UFRJ

Detection of Depression Symptoms using Social Media Data

cores
Laboratório de
Computação Social e
Análise de Redes Sociais

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Summary

Context

- Depression is one of the most reported mental diseases in the world. Sometimes called century illness[a] and the third lead cause of disability [18].
- Depression afflicts more certain groups than others, e.g. women to men, Europeans to Africans, people with more income.
- World Health Organization (WHO) presents that around 300 mi people suffer from some level of depression[b].
- Health Ministry in Brazil presents that 11.5 million people are affected by depression.[c]

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[a]www.theguardian.com/news/2018/jun/04/what-is-depression-and-why-is-it-rising
[b]www.who.int/en/news-room/fact-sheets/detail/mental-disorders
[c]www.blog.saude.gov.br/index.php/materias-especiais/52516-mais-de-onze-milhoes-de-brasileiros-tem-depressao

Motivation

- People share with other users their social interests and preferences on Social Media.
- Plenty of data about behaviour, habits, interests, friendship and so on.

Context

- *Horvitz* report *infodemiology* as the use of digital information to inform the population about health policies, earlier epidemics identification and identify potentially affected individuals[17].

- *Lech & Eds* present two main challenges in *mental health informatics*. Provide health care services to remote and non-assisted populations, and turn health services more effective on cost[22].

Applications of Mental Health Informatics

- Telemedicine
- Automatizes Evaluation Systems
- Online Support and Information Management

Initial Research Questions

Is it possible to identify psychological diseases symptoms, more specifically depression symptoms, from social media users content?

The collected information from social media is sufficiently robust to determine if a user has depression or its symptoms?

Which computational methods and efforts were created or used to understand emotional behavior from a social media user?

Justification

Academic Relevance

This work intend to contribute mainly on social network area, and somewhere between machine learning and recommendation systems. For studying if social media data is adequate to comprehend a person behaviour related to depression.

Practical Relevance

Prior contribution(academic) can improve how data is consumed by professionals in health service as psychologists and physicians, and also can auxiliate in order to construct more accessible health services to groups of people with less resources.

Methodology

Design Science Research (DSR) was selected due to its pragmatical approach for a given context. Based on [15], we can identify the three cycles in order to create at the end, an relevant artifact. Pimentel et al. [31] has presented an overview of different aspects of DSR from many authors. Moreover the authors suggest a framework to implement DSR in a research topic.
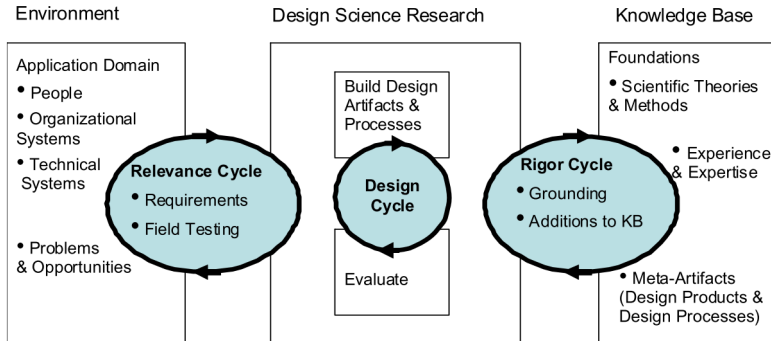
Methodology

