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Seasonal Variation in Collective Mood via Twitter Content and Medical Purchases

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Abstract. The analysis of sentiment contained in vast amounts of Twitter messages has reliably shown seasonal patterns of variation in multiple studies, a finding that can have great importance in the understanding of seasonal affective disorders, particularly if related with known seasonal variations in certain hormones. An important question, however, is that of directly linking the signals coming from Twitter with other sources of evidence about average mood changes. Specifically we compare Twitter signals relative to anxiety, sadness, anger, and fatigue with purchase of items related to anxiety, stress and fatigue at a major UK Health and Beauty retailer. Results show that all of these signals are highly correlated and strongly seasonal, being under-expressed in the summer and over-expressed in the other seasons, with interesting differences and similarities across them. Anxiety signals, extracted from both Twitter and from Health product purchases, peak in spring and autumn, and correlate also with the purchase of stress remedies, while Twitter sadness has a peak in the Winter, along with Twitter anger and remedies for fatigue. Surprisingly, purchase of remedies for fatigue do not match the Twitter fatigue, suggesting that perhaps the names we give to these indicators are only approximate indications of what they actually measure. This study contributes both to the clarification of the mood signals contained in social media, and more generally to our understanding of seasonal cycles in collective mood.

Keywords: Social Media Mining, Emotions, Human Behaviour, Periodic Patterns, Computational Neuroscience.

1 Introduction

The existence of seasonal structures in the contents of Twitter has been known for some time [3], and these are believed to reflect (also) patterns of seasonal variation in people's sentiment. In 2016 [1] comparable patterns of variation were also detected in the query log of Wikipedia, showing seasonal changes relative to seasonal affective disorder, panic disorder, acute stress disorder and several other mental health issues.

In this paper we add to this literature by analysing the purchasing behaviour of over-the-counter remedies directly linked to anxiety, stress and fatigue by over 10 million individuals. In total we analyse 3.87 million transactions, collected over 4 years in all UK branches of a leading Health and Beauty retailer[1], considering 48 different products.

The signals extracted from these datasets are designed to be robust to accidental changes in one specific product or keyword: they are based on the average of many standardised time series, each reflecting the relative frequency of a product or a word, so that changes in the signal reflect coordinated changes of multiple words or products.

Twitter data was interrogated to measure: anxiety, sadness anger, and fatigue; Health product transactions was mined to measure anxiety, stress, and fatigue. As such the lists of keywords extracted from Twitter and the categories of products extracted from retail transactional logs were related - but there was no expectation that the resulting outputs should actually be measuring the same phenomenon, as the lists were compiled for different purposes and the measures performed on 2 different streams of data.

From Twitter we have extracted keywords denoting each aspect of the negative sentiment in the Linguistic Inquiry and Word Count (LIWC) [9]. Based on these word lists we compiled a 4 years indicator of the negative moods on the social platform. We have also extracted an indicator of fatigue based on the PANAS psychological word list [11]. Examples of mood and fatigue keywords are provided in Appendix. A comparison was then made between the seasonal timing of those indicators and the purchase patterns of consumers at the health and beauty stores across the depth and breadth of the UK. The transactions that we considered for analysis correspond to the bestsellers products in the search results of the retailer's online web interface, for the queries *anxiety*, *stress*, and *fatigue*.

In analysis, all signals show a clear seasonal behaviour, with all being under expressed in the summers. Additionally, 2 fundamental types of signals are evident, perhaps pointing to different underlying mechanisms: 1. signals which peak in the Winter (eg: Twitter sadness); and 2. signals which peak in the middle of seasons (eg: remedies for anxiety and Twitter anxiety). More specifically, both Twitter and Anxiety-related product signals peak in spring and autumn, with the indicator for stress-related health products also showing similar seasonal peaks. In contrast, Twitter sadness, Twitter anger and fatigue-related products all show a single mid-winter peak. Surprisingly, fatigue-related products do not

[1] The data for purchases of over-the-counter Health products comes from a major UK Health and Beauty retailer. This partner has an NDA agreement with N-LAB (JG, University of Nottingham). As per the NDA, we are awaiting the authorisation to disclose the identity of the retailer. The raw data provided is commercially owned and therefore cannot be published in order to respect commercial sensitivity. However, examples of health and fatigue related products for which data has been made available are detailed in the Appendix - Examples of health and fatigue related products, but have been partly anonymised to respect this agreement.

