Towards Suicide Prevention:

Early detection of depression on social media

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EXCELENCIA MARÍA DE MAEZTU

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Motivation

800,000
people die due to suicide every year

40
seconds a new death by suicide

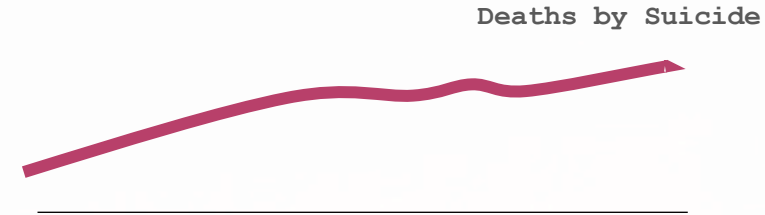
2nd
leading cause of death among 15–29-year-olds

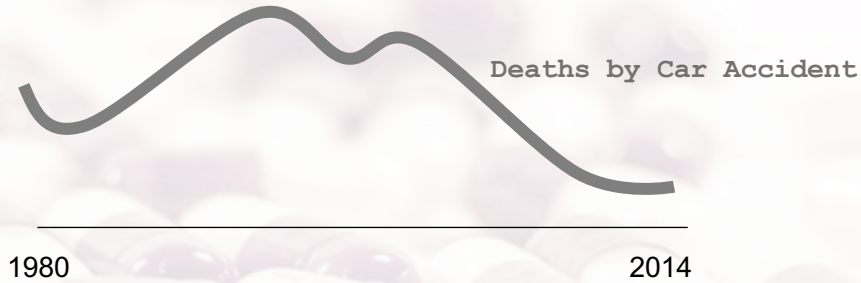
78%
global suicides occur in low- and middle-income countries

World Health Organization

Motivation


Deaths by Suicide
3910
Spain, 2014
Deaths by Car accident
1873


Deaths by Suicide
1980
2014


Deaths by Car Accident
1980
2014

Motivation

90% of suicides can be attributed to mental illnesses

Depression is the leading one

Background

Social media and depression

Depressive Moods of Users Portrayed in Twitter (Park,2012)

- People that suffers from mental disease tend to post more about it.

A content analysis of depression-related Tweets (Cavazos-Rehg, 2016)

- Tweet content could help to identify depression

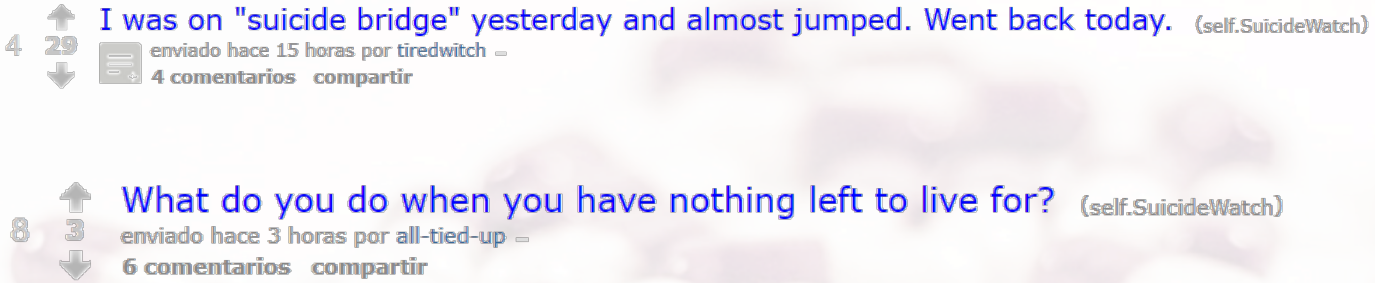
Social media as a measurement tool of depression in populations (De Choudhury, 2013)

…

Background

Early Risk Detection

A Test Collection for Research on Depression and Language Use (Losada, 2016)



Background

Early Risk Detection

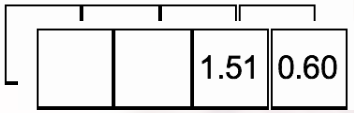
A Test Collection for Research on Depression and Language Use (Losada, 2016)