Peffers[30] states the research process in six stages. The author specifically proposes a *Design Science Research Methodology* (DSRM).
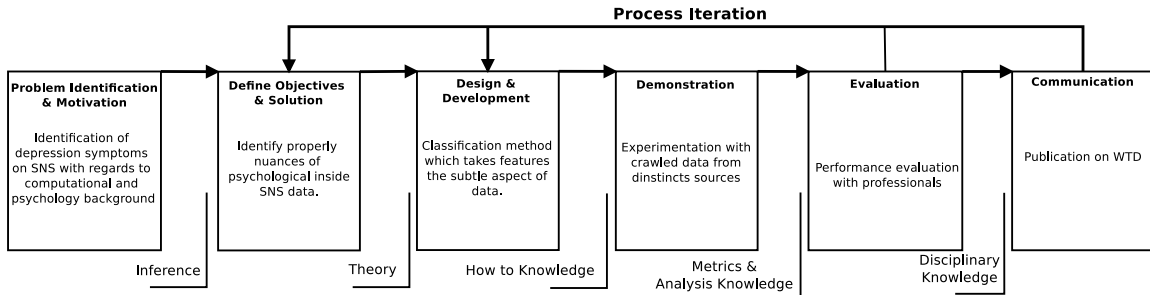
Figure: Research stages based on DSRM from [30].

cores

We establish which cycles will comprehend each component to fullfill DSR requirements.
Taking into account Wieringa approach [40].

- Systematic Literature Review - Related to Empirical Cycle
- Experiments to test and validate initial classification models - Related to
  Design/Engineering Cycle.

Research Questions

- Is it possible to identify symptoms of psychological diseases on social media platforms?
- Is there a diagnosis method which only uses social media data?
- Would the social media platform be useful for professionals?
- Assuming there exist such methods, which type of techniques are used on them?
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- What and how is composed the state of the art?

Systematic Literature Review

Still in progress.

- ("Social Media" OR "Social Network" OR "Complex Network") AND (Depression OR "Major Depressive Disorder")
- $2013 \geq published \leq 2018$
- 22 from ACM and 25 from IEEE bases

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: SLR criteria for inclusion and exclusion.

Systematic Literature Review

Chen et al. have detected eight basic emotions and calculated the overall intensity (strength score) of the emotions extracted from all past tweets of each user[4].

Approach:

- "...identify users with or at risk of depression by incorporating measures of eight basic emotions as features from Twitter posts over time, including a temporal analysis of these features."
- Data obtained from expressions: "I was/have been diagnosed with depression."
- Contributions:
  - Emotions are the analyzed features
  - Data analysis over time
  - Explore how time series analysis can help on task of identify depressive users
- Features:
  - Non-temporal: 9 entries emotion feature vector (emotions + Emotion Overall Score)
  - Temporal: Timestamp for each emotion score

Systematic Literature Review

Vedula and Parthasarathy 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[38].

Approach:

Examine network effects related to:

- participation (passive: tweets a user is exposed to, retweets or mentions a user receives; active: mentions, retweets and conversations made by the user)
- engagement (content (e.g., linguistic cues, emotion) and relational dynamics (e.g., conflict/support, influence))
- Ego-neighborhood (size, centrality and affinity to form clusters or communities)

Systematic Literature Review

De Choudhury et al. have used crowdsourcing to obtain data from twitter by people who were clinically diagnosed with depression. They also have constructed a corpus and developed a probabilistic model. The trained model classifies if a post indicates depression[12]. Similarly, *et al* have applied the same analysis to replicate the results in a group of japanese users[37].

- Problem:
  - Characterize levels of depression in populations.
- Approach:
  - Crowdsourcing to build a large corpus of postings on Twitter that have been shared by individuals diagnosed with clinical depression.
  - Probabilistic model trained on this corpus to determine if posts could indicate depression
  - Social media depression index that may serve to characterize levels of depression in populations

