

# Exposing Paid Opinion Manipulation Trolls

Preslav Nakov

Qatar Computing Research Institute, HBKU

September 10, 2019 Lugano, Switzerland

# "Fake News": A Weapon of Mass Deception

NEWSWEEK MAGAZINE

#### How Big Data Mines Personal Info to Craft Fake News and Manipulate Voters

BY NINA BURLEIGH ON 6/8/17 AT 1:01 PM



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INDY100



desde \$9

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Hoteles en Portland desde \$60

Reserve ahora



Hoteles en Mascate desde \$25

Reserve ahora



## Fake news handed Brexiteers the referendum - and now they have no idea what they're doing



'Would we have won without immigration? No. Would we have won without...the NHS? All our research and the close result strongly suggests no. Would we have won by spending our time talking about trade and the single market? No way'

Andrew Grice | @IndyPolitics Wednesday 18 January 2017 16:45 | 157 comments







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#### **INTERNATIONAL**

Schlagzeilen | DAX 11.792,85 | Abo

English Site > Germany > Alternative for Germany > Germany: AfD Populists Dominate on Facebook

#### **Facebook Frenzy**

#### **How the German Right Wing Dominates Social Media**

A comprehensive analysis has revealed the degree to which German right-wing populists from the Alternative for Germany (AfD) party are dominating the social media landscape. They might be getting help from abroad.

By Jörg Diehl ♥, Roman Lehberger ♥, Ann-Katrin Müller ♥ and Philipp Seibt ♥



https://www.spiegel.de/international/ germany/germany-afd-populists-dominateon-facebook-a-1264933.html

POLITICO

Polling \* Brussels Brexit Policy \* Newsletters \* POLITICOPRO



Polling from across Europe. Updated daily.

(), window.confirm(wp ,e.trigger("themes anshotCheck: function(a)(www. lick .close-full-over preview"), render: function rter.navigate(c.router. .removeClass("ifr :rigger("preview:cl ,this.\$el.toggleClass :view-device",c),this .attr("aria-presses", [0]) Half of European voters may have viewed Russianbacked 'fake news' Kremlin-backed campaigns are promoting extremist views and amplifying them to sow discord, says cyber firm. By MARK SCOTT | 5/7/19, 12:45 PM CET | Updated 5/8/19, 7:00 PM CET

https:// www.politico.eu/ article/europeanparliament-russiamcafee-safeguardcyber/

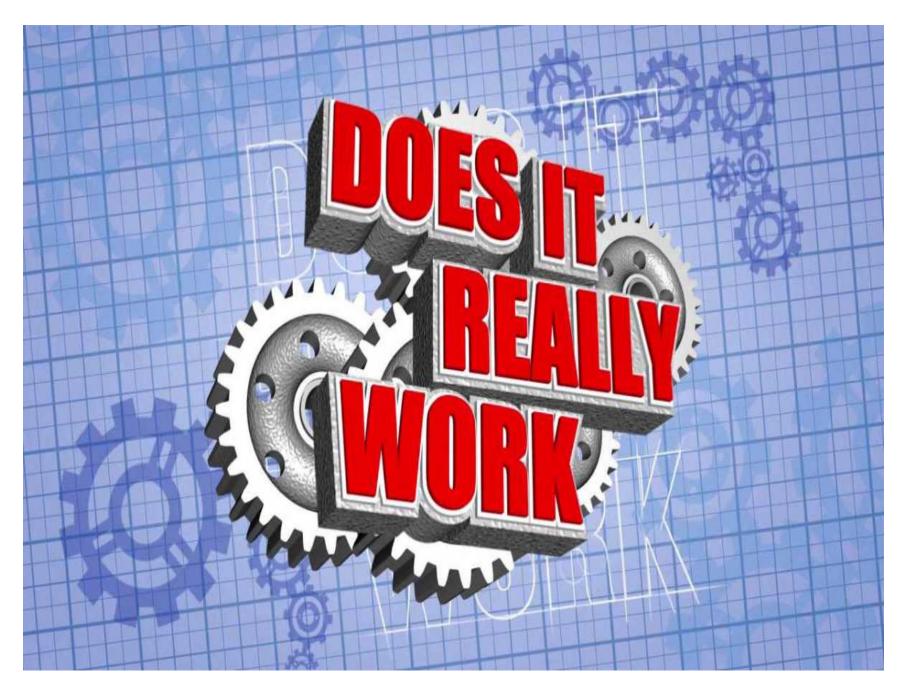
# Half of Americans see fake news as bigger threat than terrorism, study finds

Almost 70% of Americans feel fake news has greatly affected their confidence in government institutions, a new study says



https://www.theguardian.com/us-news/2019/jun/06/fake-news-how-misinformation-became-the-new-front-in-us-political-warfare

▲ Lawmakers have yet to take concrete action against fake news and misinformation. Photograph: Erik McGregor/Pacific/Barcroft







#### Hillary Clinton Blames the Russians, Facebook, and Fake News for Her Loss









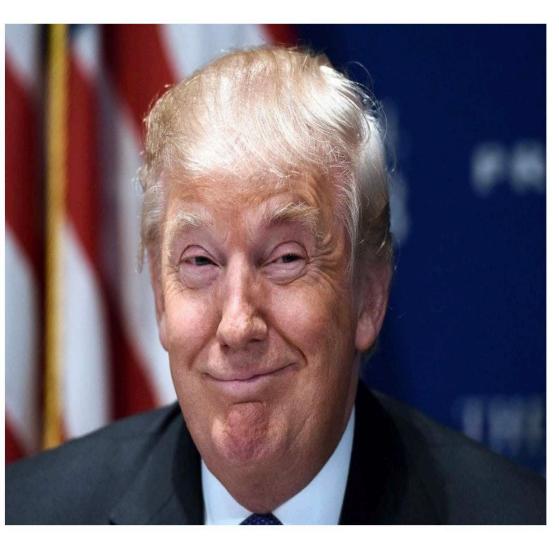


# FACEBOOK EXPOSED 87 MILLION USERS TO CAMBRIDGE ANALYTICA



https://www.wired.com/story/facebook-exposed-87-million-users-to-cambridge-analytica/

# Donald Trump will be president thanks to 80,000 people in three states





https://
www.washingtonpost.com/news/
the-fix/wp/2016/12/01/donaldtrump-will-be-president-thanksto-80000-people-in-three-states/

Donald Trump speaks in Washington in 2014. (Jewel Samad/AFP/Getty Images)



#### Magazine

#### The city getting rich from fake news

By Emma Jane Kirby **BBC News** 

O 5 December 2016 Magazine



Many of the fake news websites that sprang up during the US election campaign have been traced to a small city in Macedonia, where teenagers are pumping out sensationalist stories to earn cash from advertising.

My partner vanished without warning. I had to OCCRP

SPOOKS AND SPIN: INFORMATION WAR IN THE BALKANS . THE SECRET PLAYERS BEHIND MACEDONIA'S FA.



Credit: Nake Batev / Getty Images

A joint investigation by the Organized Crime and Corruption Reporting Project (OC-CRP) and partners has uncovered new information that rewrites the story of the fake news boom in the Macedonian town of Veles.

A week before Election Day in 2016, BuzzFeed News revealed that young men and teens in Veles were running over a hundred websites that pumped out often false vi-In today's Magazine ral stories that supported Donald Trump.

> Media outlets from around the world descended upon Veles to tell the story of how the so-called fake news teens — many of whom had a shaky understanding of English — made large sums of money from digital ads shown next to their misleading stories

by Saska Cvetkovska, Aubrey Belford, Craig Silverman, and J. Lester Feder 18 July 2018



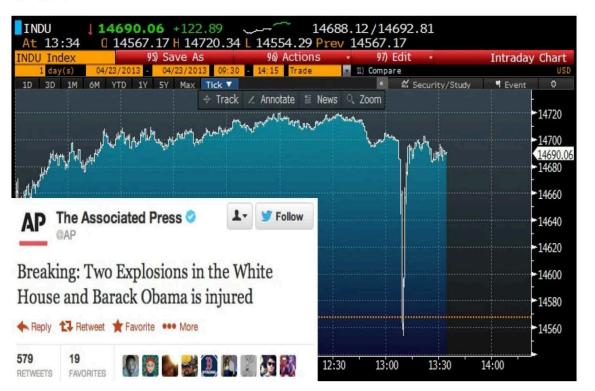




Above: A man reads a magazine near a newsstand in Skopje, Macedonia, 2017. Credit: Nake Batev / Getty Images

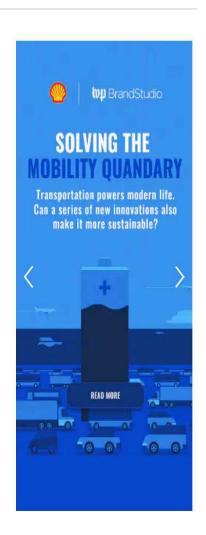
# Syrian hackers claim AP hack that tipped stock market by \$136 billion. Is it terrorism?

By Max Fisher April 23, 2013



This chart shows the Dow Jones Industrial Average during Tuesday afternoon's drop, caused by a fake A.P. tweet, inset at left.

At 1:07 p.m. on Tuesday, when the official Twitter account of the Associated Press sent a <u>tweet</u> to its nearly 2 million followers that warned, "Breaking: Two Explosions in the White House and Barack Obama is injured," some of the people who momentarily panicked were apparently on or near the trading floor of the New York Stock Exchange.





# UNICEF blames anti-vaxxers for the 300% spike in global measles outbreaks

Published: Apr 25, 2019 3:49 p.m. ET





'The ground for the global measles outbreaks we are witnessing today was laid years ago,' report says



#### **Measles: Four European nations lose** eradication status

https://www.bbc.com/news/health-49507253





Share



Measles has returned to four European nations previously seen as free of the illness, according to the World Health Organization (WHO).

The disease is no longer considered eradicated in Albania, the Czech Republic, Greece and the UK.









WORLD

#### Viral WhatsApp Messages Are Triggering Mob Killings In India

4:13

+ QUEUE

July 18, 2018 · 9:12 AM ET

DOWNLOAD

LAUREN FRAYER 🛐 🧿 💆





**EMBED** 



















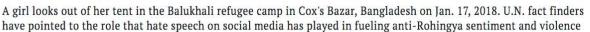
#### U.N. Fact Finders Say Facebook Played a 'Determining' Role in Violence Against the Rohingya









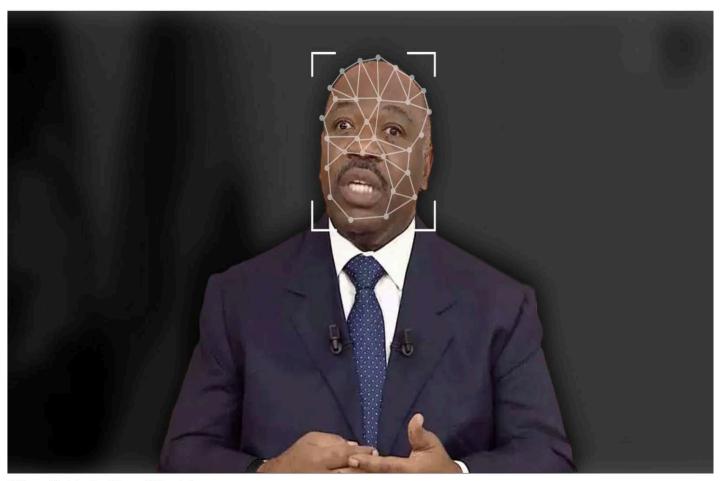


# A Military Coup in Gabon Inspired by a Potential Deepfake Video is Our Political Future



Ty Joplin

Published May 8th, 2019 - 09:54 GMT



https://www.albawaba.com/news/military-coup-gabon-inspired-potential-deepfake-video-our-political-future-1284760

Ali Bongo (Youtube, Rami Khoury/Al Bawaba)