Messages from depressive users

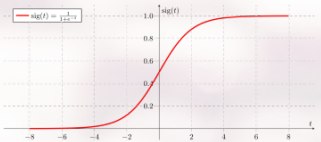
reddit

Messages from NON-depressive users

TF*IDF vectorization



Logistic Regression



Evaluation

- Precision
- Recall
- F-measure
- ERDE

Background

Early Risk Detection

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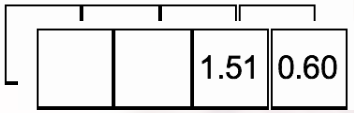
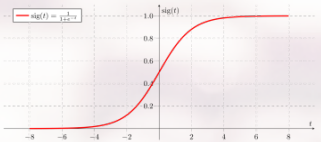


Logistic Regression



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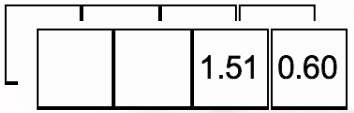
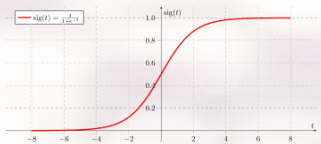


Logistic Regression



Evaluation

- Precision
- Recall
- F-measure
- ERDE

Proposal

Propose a *new model* for early-risk detection of depression by:

- **Extracting** text **features** in a more accurate way.

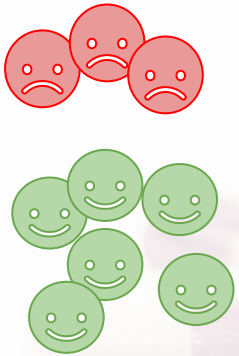
Proposal

Propose a *new model* for early-risk detection of depression by:

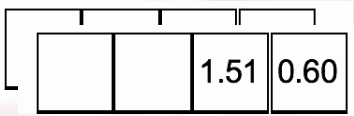
- **Extracting** text **features** in a more accurate way.

+ Dimensionality Reduction
+ Sentiment Analysis

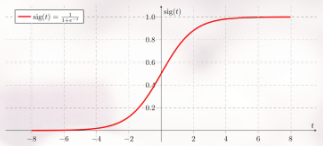
reddit



TF*IDF vectorization



Logistic Regression



Evaluation

- Precision
- Recall
- F-measure
- ERDE

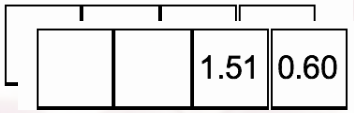
Proposal

Propose a *new model* for early-risk detection of depression by:

- **Exploring** the behaviour of **classic** and **modern** machine learning techniques
- Studying if **genetic algorithms** can help in detecting depression in social media

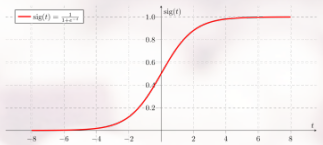
reddit

TF*IDF vectorization



+ KNN, SVM, RF, Soft-Voting
+ Parameter optimization (genetic alg.)

Logistic Regression



Evaluation

- Precision
- Recall
- F-measure
- ERDE

Dataset

A Test Collection for Research on Depression and Language Use (Losada, 2016)

125 depressed users

752 non-depressed users

messages/user: 10 - 2000 (average = 607)

Dataset

- **Training set:**

83 users

403 users

messages/user: 10 - 2000 (average = 607)

- **Evaluation set:**

52 users

349 users

Data pre-processing (1/3)

TF*IDF vectorization

$$w_{i,j} = \mathrm{tf}_{i,j} \cdot \log \frac{N}{n_i}$$

$w_{i,j}$ weight assigned to term *i* in document *j*

$\mathrm{tf}_{i,j}$ number of occurrence of term *i* in document *j*

N number of documents in entire collection

n_i number of documents with term *i*

$W_{i,j}$

	Message 1	2	3	4
complicated			1.51	0.60
sadness	0.50	0.13	0.38	
me	0.63		0.50	0.38
great				
interesting		0.60		
depression	0.90		2.11	
boyfriend		0.75	0.13	0.50
…	1.20			

Data pre-processing (1/3)