Reference	Method/Model/Algorithm	Features	Psychological Approach	Dataset	Behaviour Variation
[36]	CNN - CReLU	LIWC		CLEF e-Risk(Reddit)	No
[42]	SVM w/ RBF kernel; PCA	LIWC, demography, activities, post time	CES-D	Facebook myPersonality	Yes†
[34]	RMN?			Reddit	Yes†
[19]	SVM, RF, DL*	Information about generated content (content, interactions, privacy and behavior)	TMHQ	Facebook Users volunteers	No
[28]	NLP (lexical construction approach)		CES-D for lexical construction	Filtered Tweets	No
[24]	Undefined	Undefined			
[35]	Logistic Regression	subset processed from LIWC	Professional Validation	Tumblr API	No
[1]	Weighted Network Model, NLTK, SNA			depressionforums.org	No
[33]	Own Method	LIWC, LDA		LiveJournal.com	No
[9]	Lasso	ANEW, LIWC, LDA		LiveJournal	No
[8]	Non-Negative Matrix Factorization	ANEW		LiveJournal	No
[7]	Nonparametric Clustering, Hierarchical Dirichlet	ANEW, LDA		LiveJournal.com	No
[5]	BoW			Undefined source	No
[25]	Hypothesis Test			Filtered Tweets	No
[21]	PCA(not main)	ANEW, LIWC, Tweet metadata, timezone		Filtered Tweets	Yes†
[26]	Lasso	ANEW, LIWC, LDA		LiveJournal.com	No
[14]	Quant. Analysis	Depression Ontology			Yes†
[6]	Quant. and Behaviour Analysis	Sentiment and Linguistic(LIWC), ANEW		LiveJournal	Yes★
[39]	Decision Tree	Relationship's Topology		Sina Micro-blog	No

Table: Review of Literature approaches from IEEE. Where † stands papers where analysis over time were made but not used in model creation task, consequently ★ stands for the inverse.

Reference	Method/Model/Algorithm	Features	Psychological Approach	Dataset	Behaviour Variation
[11]	SVM w/ kernel	Engagement(avg. n. of posts, replies and retweets), Ego-Network(n. of followers and followees), Polarity Emotion(LIWC and ANEW), Linguistic(LIWC)		Twitter	
[12]	SVM	Post Features(Emotion, Time, Ling., n-grams) User Features(n. of posts, replies and retweets)	CES-D	Twitter and Crowdsourcing	Yes†
[10]	Quant. and Qual. Analysis	Activity(n. of posts), Emotion(LIWC) Linguistic(LIWC)		Twitter and Crowdsourcing	Yes
[16]	Quant. and Qual. Analysis	Network components(degree, triangles, clustering)	PHQ-9	TrevorSpace	No
[41]	Qual. and Linguistic Analysis	LIWC		Twitter	No
[29]	Quant. and Qual. Analysis	Profile, Application and Posts Activities, Likes and Comments Interactions, Perceived Mood	CES-D	Faceboook App	Yes†
[37]	SVM w/ kernel	BoW, LDA, Sent. Ratio, tweet metadata, n. of following and followers	CED-D	Twitter	
[20]	linear SVM	N-grams, LIWC, discourse relation graph	Professional Validation	Reddit subgroup	No
[23]	Qualitative Analysis			SunForum	No
[13]			Twitter		
[38]	Gradient Boosted DT + CV	topology, social media metadata	CES-D	Twitter(API)	Yes⋆
[2]	Qualitative analysis			Instagram(API)	No
[43]	Topic Identification, Sent. Analysis, Multi-Label Classification	LDA, Lexicon(depression related terms)	PHQ-9	Twitter	Yes⋆
[3]				Reddit	Yes
[27]	SVM and LIWC	LIWC and word occurrence		(SMS and email), Facebook, Twitter web browsing history, mental health history	No
[4]	(SVM, RF) + CV	Emotive(Ontology), Temporal, Non-temporal(emotions vectors), LIWC		Twitter	Yes⋆
[32]	Non-Sequential(SVM), Sequential Model(RNN)	Words, DepWords, DepEmbed, MetaMap		CLEF eRisk 2017	No
[44]	Double Input CNN	Text (Semantic Content) & External (Text Characterization)		Tree Hole	No

Table: Review of Literature approaches from ACM. Where † stands papers where analysis over time were made but not used in model creation task, and ⋆ stands for the inverse.