#### Web creator Tim Berners-Lee blasts Facebook, saying it makes his invention easy to 'weaponize'

Published: Mar 19, 2018 4:40 a.m. ET





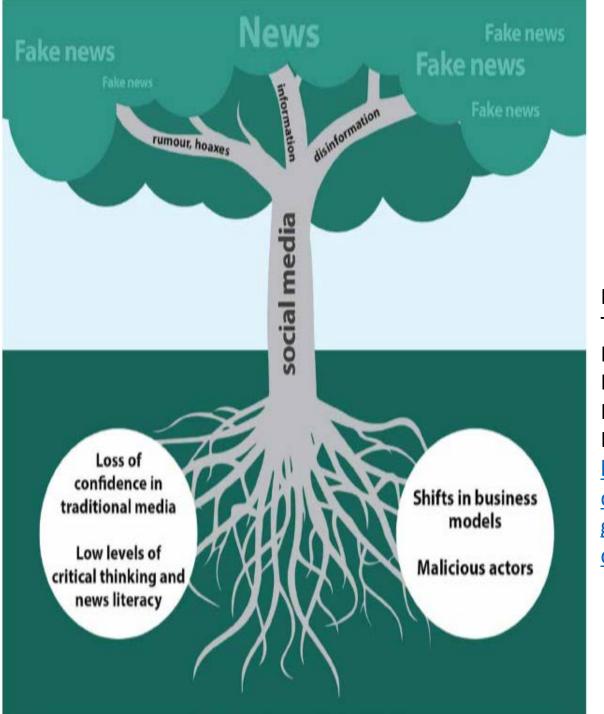






On World Wide Web's 29th birthday, Tim Berners-Lee criticizes its "gatekeepers" such as Facebook and suggests more regulation





By UNESCO - World
Trends in Freedom of
Expression and Media
Development Global
Report 2017/2018, CC
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curid=70286494

## The Role of Trolls

#### Problem







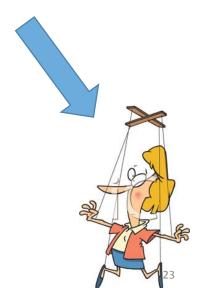


Internet trolls



Companies





PAN@CLEF 2019: Preslav Nakov Exposing Paid Opinion Manipulation Trolls (keynote talk)

### Trolling in Politics: Astroturfing

•In political science, it is defined as the [process of seeking electoral victory] or legislative relief for grievances by [helping political actors find and mobilize a sympathetic public], and is designed to create the image of public consensus where [there is none].

### Paid Manipulation Internet Trolls

## **Atlantic**

BUSINESS

## The Covert World of People Trying to Edit Wikipedia—for Pay

Can the site's dwindling ranks of volunteer editors protect its articles from the influence of money?



Adapted from Wikimedia / Lauren Giordano / The Atlantic

#### Propaganda Internet Trolls





## Russian 'troll factory' sued for underpayment and labour violations

Secretive agency that hires people to write pro-Kremlin propaganda reluctantly brought into spotlight after former employee takes it to court



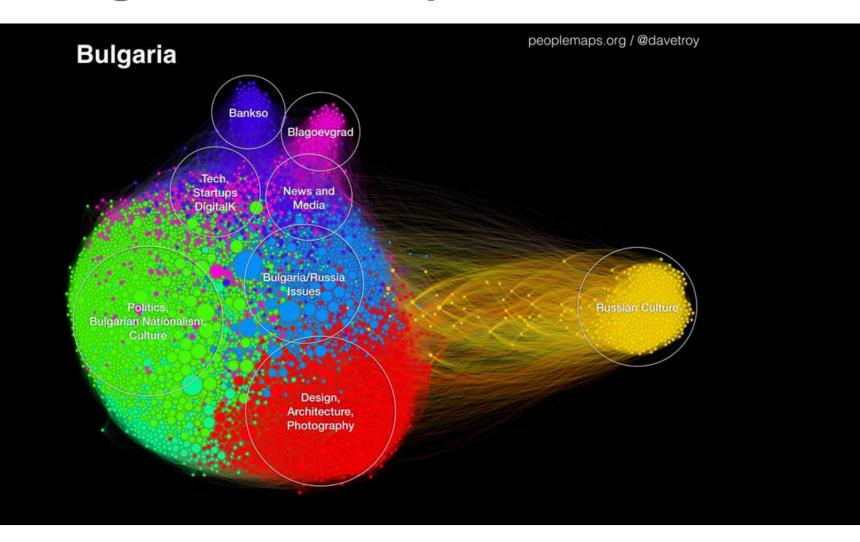
#### Most popular in US



Jennifer Lawrence to be paid \$8m more than Chris Pratt for Passengers

They are so real...

## The Bulgarian Twitter Space







New visualization: Bulgaria Twitter Users. Presented this morning at #digitalk2015 in Sofia, Bulgaria!



## Can We Stop the Trolls?

## **Option 0: Launch Your Own Trolls**





Daily Beast: Baltic elves take on pro-Kremlin trolls in online propaganda war



#### **Option 1: Gentlemen's Agreement**

(e.g., Bulgarian Political Parties Against Paid Trolls)

НАЧАЛО | БЪЛГАРИЯ |

## Партиите тържествено си обещаха да не ползват тролове в интернет



18:30 | 20 май 2015 | 5 коментара







Реформаторският блок, ГЕРБ, БСП, ПФ и ПГ на БДЦ подписаха декларация да не използват умишлено платени коментатори (тролове) в интернет пространството. АБВ и ДПС се възмутиха, че не са ги поканили.

Партиите няма да използват и партийно или фирмено организирани тролове с цел разпространение на заблуди и клевети, насаждане на омраза или манипулативни внушения



за политически опоненти и други участници в публичния живот, което да се публикува в интернет, обещаха помежду си парламентарните формации.

Инициативата за пожелателното споразумение е на депутата от РБ Антони Тренчев, а до парафирането на "документа" се стигна след проведена кръгла маса по темата миналата седмица.

Под декларацията, че няма да ползват тролове не са се подписали от АБВ, ДПС и "Атака".

"Това е първа крачка за разрешаване на проблема и за регулацията му в интернет", посочи Тренчев.

#### **Option 2: Expose Widely the Known Trolls**



Не се чудете като четете как ЕС забранява шкембето, розовия домат, кръщенетата... Точно същите истории ги разпространяваха и у нас, ако помните. Не четете тези медии и хора сред приятелите си, които пишат врели-некипели... или се опитайте да им обясните защо не трябва да вярват на медии, които си измислят - като случая със забраната на кръщенетата, които не умеят да различат не-новините style от нормална медия. Прекъснете разпространението на фалшивите новини - иначе участвате в хибридната война...



#### A Powerful Russian Weapon: The Spread of False Stories

Using both conventional media and covert channels, the Kremlin relies on disinformation to create doubt, fear and discord in Europe and the United States.

NYTIMES.COM I BY NEIL MACFARQUHAR

#### **Option 3: Block the Trolls**

#### **TC NEWSLETTERS**

Get TechCrunch News Delivered To Your Inbox Sign Up Here

#### Wikipedia Bans Hundreds Of "Black Hat" Paid Editors Who **Created Promotional Pages On Its Site**

Posted 13 hours ago by Sarah Perez (@sarahintampa)

603







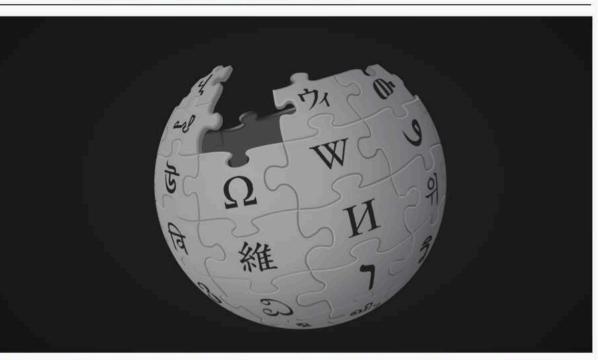












Sometimes Wikipedia's reliance on volunteers to craft its online content comes back to bite



News Video Events CrunchBase

ors on the English

g in "undisclosed

paid advocacy." In other words, they were posting promotional articles to the user-editable online encyclopedia, without revealing that they were paid to do so.

## **Option 4: Sue the Trolls**



#### Amazon sues 1,000 'fake reviewers'

Online retailer files lawsuit in US against people whose names it says it does not know, claiming they offer reviews for sale





## What we Need is to Automatically Find & Filter Trolls and Their Comments

# theguardian

# Comments on articles are valuable. So how to weed out the trolls?

## Joseph Reagle

It's the question facing every website that allows comments: how to curb abuse without neutering the conversation

Sunday 17 April 2016 14.02 BST

ast month, the technology news site Engadget announced it was "shutting down our comments ... see you next week". The deployment of a new comment system hadn't worked as hoped.

Its community manager noted that a good comments section has "users who feel a sense of duty and kinship, who act as a community"; an exceptional one "informs its readers, corrects authors and provides worthwhile insights in a polite and constructive manner".

## Can we Find Trolls Automatically?

Probably, if we have training data...

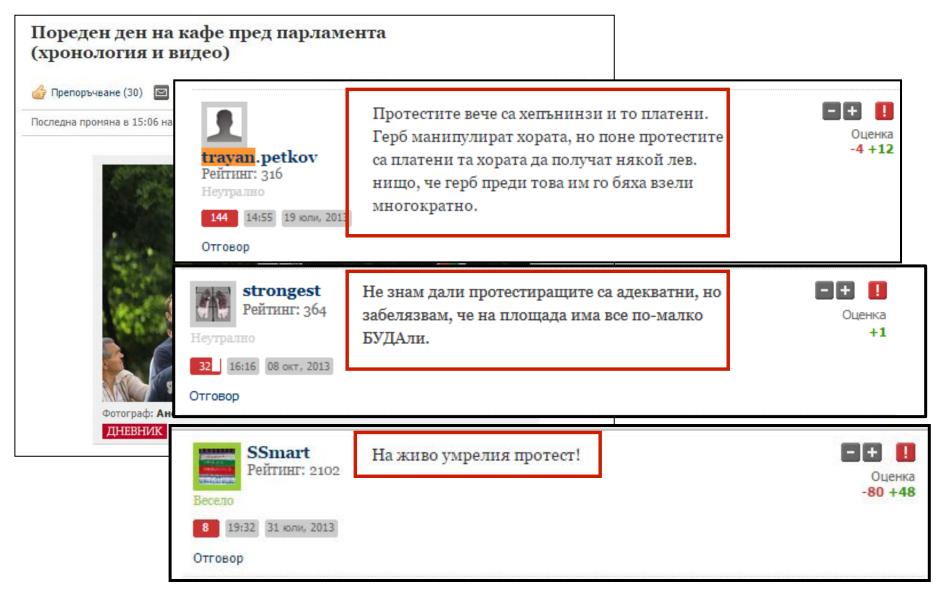


# Political Trolls in Bulgaria: Historical Context

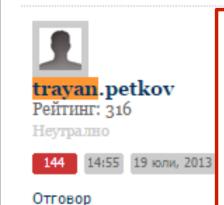


Protests against the government in Bulgaria (2013-2014)

#### In the Forums...



#### In the Forums...



Protests are already "happenings" and they **are** paid.

GERB(political party) manipulate people, but at least the protests are paid, so people get some money, no matter that they (previous government) have stolen much more from them.





I don't know if the protesters are adequate but I see a lot of **FOOLish people** there.





Live from the **dead** protest..