	Twitter content	Health products
sampling interval	4 years	4 years
sampling frequency	hourly	daily
sampling locations	54 largest urban centers in UK	$> 1,000$ postcodes in UK
sampling starts	January 2010	January 2012
sampling ends	November 2014	November 2015
sampling issues	year 2012 was removed	N/A
population size	N/A	$>$ 10M consumers
volume	800M tweets	3.87M consumers

Table 1. Summary of data and sampling.

match the Twitter fatigue signal. This suggests that perhaps the names we give to these indicators are only approximate indications of what they measure.

The sales patterns of Health products relating to fatigue fit with a shorter winter daylength, showing a prolonged plateau from mid-December to April. Interestingly purchases for stress and anxiety seem to have a delayed onset around the beginning of February - suggesting the necessity for some longer term biological processes before they are triggered - although there is also a peak in the Autumn as there is for Twitter anxiety and fatigue. Intriguingly, anxiety peaks in the period where the rate of change in daylength is maximal.

2 Data

A summary of the 2 datasets used in this study is provided in Table 1. Below we first describe our collection pipeline that we have used to gather public microposts from Twitter UK every 10 minutes, then we provide a short description of the UK health and beauty retailer's data.

2.1 Twitter microposts

Using the Twitter API, we collected tweets in the period from January 2010 to November 2014, querying for tweets in the 54 largest towns and cities in the UK without specifying keywords or hashtags. For each tweet, we collected the anonymised textual content, a collection date and time, and information about the location of the tweet (within 10km of one of the 54 urban centres). We automatically removed messages containing standard holiday greetings as they contained mood-related words while not necessarily representing an expression of mood (see Appendix - Greeting messages). Due to collection problems we also removed from our collection the year 2012 and the months of November and December 2014. As a result, we have 800M individual tweets covering the time intervals between January 2010 and November 2014. Each tweet was tokenized using a tool designed specifically for Twitter text [2]. Hyperlinks, mentions and hashtags were discarded, along with words containing only special characters (e.g. emoticons).

2.2 Pharmaceutical transactions

Fine grained transactional data was sourced from a major UK health and beauty retailer. Time series of daily purchase counts for over-the-counter health and beauty products were mined directly from raw point-of-sale transactional logs. This process produced datapoints for 48 items, with all time series covering the period of 1st January 2012 to the 4th November 2015 (a temporal extent of 1,403 days). In total, these series reflect the purchase decisions of over 10 million consumers and represents 3.8 million individual purchases at stores across the UK. In order to respect commercial confidentiality the raw count of sales of each product on a given day was divided by the total number of sales on that day, obtaining a relative frequency, at the source. Also any potentially identifying information relating to customers was strictly removed prior to any analysis being undertaken.

3 Detection of collective moods and fatigue

From Twitter we have extracted keywords denoting each aspect of the negative sentiment in the Linguistic Inquiry and Word Count (LIWC) [9]. Based on these word lists we compiled a 4 years indicator between January 2010 and November 2014 formed by 414 words for sadness, 956 for anger, and 450 for anxiety. We also extracted from Twitter an indicator of fatigue based on the PANAS psychological word list [11], formed by just 4 words.

We compared the seasonal timing of these textual indicators with the purchase patterns of consumers at the health and beauty stores. Specifically, the health retailer's online web interface was queried to determine the top 30 best-seller products in each of the categories of anxiety, stress, and fatigue. These queries, issued in May 2017, yielded 14 products for anxiety, 12 products for fatigue, and 30 products for stress. After manually screening these lists, mass point-of-sale dataset were interrogated allowing us to compile a 4 years indicator for each item for the interval of January 2012 to November 2015. Only 3 remedies occurring via the retailer's web interface were omitted from the indicators, with one being aimed at healing baby stress and 2 others not appearing within the anonymized transaction logs over the period examined. We also found that remedies for stress did overlap with remedies for anxiety: 8 products were shared in the 2 categories. In this study we treat these 2 categories separately.

