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Measuring Social Jetlag in Twitter Data

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Abstract

Social constraints have replaced the natural cycle of light and darkness as the main determinant of wake-up and activity times for many people. In this paper we show how Twitter activity can be used as a source of large-scale, naturally occurring data for the study of circadian rhythm in humans. Our year-long initial study is based on almost 1.5 million observations by over 200,000 users. The progression of the onset of Twitter activity times on free days in the course of the year is consistent with previous survey-based research on wake times. We show that the difference in wake-up time (implicating lack of sleep) on weekdays compared to Sundays is between 1 hour and over 2 hours depending on the time of year. The data also supports the assertion that Daylight Saving Time greatly disrupts the easing of social jetlag in the Spring transition.

Introduction

Human schedules are determined by biological and social constraints: Biologically, human activity is controlled by the light/dark rhythm and makes us diurnal animals. Socially, our activities, especially on weekdays, are controlled by our work schedules and other societal conventions. The interaction of these kinds of constraints is an area of active study in biology, but also impacts other fields such as health, education, and public policy (Au et al. 2014). In this paper we show how Twitter activity can be used as a data source for the study of circadian rhythm in humans, in addition to focussed sleep studies.

Twitter is a social medium for real-time interaction. Many users keep their smartphone in their bedrooms, their last and first act of the day is often to check Twitter. We therefore hypothesize that Twitter activity can indicate wake times for its users. In this paper, we first provide some basic background on the circadian rhythm in humans, as well as the usage of Twitter data as a social sensor. Based on large-scale wake-up data collected from Twitter over a year-long period, we estimate daily onset of Twitter activity times in German Twitter data. The basic progression of activity time onset on free (=non-work) days over the year closely matches previously reported observations from sleep studies or questionnaires (Kantermann et al. 2007), but it is based on observations from more than 200,000 users in our study.

In the following, we quantify the extent to which wake-up times differ by using alarm clocks on work days (sleep is cut short in the morning). In our data, wake-up times on weekdays are between 50 minutes and over two hours earlier than on weekend days, throughout the year. In the Spring, just when the gap is beginning to shrink due to earlier sunrises and earlier free day activity times, Daylight Saving Time disrupts the alignment again.

Previous Work

Studying Daily Sleep-Wake Rhythm in Humans

Most plants and animals, including humans, have biological clocks which allow them to optimally time activities such as eating, sleeping, and breeding (Kreitzman and Foster 2011). The primary synchronization source for the 24 hour (circadian) clock is sunlight. The development of a technological society has greatly changed human beings' typical exposure to light and darkness, leading to changes in circadian rhythm (e.g., changing sleep and activity patterns). Many people now go to sleep much later than they would if they were exposed to natural sunlight during the day, and darkness free of light pollution in the evening (Wright et al. 2013). Because of this, about 80% of the population uses alarm clocks to wake up before they have achieved enough sleep (Roenneberg et al. 2012). This leads to widespread sleep deprivation, which has negative effects on many aspects of life, such as health, performance, and education.

Chronobiologists often use sleep diaries (Carney et al. 2012) or questionnaires (Roenneberg, Wirz-Justice, and Merrow 2003) to classify individuals by chronotype: their typical sleep and wake times on days when they are free of social obligations. These studies have shown that for day shift workers there is a large difference between sleep on work days and free days, a phenomenon termed "social jetlag" (Wittmann et al. 2006), defined as the difference in midsleep time between work and free days. Furthermore, studies have shown that that the size of sleep deficits is currently rapidly increasing (Roenneberg et al. 2012). At temperate latitudes during periods when Daylight Saving Time (DST) is not used, wake timing on free days tracks sunrise timing

(Kantermann et al. 2007). The magnitude of social jetlag is smallest immediately before the transition to DST, suggesting that eliminating or shortening the length of DST could have beneficial public health effects.

Studies on human circadian rhythm have been carried out based on participatory experiments, which often necessitate limited sample sizes. Roenneberg (2013) has argued that much larger sample sizes of real-world data are needed to improve our current understanding of human sleep-wake patterns. In this paper, we show that social media data from communities such as Twitter can provide this kind of data.