Отговор

Отговор

## 50,000+ People on the Streets



# Notable presence of government supporters in the Web forums

## **Accusations of Using Paid Trolls**



# Илияна Йотова плащала за тролове по 1500 лв. на месец

Автор: Биволъ Дата на публикуване май 23, 2014 В: Досиетата Бъ, Потеря, Тролгейт



# **Accusations of Using Paid Trolls**



BULGARIAN SOCIALIST MEP PAID 1 500 LEVS (€ 750) PER MONTH FOR INTERNET TROLLS

# BULGARIAN SOCIALIST MEP PAID 1 500 LEVS (€ 750) PER MONTH FOR INTERNET TROLLS

Posted By: Биволъ Posted date: May 23, 2014 In: Investigations, The B-files, Trolls gate



Capture\_2014-02-15\_a\_22.52.48

The July 24, 2013, offer of the company "Leadway Media Solutions" to Bulgarian MEP **Iliyana Yotova**, from the group of the **Party of European Socialists** 

https://bivol.bg/en/trolls-yotova-1500-english.html

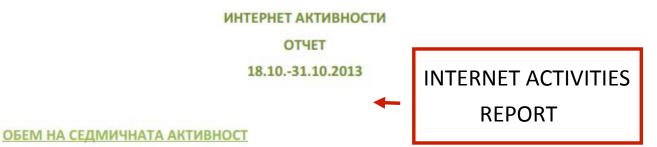
# Extract from a "Reputation Management" Contract

"Публикуване на 250 коментара на месечна база в Интернет пространството от виртуални потребители с разнообразни, типизирани и еволюиращи профили от различни (неповтарящи се) IP адреси с цел информиране, промотиране, балансиране или противодействие. Интензивността на осъществяваното онлайн присъствие ще е адекватно разпределена и ще съответства на политическата ситуация в страната."

wirtual users with varied, typical and evolving profiles from different (non-recurring) IP addresses to inform, promote, balance or counteract. The intensity of the provided online presence will be adequately distributed and will correspond to the political situation in the country."

### **Leaked Reports**

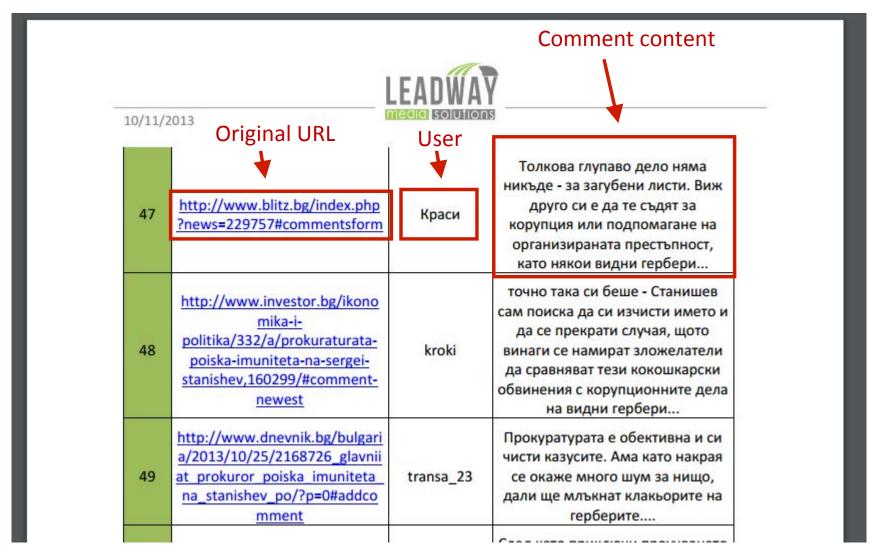




I. През отчетния период са публикувани 1200 коментара (1058 във форуми и 142 във Facebook), позиционирани в 38 онлайн медии. Коментарите, коите се генерират на база медийните изяви на представтели на управляващата партия не просто подкрепят политиката на правителството, но се стремят да разясняват конкретните секторни политики, като се обяснява очаквания ефект от предприетите управленски мерки. Активно разпространяваме в онлайн пространството тезите на партията-мандатоносител по всички актуални теми, провокиращи разнопосочни реакции в обществото. Целта е до аудиторията системно да достигат аргументи в подкрепа на наложителността и правилността на стъпките на правителството.

http://bsptrolls.bivol.bg/media/bsptrolls/2013-10-18-2013-10-31.pdf

## Leaked Reports = Golden Data?



10,150 paid comments: ~2,000 in Facebook, and ~8,150 in news community forums

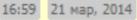
# More Troll Accusations



# Example Accusation of Trolling







До коментар [#1] от "Gianpiero":

До коментар [#2] от "comtec":

До коментар [#4] от "comtec":

До коментар [#3] от "Night Rider":

Отговор

Първата редица тролчета

седнали на столчета,

чукат по слвишите, туй, що други са им

написали!

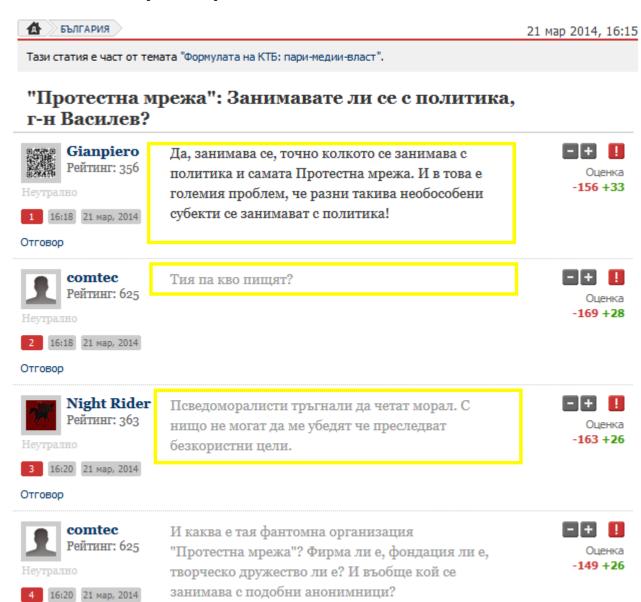
И аз съм от пртестната мрежа!

И аз стоя зад Асен и другите!

Който иска - търси начин, Който Не - търси оправдание,

-5 + 29

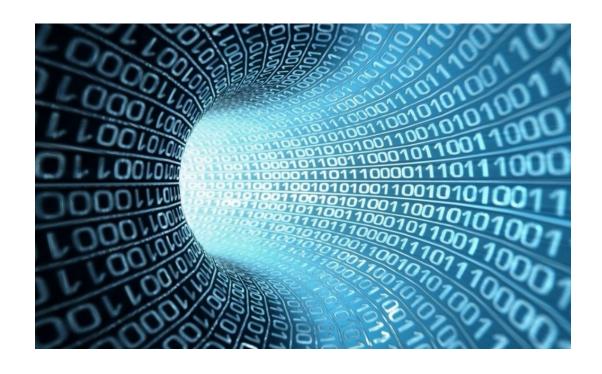
# Posts by Exposed Trolls



Article:

Comments:

# Our Data



# Our Dataset (from Dnevnik.bg)

Object	Number*		
Publications	34,514		
Comments	1,930,818		
- Comment replies	897,806		
Users	14,598		
Topics	232		
Keywords/tags	13,575		

<sup>\*</sup>Politics topics, Period 01.01.2013 – 01.04.2015, Dnevnik.bg

Plus the 10,150 paid comments from Leadway

# Experiment 1: Finding <u>Mentioned</u> Opinion Manipulation Troll <u>Users</u>

Todor Mihaylov, Georgi Georgiev, Preslav Nakov. *Finding Opinion Manipulation Trolls in News Community Forums*. **CoNLL-2015**, pp. 310-314

#### Method

Define "trollness":

A user who is called a troll by several people is likely to be one.

Create a labeled dataset.

Define and extract features.

- Train and evaluate an SVM classifier with different
  - "troll" class definitions
  - feature groups

September 10, 2019

# Users expose other users as trolls ... after the publication of the leaked documents



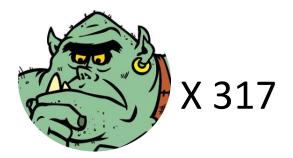
"To comment from "Rozalina": You, trolls, are so funny:) I saw the same signature under other comments:)"



"To comment from "Historama": **Murzi**, you know that you cannot manipulate public opinion, right?"

#### Labels & Data

- Trolls: users called *troll* or *murzilka* by at least 5 distinct users
- Non-trolls: users (w/ 100+ posts) that have never been called so





X 964

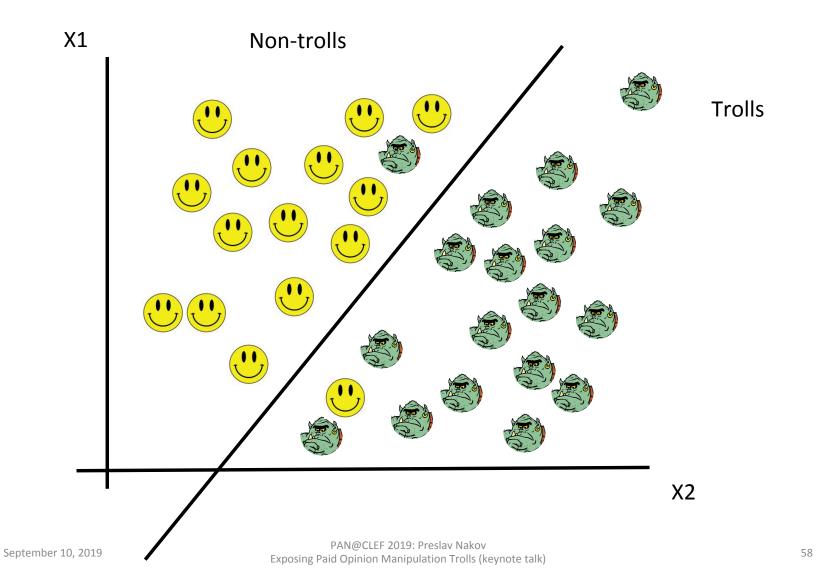
# Feature Types (w/ Our Assumptions)

- Vote-based features. People vote troll comments low.
- Comment-to-publication similarity. Trolls like to change topic.
- Comment order-based features. Trolls like to comment first, to get maximum attention.
- Top loved/hated comments. Troll comments are often hated.
- Comment replies-based features. Trolls tend to provoke or to engage in discussions.
- Time-based features. Paid trolls tend to write during working days and working times.

All the features are scaled, i.e., divided by the number of comments, the number of days in the forum, the number of days with more than one comment.

Total: 338 scaled features

# SVM to Classify Users as Trolls vs. Non-trolls



# Results: Ablation Excluding Some Feature Groups

Features	Accuracy	Diff
AS + Non-scaled	94.37(+3.74)	19.13
AS - total comments	91.17(+0.54)	15.93
AS - comment order	91.10(+0.46)	15.85
AS - similarity	91.02(+0.39)	15.77
AS - time day of week	90.78(+0.15)	15.53
AS - trigg rep range	90.78(+0.15)	15.53
AS - time all	90.71(+0.07)	15.46
All scaled (AS)	90.63	15.38
AS - top loved/hated	90.55(-0.07)	15.30
AS - time hours	90.47(-0.15)	15.22
AS - vote u/down rep	90.47(-0.15)	15.22
AS - similarity top	90.32(-0.31)	15.07
AS - triggered cmnts	90.32(-0.31)	15.07
AS - is rep to has rep	90.08(-0.54)	14.83
AS - vote up/down all	89.69(-0.93)	14.44
AS - is reply	89.61(-1.01)	14.36
AS - up/down votes	88.29(-2.34)	13.04

# Results: Performance of Individual Feature Groups

Features	Accuracy	Diff
All Non-scaled	93.21	17.95
Only vote up/down	87.67	12.41
Only vote up/down totals	87.2	11.94
Only reply up/down voted	86.1	10.85
Only time hours	84.93	9.68
Only time all	84.31	9.06
Only is reply with rep	82.83	7.57
Only triggered rep range	82.83	7.57
Only day of week	82.28	7.03
Only total comments	82.28	7.03
Only reply status	80.72	5.46
Only triggered replies	80.33	5.07
Only comment order	80.09	4.84
Only top loved/hated	79.39	4.14
Only pub similarity top	75.25	0
Only pub similarity	75.25	0