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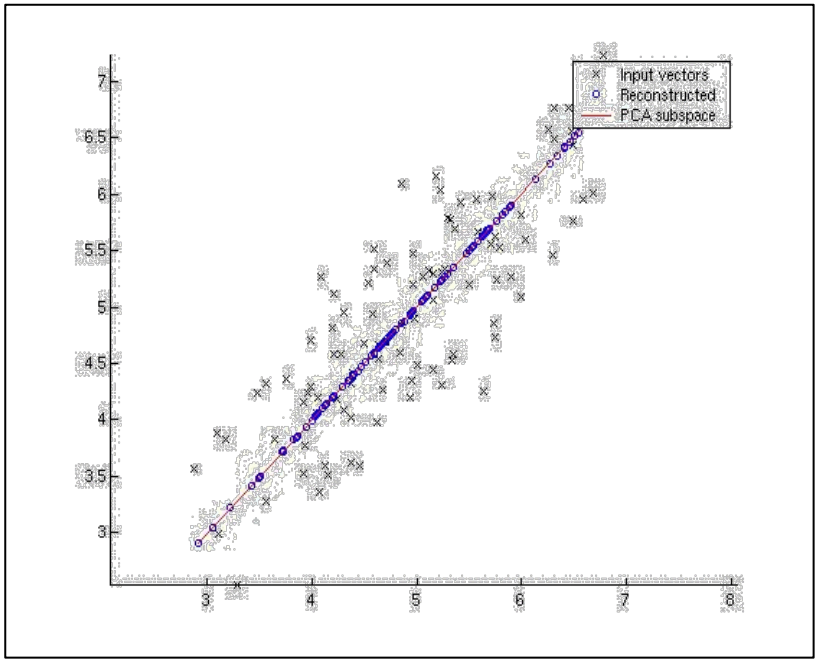
great				
interesting		0.60		
depression	0.90		2.11	
boyfriend		0.75	0.13	0.50
…	1.20			

Almost 13k features!!

Data pre-processing (2/3)

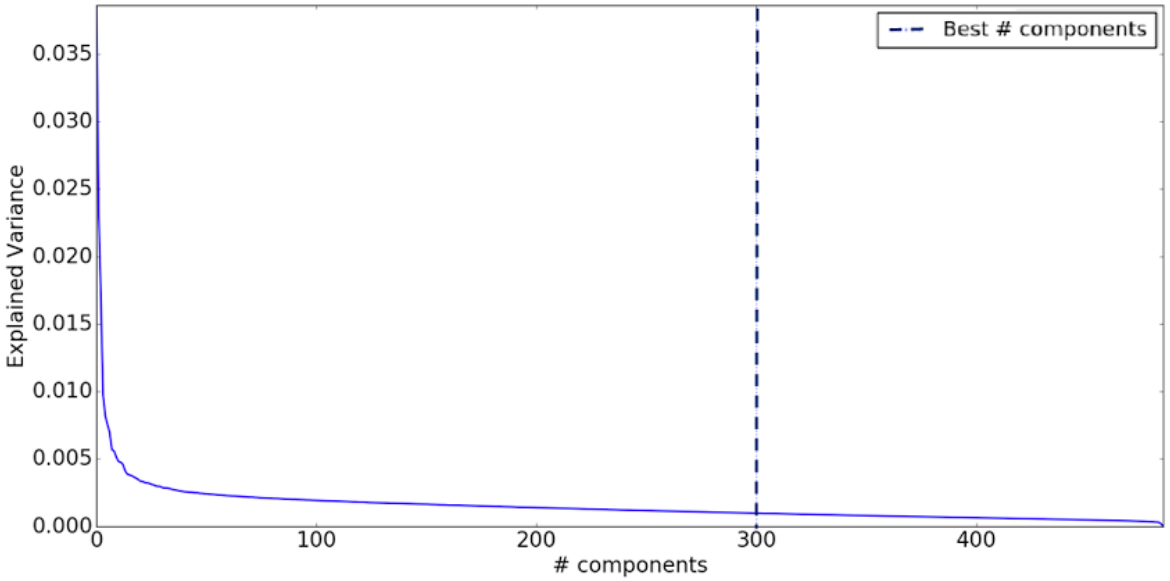
Principal Component Analysis (PCA)



Principal Component Analysis used to find the 1D representation of the input 2D data with the minimal reconstruction error.

Data pre-processing (2/3)

Principal Component Analysis (PCA)



Almost 13k features!!

