Detecting Individuals with Depressive Disorder from Personal Google Search and YouTube History Logs

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Abstract

Depressive disorder is one of the most prevalent mental illnesses among the global population. However, traditional screening methods require exacting in-person interviews and may fail to provide immediate interventions. In this work, we leverage ubiquitous personal longitudinal Google Search and YouTube engagement logs to detect individuals with depressive disorder. We collected Google Search and YouTube history data and clinical depression evaluation results from 212 participants (99 of them suffered from moderate to severe depressions). We then propose a personalized framework for classifying individuals with and without depression symptoms based on mutual-exciting point process that captures both the temporal and semantic aspects of online activities. Our best model achieved an average F1 score of 0.77 ± 0.04 and an AUC ROC of 0.81 ± 0.02.

1 Introduction and Related Work

According to the National Institute of Health, it is estimated that more than 17 million adults in the United States have at least one major depressive episode every year. This number represents 7.1% of all U.S. adults[1]. Nonetheless, very few patients in need received immediate and proper medical interventions [10, 20]. The prevalence of mental illness has become one of the most significant burden for the economy and human well-beings in the U.S. [21].

Traditional care delivery methods have failed to ameliorate the rampant depression problems among large populations. The impeded help delivery is mostly due to the exacting traditional screening approaches such as in-person interviews. The current healthcare system requires patients to actively

https://www.nimh.nih.gov/health/statistics/major-depression.shtml
reach out to caregivers and be physically presented in clinics for assessments. However, such practice may be blocked by time availability, expenses, and the unawareness of the patients. Moreover, the diagnosis is prone to concealing information and social stigmas as the patients may not be willing to reveal all personal details, especially among teenagers [6, 9].

A non-invasive technique in mental health surveillance and intervention can be based on online ubiquitous data. As many individuals spend their lives online every day for a considerable amount of time, the digital footprints left behind may capture the cognitive and mental states of mind of the user at different moments. Most importantly, these digital traces may preserve information that is useful in flagging users at risks of mental health problems. Extensive researches have probed pervasive online data for various mental illnesses. Reddit [18, 7, 8] and Twitter [3] have been explored to detect anxiety and depression. [17] provided a comprehensive review on utilizing social network sites to examine anxiety and depressive disorders. More detailed evaluations of depression targeting young adults were also performed, as in [16], and a positive correlation was found between social media usages and depressive disorders.

Yet, as it has long been critically addressed, public online platforms are subject to self-censorship where users with mental health difficulties may refrain from generating contents due to peer stigmas, creating a false negative image. Besides, many of the above work merely detects population-level mental disorders but fails to establish a personalized healthcare model that is more clinically meaningful. To tackle these problems, some studies have investigated building individual-level mental tracking systems from private online data. One promising data source is personal search history, and it has been applied in detecting low self-esteem [22] and schizophrenia spectrum disorders [2] among young individuals. [23] furthered the experiment with YouTube histories to both detect and predict anxiety disorders among college students.

Inspired by these results, this study focuses on the task of depressive disorder detection with a similar data collection pipeline as [23]. However, instead of relying on explicit predefined labels for search logs and YouTube videos through the Google NLP API or LIWC [19], we leverage distributional phrase embeddings for semantic information. Furthermore, different from [22, 23, 2] where the researchers utilized rule-based temporal features such as hourly activity counts and late night engagements, we exploit the potential of multidimensional mutual-exciting point processes in integrating the stochastic and semantic aspects of online activities. The intuition is that online activities with distinct semantics may trigger one another at different times, and this may characterize the behaviors of users with and without depression symptoms. Our best model achieved an average weighted F1 score of $0.77 \pm 0.04$ and an AUC ROC of $0.81 \pm 0.02$ in the depression classification task.

2 Data

Our data consists of two parts: i) personal longitudinal Google Search and YouTube engagement logs and ii) Patient Health Questionnaire-9 depression survey responses (PHQ-9) [14] from the participants. Similar to [23], we utilized the Google Takeout platform to collect individual-level Google Search and YouTube engagement data. Each participant must be 18-year-old with an active Google account to qualify for the study. The PHQ-9 survey responses were collected via face-to-face interviews, and a final score was calculated from each participant. Given the proprietary nature of the data collected and the safety of human participants involved, our data collection pipeline has been thoroughly vetted and approved by our Institutional Review Board (IRB).

In total, 223 participants volunteered in the study, and 212 of them provided valid online data and PHQ-9 responses. 98% of the participants were undergraduate students, and the rest 2% were graduate student. All of them came from the same college in the U.S. 69% of the participants were female, and 28% of them were male. The rest 3% reported non-binary genders.