A description of the categories used in each data source is provided in Table 2. Examples of keywords used on the social platform and products on the retailer's online web interface are provided in Appendix to illustrate each category.

4 Methods

Each indicator was compiled following the steps described in [1]. The procedure was slightly modified to account for potential sales or promotional days on individual items in the pharmaceutical data: for a given remedy, the number of

	Category description	Nb words/products	Nb series' with gap $\leq$ 1 year
twitter anxiety	liwc	450 words	450 words
twitter anger	liwc	956 words	947 words
twitter sadness	liwc	414 words	413 words
twitter fatigue	panas	4 words	4 words
health-products anxiety	bestseller products	14 products	13 products
health-products fatigue	bestseller products	12 products	4 products
health-products stress	bestseller products	27 products	18 products

Table 2. Summary of the categories.

transactions relative to the total number of transactions was clipped to within 3 standard deviations of the 4 years series' average.

The seasonal pattern was then computed by combining the 4 yearly time series into one, by using for each day of the year the median value across all 4 years (to remove the influence of unusual events). We then smoothed the resulting time series by using a centered 91 days window as described in [1]. This was the case for all indicators used in this study, and means that while we can appreciate yearly and bi-annual patterns, we cannot make statements about shorter period changes (e.g weekly patterns).

5 Results

All signals from Twitter and from the pharmaceutical data are summarized by their seasonal pattern in Figure 1, aligned for comparison. Levels of expression above average are illustrated as plain semi-arcs on Figure 3. The indicators show a clear seasonal behaviour, all being under expressed in the summers, with some peaking in the Winter (e.g Twitter sadness and anger), others peaking in the mid-seasons (e.g health products anxiety and stress, Twitter anxiety, and the fatigue signals from both sources).

In more detail, we can observe from this data that health products relating to fatigue fit with shorter winter daylength with a prolonged plateau from mid-December to April. Interestingly stress and anxiety seem to have a delayed onset around February, suggesting the necessity for some longer term biological processes before they are triggered. Although the pattern does re-express in the Autumn, at a period marked with anxiety on Twitter. In [1] a significant association was found between periods of over-expressed anxiety on Twitter and periods of rain.

Assessing similarity between each pattern we also find that remedies for anxiety and for stress correlate very strongly with Twitter fatigue (r=0.80 and r=0.83). Our results also show that expressions of anxious feelings on the social platform can be associated with stress and anxiety in the population (r=0.62 and r=0.57). More specifically we found that amongst the mood patterns measured on Twitter, anxiety was the most similar to purchases for stress and anxiety; sug-