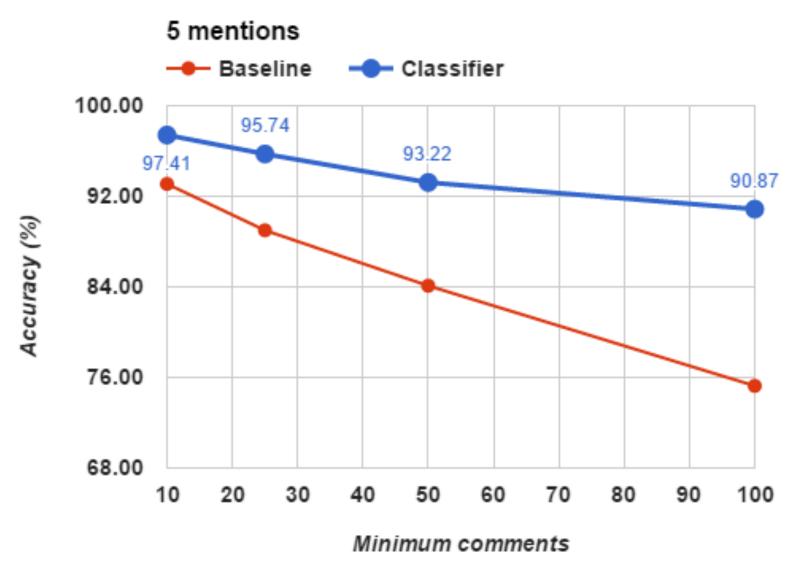
# Results: Impact of Number of Mentions

Min				
mentions	3	4	5	6
Trolls	545	419	317	260
Non-troll	964	964	964	964
Accuracy	85.49	87.85	90.87	92.32
Diff	21.60	18.15	15.61	13.56



Improvement over the majority class baseline

### Results: Impact of the Minimum Number of Comments



### Summary

- Experimented with a large number of features
  - both scaled and non-scaled
- Achieved accuracy of 82-95%
- The nature of our features means that our troll detection works best for ``elder trolls'' with at least 100 comments in the forum.

#### Discussion

- As the minimum number of comments increases, the improvement of our classifier over the baseline also increases.
- The more we know about a user, the better we can predict whether s/he will be seen as a troll by other users.
- The results of experiments with different features groups show that most of our assumption were confirmed.

# Experiment 2: Finding <u>Paid</u> Opinion Manipulation Troll <u>Users</u>

Todor Mihaylov, Ivan Koychev, Georgi Georgiev, Preslav Nakov. *Exposing Paid Opinion Manipulation Trolls*. **RANLP-2015**, pp. 443-450.

#### Method

Define "trollness":

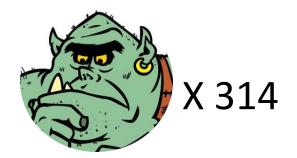
A user who is called a troll by several people is likely to be one.

- Create a labeled dataset:
  - Mentioned trolls
  - Non-trolls
  - Paid trolls
- Extract features.
- Train an SVM classifier: <u>mentioned</u> trolls vs non-trolls
- Test the classifier: <u>paid</u> trolls vs. non-trolls

September 10, 2019 66

#### Labels & Data

- Trolls: users called *troll* or *murzilka* by at least 5 distinct users
- Non-trolls: users (w/ 100+ posts) that have never been called so
- Paid trolls: from Bivol/Leadway





X 964



## Feature Types

- Vote-based features. People vote troll comments low.
- Comment-to-publication similarity. Trolls like to change topic.
- Comment order-based features. Trolls like to comment first, to get maximum attention.

# Same as before

 lime-based features. Paid trolls tend to write during working days and working times.

All the features are scaled, i.e., divided by the number of comments, the number of days in the forum, the number of days with more than one comment.

Total: 338 scaled features

# Results: Ablation Excluding Some Feature Groups

Features (Bottom is better)	Acc	Р	R	F
All Scaled (AS)	0.88	1.00	0.75	0.86
AS - comment order(Scaled-S)	0.88	1.00	0.75	0.86
AS - is reply (S)	0.88	1.00	0.75	0.86
AS - is reply to has reply (S)	0.88	1.00	0.75	0.86
AS - similarity (S)	0.88	1.00	0.75	0.86
AS - similarity top (S)	0.88	1.00	0.75	0.86
AS – top loved hated (S)	0.88	1.00	0.75	0.86
AS - total comments (S)	0.88	1.00	0.75	0.86
AS - trigg replies range (S)	0.88	1.00	0.75	0.86
AS - trigg replies total (S)	0.88	1.00	0.75	0.86
AS - vote up/down total (S)	0.88	1.00	0.75	0.86
AS - time (S)	0.75	1.00	0.50	0.67
AS - time hours (S)	0.75	1.00	0.50	0.67
AS - vote up/down reply stat(S)	0.75	1.00	0.50	0.67
AS - time day of week (S)	0.63	1.00	0.25	0.40
AS + Non Scaled (NS)	0.63	1.00	0.25	0.40
AS - vote up/down all (S)	0.38	0.00	0.00	0.00

# Results: Performance of Individual Feature Groups

Features (Top is better)	Acc	Р	R	F
only day of week (S)	0.88	0.80	1.00	0.89
only reply status (S)	0.75	0.75	0.75	0.75
only time hours (S)	0.75	0.75	0.75	0.75
only top loved hated (S)	0.75	1.00	0.50	0.67
only comment order (S)	0.63	0.67	0.50	0.57
only vote up/down is reply (S)	0.63	0.67	0.50	0.57
only similarity top (S)	0.63	1.00	0.25	0.40
only triggered replies range (S)	0.63	1.00	0.25	0.40
only is reply to has reply (S)	0.50	0.50	0.25	0.33
only similarity (S)	0.50	0.50	0.25	0.33
only time (S)	0.50	0.50	0.25	0.33
only total comments (S)	0.50	0.50	0.25	0.33
only triggered replies total (S)	0.50	0.50	0.25	0.33
only vote up/down all (S)	0.50	0.50	0.25	0.33
only vote up/down total (S)	0.50	0.50	0.25	0.33
All Unscaled	0.50	0.00	0.00	0.00

# Testing on Mentioned vs. Paid Trolls

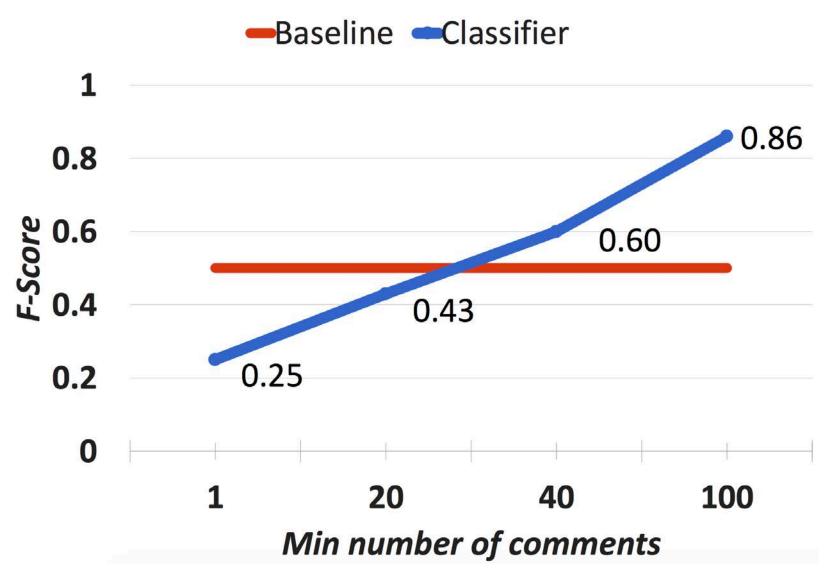
Min mentions	3	4	5	6
Mentioned Trolls	536	416	314	269
Non-troll	536	416	314	269
Accuracy	0.75	0.88	0.88	0.75
F-score	0.67	0.86	0.86	0.67

Finding paid trolls with 100+ mentions (4~trolls + 4 non-trolls). Training with AS features, and users with 150+ comments and varying minimum number of mentions as a troll.

Min mentions	3	4	5	6
Mentioned Trolls	536	416	314	269
Non-troll	536	416	314	269
Accuracy	0.83	0.87	0.91	0.92
F-score	0.83	0.87	0.91	0.92

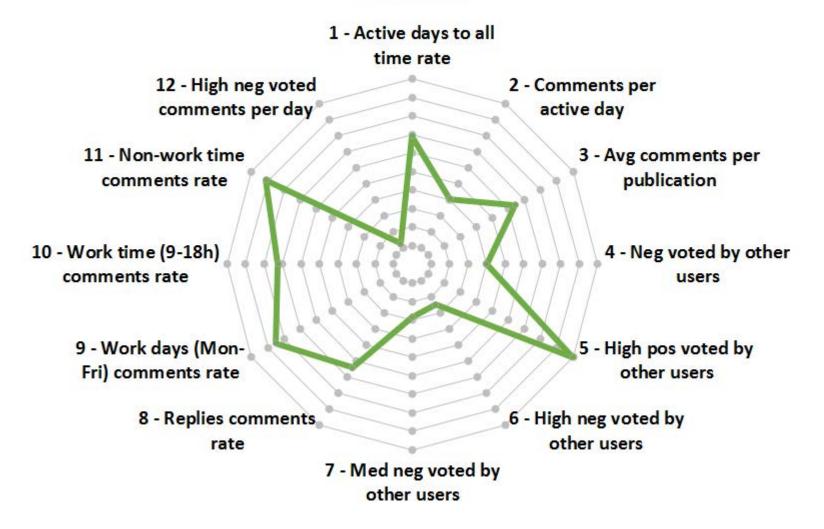
Finding "mentioned" trolls (cross-validation on the training dataset). Training with AS features, and users with 150+ comments and varying minimum number of mentions as a troll.

