Temporal Arcs of Mental Health: Patterns Behind Changes in Depression over Time

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***Abstract*—Depression has been shown to follow seasonal patterns, with more episodes in the winter. In this paper, we draw inspiration from work on the emotional arcs of stories to uncover the patterns that individual users follow on the social media platform Reddit. By grouping users by their temporal arcs across a year, we identify four dominant arcs that can be connected to varied changes in depression throughout the year. The arcs that we uncover demonstrate interesting patterns that individual users follow beyond the patterns represented by the mean behavior among all users. Furthermore, the shapes of these arcs are consistent for both community and language-based metrics.**

***Index Terms*—depression, LIWC, time series, social media**

I. Introduction

It has long been observed that episodes of depression are seasonal, often peaking in the winter [1]. This is consistent with computational findings using search keyword counts and depression classification algorithms [2], [3]. While it is less common, some studies have also identified the existence of summer-related depression [4], a phenomenon that has also been connected to some groups in computational studies [5]. We take inspiration from work on the emotional arcs of stories and use singular value decomposition (SVD) to uncover the latent structure of metrics related to depression, revealing varied patterns in severity over time among users.

In our work, we begin by examining the overarching seasonal pattern of a large group of users. We then create groups of users that are representative of distinct patterns that are not revealed by the average statistics across the full dataset. Prior work has largely considered only binary representations of these patterns. However, the psychology literature indicates that depressive episodes are often cyclical or seasonal [1], and these patterns are not captured by simply considering behavior before and after a certain point in time.

Drawing inspiration from work on the emotional arcs of stories [6], we use SVD to uncover a set of patterns underlying depressed user's behavior on social media that are both distinctive enough to capture the seasonal and recurrent nature of depression, and interpretable enough to meaningfully group large sets of users together. To do so, we build a dataset of users who self-report their depression diagnosis on Reddit [7] and extract yearly time series using two metrics that can be viewed as proxies for their need for mental health support and their emotional and cognitive state.

In this paper, we address the following research questions:
RQ1: What are the global seasonal patterns of posts in mental health subreddits and linguistic features connected to the emotional and cognitive state of depressed users?
RQ2: How can we characterize individual's activity to create temporal arcs? How do these arcs correspond with global seasonal patterns and previously identified patterns of depression?

We find support for four dominant temporal arcs. Two of the arcs, rising and falling, represent sustained positive or negative change in a user's mental health through the year. The remaining two arcs demonstrate patterns that bring to mind seasonal affective disorder (SAD).

II. Related Work

A. Seasonal Depression

The diagnosis "seasonal affective disorder" (SAD) is connected to the well-known phenomenon of depression being more common in the colder, darker months [8]. The Diagnostic and Statistical Manual of Mental Disorders (DSM) V defines depressive disorders with a seasonal pattern by the regular onset of major depressive episodes at the same time of year, with full remission between those episodes [1]. Additionally, the seasonal episodes must substantially outnumber non-seasonal episodes for the individual throughout their lifetime. While seasonal affective disorder typically occurs in the winter, some people also experience summer-onset SAD.

In addition to studies occurring in psychology labs, computational techniques have been used with user-generated data to study seasonal depression. Classifiers have been found to predict higher rates of depression in summer months [3], and researchers have found seasonal trends in the number of Google searches for the "depression" keyword [2] and prevalence of tweets mentioning depression [5].

B. Measuring Change in Mental Health Using Social Media

A number of studies have used data from social media to quantify changes in mental health over time. These changes are often quantified with respect to a global event, e.g., the

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COVID-19 pandemic [9], [10] or celebrity suicides [11]. Other work has quantified changes with respect to events that impact individuals, such as revealing a schizophrenia [12] or depression [13] diagnosis. Beyond specific events, researchers have looked at long-term effects of participating in metal health communities [14], characteristics associated with increased and decreased participation in those communities [15], and characteristics associated with beginning to post in suicide support communities [16], [17].

C. Emotional Arcs of Stories

Kurt Vonnegut introduced the idea that stories have shapes that can be plotted, with the x-axis representing the progression of time within the story from beginning to end and the y-axis representing good to ill fortune of the characters [18]. In a 2016 computational study, sentiment analysis was used along with various methods for grouping time series together to uncover six emotional arcs that make up most stories [6]. These included arcs that are widely adopted literature, such as “rags to riches” and “man in a hole.” In our work, we employ methods that have been used to uncover emotional arcs to discover a set of individualized patterns among Reddit users with diagnosed depression. This allows us to create what we refer to as “**temporal arcs of mental health**.”

III. Data

Our dataset is collected from the Pushshift Reddit dataset [19]. We collect a list of users with self-reported depression using the method from [7], and retrieve all posts and comments from those users. We use the filtering criteria explained in §IV-B2 to create a set of year-long time series with monthly values that are used in our analysis. We build these series for the years 2010–2019. For each user, we add their yearly time series to the data if the filtering criteria is met.[1] Some users from existing lists of bots are excluded. There are 31,294 user - year pairs in the dataset, with 16,103 unique users (most users appear in the dataset during only one year).