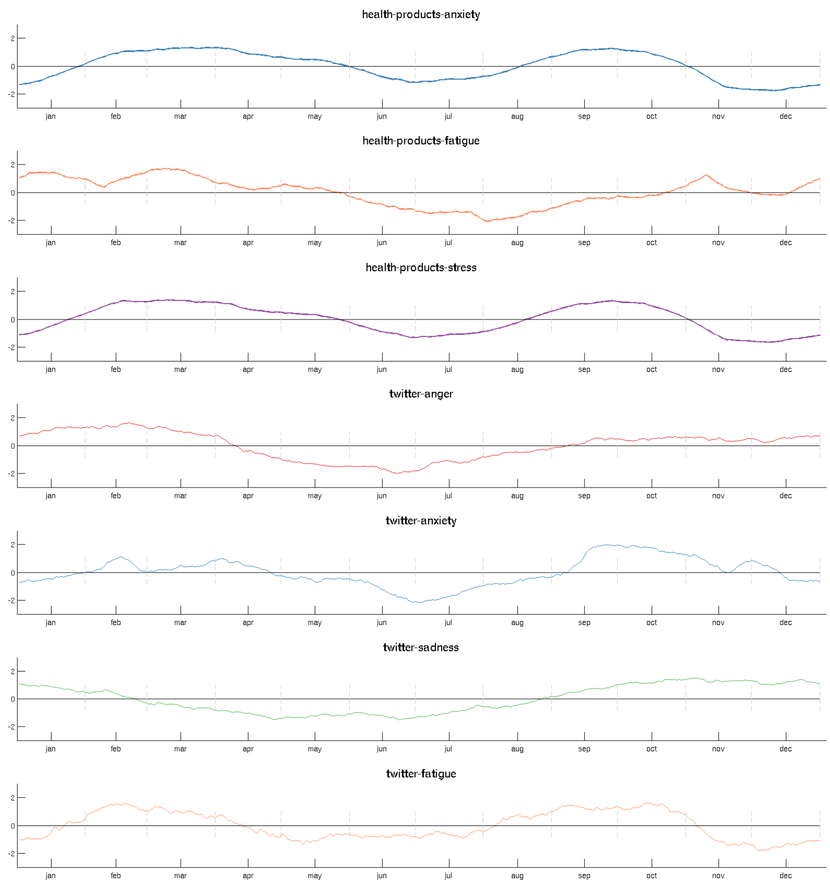

Fig. 1. Seasonal patterns relative to the negative moods evident in Twitter data and Remedy sales. Each pattern is aligned for comparison.

gesting a strong agreement between the social platform and purchase behaviours in the population.

In spite of their late winter and late autumn overlap we found no significant association between purchase patterns for fatigue and expressions of fatigue on Twitter (r=0.09), it is the dip in the 3 months period surrounding the end of year festivities (November/December/January), and the onset of Twitter fatigue early in the Autumn that differentiate them. Health products fatigue was strongly correlated with expressions of anger on Twitter (r=0.69). In addition to dark days and cold weather [1], this result shows that periods of fatigue (as measured by purchases of specific products) also associate with angry moods (as measured by words used on Twitter).

The strength of the pattern's oscillation is summarized for each indicator by the percentage of variance explained in the 4 years series (see Table 3). With

Indicator	% Var. expl.
health-products stress	$33.5\%^{(*)}$
health-products anxiety	$28.6\%^{(*)}$
twitter anger	$03.0\%^{(*)}$
twitter sadness	$02.7\%^{(*)}$
health-products-fatigue	$02.5\%^{(*)}$
twitter anxiety	$01.2\%^{(*)}$
twitter fatigue	$00.8\%^{(+)}$

Table 3. Percentage of the indicator's variance that can be explained by the seasonal pattern in the 4 years interval. The indicator was detrended using a 2 years window. $^{(*)}$ indicates significance at 1% level, and $^{(+)}$ at 5% level; significance is assessed in a Monte Carlo simulation using N=1,000 random permutations of the indicator.

a maximum of 33.5% of variance explained for stress remedies, our indicators of purchase behaviour in the UK population are generally more seasonal than our indicators of collective moods on Twitter. In the 4 years intervals the social platform not only reacted to the seasons but it also responded to other significant events: for example in a recent study we found common change-points between the moods in Twitter and the gbp/euro rate in the hours following the vote for the EU membership referendum (brexit) [5].

Another striking difference that emerges from Figure 1. is that some patterns seem to experience 2 peaks in the middle-seasons, while other experience only 1 major resurgence in the Winter.

We detailed these 2 types of behaviour by separating the patterns that experience a single peak in the year from those that over-express twice a year. For this purpose we overlaid on each pattern an idealized sine wave that maximally explains the variance in the indicator between a period of 1 year or 6 months (see Figure 2).

We found that health products anxiety/stress and Twitter anxiety experienced 2 peaks in the year, with the first occurring in March and the second in September; while fatigue related sales in the population as well as Twitter anger and sadness showed one single periodic resurgence concentrated in the winter months. Note that the lists of products for anxiety and stress do have an intersection (8 products out of 27 in stress and in 14 anxiety) which can partly account for this similarity.

6 Conclusion

Seasonal affective disorders (SAD) is well described [7], mostly for the depressive symptoms occurring at the beginning of autumn and persisting until the end of winter. But seasonal changes also occur in healthy controls [12]. This is just one of the many seasonal variations that can affect mood and metabolism [8]. The typical symptoms of SAD include irritability, sadness, fatigue, decreased activity

