Introdução

Depression is one of the most reported mental diseases in the world. Some people call it the century illness due to its dangerousness[1]. The Global Burden of Disease indicates depressive disorders as the third lead cause of disability [1]. From 1990, it was the fourth lead cause. The Institute for Health Metrics and Evaluation depicts the progression of depression over the years as a stable disease[2], as confirmed also by [2]. However, as a contrast to this stability, depression afflicts more certain groups than others. Such as women to men, Europeans to Africans, and people with more income. É apresentado no Apêndice a Figura 1, demonstrando essa estabilidade na evolução dos caos nos diferentes continentes.

World Health Organization (WHO) presents that around 300 million people from different ages suffer from some level of depression[3]. Some of these symptoms are, for example, depressed mood in most of the day, loss of interest in regular activities, weight loss, and insomnia. The Health Ministry in Brazil presents that 11.5 million people are affected by depression[4].

It is a challenge to identify sick people in the early phase of depression. Someone depressive can face impediments like cost, social prejudice, and even a personal obstruction. Moreover, the reverse path is also a problem. Due to the great number of depression occurrences, it can be an obstacle for institutes and professionals to reach these who face a mental disease and its variants. [3] highlights the urgency in early identification and prediction of depression and its symptoms due to the difficulties to detect these symptoms in initial stages. [4] presents that 34% of health search is made on social media, and 59% of adults look for health information on the internet. Sometimes, due to the location or economical scenario,it is *costly impending* to get help from one professional. *Infodemiology* and *digital disease detection* are correlated terms to describe the use of digital platforms and tools to improve social health. They can be translated as efforts to tackle epidemics, identify individuals at risk, and communicate candidate urgent illness. The use of technology directly supports institutions, professionals, and even aids people to make themselves aware of some diseases [5]. Social media has proved that people are using online platforms to publish their social interests and preferences to share with other users. Through social media, a user can connect to their friends, relatives, and even unknown ones. The content generated on these platforms looks like good sources of information that could help when dealing with disease detection or connection among a psychologist and one depressive patient. Due to the described scenario above, to identify and attend someone who could be a potential depressive patient, in a fast and unobtrusive way, seems to be very helpful for both patient and professional. The task of identifying some disease, even if it is not depression, can be challenging, but at the same time relevant to investigate if it is possible to identify signs, symptoms of depressive behavior on social media platforms. Due to the plenty of data offering, select what is the most effective, precise and representative data can be challenging. Therefore, choose a reliable technique and a consistent method analysis can require a great amount of research.

This paper aims to propose a new method to identify depression symptoms in social media platforms. Relied on the literature review, we believe this proposal highlights a research approach that was not investigated extensively. One initial research question can be defined as follows: ***Is it possible to identify psychological diseases symptoms, more specifically depression symptoms, from social media users content?*** The research question generally reaches initial doubts. Novel questions will be noted as the research goes forward. Although it is an in-progress research, with its stages and processes under validation, the following sections try to systematize the methodological steps to understand depression phenomena and how it affects people on social media. Whether is possible to identify a behavior from someone depressive, are these behaviors similar over some point of view?

[1] www.theguardian.com/news/2018/jun/04/what-is-depression-and-why-is-it-rising

[2] Reproducible on http://ihmeuw.org/51aj

[3] www.who.int/en/news-room/fact-sheets/detail/mental-disorders

[4] www.blog.saude.gov.br/index.php/materias-especiais/52516-mais-de-onze-milhoes-de-brasileiros-tem-depressao

Depressão

Proposta de Pesquisa

Trabalhos Correlatos

The 11th International Disease Classification (ICD 11) classifies depression as a disease when it is diagnosed in someone's behavior. An event where the person has lost something e.g. job, some close person, etc. could start depression symptoms. This disease is also dangerous because of its extreme consequences. Depression, according to ICD 11, can lead to suicide ideation and suicide as consequence[6]. As a first step in order to investigate the problem of identification of depressive people on social media.

