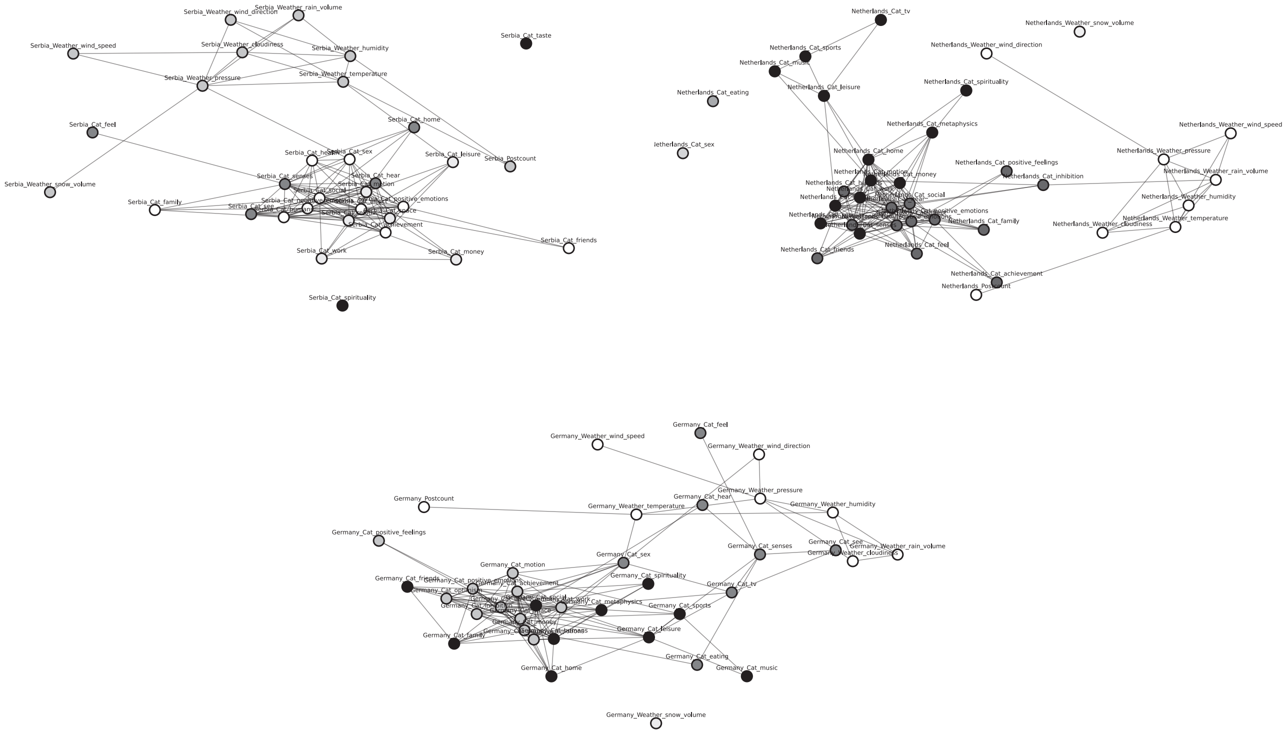


Figure 6: An example of network and community structure of countries belonging to Group 2