Reference	Emot./Sent.	Linguis.	Topic	Other	Content Metadata	User Profile	Platform	Other Users	Both	Group Charac.	Longitud. Variation
Fang, 2014 [14]	x										
Nguyen, 2014 [26]	x	x	x								
Larsen, 2015 [21]	x	x									
Nambisan, 2015 [25]							X				
Chomutare, 2015 [5]			x	x							
Dao, 2015 [7]	x			x							
Dao, 2016	x						x				
Dao, 2016	x	x	x								
Saha, 2016 [33]	x	x	x								
Akay, 2016 [1]	x	x						x		x	
Simms, 2017 [35]	x	x									
Oyong, 2018 [28]		x		x							
Katchapakirin, 2018 [19]	x	x			x	x			x		
Silveira, 2018 [34]				x					x	x	
Wongkoblap, 2018 [42]	x	x			x	x			x		
Trotzek, 2018 [36]	x	x			x						
DeChoudhury, 2013	x	x							x		
DeChoudhury, 2013	x	x		X	x				x		
DeChoudhury, 2013	x	x					x				x
Homan, 2014 [16]								x		x	
Wilson, 2014 [41]		x									
Tsugawa, 2015 [37]	x		x	x	x				x		
Kavuluru, 2016 [20]	x			x							
DeChoudhury, 2017 [13]	x	x	x								
Vedula, 2017 [38]	x	x							x	x	
Yazdavar, 2017 [43]	x	x	x								x
Bagroy, 2017 [3]				x							x
Nobles, 2018 [27]	x	x		x							
Chen, 2018 [4]											x
Sadeque, 2018 [32]		x		x							
Zhao, 2018 [44]				x	x						

Table:

Literature Gaps

- Not all the analyzed researches take into account the psychology point of view.
- Use of psychometrics only
- Would the screening of depressive users be more robust and reliable if they take others psychology approaches?
- Is it possible to identify the same symptoms from clinical using computational techniques?
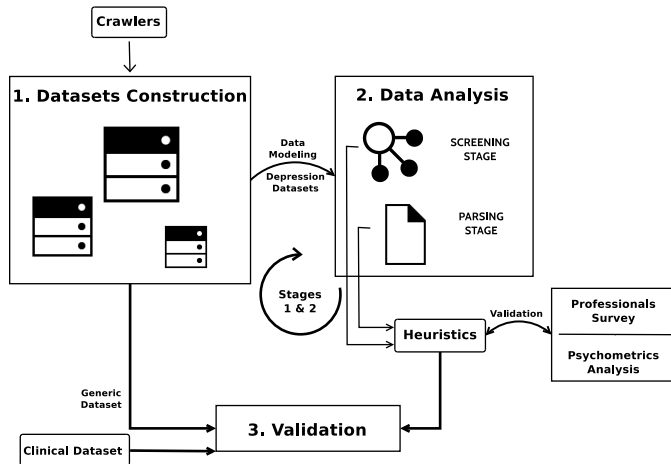- Aggregated Data Analysis vs Individual Data Analysis

Figure: Proposal Conceptual Model

Technical Challenges

- Validation with clinical data
- Datasets to train classification model
- Reliable data, taking into account people consent
- Improve Computer Science area

Schedule

- Submission to WTD on SBBD (08/07)
- Proposal writing - In progress - First issue 15/07
- Qualification - End of August
- Ending of 1st Cycle
- Ending of 2nd Cycle

- BE INCLUDED 1) Classificação dos trabalhos encontrados no mapeamento, ressaltando: Objetivo do trabalho, Abordagem utilizada, Técnicas utilizadas (algoritmos e métricas), Principais desafios levantados (ou trabalhos futuros).
2) A partir do material que vc. leu, destacar o conjunto de teorias/referências que vão embasar o seu problema e a sua motivação (Conjecturas Teóricas)
3) Quadro explicativo, com as métricas/features que os trabalhos relacionados usam e as métricas/features que vc. pensou em incluir na sua proposta. Este quadro deve ter: o nome da métrica/feature, explicação sucinta sobre a métrica/feature, referência (ao trabalho que a usou), justificativa do seu uso.

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Discovering latent affective dynamics among individuals in online mental health-related communities.
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