An Automatic Screening for Major Depressive Disorder from Social Media in Thailand

Siranuch Hemtanon[1]
Nichnan Kittiphattanabawon[2]
[1]Doctor of Philosophy Program in Management of Information Technology, School of Informatics, Walailak University,
Email Mitnuchie@gmail.com
[2]Lecturer, Management of Information Technology, School of Informatics, Walailak University,
Email knichcha@wu.ac.th

Abstract

The MDD patients do not often realize their own risk of being MDD and hardly access to treatments in its early state. Thus, widely screening test is necessary to prevent and control the mental disorder. This paper presents a method for screening major depressive disorder (MDD) from Thai posts in social media. Unlike using questionnaire which requires a person to personally perform, the proposed method can help in an MDD screening task to cover in mass-screening on social media. The machine-learning based classification is exploited to develop a model in discriminate positive and negative risk of being MDD according to Thai screening questionnaire (2Q). From evaluation, the best machine-learning technique for the task was support vector machine for 0.94 F-measure score. From the screening model, we also found top-10 Thai terms that are positively informative for a risk of being MDD.

Keywords: Text classification, Major depressive disorder, Mass-screening test, Mood analysis

บทคัดย่อ

ผู้ป่วยโรคซึมเศร้ามักไม่ตระหนักถึงความเสี่ยงของตนเองในการเป็นโรค ทำให้ไม่สามารถเข้าถึงการรักษาในสภาวะเริ่มต้นได้ ดังนั้นการตรวจคัดกรองเป็นสิ่งจำเป็นในการป้องกันและควบคุมการก้าวหน้าของโรค บทความนี้นำเสนอวิธีการคัดกรองโรคซึมเศร้าจากการโพสต์ข้อความภาษาไทยในสื่อสังคมออนไลน์โดยอ้างอิงจากการใช้แบบสอบถามที่ต้องการให้บุคคลดำเนินการเป็นการส่วนตัว วิธีการที่นำเสนอสามารถช่วยในงานตรวจคัดกรองโรคซึมเศร้าเพื่อครอบคลุมในการตรวจคัดกรองผ่านสื่อสังคมออนไลน์ การจัดหมวดหมู่ด้วยเทคนิคการเรียนรู้ของเครื่องถูกใช้ในการพัฒนาแบบจำลองในการแยกแยะความเสี่ยงด้านบวกและด้านลบของการเป็นโรคซึมเศร้าตามแบบสอบถามการคัดกรอง (2Q) จากการประเมินผลเทคนิคการเรียนรู้ด้วยเครื่องที่ดีที่สุดสำหรับงานคือ Support Vector Machine ด้วยคะแนน F-measure 0.94 จากรูปแบบการคัดกรอง นอกจากนี้เรายังพบคำศัพท์ภาษาไทย 10 อันดับแรกที่ให้ผลเชิงบวกที่เกี่ยวข้องสำหรับความเสี่ยงในการเป็นโรคซึมเศร้า

Introduction

Major Depressive Disorder (MDD) is a mood disorder causing a persistent feeling of sadness and loss of interest [1]. MDD is one of the most common mental disorders found in entire world, and the patients are mostly unaware of it. Thus, some people with MDD never recognize themselves and seek for treatment [2] despite the MDD is well-studied and treatable [3][4]. MDD can cause the one to experience feelings of restlessness or an urge to harm oneself or to commit suicide at worst. The current and widely used method to detect the person with MDD is the use of questionnaires called Patient Health Questionnaire-2 (PHQ-2) and Patient Health Questionnaire-9 (PHQ-9) [5] for screening and detecting, respectively. However, since the symptoms of the MDD implicitly affects the patients, the person at risk may not care or is unable to apply to the questionnaires. In Thailand, MDD is the most mental disorder while about 4% of risk persons are accessed to the health-care service [6].

In this work, we aim to develop a platform to screen persons with a risk of having MDD using their posts on social media, which is Facebook. Since social media is a channel for ones to express their thoughts and opinions freely, the words in the post may reveal the signs of their MDD. Terms related to depressive manifestation and symptom according to MDD guideline [5] and PHQ-2 are automatically detected using natural language processing techniques to classify the risk of having MDD. The platform thus can help to primarily monitor the risk of MDD patients and directs them for proper treatments.