# Results: Impact of Minimum Number of Comments



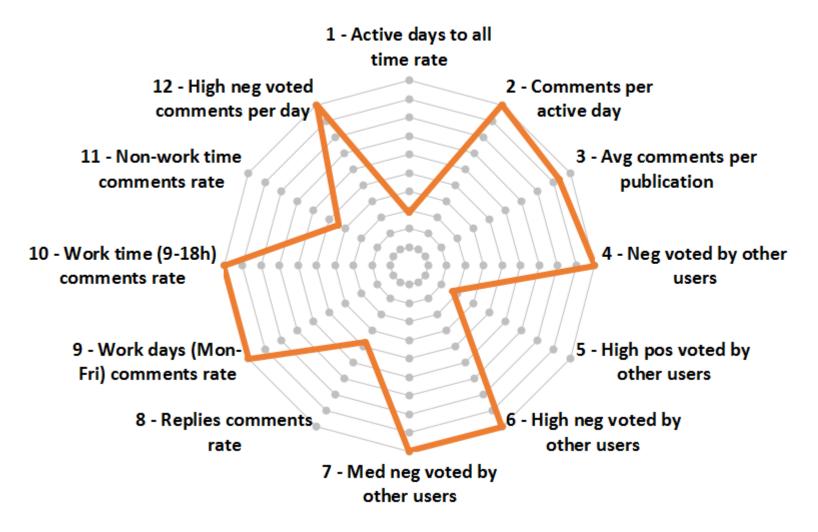
#### **Non Trolls**



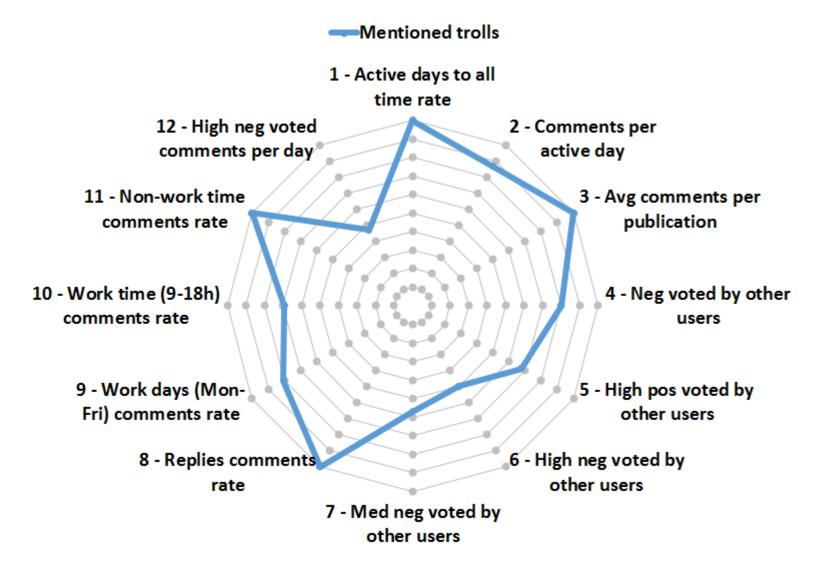


#### **Paid Trolls**

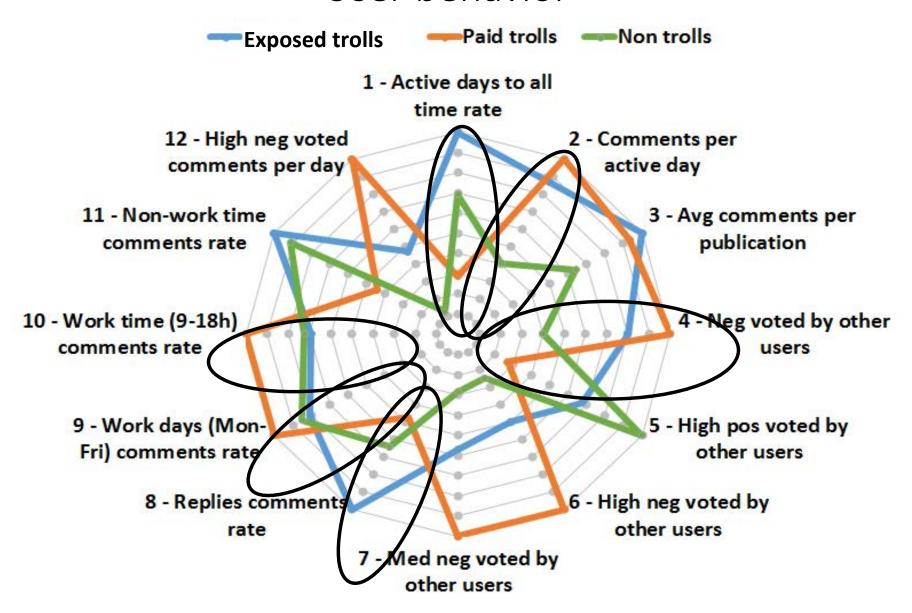
#### Paid trolls



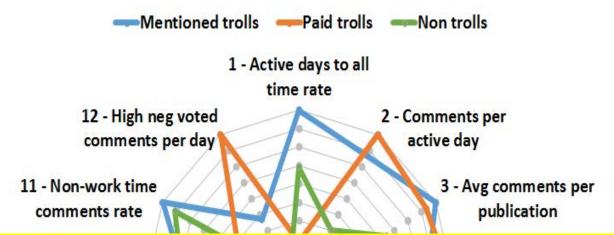
#### **Mentioned Trolls**



#### User behavior

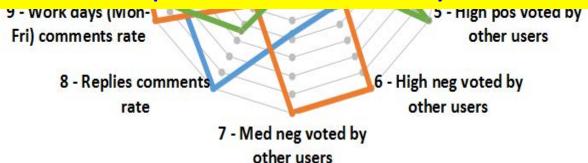


#### Mentioned vs. Paid vs. Non Trolls



Preslav Nakov, Tsvetomila Mihaylova, Lluís Màrquez, Yashkumar Shiroya, Ivan Koychev: *Do Not Trust the Trolls: Predicting Credibility in Community Question Answering Forums*. RANLP 2017: 551-560

"Trollness" is the most important feature for credibility detection in Qatar Living!



Todor Mihaylov, Tsvetomila Mihaylova, Preslav Nakov, Lluís Màrquez, Georgi Georgiev, Ivan Koychev: *The dark side of news community forums: opinion manipulation trolls.* Internet Research 28(5): 1292-1312 (2018)

#### Discussion

- As the minimum number of comments increases, the improvement of our classifier over the baseline also increases.
- The more we know about a user, the better we can predict whether s/he will be seen as a troll by other users.
- Paid Trolls are similar to Mentioned Trolls, but there are also differences.
- Unfortunately, we have too few paid trolls...

# Experiment 3: Finding Opinion Manipulation Troll <u>Comments</u>

Todor Mihaylov, Preslav Nakov. *Hunting for Troll Comments in News Community Forums*. **ACL-2016.** 

#### Method

Define "trollness":

- Same as before (but focusing on comments)
  - mentioned trolls vs. non-trolls
  - <u>paid</u> trolls vs. non-trolls

## Manual Checking of Troll Accusations (whether they are accusations; not whether true)

#### Annotate comments

- 1,140 comments containing the words "troll" or "murzilka"
- two annotators: Kappa = 0.82

#### Found

agree on 578 actual accusations

#### A simple classifier can find actual accusations

- Bag of words, Word N-grams, Stemmed BoW
- F-score = 0.85

## Labels & Data (comments, not users!)

• Trolls: users called *troll* or *murzilka* by at least 5 distinct users

• Non-trolls: users (w/ 100+ posts) that have never been called so

• Paid trolls: from Bivol/Leadway





X 650





X 578

## Feature Types (1)

- Bag of words
- Bag of stems
- Word n-grams
- Char n-grams
- Word prefix
- Word suffix
- POS tag distribution: coarse- and fine-grained
- Named entities

## Feature Types (2)

- Emoticons
- Punctuation counts
- Word2Vec clusters
- Sentiment scores: from lexicons
- Bad words: from lexicons + word2vec expansion
- Mentions of Bulgarian politicians and their nicknames.
- Metadata: comment rank, time and day of posting.

## <u>Mentioned</u> vs Non-troll Comments: Ablation Excluding Some Feature Groups

Features	F	Acc
All – char n-grams	79.24	78.54
All - word suff	78.58	78.20
All – word preff	78.51	78.02
All - bow stems	78.32	77.85
All - bow with stop	78.25	77.77
All − bad words	78.10	77.68
All – emoticons	78.08	77.76
All – mentions	78.06	77.68
All	78.06	77.68
All - (bow, no stop)	78.04	77.68
All - NE	77.98	77.59
All – sentiment	77.95	77.51
All - POS	77.80	77.33
All - w2v clusters	77.79	77.25
All – word 3-grams	77.69	77.33
All — word 2-grams	77.62	77.25
All – punct	77.29	76.90
All – metadata	70.77	70.94

## <u>Paid</u> trolls vs Non-troll Comments: Ablation Excluding Some Feature Groups

Features	$\mathbf{F}$	Acc
All – char n-grams	81.08	81.77
All - word suff	81.00	81.77
All – word preff	80.83	81.62
All - bow with stop	80.67	81.54
All – sentiment	80.63	81.46
All — word 2-grams	80.62	81.46
All - w2v clusters	80.54	81.38
All – word 3-grams	80.46	81.38
All – punct	80.40	81.23
All – mentions	80.40	81.31
All	80.40	81.31
All - bow stems	80.37	81.31
All – emoticons	80.33	81.15
All - bad words	80.09	81.00
All - NE	80.00	80.92
All - POS	79.77	80.69
All - (bow, no stop)	79.46	80.38
All – metadata	75.37	76.62

## <u>Mentioned</u> vs Non-troll Comments: Individual Feature Groups

Features	F	Acc
All	78.06	77.68
Only metadata	84.14	81.14
Sent,bad,pos,NE,meta,punct	77.79	76.73
Only bow, no stop	73.41	73.79
Only bow with stop	73.41	73.44
Only bow stems	72.43	72.49
Only word preff	71.11	71.62
Only w2v clusters	69.85	70.50
Only word suff	69.17	68.95
Only word 2-grams	68.96	69.29
Only char n-grams	68.44	68.94
Only word 3-grams	64.74	67.21
Only POS	64.60	65.31
Sent,bad,pos,NE	63.68	64.10
Only sent,bad	63.66	64.44
Only emoticons	63.30	64.96
Sent,bad,ment,NE	63.11	64.01
Only punct	63.09	64.79
Only sentiment	62.50	63.66
Only NE	62.45	64.27
Only mentions	62.41	64.10
Only bad words	62.27	64.01
•		

## <u>Paid</u> trolls vs Non-troll Comments: Individual Feature Groups

Features	F	Acc
All	80.40	81.31
Sent,bad,pos,NE,meta,punct	78.04	78.15
Only bow, no stop	75.95	76.46
Only word 2-grams	75.55	74.92
Only bow with stop	75.27	75.62
Only bow stems	75.25	76.08
Only w2v clusters	74.20	74.00
Only word preff	74.01	74.77
Sent,bad,pos,NE	73.89	73.85
Only metadata	73.79	72.54
Only char n-grams	73.02	74.23
Only POS	72.94	72.69
Only word suff	72.03	72.69
Only word 3-grams	69.20	68.00
Only punct	66.80	65.00
Only NE	66.54	64.77
Sent,bad,ment,NE	66.04	64.92
Only sentiment	64.28	62.62
Only mentions	63.28	61.46
Only sent,bad	63.14	61.54
Only emoticons	62.95	61.00
Only bad words	62.22	60.85

#### Discussion

- Paid trolls' comments similar to mentioned trolls'
  - ✓ Paid trolls vs non-trolls comments: 80-81% accuracy
  - ✓ Mentioned troll vs. non-troll comments: 79-80% accuracy
- We cannot directly compare mentioned troll and paid troll comments as they were posted in different time spans.
  - ✓ Mentioned troll accusation went viral after the documents were leaked.
- Non-troll comments are not gold.

## Summary

## Summary

#### Conclusion

- ✓ New, useful definition: A user who is called a troll by several people is likely to be one.
- ✓ New datasets with troll data (Bulgarian)
- ✓ Evaluated several feature groups
- ✓ Experiments
  - Troll profile behavior detection 90-96% accuracy
  - Troll comment detection **80-84% accuracy**

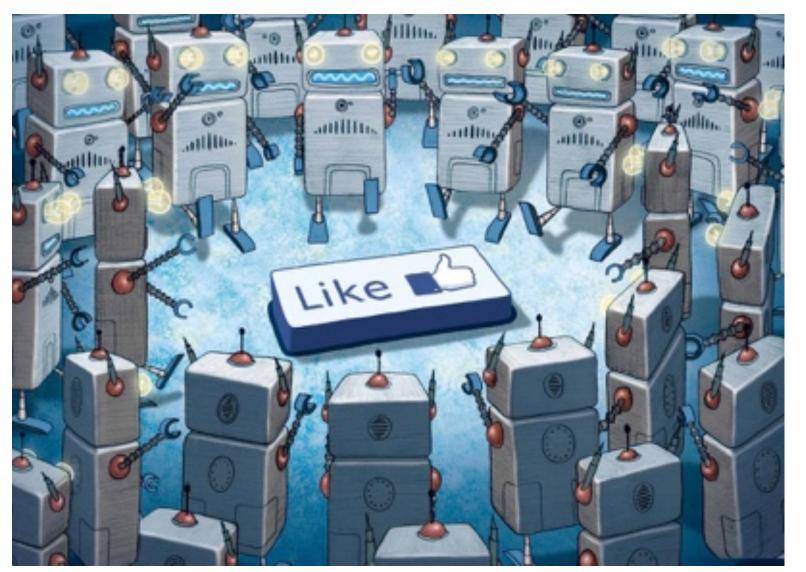
#### Future Work

- ✓ Combine user- and comment-level features
- ✓ Apply to other community forums and other languages.
  - √ (work-in-progress) trollness top features for credibility (English)

# Typology of Manipulative Users

## **Social Bots**

**Social bots:** accounts that are programmatically controlled to produce content and to interact with other users



## Finding Social Bots (2)

https://botometer.iuni.iu.edu/

## Botometer<sub>®</sub>

An OSoMe project (bot-o-meter)



Botometer (formerly BotOrNot) checks the activity of a Twitter account and gives it a score based on how likely the account is to be a bot. Higher scores are more bot-like.