Twitter Data as a Social Sensor

Environmental factors affect human behavior, and cause noticable effects on aggregate Twitter data (cf. Hannak et al., 2012). Some of this research exploits the temporal nature of Twitter data, such as flu trend prediction (Achrekar et al. 2011), earthquake observations (Sakaki, Okazaki, and Matsuo 2010), event extraction (Ritter et al. 2012), etc. In most cases, however, the smallest unit for modelling is the *day*. For example, Achrekar et al. (2011) show the correlation between daily Twitter mentions of flu symptoms and CDC records of reported flu cases. Though they also provide a plot of the hourly Twitter usage in their study region (ibid., Figure 4), the time of day does not influence their temporal model. In contrast, in this paper we study specifically the fine-grained timing of Twitter activity as a sensor to sleep and wake times.

In addition, several large-scale studies have analysed aggregate behavior of Twitter users and its evolution over time. Liu, Kliman-Silver, and Mislove (2014) present a comprehensive overview of tweets sent 2006-2014 including user characteristics, languages, etc. Rios and Lin (2013) analyse the temporal footprint of all geo-tagged tweets from several major cities and observe later peaks on the weekends as well as during the summer school break for NYC. In this paper, we address specifically wake-up times and quantify them.

Data

While dedicated participatory experiments will yield the most accurate sleep-wake rhythm data for humans, we intend to show how it is already possible to study the behavior of large populations via their use of social media. The public nature of tweets makes Twitter an ideal and non-invasive method for studying the real-world activity behavior of hundreds of thousands of people. One downside of the expanded pool is the lack of related data collected in clinical studies, such as age, whether individual participants work shifts, whether they are retired or unemployed, and whether they are often awakened by young children, pets, or a sleeping disorder. Nevertheless, social media allows observing population-level effects from events such as holidays or the onset of Daylight Saving Time.

Twitter data necessarily measures presence on social media, not actual sleep and wake times. In this study we track the greeting "Guten Morgen" ('good morning') as a proxy for wake-up times. Since many Twitter users check social media first thing after they wake up (often still in bed), and

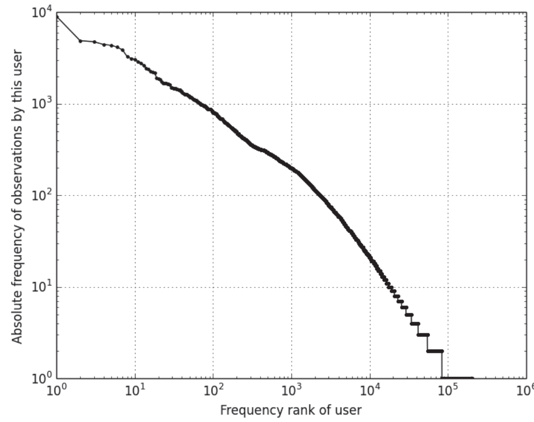

Figure 1: Users by their frequency of observation.

these users are more likely than casual users to start each day with a greeting, we will use observations of the phrase 'good morning' as an indicator of wake times.

One potential difficulty in using social media data to study circadian behavior is the fact that wake timing on free days is influenced by sunrise, which depends on both latitude and longitude. This means that for such data to be useful, either the position of the users must be known, or else the users must all come from a restricted area on the globe. Since geotagged tweets are very rare (~1-2% of all tweets (Scheffler 2014)), and further, only a small subset of Twitter users ever allows geolocation tags, we chose the tweet language (German) to restrict the geographical origin of the large majority of the data to the German-speaking area in Europe.

We follow the method in (Scheffler 2014) to collect German language Twitter data each day between August, 15, 2014 and August 14, 2015. Tweets were filtered from the streaming API by German stop words (with the addition of 'morgen') and then language filtered using langid (Lui and Baldwin 2012). The general temporal distribution of the data matches the distribution in other corpora (Scheffler 2014, Figure 4). We have then extracted all tweets which contain the phrase "Guten Morgen" (non-case-sensitive), excluding retweets. Days in which data was missing during the crucial potential wake times were excluded from the analysis.