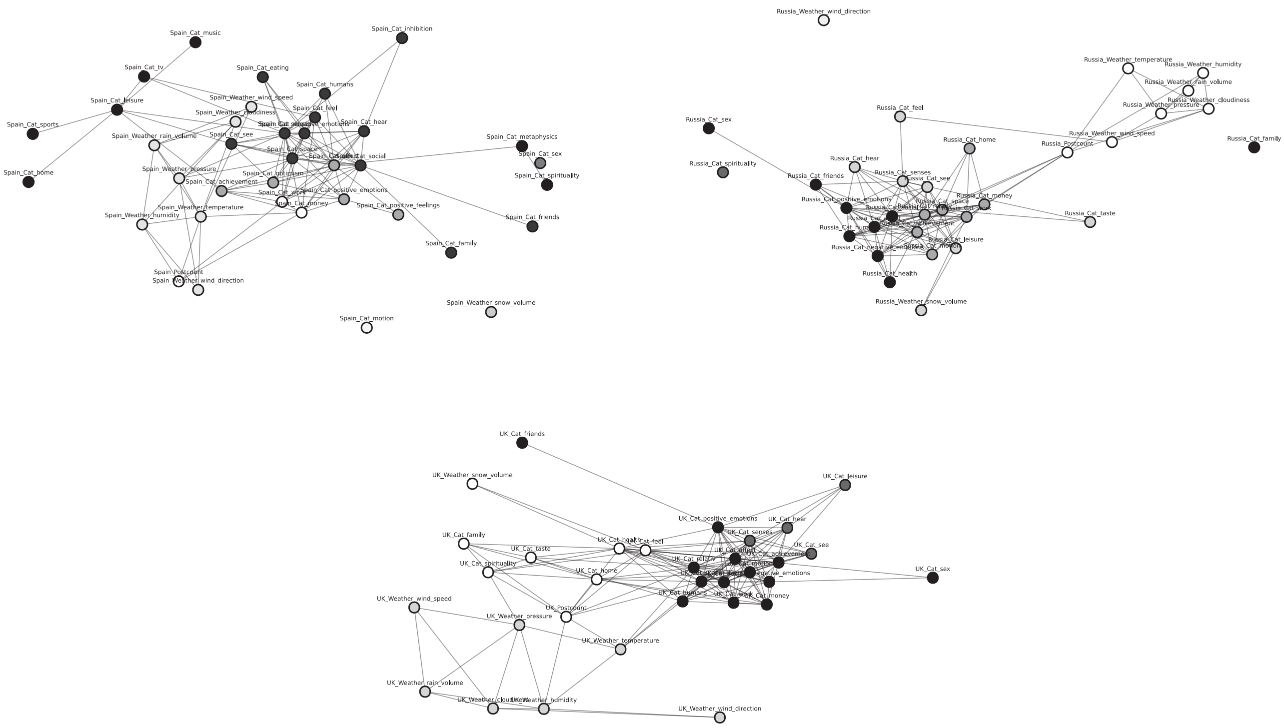
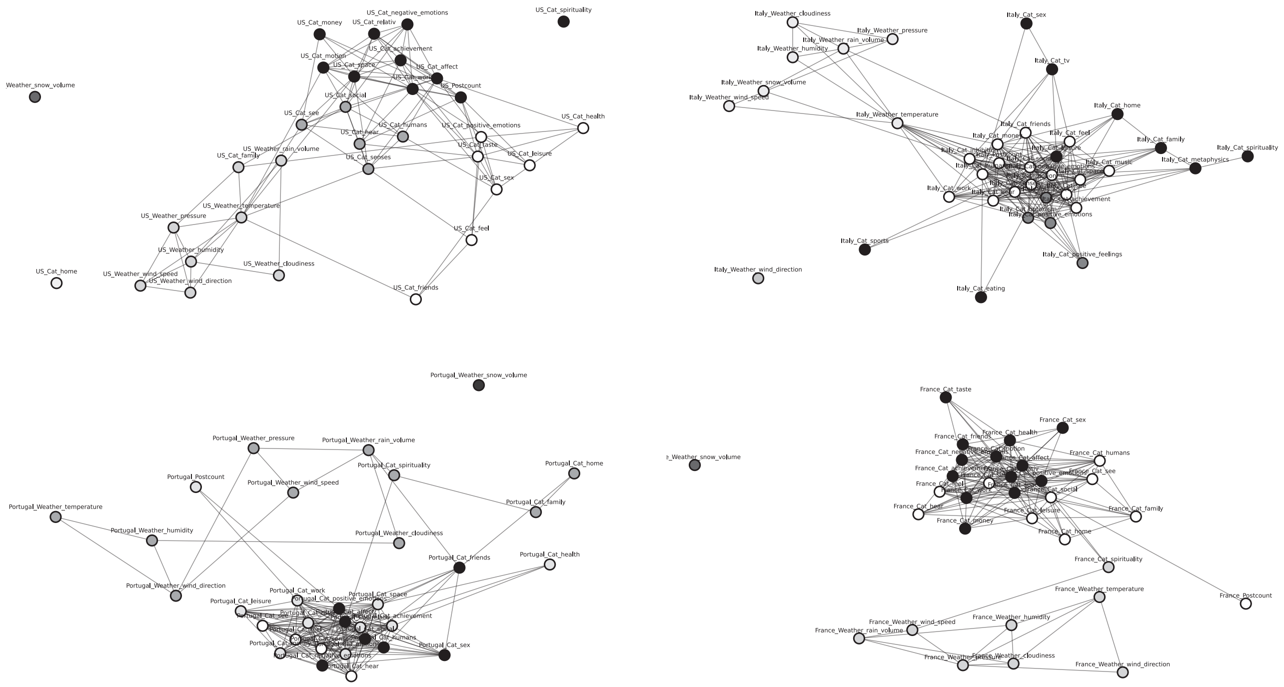


Figure 7: An example of network and community structure of countries belonging to Group 3



Discussion

In short, this inquiry answers all research questions. Weather parameters are not only correlated with positive and negative affect, which is found by most of the previous studies, but with other psychological categories as well. Also, humidity and air temperature are correlated the same way with Post Count of Twitter users in all examined countries.

