Fake news detection

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Agenda

1. Overview
2. Project goal
3. First stages
4. Collecting data
5. Data structure
6. Method
7. Result
8. Conclusions

Overview

- » Fake news is a false information intentionally published to mislead people
- » Fake news are used to manipulate people in order to gain some profit
- » Fake news are mainly spread by publishing in social media like: Facebook, Twitter

Project goal

The goal of the project is to construct a mechanism that will be able to classify fake news. As classifications, we mean choosing a binary label that will indicate whether the article is fake news or not

First stages

1. Analyzing given paper (Fake News Detection on Social Media: A Data Mining Perspective) to gain knowledge about field of study
2. While analyzing we found another paper, which begun to be our base (FakeNewsNet: A Data Repository with News Content, Social Context and Spatiotemporal Information for Studying Fake News on Social Media)

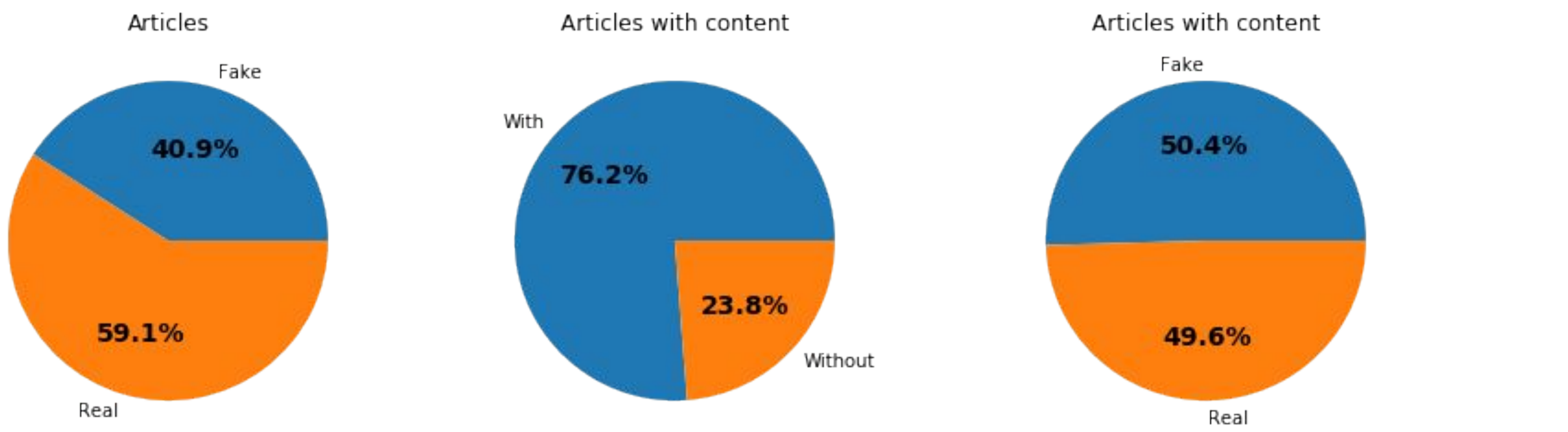
Collecting data

1. We decide to focus on dataset called FakeNewsNet. More precisely we decide to analyze only one part of it containing articles from website Politifact.
2. To collect data we use FakeNewsNet’s authors script. This script allowed us to download all articles and tweets releted to them
3. Only need to be done by us was creating Twitter-Api-Key

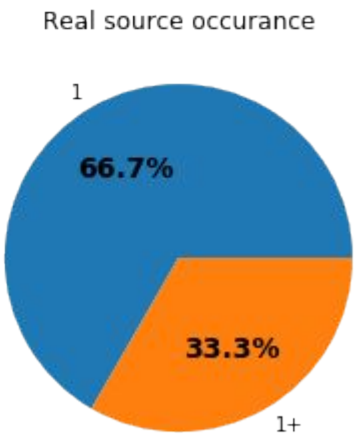
Data structure

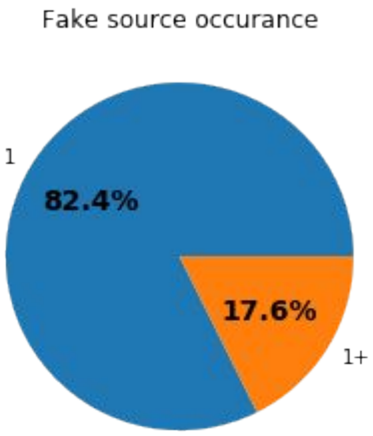
1. Dataset divide to two parts - fake and real articles
2. Article - a lot of information, eg. : url, title, content, sourcem, keywords, description, authors, publishing date
3. Tweets - text, creating date, retweet count, like count, contributors etc.
4. Users - user name, screen name, location, description, followers count, friends count, creating date

