Rumour As an Anomaly:

Rumour Detection with One-Class Classification

Amir Ebrahimi Fard, Majid Mohammadi,
Scott Cunningham, and Bartel van de Walle

IEEE TEMS
Technology & Engineering Management Society

ICE

TU Delft

Overview

- Context and Problem statement
- Related work
- Rumour as an anomaly
- Data
- Features
- Algorithm
- Experimental setup
- Findings
- Future directions

TU Delft

Context and Problem Statement

- Rumour definition
- Ancient phenomenon
- Role of social networks
- Consequences
- Take an action
- Solutions

We would like to identify rumours in online social networks using artificial intelligence

Background and Related Work

- The main contributions in computational rumour detection:
  - Data
  - Features
  - Algorithm
  - Pattern

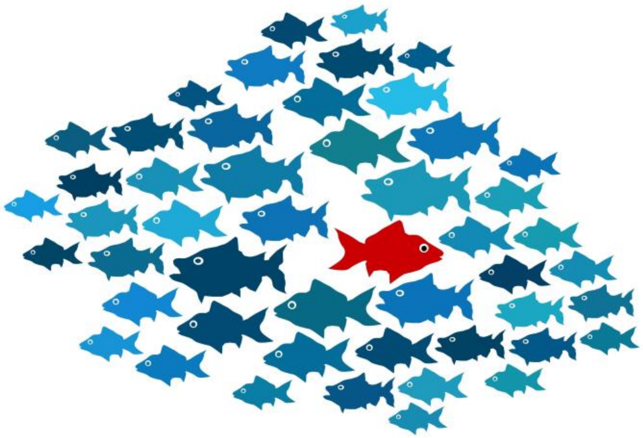
Our approach is called anomaly detection

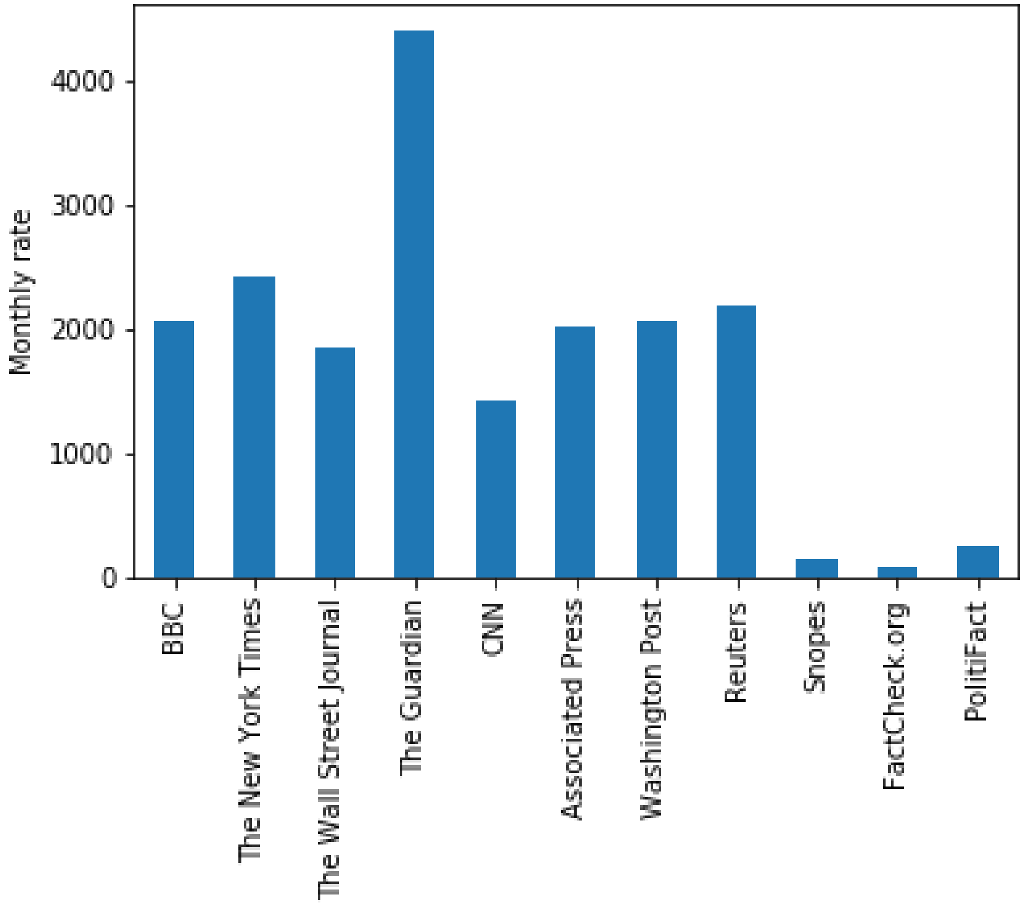
Rumour as an Anomaly

- What is an anomaly?