Although depression is the common name in society, the Manual of Mental Disorder Diagnostic (DSM-V) details different types of depression. The most common and more general is the major depressive disorder (MDD), though each variant of depression is covered by the term *Depressive Disorder*. Alternatives of that kid of disorder are *transtorno disruptivo da desregulação do humor*, *transtorno depressivo persistente (distimia)* and *transtorno disfórico pré-menstrual*. The DSM-V also lists the characteristics for diagnosis of each variant. We can list from MDD diagnosis criterias e.g. insomnia or over sleep, depressive mood in most part of the day, lost of interest in activities and weight loss. DSM-V also highlights that a group of at least 5 symptoms must occur in a time period of two weeks. Depression symptoms and characteristics are very similar to Freud's description of melancholia [7].

0.1 Current Approaches

For the literature selection, we have applied a systematic literature review **(SLR)** in order to have a deeper insight from the most recent research that tackles depression detection in social media. SLR allows to create protocols that can be reused by other researchers and therefore give to research transparency and reproducibility. This stage is under construction yet and it is intended to include two more bases. The SLR until this moment was done searching for articles in ACM and IEEE bases. It has been searched the string *("Social Media" OR "Social Network" OR "Complex Network") AND (Depression OR "Major Depressive Disorder")*. Including only works from 2013 until 2018, from computing area which have used social media as a data source. The inclusion and exclusion criteria are listed below in Table 1. At the final stage, there was a total number of 47 selected papers. There were 22 papers from ACM Library and 25 papers from IEEE Explore.

Inclusion	**Exclusion**
Directly tackles depression	Out of 2013-2018 scope
Have computational approach	Not written in english or portuguese
Attend both approaches	It is not a primary study
-	It does not have abstract
-	It does not have computing contribution
-	It has less than 4 pages

Table 1: SLR Criterias for inclusion and exclusion.

It may not seem clearly, but can be listed main objectives from read articles are: identify what symptoms are searchable in social media and will compose a model as features; create a model which classifies an unseen user as potential depressive or not. The problem of dealing with depression and social media can be understand as a search for people who suffer the symptoms of depression.

A good amount of articles relies on natural language processing (NLP) to make a systemic analysis over the text in social media publications. Not all the analyzed researches take into account the psychology point of view.

The effect of taking into account existing approaches from psychology is that the analysis will be more robust and reliable since the psychology research area already addresses mental disease problems. It is a challenge align quantification made by metrics e.g. NLP, social network analysis and other techniques to the cognition of a psychologist on ordinary clinical treatment.

[8] has developed many articles and researches about the measurement of depression in population using social media information. The authors in this work have been made use of psychometrics questionnaires. Psychometrics represents the theory and technique of measuring mental processes and it is applied in Psychology and Education. It is an interesting approach, although it is questionable due to how it simplifies the whole process of understanding someone's behavior. In [8], crowdsourcing is applied to obtain data from twitter by people who were clinically diagnosed with depression. With this data, they have constructed a corpus and developed a probabilistic model. The trained model classifies if a post indicates depression. Similar to previous work, Tsugawa et al [9] have applied the same analysis to replicate the results in a group of users from Japan.

[10] present how activities on Facebook are associated with depressive states of users in order to raise awareness to depression at the University where the study was conducted, which had seen an increase in the suicide rate of its students. [11] explore self-disclosures posts in Instagram. In this article, the authors have used content from posts tagged with #depression to understand what rather sensitive disclosures do people make on Instagram. The work in [12] is a qualitative study that tries to understand how is the behavior and comprehension of the Chinese population about depression. It is a qualitative study and differs from prior ones. [13] conduct an observational study to understand the interactions between clinically depressed users and their ego-network when contrasted with a group of users without depression. They identify relevant linguistic and emotional signals from social media exchanges to detect symptomatic cues of depression. [14] have applied text classification using Convolutional Neural Networks to classify depression using text analysis. [15] also have used neural networks to identify patterns on time periods when the risk of a suicide attempt is increasing in SMS texts. [16] incorporate temporal analysis of user-generated content on social media for capturing symptoms. They have developed a statistical model that emulates traditional observational cohort studies conducted through online questionnaires and extract and categorize different symptoms of depression and modeling user-generated content in social media. [17] detected eight basic emotions and calculated the overall intensity (strength score) of the emotions extracted from all past tweets of each user. After that, they have generated a time series for each emotion of every user in order to generate a selection of descriptive statistics for this time series.