In all, the data set contains 1,443,004 observations (tweets), made by 206,633 users. Figure 1 shows the observed user frequency ranks by the absolute number of tweets they contributed to the data set (log-log scale). The most prolific user (rank = 1) was captured tweeting 'good morning' almost 10,000 times in the study period.[1] The slight bulge in the curve around 200-300 tweets indicates that relatively more users tweeted a morning greeting exactly that often (approximately once per day).

[1] Many users greet several of their followers individually. This may mark their own wake-up time, or alternatively the wake-up time of the intended addressee.

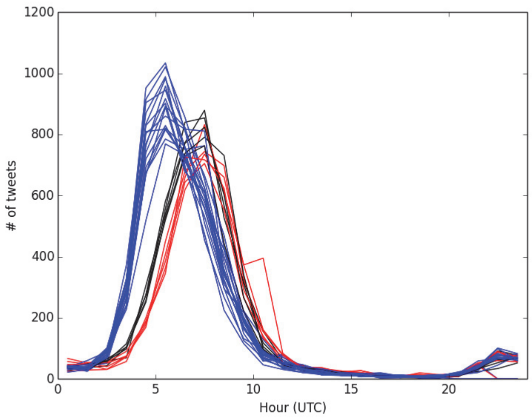

Figure 2: Hourly tweets containing ‘Good morning’ for each day in the first month of study (2014/8/15–2014/9/14). Blue = Mon-Fri, black = Sat, red = Sun.

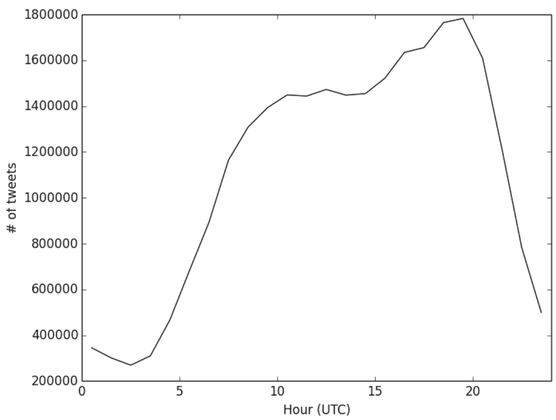

Figure 3: All tweets by hour during the first month.

Analysis and Results

Figure 2 shows hourly counts of tweets containing ‘good morning’ during the first month of the study time. First, we observe that the bulk of the greetings each morning realistically reflects onset of activity times between 4:30 and 8:00 local time (UTC+2) on weekdays (shown in blue). This is markedly different from the temporal distribution of all tweets, which shows the highest activity in the late afternoon and evening (see Figure 3). In addition, the onset of activity on Twitter is much steeper and earlier when measured using just the tweets containing ‘good morning’ (Fig. 2) rather than all tweets (Fig. 3). Saturday (shown in black) and especially Sunday (in red) activity times are shifted by about an hour from the weekday times.

In order to reduce noise and gain a better picture of the long-term trend in wake-up times, we have approximated the onset of Twitter activity for each day geometrically as the time when the morning tweet rate is half of the peak for

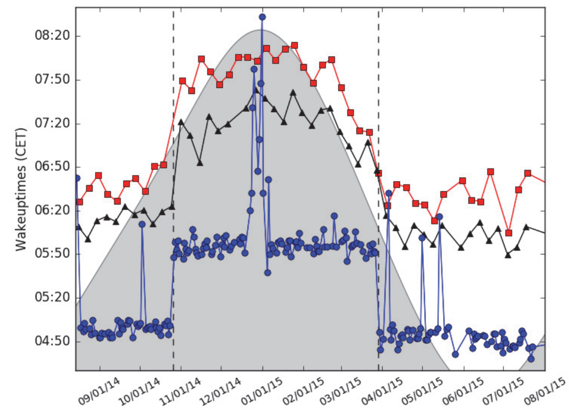

Figure 4: Daily onset of Twitter activity times over the study period (CET). Blue circles = weekdays (Mon-Fri), black triangles = Saturdays, red squares = Sundays. Vertical dashed lines = transition from/to DST; dawn is shown in the grey-white transition.