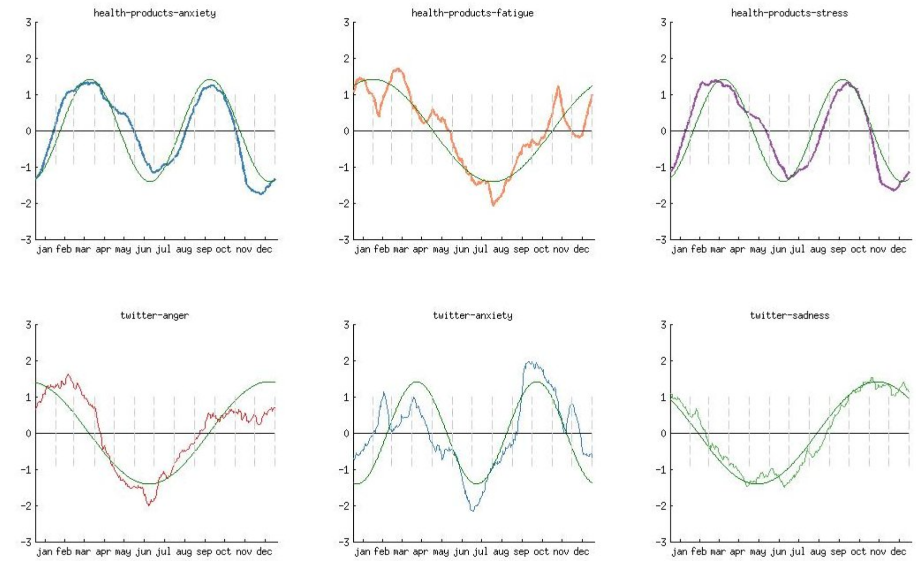

Fig. 2. Yearly and bi-annual patterns. Purchase patterns relative to anxiety, fatigue, and stress (first row) in the retailer's transaction logs; textual patterns relative to anger, anxiety, and sadness on the social platform (second row). An idealized sine wave of period 1 year (resp. 6 months) is overlaid on the yearly (resp. bi-annual) patterns.

and libido, and changes in eating behaviour [10, 6]. From a Neuroendocrinological perspective, median cortisol levels are lowest in the summer solstice quarter and over 8.5% higher in the winter solstice quarter [4].

We have compared 2 different classes of signals that are expected to capture variations in collective mood over the general UK population. One class of signals is formed by Twitter content collected over a period of 4 years, the other is formed by sales of over-the-counter Health Products in the UK, for items classed as related to anxiety, stress, fatigue.

We see broad agreement but also intriguing differences in the findings. Expressions of anxiety on the social platform associate strongly with purchase of anxiety and stress related health products in the population. Winter Remedies for fatigue also fit with expression of angry moods on Twitter and to a lower extent with the periodic resurgence of sad feelings in the winter months.

On the other hand, the fatigue that we extracted from Twitter could not be explained entirely with purchase of fatigue related medications. We found that the 3-month period between November and January was marked with under-expressed fatigue on the social platform, a behaviour that was not pronounced to the same extent in the transactions for fatigue.

The key finding from the neurophysiological viewpoint is yet another confirmation of the strong circannual patterns followed by sentiment and mood, with more positive affect in the summers and more negative affect in the win-