300

Data pre-processing (3/3)

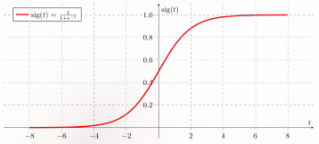
Adding extra features

- Valence Aware Dictionary and sEntiment Reasoner (VADER)

```
Make sure you :) or :D today!---------------------------------- {'neg': 0.0, 'neu': 0.294, 'pos': 0.706}
Today SUX!----------------------------------------------------- {'neg': 0.779, 'neu': 0.221, 'pos': 0.0}
Today only kinda sux! But I'll get by, lol----------------------- {'neg': 0.179, 'neu': 0.569, 'pos': 0.251}
```

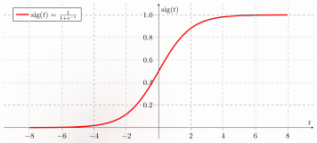
Machine learning algorithms

Logistic Regression:

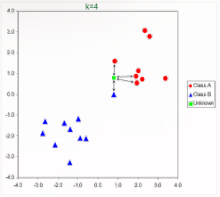


Machine learning algorithms

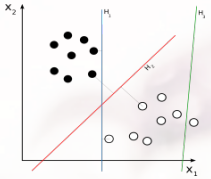
Logistic Regression:



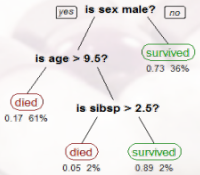
K - Nearest Neighbours:



Support Vector Machine:

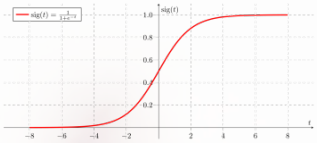


Random Forests:



Machine learning algorithms

Logistic Regression:



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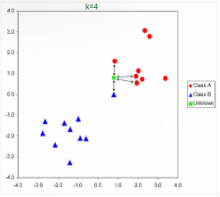

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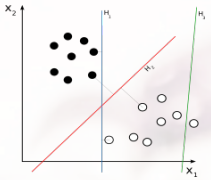

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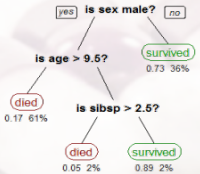
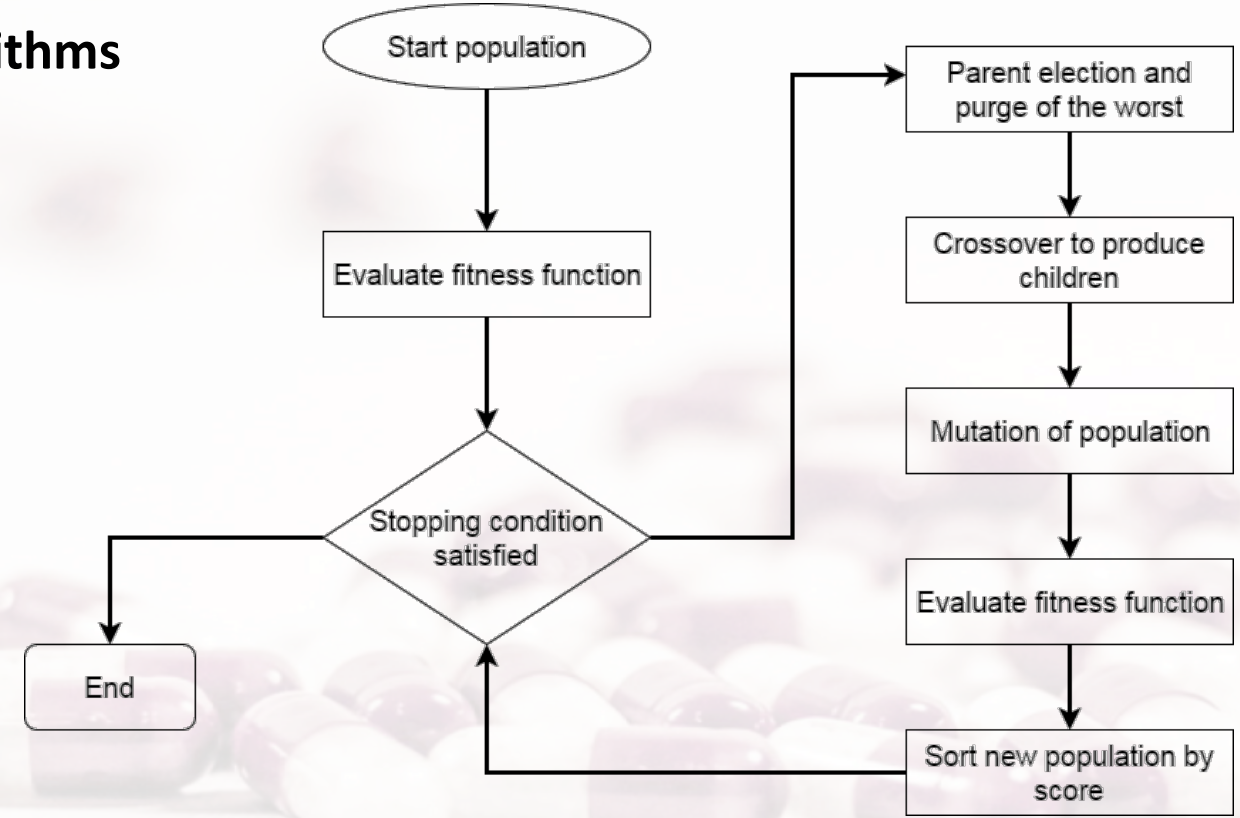