Research Objectives

1. To develop a tool for screening major depressive disorder persons in risk through their verbal expression via social media
2. To study Thai terms representing a sign for major depressive disorder

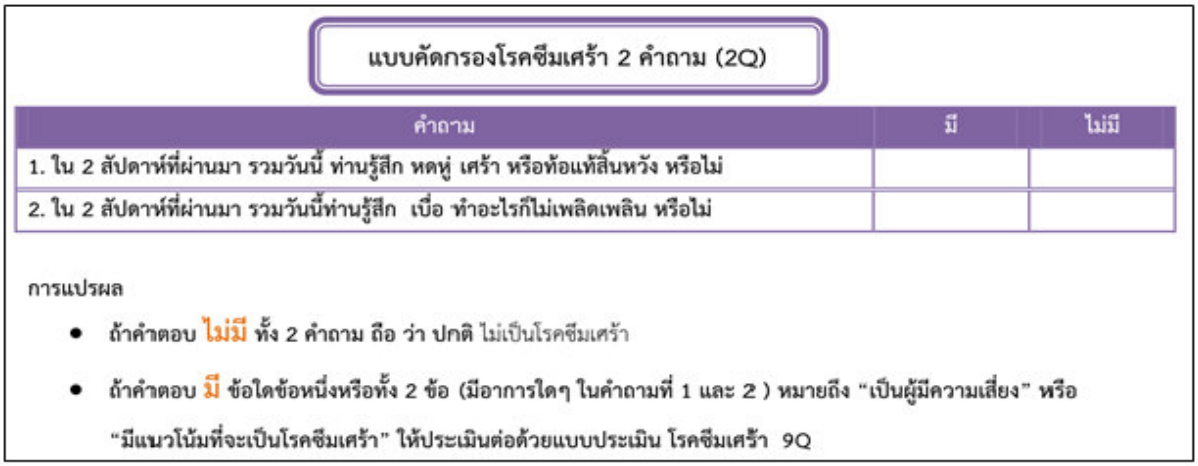
Related Works

1. Major Depressive Disorder and Its Detection

Major depressive disorder (MDD) is a mood disorder that presents with either a persistent feeling of sadness or loss of pleasure [1]. MDD potentially becomes a chronic illness of considerable morbidity with a high rate of relapse and recurrence [7]. It is very possible that most of MDD patients who are suffering from MDD do not seek help since they may lack of insight into their medical condition; the stigma associated with the label of mental illness; and financial factors [8]. Despite MDD is evidentially treatable, most of the patients do not get cured in time and lost the benefits of early treatments which result in better outcome [8].

MDD comes with symptoms of insomnia, low mood, anhedonia and suicidal thoughts [5] which leads to tremendous loss. To prevent late detection of MDD, Department of Health, Thailand has published Questionnaire into 2 sets for MDD screening (2Q) and detection (9Q). The 2Q is for screening a risk of being MDD with two simple questions as shown in Figure 1.

The 2Q returns as MDD risk if both questions are answered with positive result. With the positive result, the person in risk will be asked to answer 9Q questionnaire for detecting and severity diagnosis for MDD. The screening is an important medical procedure since diagnosis for all Thai citizen costs tremendously. Furthermore, 9 questions (9Q) may consume too much time once applied to all Thais.



แบบคัดกรองโรคซึมเศร้า 2 คำถาม (2Q)

คำถาม	มี	ไม่มี
1. ใน 2 สัปดาห์ที่ผ่านมา รวมวันนี้ ท่านรู้สึก หดหู่ เศร้า หรือท้อแท้สิ้นหวัง หรือไม่		
2. ใน 2 สัปดาห์ที่ผ่านมา รวมวันนี้ท่านรู้สึก เบื่อ ทำอะไรก็ไม่เพลิดเพลิน หรือไม่		

การแปรผล

- ถ้าคำตอบ ไม่มี ทั้ง 2 คำถาม ถือ ว่า ปกติ ไม่เป็นโรคซึมเศร้า
- ถ้าคำตอบ มี ข้อใดข้อหนึ่งหรือทั้ง 2 ข้อ (มีอาการใดๆ ในคำถามที่ 1 และ 2) หมายถึง "เป็นผู้มีความเสี่ยง" หรือ "มีแนวโน้มที่จะเป็นโรคซึมเศร้า" ให้ประเมินต่อด้วยแบบประเมิน โรคซึมเศร้า 9Q

Figure 1. 2Q for screening MDD in risk from Department of Health, Thailand

However, a questionnaire requires the person in risk to answer the question personally for the best outcome. Those who have low mood and uneasy with MDD symptom or are in denial state of having MDD may not sincerely answer the questionnaires. Another method to detect MDD is to monitor behaviour of person in question. However, the issue of lacking medical personnel for the task is still carrying on.