Use of this service requires Twitter authentication and permissions. (Why?)

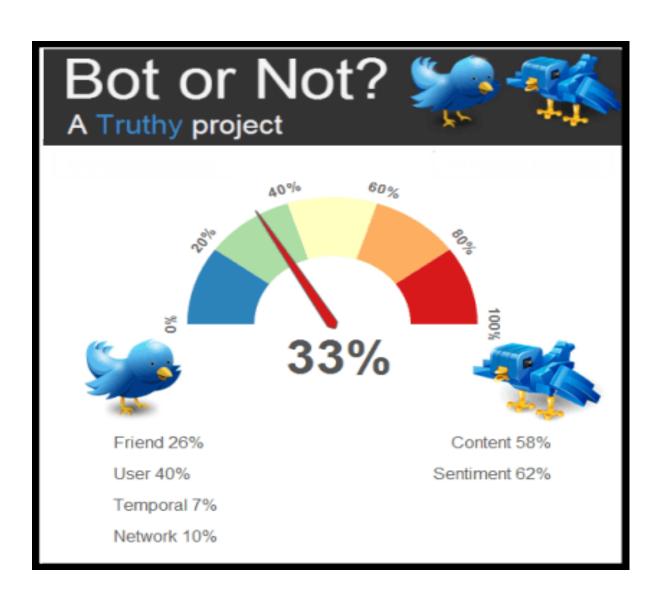
If something's not working or you have questions, please contact us only after reading the FAQ.

Botometer is a joint project of the Network Science Institute (IUNI) and the Center for Complex Networks and Systems Research (CNetS) at Indiana University.

@ScreenName Check user Check followers Check friends

## Finding Social Bots (2)

https://botometer.iuni.iu.edu/



### **Trolls**

**Trolling:** malicious online behavior that is intended to disrupt interactions, to aggravate interacting partners, and to lure them into fruitless argumentation in order to disrupt online interactions and communication. (BUT can also mean opinion manipulation)



## Sock Puppets

**Sockpuppets:** people who assume a false identity in an Internet community and then speak to/about themselves while pretending to be another person.

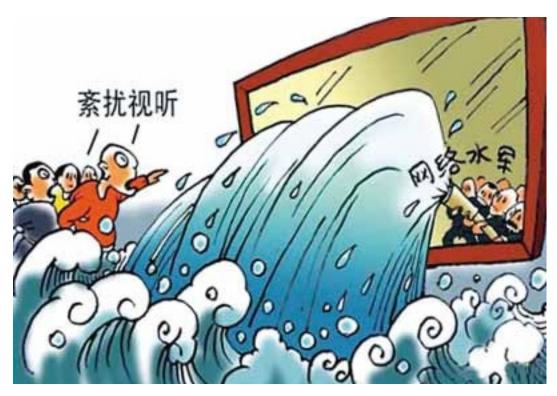


## Astroturfers



## Internet Water Army

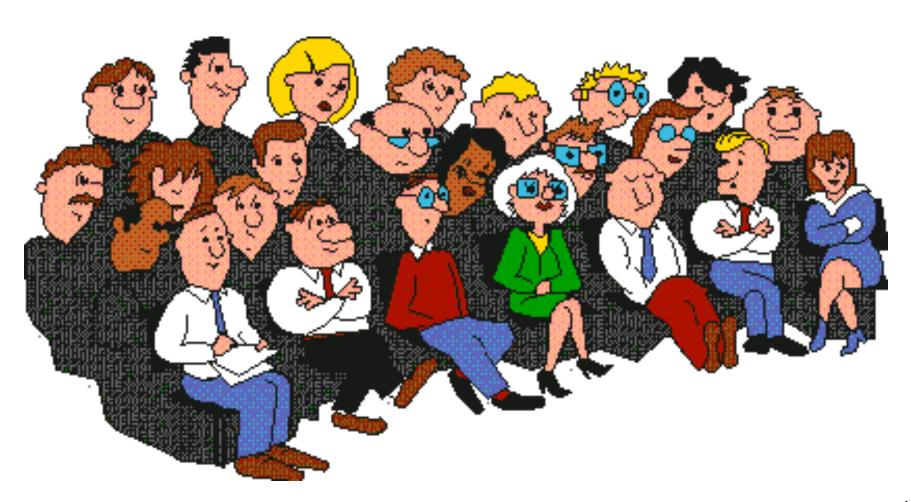
**Internet Water Army:** a large number of people who are well organized to flood the Internet with purposeful comments and articles.



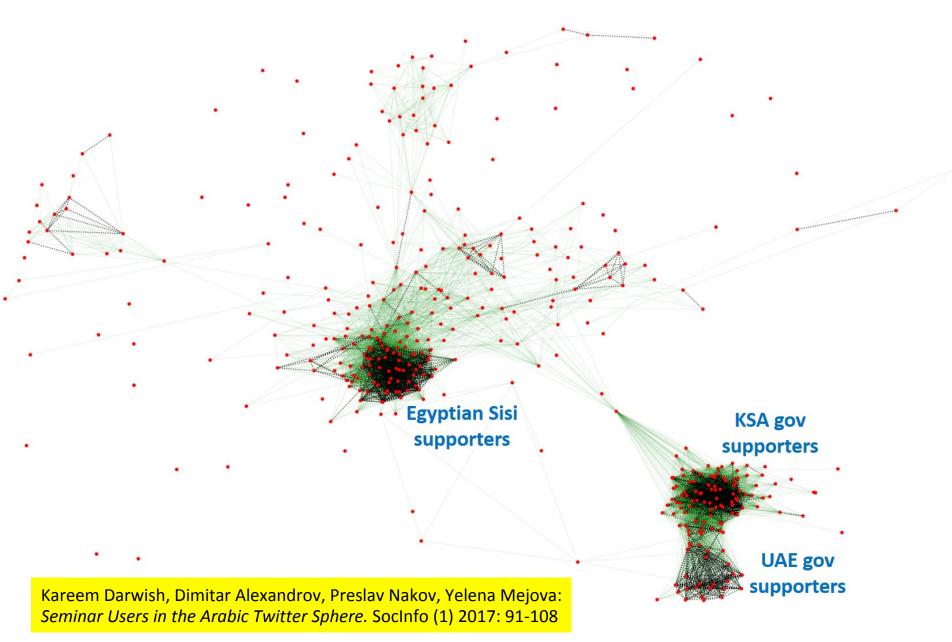


## "Seminar Users"

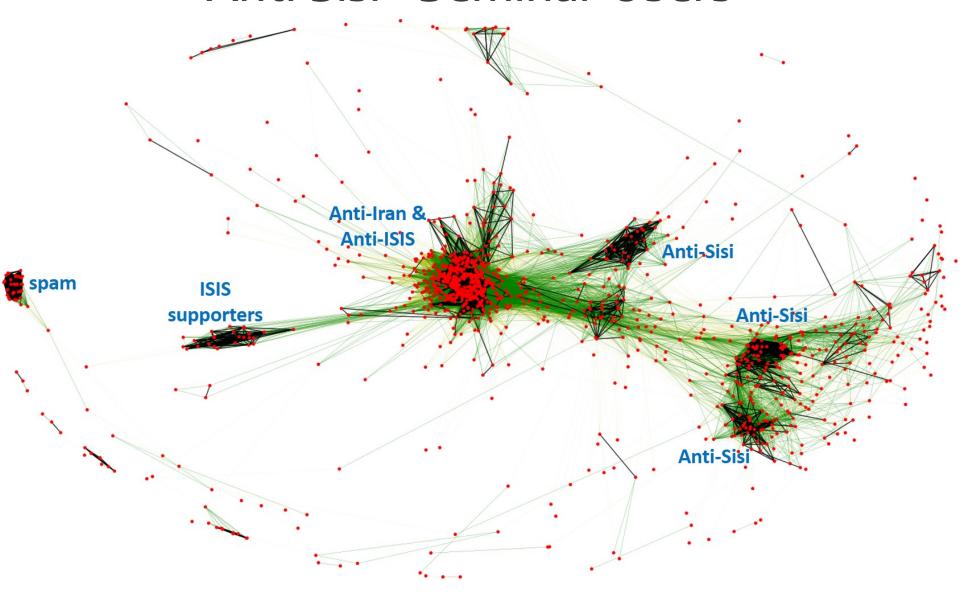
"Seminar Users": social media users engaged in propaganda in support of a political entity.



## Pro-Sisi "Seminar Users"



## Anti-Sisi "Seminar Users"



# Understanding the Role of Political Trolls in Social Media

Atanas Atanasov, Gianmarco De Francisci Morales and Preslav Nakov: Understanding the Roles of Political Trolls in Social Media. **CoNLL 2019** 

## **NewScientist**

News Technology Space Physics Health Environment Mind Video | Tours Events Jobs

#### Fake news travels six times faster than the truth on Twitter



















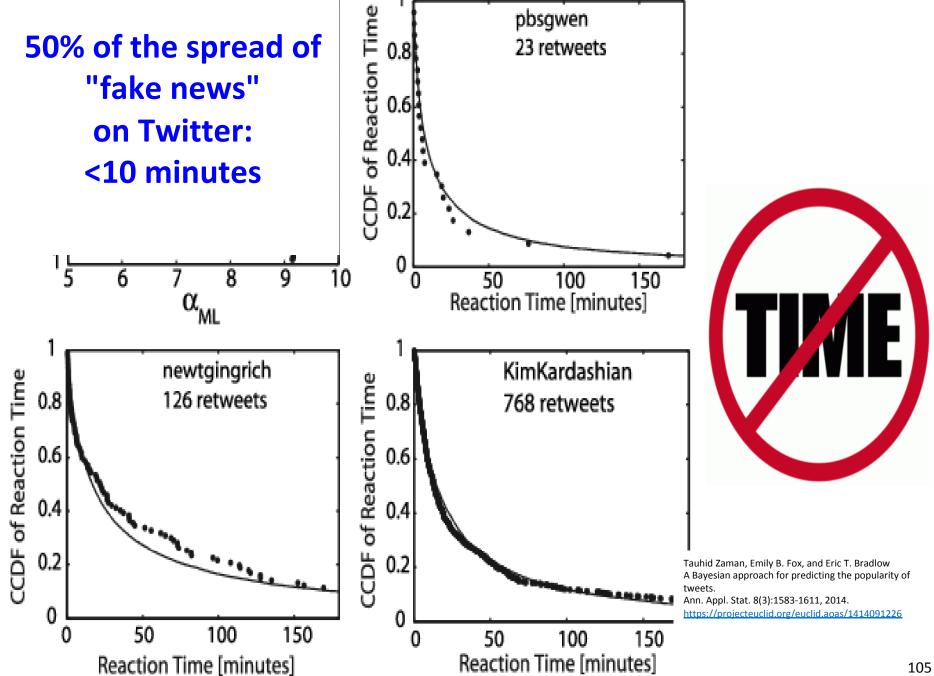
TECHNOLOGY 8 March 2018

By Chris Stokel-Walker



https://www.newscientist.com/article/2163226-fake-newstravels-six-times-faster-than-the-truth-on-twitter/

the



# To Understand the Trolls Strategy, We Need to Understand Their Role

#### Understanding the Roles of Political Trolls in Social Media

Role	Users	Tweets	User Example	Tweet Example
Left	233	427,141	@samirgooden	@MichaelSkolnik @KatrinaPierson @sames-
				fandiari Trump folks need to stop going on CNN.
Right	630	711,668	@chirrmorre	BREAKING: Trump ERASES Obamas Islamic
				Refugee Policy! https://t.co/uPTneTMNM5
News Feed	54	598,226	@dailysandiego	Exit poll: Wisconsin GOP voters excited, scared
				about Trump #politics

Table 1: Summary statistics for the IRA Russian Trolls Tweets (IRA) dataset.