Analysis of findings

This exploratory study indicates that weather may have a greater impact on people in some countries than in others, and that the most impactful weather parameters to humans may be temperature, pressure and humidity. Furthermore, the study found a strong relationship between Post Count, temperature and humidity. Further research is needed to examine the possible explanations for the different impacts of weather on people in different locations, and to investigate the implications of this finding for our understanding of the influence of weather on emotions and creative work.

First of all, simple correlation analysis indicates that weather may have a greater impact in some countries, such as the US, Portugal and Italy, than in other locations. The idea that there may be different impacts of weather on people, depending on the location, is a new one. There might be many possible explanations, such as that measured locations have hotter climates than the rest of those involved in the research. However, this is just an indication that needs further examination.

The Second finding indicates that the most impactful weather parameters to humans might be temperature, pressure and humidity. This finding has been confirmed by multiple studies [25], [49], [55], [28], [31], [17], [13], [39], [25], [4]. Third finding shows that weather impacts the most to some of the measured categories, such as Post Count, Senses and Affect. Given the fact that no previous weather-mood study involved LIWC categories and Post Count, this finding is a rather new one. The noted categories are related to level of activity (Post Count), expressivity (senses) and emotions (affect). Therefore, the finding may indicate how important weather is in stimulating our overall activity and life in general.

As only 9 correlations were found to be strong (r> 0.5), it may be significant to examine what these might be. By looking at the strongest correlations, we have focused on Post Count, to discover a very strong relationship of Post Count to temperature and humidity, in all examined countries. As much as 9 strong correlations were found, and 11 moderate (r 0.2 > 0.5). However, it was found for most locations that as Post Count increases, temperature decreases and humidity increases. In fewer countries correlations are opposite, while Post Count increases, at the same time temperature increases and humidity decreases. We would not go into further speculation as to why the direction of correlations is different for France, US, Serbia, Germany, Netherlands, Italy and Spain on one side and UK, Russia and Portugal on the other side. Nevertheless, according to noted results, we suspect a very firm connection between Post Count, temperature and humidity.

Because of this, we undertook further advanced methods to check this finding, such as multiple regression, tools and methods from complex networks theory. These methods were used to analyze relations between the time series. As it can be seen in Figure 1, impact of temperature to Post Count had been clearly registered. The same can be concluded when the community structure analysis is performed, for networks obtained for the time lag k=8, especially in Figure 5-6, which illustrated Post Count, as a category heavily influenced by weather parameters in 6 countries. Post Count in the remaining 4 countries illustrated in Figure 7 didn't belong to weather parameters. Although there were some deviations from the rule, lots of evidence showed a firm connection between weather parameters and Post Count in all countries.

This is the first weather-mood study that considered more than one non-English speaking country. In fact, given the fact that the study examined 10 countries, results of this inquiry may be a good starting point for similar ones.

This finding might be important because Post Count can be connected to the overall quantity of emotions that are being expressed. If we publish more posts chances are great we would express both positive and negative emotions through them. Having more positive emotions is connected to happiness, despite the fact that negative emotions will follow up, as well [12]. That means, if this analogy is correct, that weather might dictate when we would feel more or less happy overall. This might relate to creative context as well, because if the time when we publish more posts is affected by weather, that means the same time could be more susceptible for creative work. Finally, it would be useful to examine if we're ready to receive messages better, advertisements for example, at the times when we publish more posts.

In conclusion, this study has identified the weather parameters that have the greatest influence on mood and Post Count, as well as the countries where the influence seems to be the greatest. It has shown that, in some countries, temperature, pressure and humidity have a strong influence on Post Count and that, in some countries, Post Count has a strong correlation with temperature and humidity, while in others the correlation is reversed. Finally, it has shown that Post Count may be a good indicator of overall emotion and, potentially, of creative potential, which can be used in marketing. Further research is needed to understand the implications of these findings and to see how they might be applied in practical contexts.

Implications for advertising

The relationship between weather and Twitter users' activity is an interesting concept for marketers and advertisers to consider. Understanding the correlation between weather and the activity of users on Twitter can give companies a competitive edge. By analyzing the user activity and weather conditions in different countries, marketers and advertisers can better target their campaigns to achieve higher returns on investment.

One of the most effective ways to use this information is to launch campaigns during times when Twitter users are most active and receptive to messages. By understanding the influence of weather on user activity and sentiment, companies can create targeted advertising campaigns or targeted discounts that are tailored to the local weather conditions. This will allow them to reach a larger audience and drive more conversions.