Thus, this work aims to help in this task of monitoring MDD person. The use of social media such as Facebook can help in monitoring one's behaviour through their choice of words and mood expression. With the automatic classification, our goal is to help in screening the person in risk of MDD for more possibility to increase early treatment of the disorder. This is the first step for the full-scale detection of MDD which will require another behaviour analysis given in 9Q such as being insomnia and lacking motivation in the diagnosis stage.

2. Automatic Classification

Automatic classification is a task to classify documents (or items) to designate class or category automatically. It can be used in many domains such as grouping document, sentimental analysis, and disease diagnosis.

The common method for automatic classification is to exploit the labelled data to determine a category of item by considering difference in features or attributes using machine learning to create a classification model. There are many machine learning techniques which is often used for automatic classification with satisfied performance including Naïve Bayes (NB) [9], Support Vector Machine (SVM) [17], Decision Tree (DT) [9] and deep learning [10].

In terms of mental disorder detection, automatic classification had been applied in many works. The summary of well-known classification task in mental disorder detection is given in Table 1. In the Table, NLP stands for applying Natural Language Processing techniques such as syntactic parser and word collocation while ML refers to the use of machine learning to generate classification model from supervised data.

Table 1. Related works on detection of mental disorder and suicide risk using text-based classification

Papers	Techniques		Dataset
	NLP	ML	
Detection of Suicide-Related Posts in Twitter Data Streams (2018) [9]	Lexicon-based	NB, DT	Twitter posts
Google and suicides: what can we learn about the use of internet to prevent suicides? (2018) [10]	-	Regression analysis	Suicide data mortality from all American state
Analyzing the connectivity and communication of suicidal users on twitter (2016) [11]	-	TF-IDF, Uni-gram	Twitter posts
Natural Language Processing of Social Media as Screening for Suicide Risk (2018) [12]	Word vector	Deep Learning	Social media data
Detecting suicidality on Twitter (2015) [13]	-	SVM, Logistic Regression	Twitter posts
Online suicide prevention through optimized text classification (2018) [14]	Word vector	Genetic algorithms	Twitter posts

From the review, the work mostly focused on the suicide detection which is the far-end of the MDD symptoms. The suicidality act and thought should undoubtedly be prevented, but it is better to prevent the thought by early treatment of MDD. Their works show acceptable performance in terms of accuracy. However, the works were done on English language which has several supporting natural language processing tools with high accuracy and great coverage. Moreover, Thai language has unique syntactic and semantic style in use especially in social media. Thus, it is worthy to study in this matter for further references.

Research Methodology and Tool Used in This Research

1. Development of MDD Screening System from Social Media

Since a sign of MDD manifests in one's behaviors and expression, posts they made via social media could reflect their changes and feeling at that moment. In this work, we apply the technique of automated text classification to screen MDD patients from their social media (SM) posts. Targets of his work are Thai people; thus, the language for classification is Thai, and the selected social media is Facebook which is the most favorite SM in Thailand. A framework of the automated classification is sketched in Figure 2. From the framework, there are three main processes which are data cleansing, data training and screening.