Anomaly is an abnormality in the normal flow. In the anomaly detection literature, we consider something as an anomaly if it happens rarely

- In literature rumour is already addressed as a rare phenomenon in comparison with news



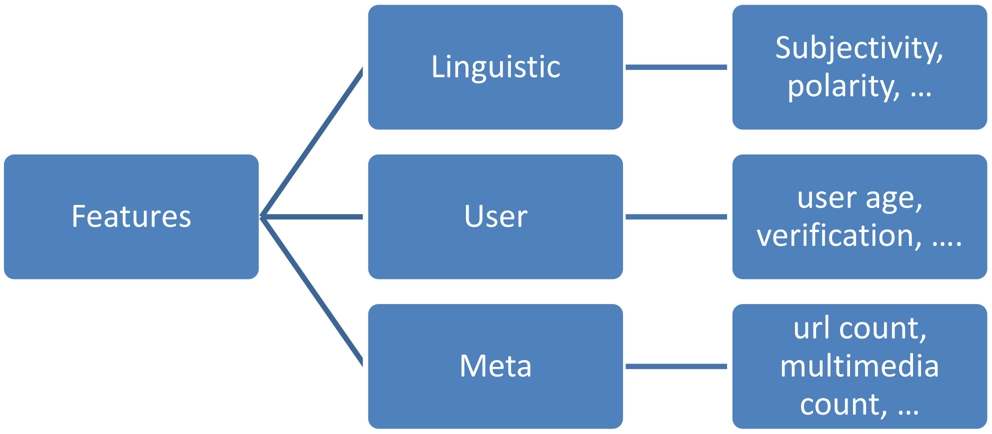


- The rate of news production is much higher than rumour production

Data and Features

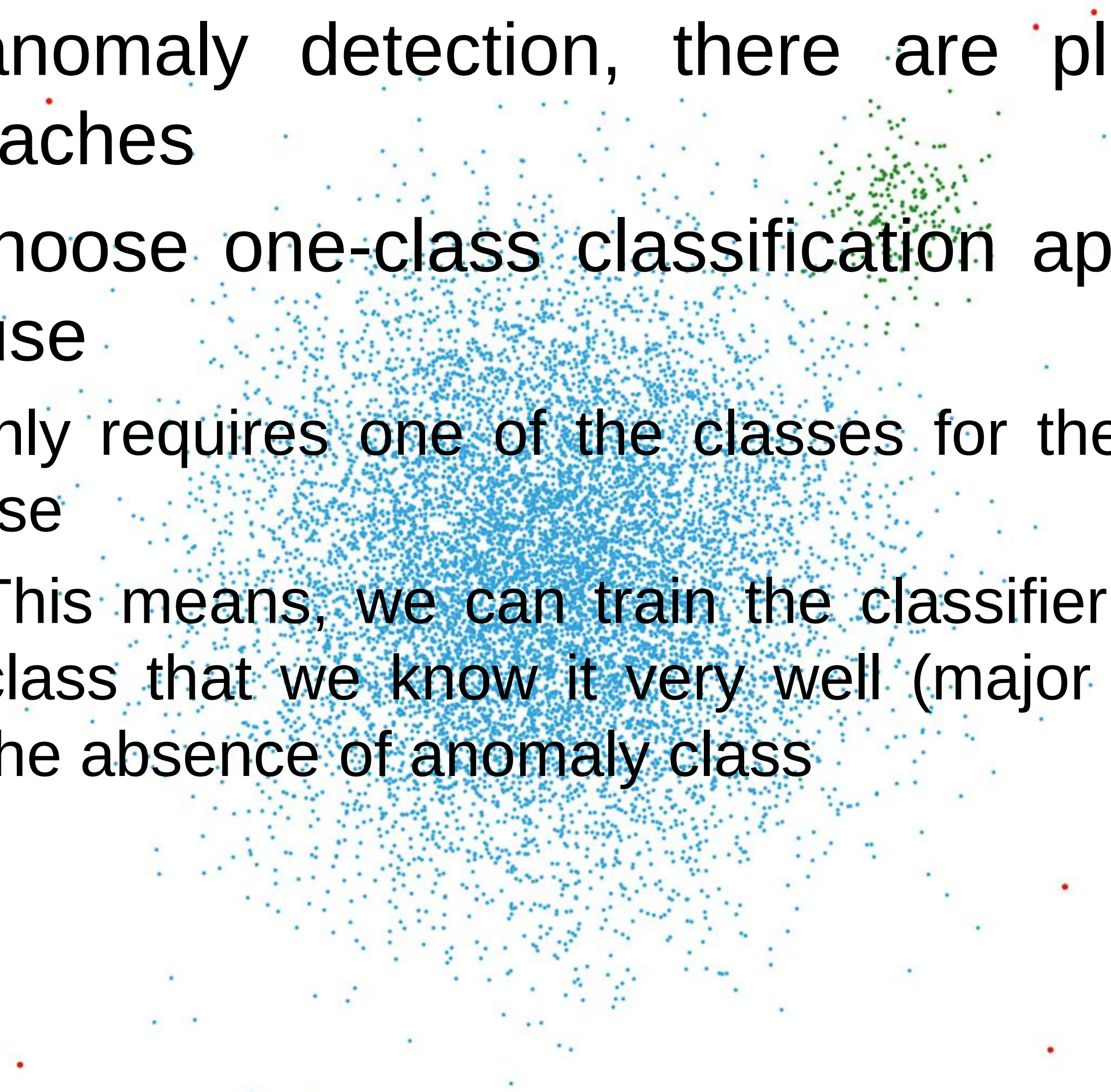
- Data
  - Available datasets from Zubiaga et al. [1]