Voting algorithm

Parameter optimization (for the voting algorithm)

Genetic algorithms

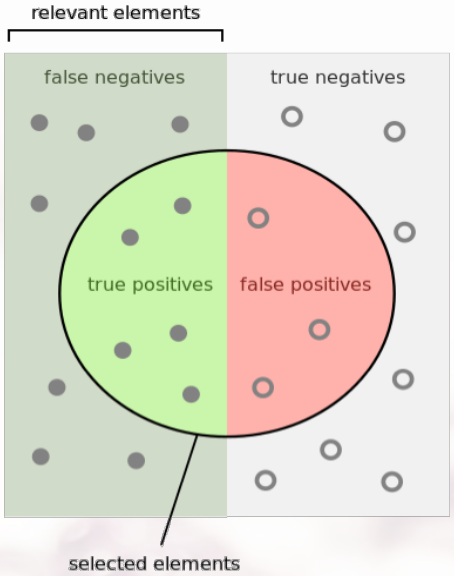


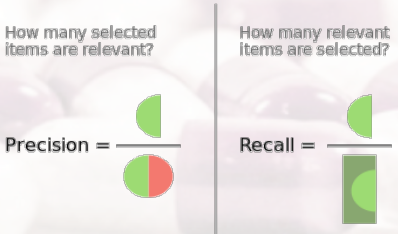
Evaluation

Precision

Recall

F-measure



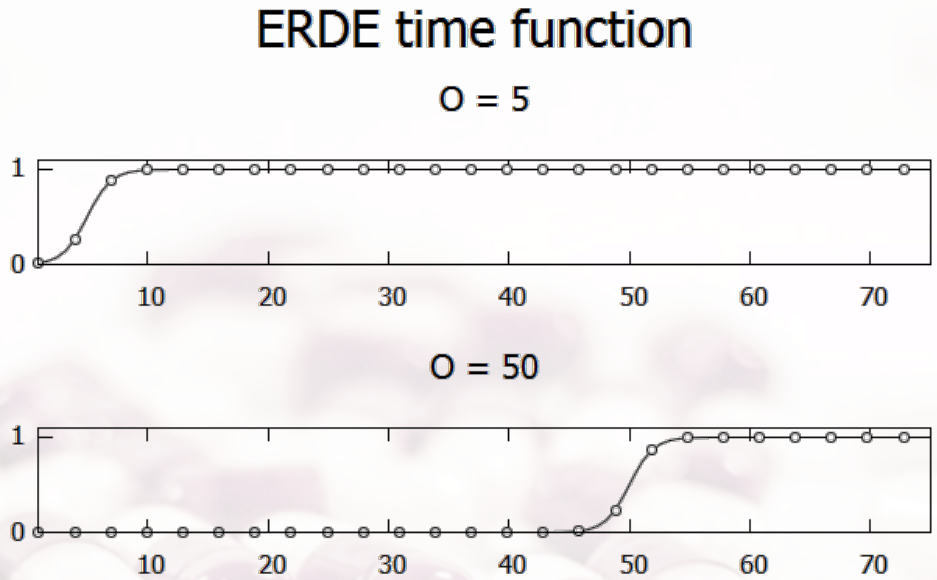


Evaluation

Early Risk Detection Error

$$ERDE_O(k) = \begin{cases} c_{fp} & if\ FP \\ c_{fn} & if\ FN \\ f_O(k)\ c_{tp} & if\ TP \\ 0 & if\ TN \end{cases}$$

$$f_O(k) = 1 - \frac{1}{1 + e^{k-O}}$$



Experimental pipeline

1. Determine **baselines**
2. Use different **ML methods** and build a Soft-Voting Algorithm
3. Refine **features**:
    a. dimensionality reduction (**PCA**)
    b. adding new features (**VADER**)
4. Parameter optimization through **Genetic Algorithms**