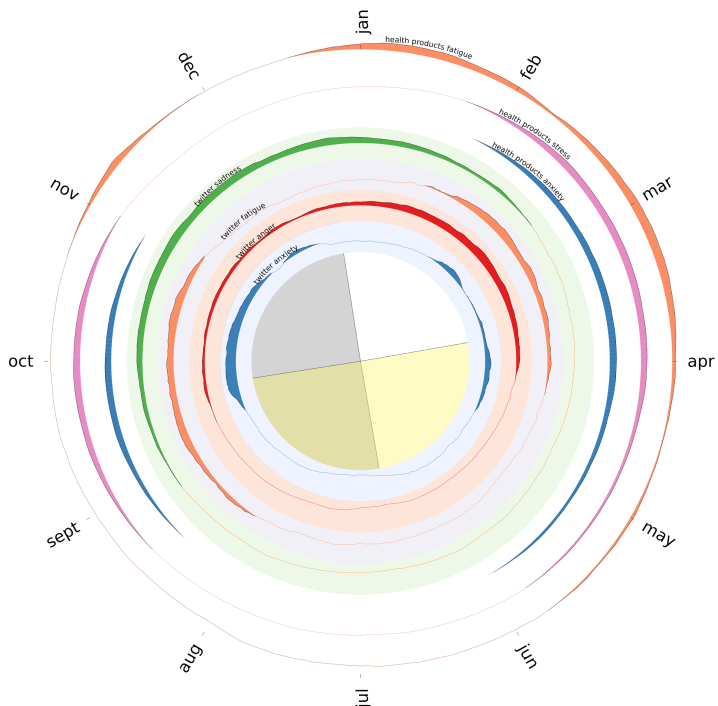

Fig. 3. Seasonal pattern of negative moods in Twitter, and patterns of purchasing behaviour for pharmaceutical remedies. Semi-arcs illustrate periods of over-expression in the smoothed series of median levels per each day of the year.

ters. Anxiety shows the same pattern both in the purchases and in the Twitter signals.

From the point of view of textual sentiment analysis, we believe that this is an important step towards the validation of a method that is widely used for sentiment analysis, but that has previously been very difficult to ground for lack of direct data about the mood of subjects.

Appendix

Greeting messages. The signal about mood could be skewed by the presence of large amounts of standardised greeting messages in specific seasons, which make use of mood related words, while not expressing the mood of the writer. These standard greeting messages were removed from the data as follows: we ignored any Twitter post containing the word happy, merry, good, lovely, nice, great, or wonderful followed by either of christmas, halloween, valentine, easter, new year, mothers' day, fathers' day, and their variants (e.g starting with a leading

	Mood words
sadness	*miss lost sad missed cry missing alone lose crying hurt low fail broke hurts losing tears loss sadly disappointed failed*
anxiety	*crazy shame worry scared awkward horrible doubt scary confused alarm worried fear upset emotional worries afraid pressure nervous avoid risk*
anger	*shit fuck hate fucking hell stupid damn bitch hit mad annoying cut kill fight crap jealous cunt piss fucked pissed*
fatigue	*tired sleepy sluggish drowsy*

Table 4. Most popular mood words extracted from Twitter based on the LIWC word lists. Our indicator of fatigue on the social platform is based on the PANAS word list, formed by just 4 words.

or separated by a dash, a space or ending with 's when applicable) was not considered for analysis.

We verified that posts matching this pattern were indeed concentrated in very specific days (the expected ones for each holiday).

Examples of mood and fatigue keywords. Table 4 illustrates the most popular words on Twitter for each indicator of mood and for fatigue. The mood keywords are based on the LIWC word lists, those for fatigue are based on the PANAS word list.

Examples of health and fatigue related product. Figure 4 gives an example of the most popular products for the searches *anxiety*, *stress*, and *fatigue* on the UK Health and Beauty retailer's online web interface, as queried on May 2017.

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anxiety	stress	fatigue
quiet life tablets	*this works deep sleep pillow spray*	*clarins men anti-fatigue eye serum*
karma st john's wort extract tablets	*bach rescue remedy dropper*	*maybelline baby skin instant fatigue blur primer*
schwabe karma mood tablets	*kalms tablets*	*clinique anti-fatigue cooling eye gel*
kalms tablets	*rescue cream*	*embryolisse smooth radiant complexion immediate anti-fatigue*
bach rescue remedy dropper 10ml	*aromatherapy pure essential oil - 20ml lavender*	*collection reviving & anti-fatigue illuminating primer*
pharmaton vitality capsules	*aromatherapy pure essential oil - 10ml lavender*	*l'oreal paris nude magique cc cream anti- fatigue*
bach rescue remedy spray	*bach rescue remedy spray*	*nuxe creme prodigieuse eye contour - anti-fatigue moisturising eye cream*
tisserand de-stress aromatherapy roller ball	*bach rescue pastilles - blackcurrant with sweeteners*	*creme prodigieuse® enriched - anti-fatigue moisturising rich cream (dry skin)*
"own-brand" stress relief tablets	*bach rescue pastilles with sweeteners*	*creme prodigieuse - anti-fatigue moisturising cream (normal to combination skin)*
vitano rhodiola rosea root extract film-coated tablets	*"own-brand" st john's wort tablets*	*wellman anti-fatigue under eye serum*

Fig. 4. Top 10 most popular Health products presented for the searches *anxiety*, *stress*, and *fatigue* on the retailer's online web interface.

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