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Algorithms of Machine Learning in the Recognition of Trolls in the Online Space

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Antisocial Content in Online Discussions

- Positive influence of social media: connectivity, learning, access to information, etc.
- While most users tend to accept social norms, others engage in antisocial behavior negatively affecting the rest of the community
- Negative impact of social media: **trolling, fake news, hoaxes, cyber bullying, harassment, flaming, rumors, hate speech, ...**
- Some forms of regulation are in demand
- Focus on **detecting trolls** in contrast to credible contributors

Trolling

- Concept „Troll“ is an Internet slang term – an individual attempting to incite conflict by publishing **offensive**, **inflammatory**, **provocative** or **irrelevant** posts.
- Impact on a society is dangerous because of an intent:
  - to over-throw the debate, to reduce its substance,
  - to **spread of a hatred** among the discussants or causing conflicts in provocative topics
  - to **change and manipulate the opinion** of a society on some important topics (votes, politicians, health...)
  - motivation can also be financial, when trolls are members of the so-called „**troll farms**” - organized groups that are paid to publish troll’s posts, propaganda, or fake news
  - chatbots, which can pass the Turing test can have the forms of so-called “trollbots”
- Trolling is becoming more and more widespread - it is important to propose means for the automatic detection of this unhealthy web phenomena

Used Machine Learning Methods

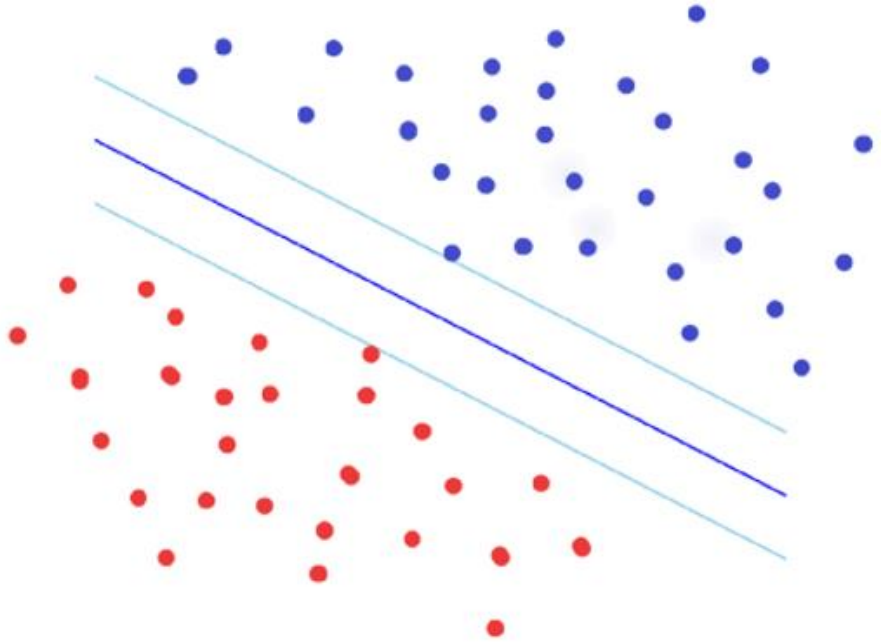
- Support Vector Machine (SVM)
  - can work with a lager attribute space than other methods (suitable for text data processing)
- Multinomial Naive Bayes Classifier (MNB)
  - suitable for attributes with discrete values
- Logistic Regression (LR)
  - only one method of regression analysis, which can be used for classification

Input for ML is a labeled training set

Output of ML is a model for final classification of an unknown contributor to troll / non-troll class, for recognition of trolls in online communities

Support Vector Machine

- SVM separates the sample space into two or more classes with the **widest margin possible**
- Originally a linear classifier
- Perform non-linear classification and based on a kernel function
- Kernel is a method which maps features into a higher dimensional space
- Only nearest points to the separating hyper-plane determine margin - they are called support vectors
- To **maximize the margin** is the primary problem of SVM



Multinomial Naive Bayes Classifier

- The probabilistic classifier based on Bayes' theorem:

$$P(A/B) = \frac{P(A)P(B/A)}{P(B)}$$

- *P(B)* can be an estimated constant β^{-1} calculated from the dataset
- Naive Bayes Classifier

$$P(y_j/x_1, \dots, x_n) = \beta P(y_j) \prod_{i=1}^{n} P(x_i/y_j)$$

- y_j is a learning class (troll, non-troll)
- x_i are nominal attributes of troll's posting
- Naive Bayes is often applied as a baseline for text classification