IV. Identifying Temporal Arcs

To study temporal changes in mental health throughout a year, we extract two metrics (§IV-A). We create time series representing how these metrics change over time and analyze the series to characterize common patterns in the data (§IV-B).

A. Metrics

The **community-based metric** captures the user’s activity in subreddits that signal their engagement with mental health support using post and comment counts in mental health subreddits (e.g., r/depression, r/Anxiety; we use a list from [7]). Post counts in mental health subreddits [9], [11] or ratios of mental health posts to posts in other subreddits [15] have been used as a proxy indicative of need for mental health support in prior work. Existing users of r/depression posting on r/SuicideWatch has similarly been used to capture the shift between depression and suicidality [16].

[1]Some users may appear in the dataset during multiple years.

The **language-based metric** captures how the words in user’s posts are indicative of their emotional and cognitive state and is based on the LIWC2015 lexicon [20]. The metric that we build from the lexicon incorporates three categories: I, SAD, and COGPROC. These categories have been associated with clinical depression and depressive episodes in prior work. In particular, I (first-person singular pronouns) indicates self-focus, COGPROC (cognitive processing) represents the author’s process of working through challenges in their lives, and SAD (sadness) represents the emotional state linked to the depressive episode [13]. We compute the percentage of words in the post in each category, then compute the sum of those percentages to create our final language-based metric.

B. Time Series Processing

1) Pre-processing: When computing the mean of user-level series, we create a time series using monthly values. These values are sums across the month for the community-based metric and averages for the language-based metric.

2) Filtering: We perform three filtering steps: (1) each user must post at least once per month, (2) each user must have at least one post in a mental health subreddit during the year, and (3) each user must have at least one post in a non-mental health subreddit during the year.

3) Singular Value Decomposition: We use SVD to discover arcs in mental health behavior throughout the year. We begin with a $n \times m$ matrix M, where the rows represent a user-year pair (see §III) and the columns represent a monthly value of one of our metrics. SVD decomposes the matrix into three separate matrices U, Σ, and V, satisfying the equation $M = U\Sigma V^T$. We focus on the right singular vectors V as our mental health arcs, and associate users with the arc for which $U\Sigma$ has the highest absolute value. We initially experimented with clustering methods on the community-based time series, however we found that these methods largely grouped users based on the presence of mental health posts in a single month.

V. Analysis of Temporal Arcs

A. Global Seasonal Patterns of Mental Health Posts

We consider the seasonal behavior of individuals who self-report their diagnosis, and create time series of monthly values for the two metrics described in §IV-A. To ensure that each user’s data is on the same scale, we convert the vector representing each user’s metrics to a unit vector; this ensures that users with more posts overall do not skew the mean.

The results are presented in Figure 1. We see that the community-based metric roughly follows a bowl-shaped pattern. However, the language-based metric largely shows a downward slope throughout the year. When considering individual dimensions, SAD follows a bowl-shaped pattern, while I and COGPROC have the same downward trend. The fall in I might be explained by an overall trend on online communities in which first-person pronouns decrease as users become more comfortable with the community [21].

These results indicate some seasonal effects for these metrics; however, like prior work, they focus only on aggregate

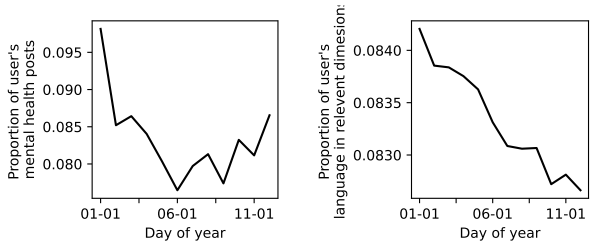

Fig. 1. Monthly distribution of the **community-based metric** (left) and the **language-based metric** (right).

behavior and do not differentiate the behavior of individual users. We take a step towards doing so in the next section, as we uncover yearly temporal arcs of mental health.

B. Temporal Arcs in Community Affiliation and Language

Using both the community-based metrics and language-based metrics, we derive temporal arcs that are representative of user's mental health over one calendar year using SVD. We compute the z-score for each user's twelve-month time series prior to performing SVD. Four prominent arcs emerge:

Rising: The metric rises throughout the year.
Falling: The metric falls throughout the year.
Hill-shaped: The metric starts low, peaks in the summer, and then falls. Because the metrics are proxies for depressive symptoms, this could be indicative of summer-onset SAD.
Bowl-shaped: The metric starts high, dips in the summer, and then increases. Because the metrics are proxies for depressive symptoms, this could be indicative of winter-onset SAD.