2.1 Depressive Disorder Measurements

The PHQ-9 score can range from 0 to 27, and a score $\geq 15$ is considered as moderate to severe depressions that may require medical interventions [14] [13]. Thus, we set the cutoff value at 15. We
labeled the participants with a PHQ-9 score ≥ 15 as the Depressed group and those with a score < 15 as the Healthy group. Out of the 212 volunteer participants, 99 (46.7%) of them belongs to the Depressed group, and the rest 113 (53.3%) of them belongs to the Healthy group.

2.2 Online History Data

For Google Search and YouTube data, the participants zipped their longitudinal online logs via the Google Takeout platform and shared with the research team. All contents that could lead to malicious linkage attacks [5] or reveal personal identities, such as name, contacts, GPS locations, and financial information, were obscured and removed by the Data Loss Prevention (DLP) API [11] from Google before the research team analyzed data. It is worth mentioning that the Google Takeout platform records and archives all the search and YouTube histories associated with each Google account. Therefore, no matter what device the participant was using (smartphones, iPad, laptops, etc), the online history would be included in the data as long as the participant was logged in with his/her/their accounts.

Each activity in Google Search and YouTube engagement logs has a timestamp to the precision of seconds. For Google Search, the engagement log contained the query input by the user. For YouTube, the engagement log contained the URL to the videos watched by the participants. We further retrieved the meta-data of the videos watched through the official YouTube API [4] including the title, duration, and the numbers of likes and dislikes. The Google Search logs and YouTube logs were merged together chronologically.

In total, we collected 1,989,372 Google Search queries and 1,078,302 YouTube watched videos from all participants. On average, the online history log spans around 5.1 years for every person.

3 Model: classifying individuals with depressive disorder

First, we obtain a semantic embedding for each Google Search and YouTube video in online history logs. We pass each search query and video title through BERT base model [4] and retrieve the CLS token (∈ R^768) as a vector representation. This procedure is done for the search queries and YouTube videos from all participants.

Next, we cluster all the online activity embeddings and identify K centers as implicit topics through k-means. Thereby, each Google Search and YouTube video can be labeled with a topic based on the cluster it belongs to. After that, the longitudinal online history log of each user can be described as a series of timestamped events with topic labels. This is further formally denoted as a marked temporal point process [1] with K mark choices. Such a data-driven topic modeling process avoids predefined explicit labels such as the Google NLP categories used in [22], which may limit the feature space and lose a considerable amount of signals.

Then, for each participant, we fit a K-dimensional Hawkes process with an exponential decay kernel, and each dimension corresponds to a topic. The intensity λ_i(t) of the Hawkes process is defined as:

\[ \forall i \in [1, ..., K], \lambda_i(t) = \mu_i + \sum_{j=1}^{K} \sum_{m:t_m < t} \alpha_{ij} \beta_{ij} \exp \left( -\beta_{ij} (t - t_m) \right) \]  

(1)

where \( \mu_i \) is the baseline intensity for topic \( i \), \( \alpha_{ij} \) is the expected number of events in topic \( i \) excited by a previous event in topic \( j \), and \( \beta_{ij} \) is the decay of intensity for topic \( i \) following an event in \( j \). This mutual-exciting point process captures the stochastic nature of online activities from different topics. Due to the well known non-convex problem [15, 24], we only optimize the baseline intensity \( \mu \in \mathbb{R}^K \) and the adjacency matrix \( \alpha \in \mathbb{R}^{K \times K} \). Decay rates \( \beta \in \mathbb{R}^{K \times K} \) are predefined such that the intensity decays slower when topic \( i \) and \( j \) are similar. Specifically, we take all the topic cluster centers \( \varphi \), and employ a RBF kernel \( \exp \left( -\|\varphi_i - \varphi_j\|^2 / \sigma^2 \right) \) to measure the similarity. The BERT embeddings provide semantic information and implicit topics for Google Search and YouTube videos, and the multidimensional Hawkes process captures the temporal interplay between online engagements. We envision that the stochastic nature of different online activities characterizes the user behavior and may be useful in distinguishing between the Depressed and Healthy groups.

https://developers.google.com/youtube/v3/docs
We grid searched through \( K \) we carried out the experiments in several 5-fold cross-validations with various hyperparameters. After the optimization, we obtain a pair of \([\alpha, \mu]\) for each user. While \( \mu \) can be used as a personalized feature vector directly, \( \alpha \) is a weighted adjacency matrix. By viewing the \( \alpha \) as a directed weighted graph, we are interested in, for each topic (vertex) \( i \), the incoming weights versus the outgoing weights. Thus, we calculate \( \phi \in \mathbb{R}^K \) such that \( \forall i \in [1, ..., K], \phi_i = \sum_j \alpha_{ji} / \sum_j \alpha_{ij} \) and use it as another feature vector.