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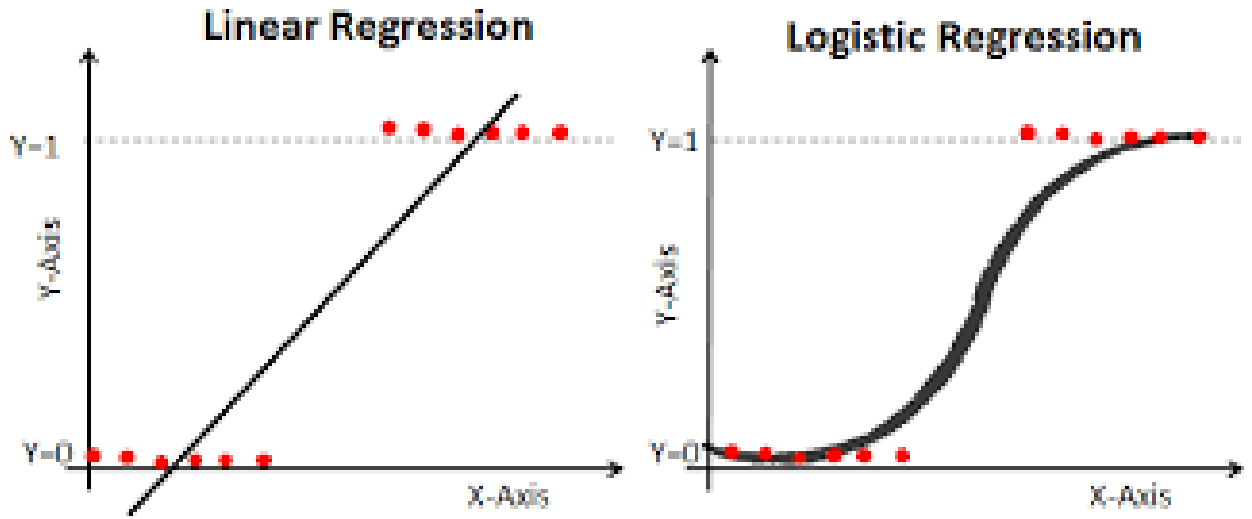
Logistic Regression

- Statistical technique to estimate parameters of a logistic model
- Linear combinations of independent variables are transformed using a specific type of logistic function - sigmoid function



- Computes the probability of a class - when the probability is greater than the given threshold, the example is classified to the class

Data Description

The service Export Comments was used to obtain data from Facebook

- the data are related to the SARS-Cov2 coronavirus pandemic in Slovakia
- comments were downloaded from the discussions on the Facebook profiles of the internet news portals “aktuality.sk” and “dennikn.sk” (portals with a significant impact)
- the comments were downloaded two days after the publication of the given paper (to ensure a certain consistency and authenticity of the data)
- we focused only on posts with the number of comments higher than eighty (since the probability of the occurrence of a troll increases with the number of reactions)
- data were downloaded for a period of one month since the outbreak of the pandemic in Slovakia

Data Description

The extracted text data were transformed to a training set with following attributes:

- Number of characters in the post
- Words count
- Average length of words
- Number of capital letters in the text
- Number of numbers in the text
- Number of “I like”

Another useful information was a measure of negativity, provocativeness, or hater in the comments of contributor:

- Positive comment
- Neutral comment
- Negative comment
- Provocative comment
- Strongly provocative
- Hateful comment.

Models Building

- The **Sci-kit package** was used for models training (SVM can work with several types of Kernel function.)

- Feature representation in the form of selected attributes
- Feature representation **enriched** by weights of words from comments of a contributor when **TF-IDF** weighting was applied

- **SVM, MNB and LR** models for recognition of troll authors were learned and **tested**

Models Testing

Results of testing machine learning models (SVM, MNB and LR) with and without the enrichment of data using TF-IDF weighting scheme

without TF-IDF		Precision	Recall	F1-rate
SVM	troll	**1,00**	0,08	0,15
	non-troll	0,56	**1,00**	0,72
MNB	troll	0,63	**0,92**	0,75
	non-troll	**0,89**	0,53	0,67
LR	troll	0,67	**0,89**	0,76
	non-troll	**0,90**	0,69	0,78

with TF-IDF		Precision	Recall	F1-rate
SVM	troll	0,36	0,38	0,37
	non-troll	0,43	0,40	0,41
MNB	troll	0,60	**0,92**	0,73
	non-troll	0,88	0,47	0,61
LR	troll	0,67	0,77	0,72
	non-troll	0,75	0,67	0,71

Conclusions

- **To identify a troll contributor**, 3 machine learning classifiers were tested
  - **SVM** model had the best results according to
    - Precision for troll recognition (FP)
    - Recall for non-troll recognition (FN)
  - **MNB** model on the contrary had the best results according to
    - Recall for troll recognition (FN)
    - Precision for non-troll recognition (FP)
  - Results of **LR** model was similar than MNB model but a little worse
- Enrichment of feature representation using TF-IDF was not beneficial
- For future, we would like to include some specific methods of machine learning with the potential to improve results
  - ensemble learning, deep neural networks learning and unsupervised learning

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THANK YOU FOR YOUR ATTENTION