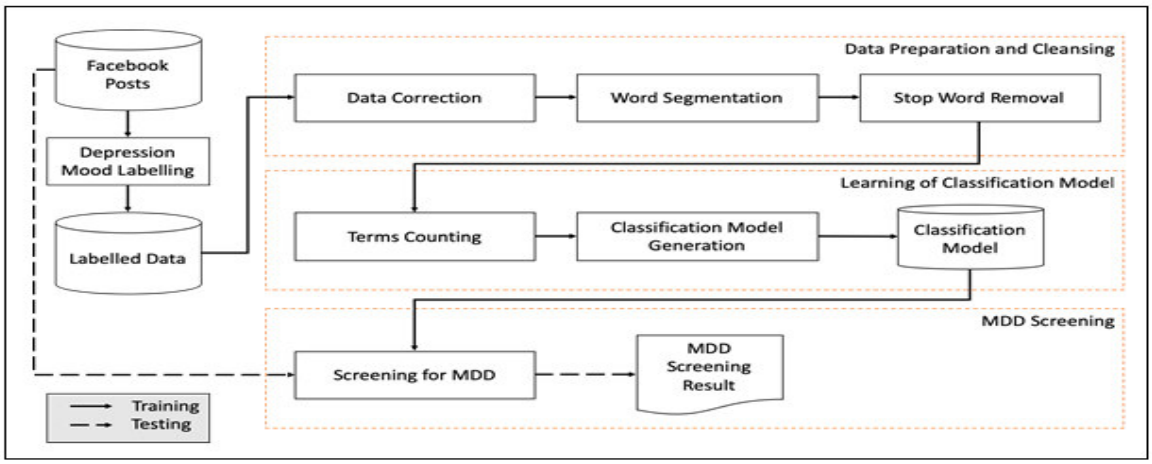


Figure 2. An overview of MDD screening framework from Thai Facebook Posts

1.1 data preparation and cleansing

Data in this work are Facebook posts in Thai. The typos and misspelling words are manually corrected to reduce noises and to prevent scattered term statistics. Moreover, it is necessary to perform word segmentation to find term boundary. The word segmentation

service selected in this work is Lexto [15] provided by NECTEC, Thailand. However, the performance of the word segmentation is not perfect and some rare and unknown terms are not properly segmented; hence, manual post-edit is applied for maintaining input quality. Last, stop words, which are functional words used for representing grammatical function with little to none meaning, are removed to maximize text processing performance in terms of computational complexity from less search space. However, since the negation word (ไม่) in Thai has a function to negate a meaning of a word or a phrase, the word is essential in the MDD screening task and keeps intact without modification or removing. An example of the data cleansing process is drawn in Figure 3.

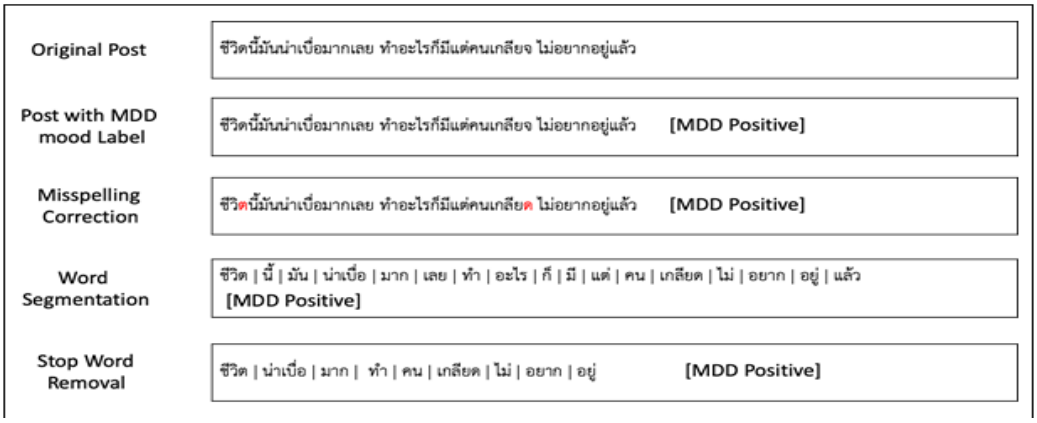


Figure 3. Examples of data preparation and cleansing process

Once the data are cleansed, the terms appeared in Facebook posts are constructed in to a vector representation. The terms and posts are aligned into a vector regarding their existence. The word-vector then will be used in a later learning process to create a classification model.

1.2 Learning an MDD Screening Classification Model

The model for classification of screening MDD persons in this work uses supervised learning technique. So, the data are labelled to 'positive' and 'negative' for screening result. The label is annotated by MDD experts regarding the mood of the posts. With the labelled data, several machine learning techniques can be applied to generate a classification model. The terms and posts are arranged in a vector as exemplified in Table 2.

Table 2. Some part of word-post vector for MDD screening

Post ID	หรูหรา	เครียด	สถานที่	เพื่อนร่วมทาง	ทุกที่	คนสนิท	...	เกลียด	Label
1	0	0	0	1	1	0	...	0	N
2	1	3	2	0	0	1	...	0	P
3	0	0	0	0	0	0	...	3	P
4	1	0	0	0	0	0	...	0	N
...	...	...	...	...	...	...	...	...	...
1500	0	2	0	0	0	0	...	1	P

In the vector example, the horizontal first line represents all terms from the entire corpus while the vertical column represents posts. Meanwhile, the last column indicates the label as P (positive) or N (Negative). The number in a vector indicates frequency of term existing in a post. In this work, two techniques are used in comparison as follows.