- Features

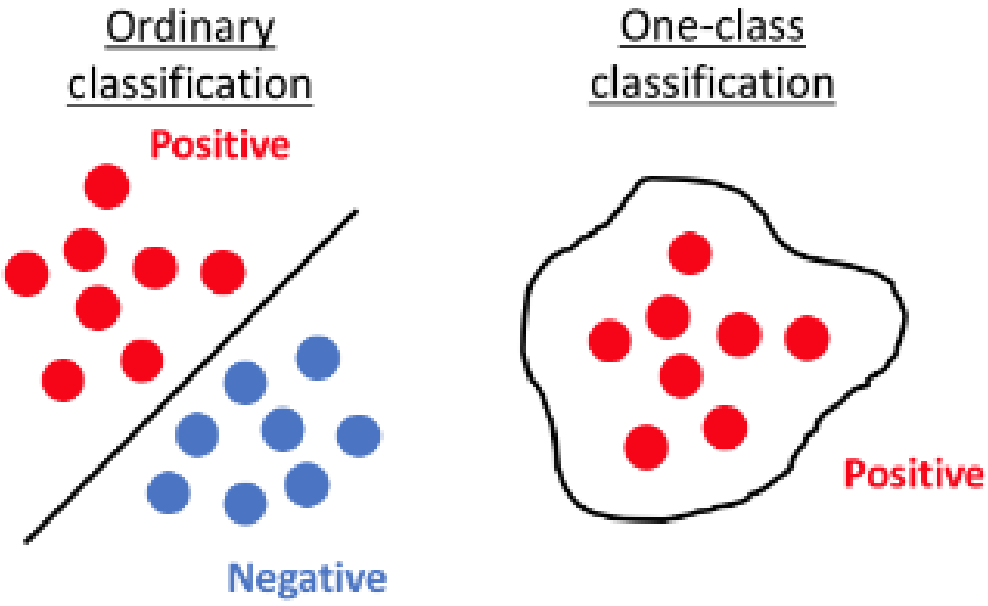


Algorithm

- For anomaly detection, there are plenty of approaches
- We choose one-class classification approach, because
  - It only requires one of the classes for the training phase
    - This means, we can train the classifier with the class that we know it very well (major class) in the absence of anomaly class



Algorithm

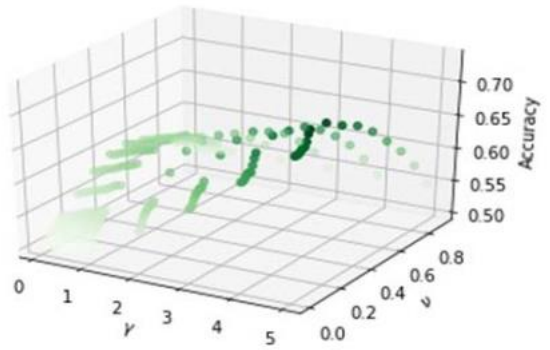

Ordinary classification
Positive
Negative
One-class classification
Positive

Experimental Setup

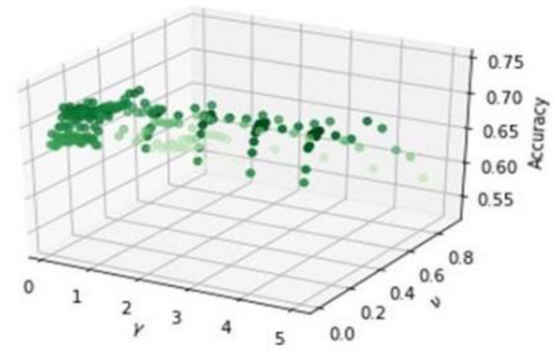
- We used One-Class Support Vector Machine (OCSVM) [2]
- We used k-fold cross validation (k=3)
- We report model performance using accuracy and F-score regarding different feature groups and different combinations of hyperparameters