- 2,973,371 tweets
- 2,848 Twitter users
- February 2012 to May 2018
- linked to the Internet Research Agency (IRA), according to the US
   House Intelligence Committee

#### Understanding the Roles of Political Trolls in Social Media

Inferred the troll's role by projecting information about media the trolls cited, among other things

Bias	Count	Example
LEFT	341	www.cnn.com
<b>CENTER</b>	372	www.apnews.com
RIGHT	619	www.foxnews.com





APPS/EXTENSIONS

SUBMIT SOURCE SUBMIT FACT CHECK

ECK SOURCES PENDING

**FACTUAL NEWS SEARCH** 

**FILTERED SEARCH** 

**LIVE TV NEWS** 

RSS

(NEW) HELP US FACT CHECK

Left Bias Left-Center Bias

Least Biased

**Right-Center Bias** 

Right Bias

**Pro-Science** 

**ORIGINAL ARTICLES/NEWS** 

Conspiracy-Pseudoscience

Questionable Sources

Q

Satire

(NEW) Re-Evaluated Sources

We are the most comprehensive media bias resource on the internet. There are currently 2500+ media sources listed in our database and growing every day. Don't be fooled by Fake News sources. Use the search feature above (Header) to check the bias of any source. Use name or url.

LATEST



#### **The Angry Patriot**

Has this Media Source failed a fact check? LET US KNOW HERE.

Share:

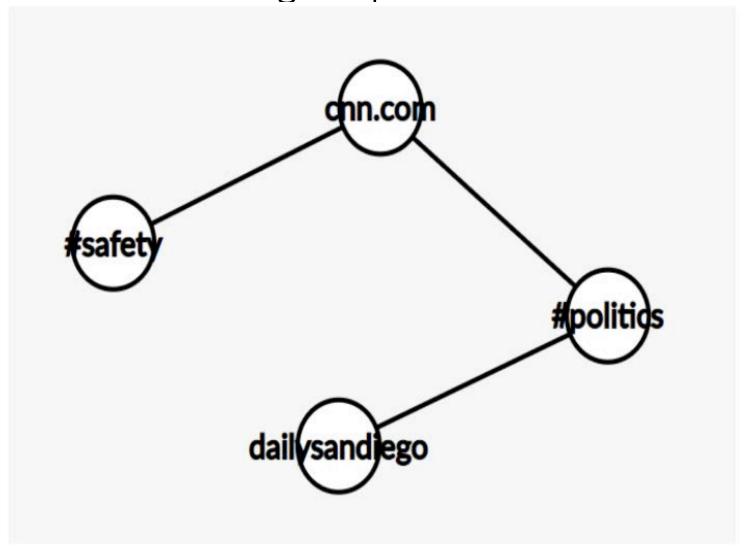


A questionable source exhibits *one or more* of the following: extreme bias, overt propaganda, poor or no sourcing to credible information and/or is fake news. Fake News is the *deliberate attempt* to publish hoaxes and/or disinformation for the purpose of profit or influence (Learn More). Sources listed in the Questionable Category *may* be very untrustworthy and should be fact checked on a per article basis. Please note sources on this list *are not* considered *fake news* unless specifically written in the notes section for that source. See all Questionable sources.

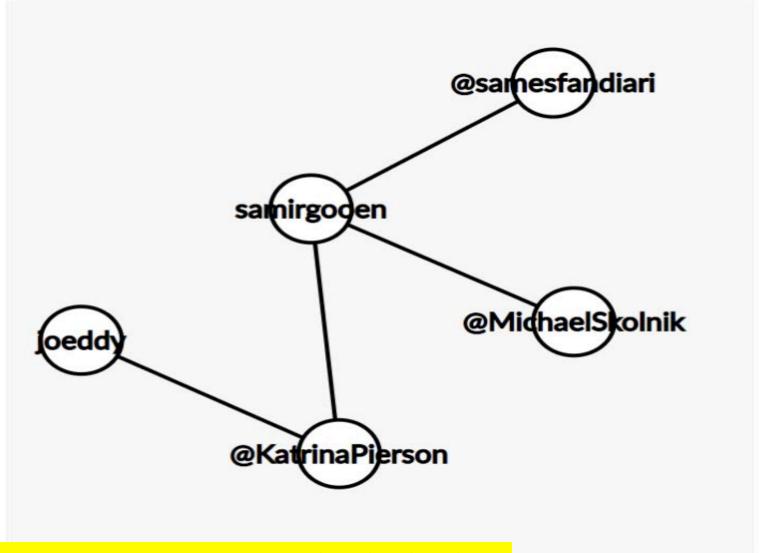
Bias: Extreme Right, Conspiracy, Propaganda, Some Fake News

Notes: The Angry Patriot is a very right wing biased website with many conspiracies and fake  $_{10}$  news stories. A very untrustworthy source that was placed on Politifact's fake news source list. (10/9/2016) Updated (6/20/2017)

## U2H: User to Hashtag Graph

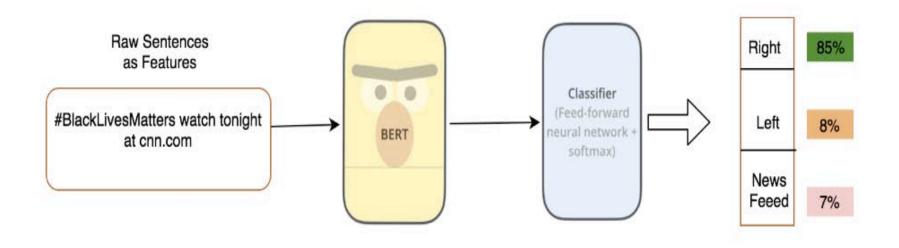


## U2M: User to User Mention Graph

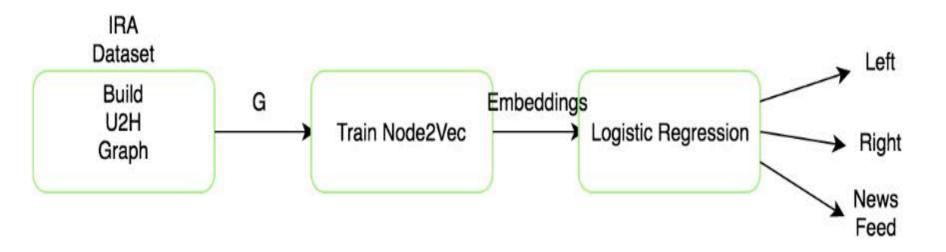


Atanas Atanasov, Gianmarco De Francisci Morales and Preslav Nakov: *Understanding the Roles of Political Trolls in Social Media.* CoNLL 2019

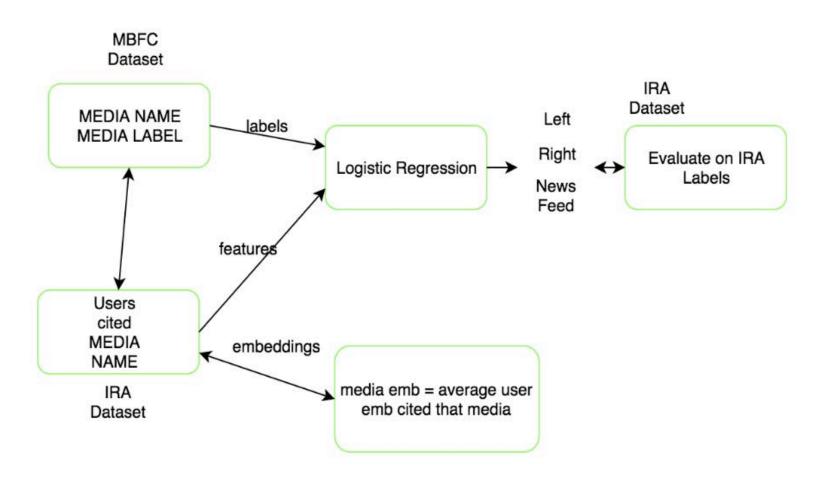
#### **BERT**



## Supervised Learning



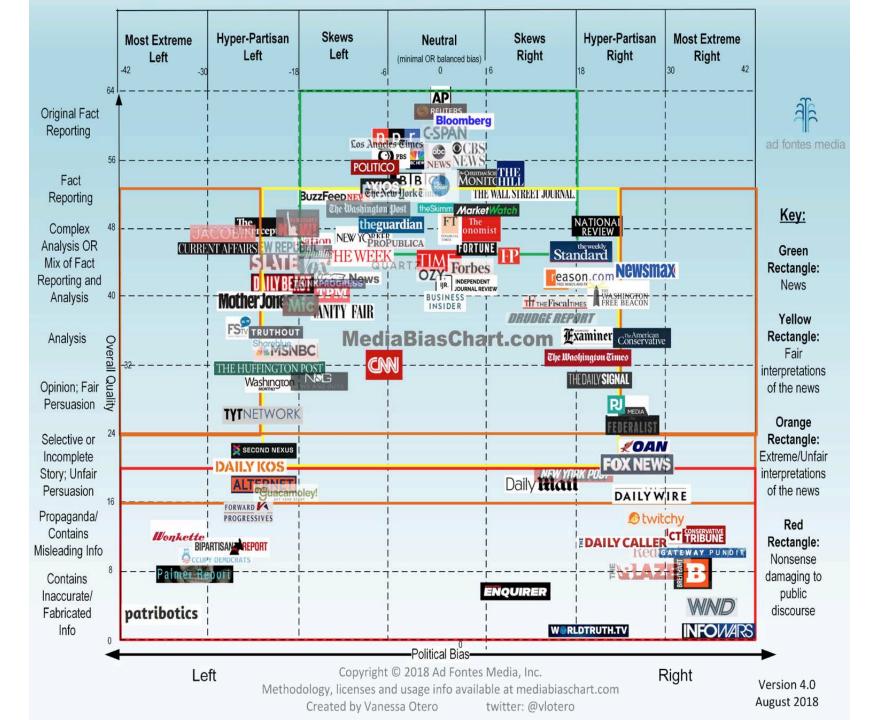
## Distant Supervision: Projecting a Label from a Medium



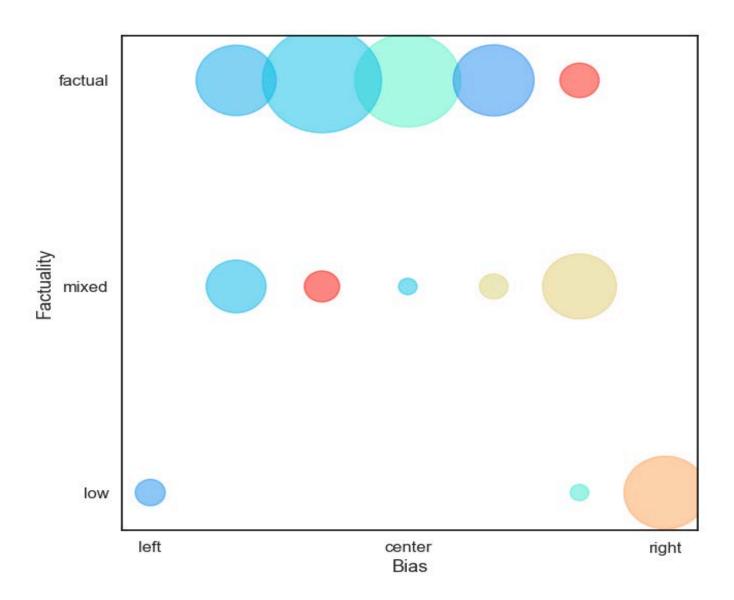
#### Understanding the Roles of Political Trolls in Social Media