- Support-Vector Machine (SVM) [16]: a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall [17].
- Naive Bayes classifier (NB) [18]: a conditional probability model using Bayes' theorem. NB model assigns class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set. [19]

The two techniques exploit the label of data for creating statistical model that separates incoming posts in a class of either positive (possible MDD) or negative (non-risk for MDD).

Experiments

1. Experiment Setting

A data set in this experiment was a collection of 1,500 Thai Facebook posts. The posts were anonymously collected in 10th December 2017. The posts were labelled with 'positive' or 'negative' for MDD screening by an MDD expert. Since the post was retrieved anonymously, personal attributes such as gender and age were not focused. For statistic, a ratio of positive and negative post was 50% each. The average number of words per post was 19.34 while the shortest post was 11 words and the longest post was 37 words.

Machine learning techniques used for classification of MDD screening were NB and SVM. Hyper parameters of the classification were set to default according to the Rapid Miner tool. The experiment was conducted using 5-fold cross validation [19] scheme. The procedure of 5-fold cross validation is as follows.

1) The data set is randomly shuffled.

2) The data set is separated into 5 groups equally as 300 posts per group.

3) For each group:

a) A data group is assigned as testing data set.

b) The remaining groups is used as a training data set for generating a screening model.

c) The model is evaluated using the left out testing data set.

d) The evaluation score is kept, and the model is discarded.

e) A testing data set is switched to another group and repeats step a-d until all groups are used as testing data set.

This procedure guarantees that each sample has the opportunity to be used in the testing data set for 1 time and used in the training data set for 4 times. The evaluation measurement in this work is precision (P), recall (R) and F-measure (F1) score. The P and R is calculated using confusion matrix as shown below.

True Positives (TP)	False Negatives (FN)
False Positives (FP)	True Negatives (TN)

The P score is obtained using (1), and the R score is calculated using (2). The F1 is then calculated using P score and R score as given in (3).

$$P = \frac{TP}{(TP + FP)} \tag{1}$$

$$R = \frac{TP}{(TP + FN)} \tag{2}$$

$$F1 = \frac{2(P \cdot R)}{(P + R)} \tag{3}$$

TP is counted if the classification result is matched to given label of the post in the testing data set. FP is counted in a case of the classified results given as positive but the label is negative while vice versa for FN.

2. Experimental Results and Discussion

Classification results of NB and SVM are given in Table 3.

Table 3. MDD screening results using NB and SVM classifier

Fold	Precision (P)		Recall (R)		F-measure (F1)	
	NB	SVM	NB	SVM	NB	SVM
1	0.94	**0.97**	**0.93**	0.91	0.94	0.94
2	0.91	**0.95**	0.90	**0.91**	0.91	**0.93**
3	0.95	**0.97**	**0.93**	0.92	0.94	0.94
4	0.97	**0.98**	**0.95**	0.92	**0.96**	0.95
5	0.93	**0.95**	0.92	0.92	0.93	0.93
Average	0.94	**0.96**	**0.93**	0.92	0.93	**0.94**

From the results, SVM classifier yielded the slightly better F-measure score for 0.01. Moreover, although the precision (P) scores from SVM were greater in every k-folds than those of NB classifier. However, the recall (R) scores of some folds, namely fold-1, fold-3 and fold-5 from NB classifier were slightly better. These results indicated that the SVM classifier returned more positive result more than those of NB, and the drawback of having more precision was the more chance for generating false-negative results. From overall, performance of both techniques was satisfied with 0.93 F1 score. Upon analysis of incorrect results, there is an issue from semantic ambiguity. Since most of Thai words are polysemous (one form with several different meanings), the words can represent different meanings in different context. This directly reduces the accuracy of the result and leads to incorrect screening. To prevent this issue in the future, a language model that considers sequence of words such as n-gram model should be applied for accounting more on contextual difference.

From the results, we can also learn that some Thai words are greatly related to positive screening result of MDD. The top 10 Thai words for positive MDD sign from the models are listed below in Figure 4. However, in practical, these words alone may not be too much informative for MDD sign since the contexts play more crucial role to either soften or strengthen the mood of the post. Thus, the more these words are used together, the more possible the poster may show the sign of MDD.