Baselines

		ERDE5	ERDE50	P	R	F1
Minority		0.113	0.113	0.13	**1.00**	0.30
Random		0.130	0.130	0.11	0.46	0.18
First	10	0.100	0.098	**0.63**	0.29	0.39
	50	0.083	0.081	0.57	0.46	0.51
	100	0.074	0.072	0.55	0.56	0.55
Logistic Regression	0.5	**0.058**	**0.052**	0.41	0.77	0.54
	0.75	0.072	0.069	0.61	0.54	**0.57**

Choosing the best baseline from the ones proposed in:

A Test Collection for Research on Depression and Language Use (Losada, 2016)

B

Learning Algorithm

		ERDE5	ERDE50	P	R	F1
Logistic Regression	0.5	**0.058**	**0.052**	0.41	0.77	0.54
Support Vector Machines	0.5	0.070	0.065	0.58	0.58	0.58
	0.75	0.091	0.089	0.78	0.35	0.48
Random Forest	0.5	0.083	0.075	0.22	0.83	0.35
	0.75	0.111	0.110	0.82	0.17	0.29
K - Nearest Neighbours	0.5	0.071	0.066	0.23	**0.88**	0.37
	0.75	0.077	0.072	0.59	0.50	0.54
Voting Algorithm	0.5	**0.058**	0.053	0.53	0.69	**0.60**
	0.75	0.091	0.088	**0.86**	0.35	0.49

TF-IDF features (almost 13k)

		ERDE5	ERDE50	P	R	F1
B	Logistic Regression	0.058	**0.052**	0.41	0.77	0.54
LA	Voting Algorithm	0.058	0.053	0.53	0.69	0.60
LA + PCA	Logistic Regression	0.065	0.060	0.49	0.65	0.56
	K - Nearest Neighbours	**0.057**	**0.052**	0.37	0.79	0.51
	Support Vector Machine	0.069	0.064	**0.59**	0.58	0.58
	Random Forest	0.106	0.099	0.15	**0.96**	0.26
	Voting Algorithm	0.062	0.056	0.58	0.65	**0.61**

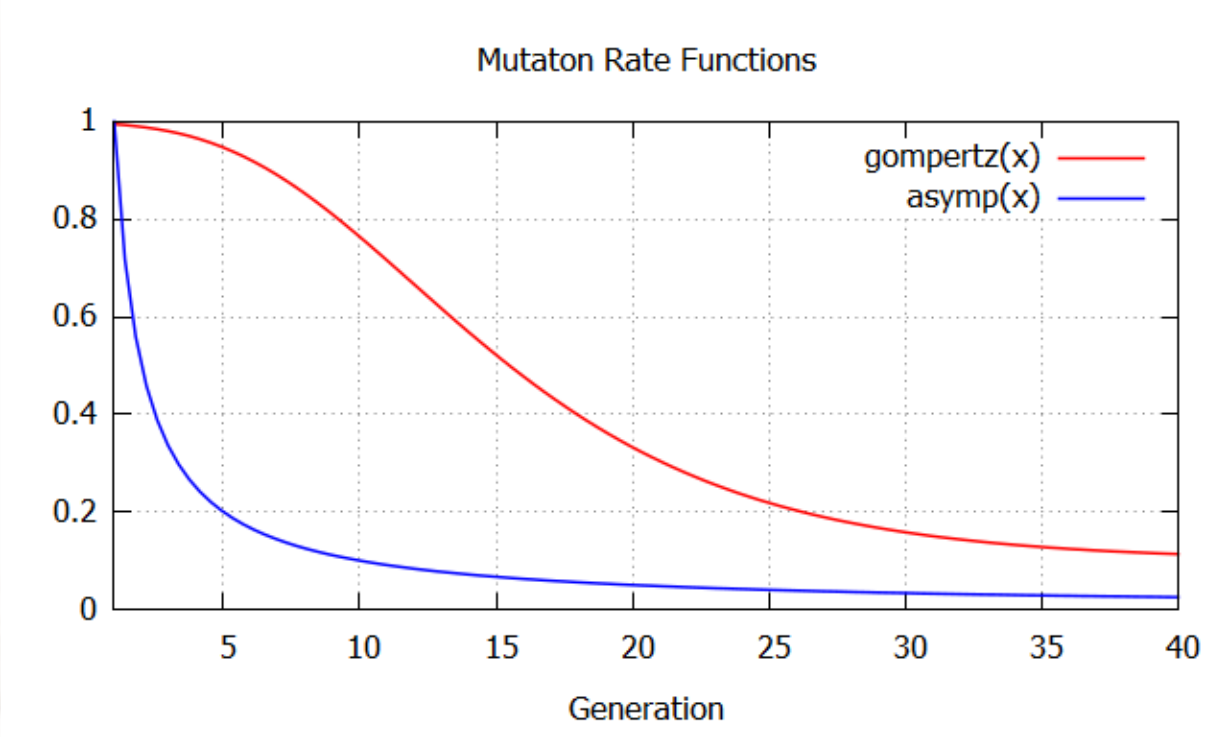
Reduced features (300)