Findings

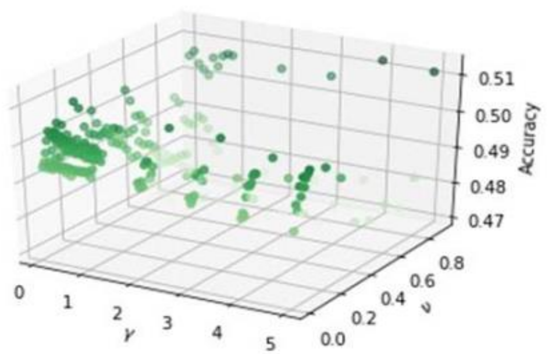
- Accuracy



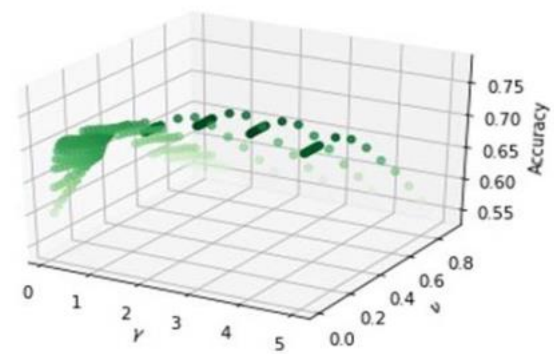
(a) Linguistic features



(b) Message features



(c) User features

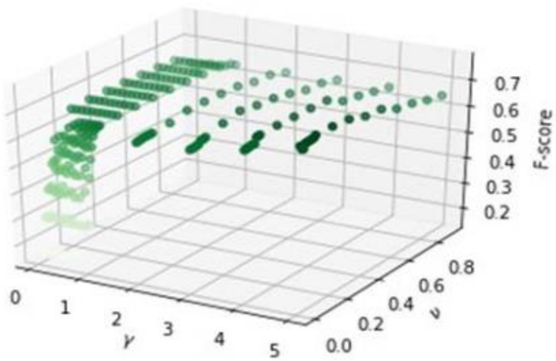


(d) Total features

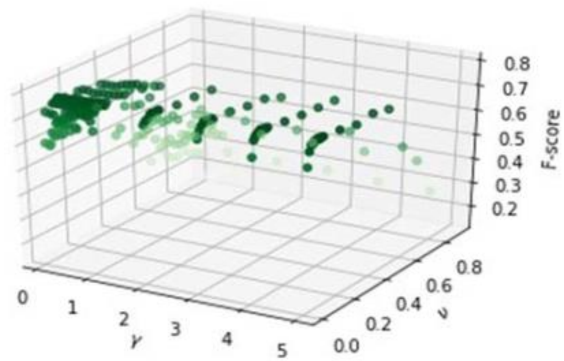
TU Delft

Findings

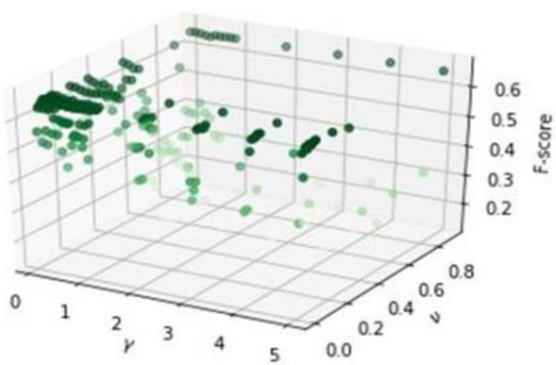
- F-score



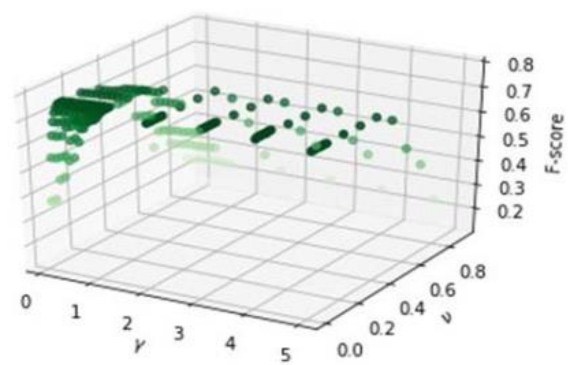
(a) Linguistic features



(b) Message features

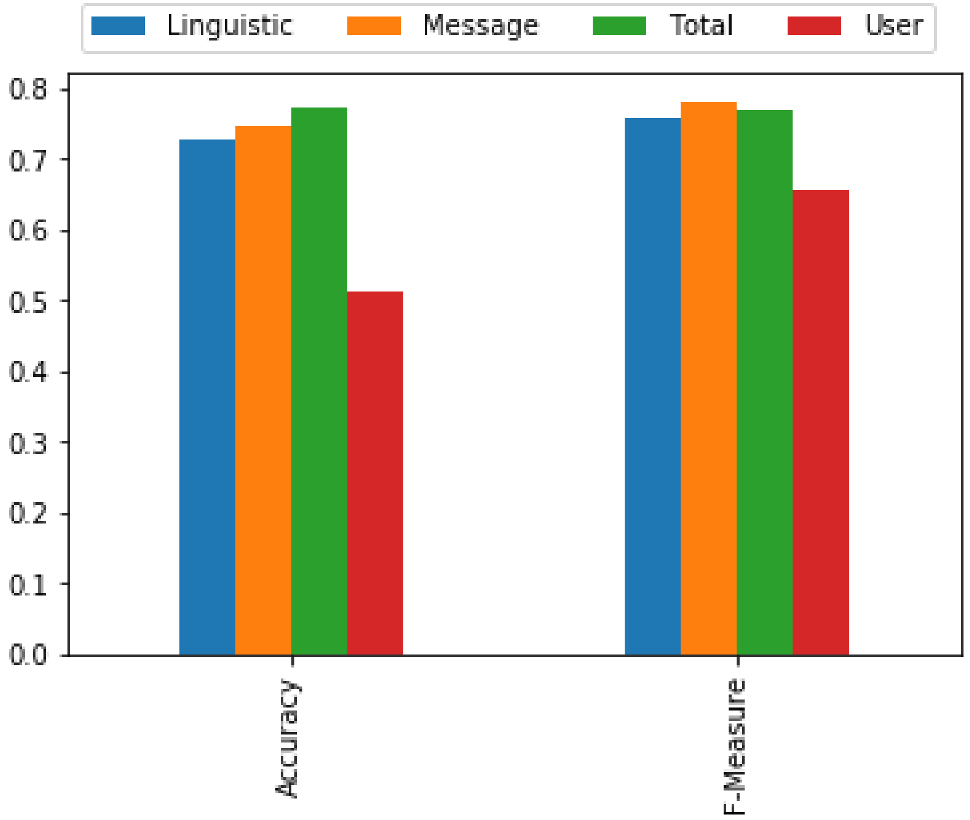


(c) User features



(d) Total features

Findings


Linguistic
Message
Total
User
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Accuracy
F-Measure

Findings

- Baseline analysis

State-of-the-art Baselines		
Classifier	Accuracy	F-measure
Zubiaga et al. [3]	-	60.7%
Ajao et al. [4]	82.3%	40.6%

TU Delft

Summary and Future work

- This is a very important and sensitive topic with crucial implications on individuals, organizations, and countries
- Computational approach is highly promising due to its low cost, scalability, accessibility, and fairly high accuracy.
- We need more collaboration with social psychologists in order to understand various characteristics of rumours
- The other avenue can be measuring the performance of other OCC algorithms

References

- [1]: A. Zubiaga, M. Liakata, and R. Procter, “Learning Reporting Dynamics during Breaking News for Rumour Detection in Social Media,” 10 2016.
- [2]: B. Schölkopf, R.C. Williamson, A. J. Smola, J. Shawe-Taylor, and J. C. Platt, “Support vector method for novelty detection,” in Advances in neural information processing systems, pp. 582–588, 2000
- [3]: A. Zubiaga, M. Liakata, and R. Procter, “Exploiting context for rumour detection in social media,” in International Conference on Social Informatics, pp. 109–123, Springer, 2017.
- [4]: O. Ajao, D. Bhowmik, and S. Zargari, “Fake News Identification on Twitter with Hybrid CNN and RNN Models,” 6 2018.


amiref_1991
a.ebrahimifard@tudelft.nl
TUDelft