On the one hand, it has been reported that depressive disorder shall be diagnosed with symptoms lasting for at least two weeks. On the other hand, while we have a fairly rich online history log for each person (5.1 years on average), we suspect few participants would have persistent depression symptoms for five years. An online history log that is too long or too short may both lose crucial behavioral signals about the depressive disorder of the user. Thus, when fitting a mutual-exciting point process for each person, we experimented with assorted durations \( D \) of time spans and truncated the longitudinal online engagement logs accordingly in each round. Concretely, for any \( D \) picked, we fitted the point process with the data \( D \) months/weeks before we received the PHQ-9 survey responses, see Section 4 for details.

Finally, we feed \( \phi \) and \( \mu \), separately, as the input to a L2-regularized Support Vector Machine with a linear kernel to classify participants with and without moderate to severe depressive disorders. The binary labels and cutoff value are stated in Section 2.1.

| Table 1: The performance of \( \mu \) features. |
|-----------------------------------------------|
|                          | Depressed | Healthy | Weighted Avg. |
| Precision                | 0.71 ± 0.08 | 0.69 ± 0.04 | 0.70 ± 0.05 |
| Recall                   | 0.80 ± 0.06 | 0.57 ± 0.17 | 0.70 ± 0.05 |
| F1 score                 | 0.75 ± 0.04 | 0.61 ± 0.10 | 0.69 ± 0.06 |
| AUC ROC                  | 0.74 ± 0.04 |

| Table 2: The performance of \( \phi \) features. |
|-----------------------------------------------|
|                          | Depressed | Healthy | Weighted Avg. |
| Precision                | 0.88 ± 0.02 | 0.71 ± 0.04 | 0.81 ± 0.04 |
| Recall                   | 0.82 ± 0.03 | 0.79 ± 0.06 | 0.82 ± 0.05 |
| F1 score                 | 0.80 ± 0.03 | 0.73 ± 0.03 | 0.77 ± 0.04 |
| AUC ROC                  | 0.81 ± 0.02 |

4 Experiments and Results

We carried out the experiments in several 5-fold cross-validations with various hyperparameters. The hyperparameters include: i) the number of implicit topics \( K \), ii) the duration \( D \) of online data truncated when fitting the \( K \)-dimensional Hawkes process, iii) the \( \sigma \) in the RBF kernel for the predefined decay rates, and iv) the regularization parameter \( C \) in the SVM.

We grid searched through \( K \in \{5, 10, 15, 20, 25\} \), \( \sigma \in \{0.001, 0.01, 0.1, 1, 10\} \), and \( C \in \{0.1, 1, 10, 100\} \). We experimented with \( D \) = 2 weeks, 4 weeks, 3 months, 6 months, 12 months, and the whole data series. For each combination of the four hyperparameters, we performed a 5-fold cross-validation. In general, we found that, when \( \sigma = 0.01 \) and \( C = 1 \), the performance was relatively the best for each pair of \( K \) and \( D \).

Across all the groups, the best performance was achieved with \( \sigma = 0.01 \), \( C = 1 \), \( K = 10 \), and \( D = 6 \) months, and we reported the detailed per-class and weighted averages in Table 1 and 2 for the baseline intensity features \( \mu \) and processed vertex weight features \( \phi \), respectively. The \( \phi \) features achieved the best average weighted F1 score of 0.77 ± 0.04 and AUC ROC of 0.81 ± 0.02 in discriminating between the two groups.

https://www.nimh.nih.gov/health/topics/depression/index.shtml
5 Discussion

In this work, we have shown that personal Google Search and YouTube histories can provide robust behavioral representations for classifying users with and without depressive disorder. By utilizing multidimensional Hawkes processes and distributional semantic embeddings, we are able to capture the interplay between activities of different implicit topics.

Yet, there are many limitations. First, given the sensitive nature of the longitudinal data collected, there remains significant obstacles for real-world applications such as data privacy and the safety of the participants. Throughout our study, the volunteer participants reserve the rights to opt-out and remove their data at any time. Also, our data storage is cloud-based and HIPAA-compliant. Moreover, a clinical decision made fully by automated computation systems rises ethical concerns inevitably. We envision such a system to take up an assisting role, at most, in offering medical suggestions. The ultimate judgement should always be made by experts who fully understand both the medical knowledge and the limitations of the models. At last, this study only focused on college students, and further investigations are required to assess the robustness of the model across populations and backgrounds.

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