1) Community-based Arcs: The four arcs that emerge from the community-based data are shown in Figure 2, including all arcs described in §V-B. The percentage of users assigned to each arc is presented in Table I. We note that surprisingly, there are more users matching the hill-shaped arc than the bowl-shaped arc (which is characterized by higher values in the winter). This may be explained in part by the nature of behavior on Reddit; once users stop posting in mental health subreddits, they may be less likely to begin posting again in those subreddits in the future, as is necessary to follow the pattern of the bowl-shaped arc. Meanwhile, the hill-shaped pattern only requires that users are active on the subreddit during one period during the year. The number of users in *other* arcs exceeds what we might expect based on prior work on emotional arcs [6]. However, it is worth noting that each user's monthly time series is incredibly sparse compared to emotion across a book, and the data is naturally generated and noisy compared to text in a novel. Due to our filtering criteria, many users follow patterns in which there is one spike indicating a mental health post, while there are no mental health posts in other months; this pattern is not represented by any arcs. Additionally, each user's time series is best represented by a linear combination of the vectors from SVD. We simplify this by only considering the most extreme weight, but future work could consider a mixture of the components for more precise analysis.

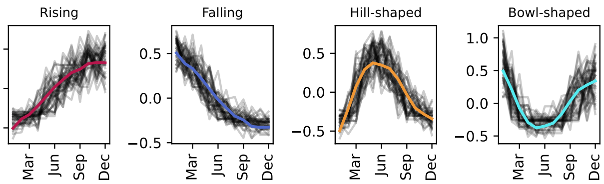

Fig. 2. Four temporal arcs of mental health based on the community-based metric. The arc is shown in color and the 40 individual user's times series with the highest weight for each arc are shown in grey.

Arc	Percentage of Users Community-based	Language-based
Rising	7.30	6.30
Falling	13.72	10.22
Hill-shaped (1 summer peak)	5.83	5.36
Bowl-shaped (2 winter peaks)	3.31	5.52
other	69.84	72.59

TABLE I
PERCENTAGE OF USERS WHOSE SEASONAL PATTERNS CORRESPOND TO EACH ARC.

2) Language-based Arcs: The mental health arcs based on the language-based metric are presented in Figure 3. We note that the same four core arcs emerge. Table I shows the percentage of users assigned to each arc. We find that the bowl-shaped pattern becomes more prominent when using the language-based metric; the lens offered by LIWC into user's behavior allows us to see an increase in depression-related language during the winter months even when users do not re-engage with mental health subreddits.

C. Discussion

When we consider the aggregate number of mental health posts for users who have self-reported a depression diagnosis throughout the year, we find that the seasonality of posts in r/depression largely reflects patterns of winter-onset seasonal affective disorder (in the Northern Hemisphere[2]). These results generally reflect what has been found in prior studies that attempt to connect online activity to seasonal patterns of depression [2], [3]. However, when we consider linguistic patterns, we find that underlying patterns of language use

[2]This is based on an assumption that the users in our dataset are located in the Northern Hemisphere, matching aggregate statistics from the Reddit platform. Location information is not available for individual users.

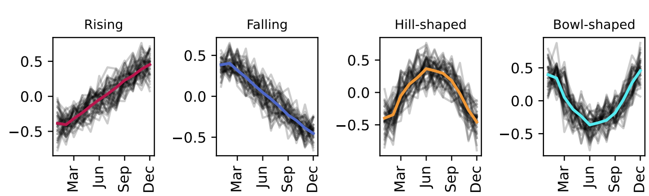

Fig. 3. Four temporal arcs of mental health based on the language-based metric. The arc is shown in color and the 40 individual time series with the highest weight for each arc are shown in grey.

that appear across social media (e.g., decrease in first-person pronoun usage over time) override seasonal patterns. Prior work using computational methods to study seasonality in online activity related to depression has tended to focus on these "global patterns" rather than examining the distinct patterns that individual users follow. To uncover these patterns, we build our temporal arcs of mental health.

We find that only the less dominant bowl-shaped arc matches the pattern of the global community-based metric, which is most reflective of winter-onset seasonal depression. However, the rising and falling arcs both have peaks suggestive of a depressive episode either in January or December. The four basic patterns that we identify represent the ways in which users interact with mental health subreddits and use language that has been connected to depression over time. The finding that the language-based bowl-shaped arc is more common than the equivalent arc for the community-based metric reveals that while users do not always re-affiliate with mental health subreddits, their language may change to indicate increased depressive symptoms.

VI. Conclusions

In this paper, we used data from social media to characterize common patterns underlying changes in mental health over a one-year period. We used SVD to gain an understanding of the underlying seasonal patterns that *individual* users follow, and found four dominant temporal arcs of mental health: rising, falling, hill-shaped and bowl-shaped. We found that on a global level, metrics such as overall post count in r/depression and the average number of posts in mental health subreddits written by users with self-reported depression tend to follow patterns that are consistent with winter-onset seasonal affective disorder. We hope that this work will facilitate more nuanced analyses of changes in depression over time that considers fine-grained patterns of individual users.

Ethical Impact Statement

This study was exempted by the IRB at University of Michigan. We followed guidelines for social media health research proposed by [22], such as anonymizing user IDs. It is worth noting that the Reddit platform has some properties (such as the proportion of males) that may make our results less likely to generalize to other platforms. Finally, the metrics we use are proxies; while they have been connected to depression in prior work, they cannot take the place of a clinician's diagnosis.

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