each day. Figure 4 shows the onset of Twitter activity for each day in the one-year period, in Central European Time (CET). Weekdays (Monday-Friday) are work days for most Germans and marked by blue circles, Saturdays are marked by black triangles, and Sundays by red squares. In addition, the gray-white transition indicates dawn in Frankfurt, Germany. All three German-speaking countries observe Daylight Saving Time (DST) and move their clocks one hour ahead in Spring (near the end of March) and back in the Fall (at the end of October). The two transitions from and to DST are indicated by the vertical dashed lines.

We observe again that the onset of Twitter activity is generally much earlier on weekdays than on weekends throughout the year, though the public holidays (Oct 3, late December, Apr 6, May 1, May 14) resemble Saturdays. During the winter and the standard Central European Time, the onset of activity on weekends tracks dawn, increasing slightly in the late Fall and shifting gradually much earlier in the Spring. After the imposition of Daylight Saving Time, however, the free day onset of activity times stay largely flat throughout the summer. This basic progression is consistent with data on wake and activity times reported in (Kantermann et al. 2007) based on survey data.

We examined the difference between onset of Twitter activity on weekdays and weekends as an indicator of social jetlag[2]. We selected the 42 weeks for which at least 3 weekdays had complete datasets and calculated the median onset of twitter activity. The median should be a more stable indicator of standard wake-up time than the mean, as single outliers due to long weekends or other holidays during the week will not contribute. The difference between weekend

[2]Though social jetlag also depends on the start of sleep times, it is reasonable to assume that users do not go to bed significantly *earlier* before free days, which means later wake-up times indicate later mid-sleep times as well.

and weekday onset of twitter activity on Saturday was 79 ± 14 minutes, while on Sunday it was 103 ± 25 minutes. However, as can be seen in Figure 4, the size of the difference is not constant throughout the year.

The weekday/weekend difference in onset of twitter activity is largest in January (∼99 minutes Saturdays, ∼140 minutes Sundays). As the sun rose earlier each morning, the weekday/weekend difference shrank until on the weekend that Daylight Saving Time began it was reduced to ∼50 minutes on Saturday and ∼55 minutes on Sunday. The weekend after DST began, the difference grew considerably, to ∼84 minutes on Saturday and ∼102 minutes on Sunday. The difference during the DST period remained relatively constant until the end of DST. At that point, the size of the difference grew rapidly, particularly on Sundays.

Discussion and Conclusion

In a *Nature* editorial, Roenneberg argued for the need to gather real-world data about sleeping habits from much larger sample sizes and for more diverse populations than has been possible in previous studies (Roenneberg 2013). Data from social media use on platforms such as Twitter provides a powerful complement to traditional and expanded study of patterns of human activity. It is reasonable to be concerned about possible confounding factors, such as changes in Twitter's users and their behavior (Liu, Kliman-Silver, and Mislove 2014), and whether general activity patterns match the ones observed on social media, but the good agreement of our observations of differences between work and free days with traditional studies indicates the viability of our approach. An important advance over previous work is that we have shown that the time profile of tweets including the phrase "good morning" is significantly different from that for all tweets, and likely provides a good proxy for wake times at a population level. We observe wake time differences of well over one hour on weekends relative to weekdays, and changes in the magnitude of social jetlag during the course of the year. It remains to be examined whether including tracking of phrases like "good night" could allow for a reasonable proxy of total sleep time.

Insufficient sleep and circadian rhythm disruption are major public health issues which are directly affected by policy decisions such as the periods of Daylight Saving Time and school and work start times (Au et al. 2014). Observations of population-level activity patterns in use of social media could contribute to evidence-based decision making, and could allow for immediate tracking of the effects of policy changes.

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