		ERDE5	ERDE50	P	R	F1
B	Logistic Regression	0.058	**0.052**	0.41	0.77	0.54
LA	Voting Algorithm	0.058	0.053	0.50	0.69	0.60
LA + PCA	K - Nearest Neighbours	**0.057**	**0.052**	0.37	0.79	0.51
LA + PCA	Voting Algorithm	0.062	0.056	**0.58**	0.65	**0.61**
LA + PCA + VADER	Logistic Regression	0.063	0.058	0.49	0.67	0.57
LA + PCA + VADER	K - Nearest Neighbours	0.058	0.053	0.38	0.77	0.51
LA + PCA + VADER	Support Vector Machine	0.072	0.066	**0.58**	0.56	0.57
LA + PCA + VADER	Random Forest	0.085	0.078	0.19	**0.96**	0.31
LA + PCA + VADER	Voting Algorithm	0.061	0.056	0.53	0.67	0.59

Reduced features (300) + sentiment features (VADER)

Genetic Algorithms

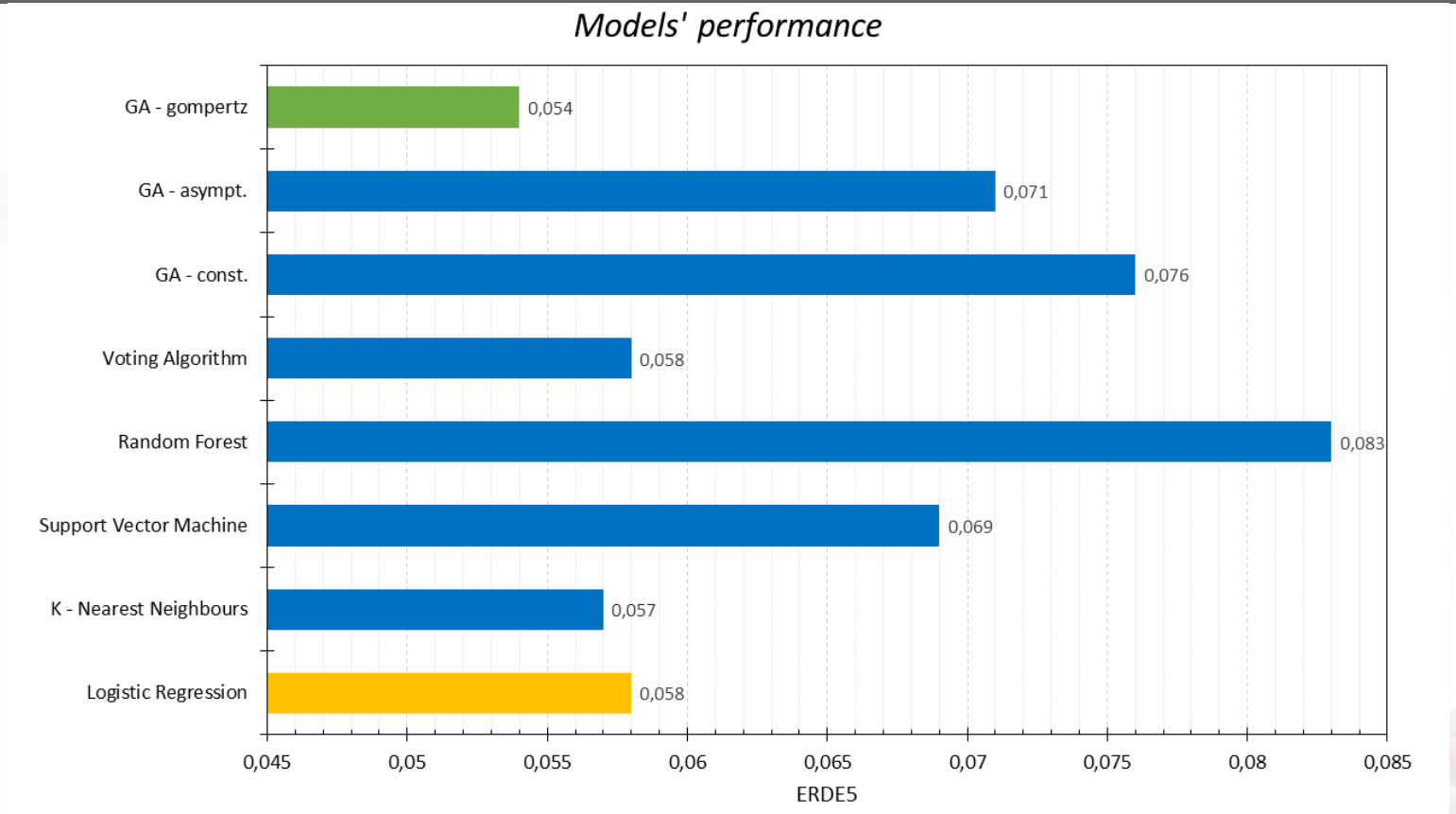
Mutation Rate functions:



		ERDE5	ERDE50	P	R	F1
B	Logistic Regression	0.058	**0.052**	0.41	0.77	0.54
LA	Voting Algorithm	0.058	0.053	0.50	0.69	0.60
LA + PCA	K - Nearest Neighbours	**0.057**	**0.052**	0.37	**0.79**	0.51
	Voting Algorithm	0.062	0.056	**0.58**	0.65	**0.61**
L+P+ V	Voting Algorithm	0.061	0.056	0.53	0.67	0.59
GA+ PCA+VADE	Constant	0.076	0.071	0.54	0.51	0.52
	Asymptotic	0.071	0.067	0.52	0.58	0.55
	Gompertz	0.069	0.063	0.53	0.60	0.56

		ERDE5	ERDE50	P	R	F1
B	Logistic Regression	0.058	0.052	0.41	0.77	0.54
LA	Voting Algorithm	0.058	0.053	0.50	0.69	0.60
LA + PCA	K - Nearest Neighbours	0.057	0.052	0.37	**0.79**	0.51
	Voting Algorithm	0.062	0.056	**0.58**	0.65	**0.61**
L+P+V	Voting Algorithm	0.061	0.056	0.53	0.67	0.59
GA+ PCA+VADE	Constant	0.076	0.071	0.54	0.51	0.52
	Asymptotic	0.071	0.067	0.52	0.58	0.55
	Gompertz	0.069	0.063	0.53	0.60	0.56
GA	Gompertz + PCA	0.061	0.055	0.53	0.67	0.59
	Gompertz + VADER	**0.054**	**0.048**	0.45	0.77	0.57

Summary


Models' performance
GA - gompertz
0,054
GA - asympt.
0,071
GA - const.
0,076
Voting Algorithm
0,058
Random Forest
0,083
Support Vector Machine
0,069
K - Nearest Neighbours
0,057
Logistic Regression
0,058
0,045
0,05
0,055
0,06
0,065
0,07
0,075
0,08
0,085
ERDE5

Conclusions

- This paper investigates how to better detect early risk of depression on social media, by optimizing time-aware classification measures: ERDE5 and ERDE50.
- We have applied different learning algorithms, and combinations of them.
- Other techniques such as dimensionality reduction and text polarity have been studied.
- We have provided further evidence for the benefit of applying genetic algorithms and text polarity (16.7% improvement regarding the baseline).

Future work

- Applying more accurate text sentiment classification to get a better representation of the input features.
- Exploring other pre-processing methods in order to reduce dimensionality.
- Trying the same approach with other datasets.

References

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