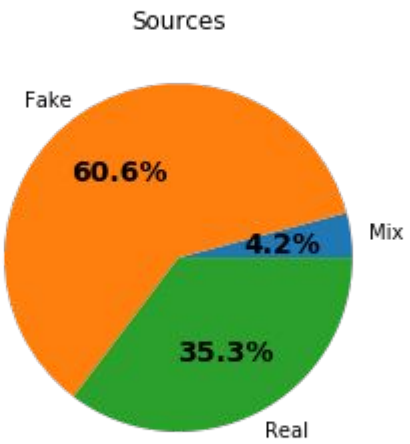
Data structure



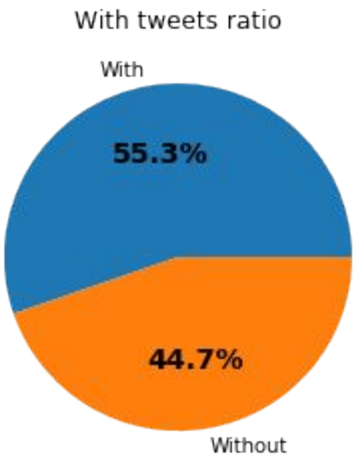
Data structure

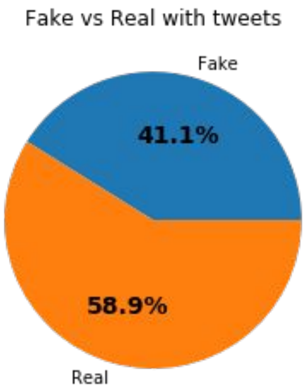


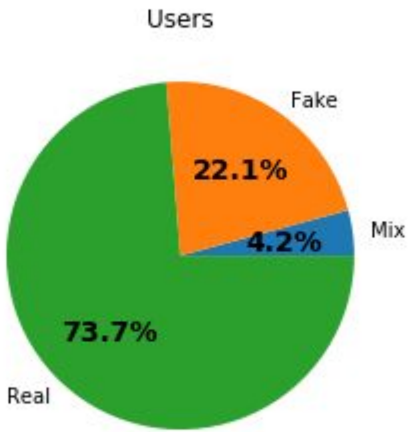


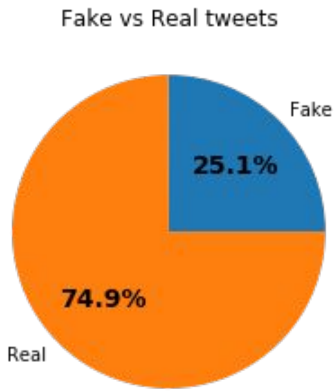


Data structure









Data structure

Tablica 4: Najpopularniejsze tematy newsów

Tytuł	Liczba artykułów
	41
CQ.com	14
- The Washington Post	13
Wiadomości, Pogoda, Outlook, Hotmail, Skype,..	11
YouTube	10
Transcripts	6
Political TV Ad Archive » PolAd	4
Time	4
LexisNexis(R) Publisher	3
MoveOn.org Political Action: 10 things to know..	3
Loading...	2

Tablica 5: Najpopularniejsze treści newsów

Treść	Liczba artykułów
	73
Need help? Contact the CQ Hotline at (80...	14
Please enable cookies on your web browse...	13
About Trendolizer™ Trendolizer™ (patent...	13
Język, w którym oglądasz YouTube, to. Mo...	11
Autoodtwarzanie Jeśli masz włączone auto...	10
Pomiń wszystko Witamy! Na osi czas spęd...	7
Używamy plików cookie, aby pomóc w perso...	5
About Your Privacy on this Site Welcome...	4
Use this guide to help you find the full...	3

Method

- Our problem can be considered as a problem of natural language processing, so we decide to involve deep learning techniques to sort it out.
- We focused only on article title and links
- You could also have interpretations that we analyze whether the article is so-called clickbaits, i.e. phenomena where the title of the article is to attract our attention, although the article has no substantive content

Method

1. In our first solution, we used the Flair library, which is one of the most popular and best libraries currently available in NLP.
2. Second solution was about using tool called AutoKeras, which offers the AUTOML solution for the popular Keras library.

Method

We trained our models in three ways:

- Title - only using titles
- Url - only using links to articles
- Mix - link and title connections via semicolon concatenation

Results

PolitiFact				
Model	Accuracy	Precision	Recall	F1
Social Article Fusion /S	0.654	0.600	0.789	0.681
Social Article Fusion /A	0.667	0.667	0.579	0.619
Social Article Fusion	0.691	0.638	0.789	0.706
Flair Title	0.816	0.761	0.805	0.782
Flair Url	0.804	0.733	0.860	0.791
Flair Mix	0.759	0.648	0.908	0.756
AutoKeras Mix	0.863	0.811	**0.918**	0.861
HPNF	0.843	0.835	0.851	0.843
UPF	**0.909**	**0.948**	0.864	**0.904**

Conclusions

- Our results are better than most of the compared results; only HPNF and UPF are more precise
- Used dataset was different than the one used in the methods from the article on which we based; would be better if authors provided the data on which they worked