Papers cited above not always take into account how psychologists infer if someone is depressive or not. We also stress that many of the real contributions rely on textual information generated by one user. Since one of the depression symptoms in ICD 11 is the inactivity, we could question if a depressive one would consistently generate online content. The context of psychology regularly deals with the subjectivity of information. Relied on that, we believe that relevant information can be extracted from other methods rather than text content. We believe that the classification of potential depressive users could be more reliable if combined with "subjective information".

Cronograma

A

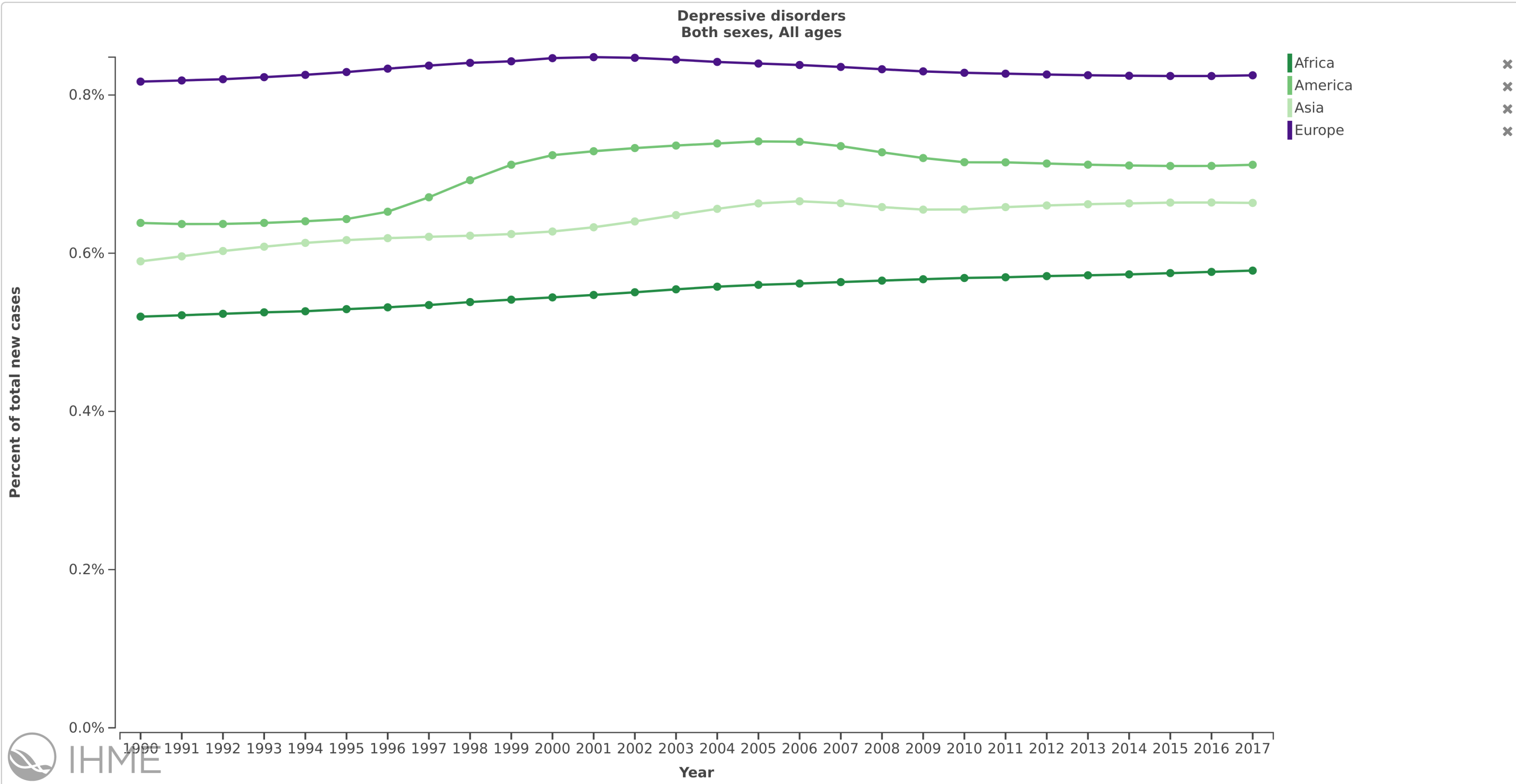

Figure 1: Depression progression over the years by global regions

References

[1] S. L. James, D. Abate, K. H. Abate, et al. Global, regional, and national incidence, prevalence, and years lived with disability for 354 diseases and injuries for 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. *The Lancet*, 392(10159):1789–1858, 2018.