• ไร้ค่า	• ตาย	• เครียด	• เบื่อ	• เกลียด
• เหงา	• พอกันที	• ทำร้าย	• ไม่สน	• โดดเดี่ยว

Figure 4. The top-rank 10 Thai words found in MDD screening classifier model

Conclusions and Future Works

This work presents a method for screening major depressive disorder (MDD) from Thai posts in social media using an automatic text-based classification. The machine-learning techniques in this work are support vector machine (SVM) and Naïve Bayes (NB). The posts from Facebook are used as data set labeled by a mental disorder expert to split between positive risk and negative risk. The supervised data are thus used for classification of MDD screening. The evaluation results of 5-fold validation showed that SVM generated a classification model of 0.94 F1 score while a model from NB obtained 0.93 F1 score. We also found the top-rank 10 Thai words related to positive MDD risk from the models. To improve the work, Thai language model of surrounding words such as n-gram should be applied in the future since consecutive words (context) has a great effect on the entire meaning of words. Moreover, an extension of the framework for detection of MDD according to MDD 9Q-Questionnaire will be researched to cover all diagnosis processes. However, text-classification alone may not be sufficient since the content of the 9Q also involves in behavior changes.

References

[1] American Psychiatric Association (2013). Diagnostic and Statistical Manual of Mental Disorders (5thed). Washington, DC: American Psychiatric Association.

[2] Kessler RC, Berglund PA, Bruce ML, et al (2001). The Prevalence and correlates of untreated serious mental illness. Health Serv Res. (pp.987–1007).

[3] Chong SA, Abdin E, Vaingankar JA, et al (2012). A Population-based survey of mental disorders in Singapore. Ann Acad Med Singapore. (pp.49–66).

[4] Moussavi S, Chatterji S, Verdes E, et al (2007). Depression, Chronic diseases, and decrements in health: results from the World Health Surveys. Lancet. (pp.851–8).

[5] Depression and suicide assessment form (Including 2q 9q and 8q assessment). DEPARTMENT OF MENTAL HEALTH Ministry of Public Health. (in Thai) Retrieved November 18, 2018, from: https://www.dmh.go.th/test/download/view.asp?id=22.

[6] Benjamas Prukkanone, Theo Vos, Melanie Bertram, Stephen Lim (2012). Cost-Effectiveness Analysis for Antidepressants and Cognitive Behavioral Therapy for Major Depression in Thailand. Journal of International Society for Pharmacoeconomics and Outcomes Research. 15(1), (pp. S3–S8).

[7] Burcusa SL, Iacono WG (2007). Risk for recurrence in depression. (pp.959–85). Clin Psychol Rev.

[8] Halfin A (2007). Depression: the benefits of early and Appropriate treatment. Am J Manag Care. (pp.92–7).

[9] Vioulès, M. J., Moulahi, B., Azé, J., & Bringay, S. (2018). Detection of suicide-related posts in Twitter data streams. IBM Journal of Research and Development. 62(1), (pp.7-1).

[10] Chandler, V. (2018). Google and suicides: what can we learn about the use of internet to prevent suicides?. Public health. 154, (pp.144-150).

[11] Colombo, G. B., Burnap, P., Hodorog, A., & Scourfield, J. (2016). Analyzing the connectivity and communication of suicidal users on twitter. Computer communications. 73, (pp.291-300).

[12] Coppersmith, G., Leary, R., Crutchley, P., & Fine, A. (2018). Natural language processing of social media as screening for suicide risk. Biomedical informatics insights. 10, 1178222618792860.

[13] O'Dea, B., Wan, S., Batterham, P. J., Calear, A. L., Paris, C., & Christensen, H. (2015). Detecting suicidality on Twitter. Internet Interventions. 2(2), (pp.183-188).

[14] Desmet, B. and Hoste, V., 2018. Online suicide prevention through optimised text classification. Information Sciences, 439, (pp.61-78).

[15] Lexto, available online at https://github.com/telember/lexto

[16] Cortes, Corinna; Vapnik, Vladimir N. (1995). "Support-Vector networks". Machine Learning. (pp. 273–297).

[17] William H.; Teukolsky, Saul A.; Vetterling, William T.;Flannery, Brian P. (2007). "Section 16.5. Support Vector Machines". Numerical Recipes: The Art of Scientific Computing (3rd ed.). New York: Cambridge University Press.

[18] Rish, I., 2001, August. An empirical study of the naive Bayes classifier. In IJCAI 2001 workshop on empirical methods in artificial intelligence (Vol. 3, No. 22, pp. 41-46). New York: IBM. Retrieved October 11, 2018, from: https://github.com/telember/lexto

[19] Russell, S. and Norvig, P., 2003. Artificial intelligence: a modern approach. 2nd. Prentice Hall.