Another benefit of using the link between weather and Twitter users' activity is that it can help companies better predict customer behavior. For example, if a company knows that the weather is going to be good in a certain region, they can anticipate that people in that region will be more likely to purchase their products or services. This can help them to plan their campaigns more effectively and maximize their return on investment.

The link between weather and Twitter users' activity can also be used to create more targeted and personalized marketing messages. Companies can use the weather data to create ads that are tailored to the local conditions, making them more relevant and engaging for users. This will help to drive more conversions and generate higher returns on investment.

In conclusion, understanding the link between weather and Twitter users' activity can be a powerful tool for marketers and advertisers. By analyzing the weather conditions and their correlations with human psychology, companies can create more effective campaigns and consequently generate higher returns on investment. This information can be used to launch campaigns at the right times, create more targeted messages, and better predict customer behavior.

In conclusion, here are three practical examples of using the findings of this study. First, a company can use this information to target their campaigns regionally by launching campaigns when Twitter users are most active. In other words, companies should adjust their advertising spending on weekly basis according to changes in weather conditions. Second, companies can create ads tailored to local weather conditions, making them more relevant and engaging for users. Third, companies can use the weather data to create discounts that are tailored to the local weather conditions, helping them reach a larger audience and drive more conversions. By using the findings of this study, companies can use the weather data to better predict customer behavior and plan their campaigns more effectively.

Limitations

However, some limitations must be noted. Although the study included a large amount of data, gathered from more than 100.000 profiles in 10 countries, during the period of 6 months, and included LIWC, complex network theory and community structure analyses, we may not claim that it captured correct sentiment. The findings were reflections of social media posts, and though this kind of methodology might be considered accurate to some degree, it would be optimal to include daily self reported emotional states. Social media posts may discover underlying emotions but they may provide rather noisy results. That is why we recommend finding a way to improve methodology for social media analyses by proposing a combined method for further inquiries.

Another limitation is that the research wasn't conducted over a one-year period in order to reflect all weather conditions due to the occurrence of COVID-19 pandemic.

In this paper, the focus was solely on the effects of weather conditions on Twitter posts. While it is true that there are other factors that can affect Twitter posts, this paper was meant to be limited to the effects of weather conditions on Twitter posts. The social factors that can affect Twitter posts include the type of content that is posted, the type of audience that is engaging with the post, the time of day the post is made, the platform the post is made on, and the language the post is made in. All of these factors can have a significant impact on the reception and engagement with a post, and can ultimately have an effect on the overall success of the post. It is important to recognize the limitations of this paper when it comes to the social factors that can affect Twitter posts. This paper does not consider the effects of any of these social factors, as the focus of the paper is solely on the effects of weather conditions on Twitter posts. Thus, any conclusions about the effects of weather conditions on Twitter posts must be made with this limitation in mind.

Also, weather measurements used in this study from free weather API may be imperfect, as they reflect data from weather stations that might be distant from research participants. We cannot know if registered weather conditions were the same, as ones experienced by all Twitter users from the analysis.

Additional limitations may arise from the representativeness of Twitter. For example, older and younger people may choose different social media, in their daily routines. In some countries Twitter is used more for expressing political attitudes and less for showing lifestyle and interacting with friends. Although we don't have introspection into the demographics of research participants, their large number may cancel some of our concerns related to capturing representative results for a major population.

We must bear in mind that climate conditions differ from country to country, in which this research study is conducted. Therefore, we don't control research by taking locations with the same climate into consideration. Of course, we had to choose locations that were included into the research because of some limitations discussed in the methodology section.

Future research

Given the fact there are many limitations, we must highlight the significance of this challenging issue, and our major findings in that context. If we know more about the impact of weather conditions on our lives, this knowledge could help our lifestyle decisions and routines both on individual and group level. For example, individuals could choose to do their creative work when weather conditions are stimulating for this kind of activity. On the other hand, brands could choose to invest more into advertising on days when their messages could be received better. These are just two ideas related to potential implications of our findings, if we presume that people are more receptive to advertising messages when they post more, which could be predicted by the weather forecast. However, the next important research that might be inspired by findings of this study might be comparison of Post Count on social media and self reported happiness. Determining the importance of Post Count and its comparison to other parameters could open up new spaces for exploration in social sciences.

Ultimately, there are no gold standards in exploration of mood – weather relationship. Thus, employing new means of analysis related to big data could give us some firm findings and important cues, such as the one captured in this inquiry. Despite all presented research challenges and inability to control numerous conditions in social media analysis, further research is strongly recommended. For example. it may be useful to train a machine learning algorithm based on a larger volume of data to see if psychological categories expressed in posts can be predicted. We certainly hope this study could give some ideas for direction of future inquiries.

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