[2] D. J. Brody, L. A. Pratt, and J. P. Hughes. Prevalence of depression among adults aged 20 and over: United States, 2013-2016. *National Center for Health Statistics*, 2018.

[3] M. Lech, L.-S. Low, and K. E. Ooi. Detection and prediction of clinical depression. In *Mental Health Informatics*, pages 185–199. Springer, 2014.

[4] N. Elkin. How America searches: Health and wellness. *Opinion Research Corporation: iCrossing*, pages 1–17, 2008.

[5] E. Horvitz and D. Mulligan. Data, privacy, and the greater good. *Science*, 349(6245):253–255, jul 2015.

[6] A. P. Association et al. *Diagnostic and statistical manual of mental disorders (DSM-5®)*. American Psychiatric Pub, 2013.

[7] S. Freud. Mourning and Melancholia. U: The Standard Edition of the Complete Psychological Works of Sigmund Freud, Volume XIV (1914-1916): On the History of the Psycho-Analytic Movement, Papers on Metapsychology and Other Works, 1917.

[8] M. De Choudhury, S. Counts, and E. Horvitz. Social Media As a Measurement Tool of Depression in Populations. In *Proc. of the 5th Annu. ACM Web Sci. Conf.*, WebSci '13, pages 47–56, New York, NY, USA, 2013. ACM.

[9] S. Tsugawa, Y. Kikuchi, F. Kishino, K. Nakajima, Y. Itoh, and H. Ohsaki. Recognizing Depression from Twitter Activity. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems - CHI '15*, pages 3187–3196, 2015.

[10] S. Park, I. Kim, S. W. Lee, J. Yoo, B. Jeong, and M. Cha. Manifestation of Depression and Loneliness on Social Networks: A Case Study of Young Adults on Facebook. In *Proc. of the 18th ACM Conf. on Comput. Supported Cooperative Work Social Comput.*, CSCW '15, pages 557–570, New York, NY, USA, 2015. ACM.

[11] N. Andalibi, P. Ozturk, and A. Forte. Sensitive Self-disclosures, Responses, and Social Support on Instagram: The Case of #Depression. In *Proc. of 2017 ACM Conf. on Comput. Supported Cooperative Work and Social Comput.*, pages 1485–1500, Portland, OR, USA, 2017. ACM.

[12] G. Li, X. Zhou, T. Lu, J. Yang, and N. Gu. SunForum: Understanding Depression in a Chinese Online Community. In *Proc. of the 19th ACM Conf. on Comput.-Supported Cooperative Work & Social Comput.*, pages 514–525, New York, NY, USA, 2016. ACM Press.

[13] N. Vedula and S. Parthasarathy. Emotional and Linguistic Cues of Depression from Social Media. *Proceedings of the 2017 International Conference on Digital Health - DH '17*, pages 127–136, 2017.

[14] X. Zhao, S. Lin, and Z. Huang. Text Classification of Micro-blog's "Tree Hole" Based on Convolutional Neural Network. In *Proc. of the 2018 Int. Conf. on Algorithms, Comput. and Artificial Intelligence*, ACAI 2018, pages 61:1—-61:5, New York, NY, USA, 2018. ACM.

[15] A. L. Nobles, J. J. Glenn, K. Kowsari, B. A. Teachman, and L. E. Barnes. Identification of Imminent Suicide Risk Among Young Adults Using Text Messages. In *Proc. of the 2018 CHI Conf. on Human Factors in Computing Systems*, CHI '18, pages 413:1—-413:11, New York, NY, USA, 2018. ACM.

[16] A. H. Yazdavar, H. S. Al-Olimat, M. Ebrahimi, et al. Semi-supervised approach to monitoring clinical depressive symptoms in social media. In *Proc. of the 2017 IEEE/ACM Int. Conf. on Advances in Social Networks Analysis and Mining 2017*, pages 1191–1198, 2017.

[17] X. Chen, M. D. Sykora, T. W. Jackson, and S. Elayan. What about Mood Swings. In *Companion Proc. of the The Web Conf. 2018*, pages 1653–1660, New York, New York, USA, 2018. Int. World Wide Web Conf. Steering Committee.