Method	Full Super	vision (T1)	Distant Supervision (T2)		
	Accuracy	Macro F1	Accuracy	Macro F1	
Baseline (majority class)	68.7	27.1	68.7	27.1	
(Kim et al., 2019)	84.0	75.0	N/A	N/A	
BERT	86.9	83.1	75.1	60.5	
U2H	87.1	83.2	76.3	60.9	
U2M	88.1	83.9	77.3	62.4	
$U2H \oplus U2M$	88.3	84.1	77.9	64.1	
U2H    U2M	88.7	84.4	78.0	64.6	
U2H    U2M    BERT	89.2	84.7	78.2	65.1	
$U2M \oplus U2H \oplus BERT$	89.0	84.4	78.0	65.0	
$U2M \oplus U2H \oplus BERT + LP1$	89.3	84.7	78.3	65.1	
$U2M \oplus U2H \oplus BERT + LP2$	89.6	84.9	78.5	65.7	

# Topical Stance of Media and Twitter Users



# Bias vs. Factuality in MBFC

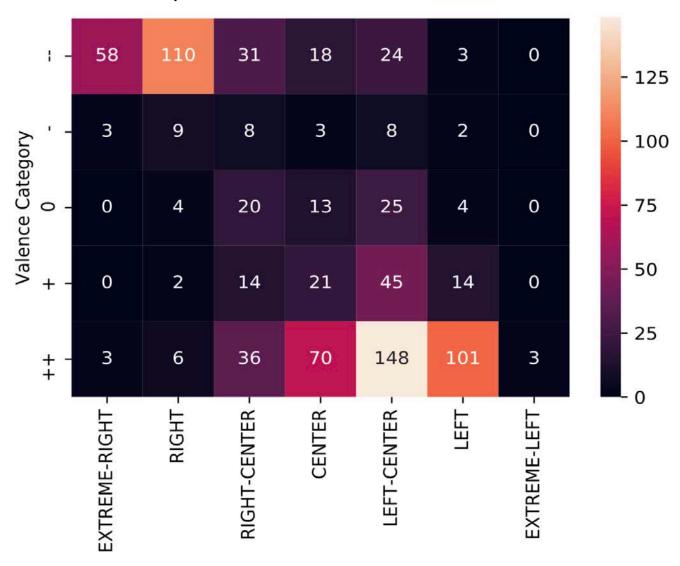


# Topical Stance of Media

Topic	Keywords	Date Range	No. of Tweets
Climate change	#greendeal, #environment, #climate, #climatechange, #carbonfootprint, #cli-	Feb 25-Mar 4,	1,284,902
	matehoax, #climategate, #globalwarming, #agw, #renewables	2019	
Gun con-	#gun, #guns, #weapon, #2a, #gunviolence, #secondamendment, #shooting,	Feb 25–Mar 3,	1,782,384
trol/rights	#massshooting, #gunrights, #GunReformNow, #GunControl, #NRA	2019	
Ilhan Omar re-	IlhanOmarIsATrojanHorse, #IStandWithIlhan, #ilhan, #Antisemitism, #Il-	Mar 1-9, 2019	2,556,871
marks on Israel	hanOmar, #IlhanMN, #RemoveIlhanOmar, #ByeIlhan, #RashidaTlaib,		
lobby	#AIPAC, #EverydayIslamophobia, #Islamophobia, #ilhan		
Illegal immigra-	#border, #immigration, #immigrant, #borderwall, #migrant, #migrants, #il-	Feb 25-Mar 4,	2,341,316
tion	legal, #aliens		
Midterm	midterm, election, elections		520,614
Racism & police	#blacklivesmatter, #bluelivesmatter, #KKK, #racism, #racist, #policebrutality,	Feb 25-Mar 3,	2,564,784
brutality	brutality #excessiveforce, #StandYourGround, #ThinBlueLine		
Kavanaugh	Kavanaugh, Ford, Supreme, judiciary, Blasey, Grassley, Hatch, Graham,	Sept. 28-30,	2,322,141
Nomination	Cornyn, Lee, Cruz, Sasse, Flake, Crapo, Tillis, Kennedy, Feinstein, Leahy,	2018 & Oct. 6-9,	
	Durbin, Whitehouse, Klobuchar, Coons, Blumenthal, Hirono, Booker, Harris	2018	
Vaccination	#antivax, #vaxxing, #BigPharma, #antivaxxers, #measlesoutbreak, #An-	Mar 1-9, 2019	301,209
benefits &	tivacine, #VaccinesWork, #vaccine, #vaccines, #Antivaccine, #vaccines-		
dangers	tudy, #antivaxx, #provaxx, #VaccinesSaveLives, #ProVaccine, #VaxxWoke,		
-	#mykidmychoice		

media	factuality	bias	Average	climate change	gun control	ilhan	immigration	midterm	police & racism	Kavanaugh	vaccine
thehill.com	Н	L-C	+	0	++	+	+	+	+	++	++
theguardian.com	Н	L-C	++	++	++	++	++	++	++	++	++
washingtonpost.com	Н	L-C	++	++	++	++	++	++	++	++	++
breitbart.com	VL	Far R									
foxnews.com	M	R									
nytimes.com	Н	L-C	++	+	++	+	+	+	++	++	++
cnn.com	M	L	+	+	++	+	++	+	+	++	+
apple.news			+	0	0	+	0	0	+	+	++
dailycaller.com	M	R									
rawstory.com	M	L	++	++	++	++	++	++	++	++	++
huffingtonpost.com	Н	L	++	++	++	++	++	+	++	++	++
truepundit.com	L										
nbcnews.com	Н	L-C	+		++	+	++	+	+	++	++
westernjournal.com	M	R									
reuters.com	VH	C	+	+	++	++	+	+	+	+	++
washingtonexaminer.com	Н	R						0			
thegatewaypundit.com	VL	Far R									
politico.com	Н	L-C	+	+	+	+	+	++	+	+	++
npr.org	VH	L-C	+	0	++	++	++	0	++	++	++
townhall.com	M	R									
msn.com	Н	L-C	+	+	+	+	0	++	0	++	0
nypost.com	M	R-C	_		0	_	_	+		_	
vox.com	Н	L	++	++	++	++	++	++	+	++	++
thedailybeast.com	Н	L	++	++	++	+	++	++	+	++	++
bbc.com	Н	L-C	+	+	+	++	++	0	+	+	++
independent.co.uk	Н	L-C	++	++	+	++	++	++	+	++	++
ilovemyfreedom.org	VL	Far R									
thinkprogress.org	M	L	++	++	++	++	++	++	++	++	++
dailywire.com	M	R									++
pscp.tv			_				0		0	_	
dailymail.co.uk	VL	R	-	_	0	_	_	_	_		
msnbc.com	M	L	++	++	++	++	++	+	++	++	
dailykos.com	M	L	++	++	++	++	++	+	++	++	
bloomberg.com	Н	L-C	+	+	++	0	++	+	0	+	++
usatoday.com	Н	L-C	+	+	+	0	+	++	+	0	+

#### Topical Stance of Media



# Propaganda

# Why Propaganda?

 "Expression deliberately designed to influence the opinions /actions of other individuals or groups with reference to predetermined ends."

Institute for Propaganda Analysis

 "The rise of the Internet [...] has opened the creation and dissemination of propaganda messages, which were once the province of states and large institutions, to a wide variety of individuals and groups."

(Bolsover and Howard, Big Data 5(4))

Weather: Seeiny and warm, 79/62

SPORTS . FINAL

Monday, September 24, 2007

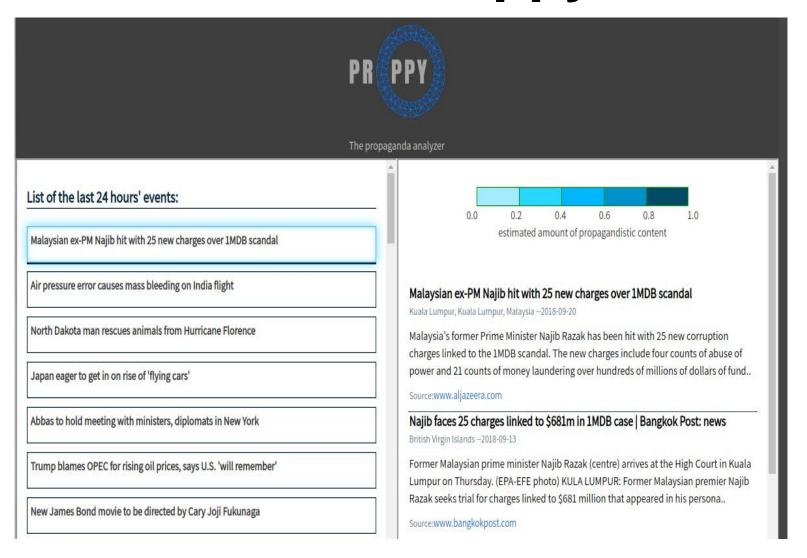
# DAILYNEWS

NEW YORK'S HOMETOWN NEWSPAPER

NYDullyNews.com

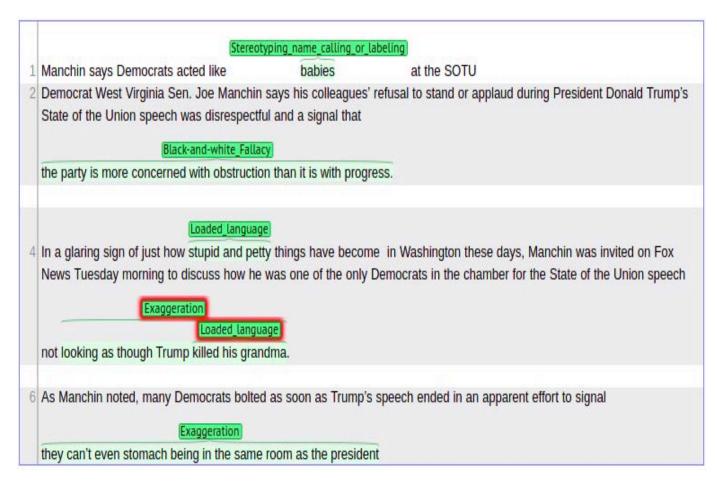


# Demo: Proppy http://proppy.qcri.org



Alberto Barrón-Cedeño, Giovanni Da San Martino, Israa Jaradat, Preslav Nakov: Proppy: A System to Unmask Propaganda in Online News. AAAI 2019: 9847-9848 reductio ad Hitlerum thought-terminating cliches whataboutism flag-waving labeling bandwagon red herring causal oversimplification minimisation straw men appeal to authority obfuscation exaggeration name calling intentional vagueness black-and-white fallacy cognitive dissonance appeal to prejudice loaded language

## Fine-Grained Propaganda Detection



#### **New Dataset**

- 18 techniques
- 350k words
- 400 man hours
- 7.3k instances

#### **Technique** • **Snippet**

loaded language • until forced to act by a worldwide storm of outrage.

name calling, labeling • dismissing the protesters as lefties and hugging Barros publicly

repetition • Farrakhan repeatedly refers to Jews as **Satan**. He states to his audience [...] call them by their real name, '**Satan**.'

exaggeration, minimization • heal the situation of extremely grave immoral behavior doubt • Can the same be said for the Obama Administration?

appeal to fear/prejudice • A dark, impenetrable and irreversible winter of persecution of the faithful by their own shepherds will fall.

flag-waving • conflicted, and his 17 Angry Democrats that are doing his dirty work are a disgrace to USA! —Donald J. Trump

flag-waving • attempt (Mueller) to stop the will of We the People!!! It's time to jail Mueller causal oversimplification • he said The people who talk about the "Jewish question" are generally anti-Semites. Somehow I don't think

causal oversimplification • will not be reversed, which leaves no alternative as to why God judges and is judging America today

slogans • BUILD THE WALL!" Trump tweeted.

appeal to authority • Monsignor Jean-Franois Lantheaume, who served as first Counsellor of the Nunciature in Washington, confirmed that "Vigan said the truth. Thats all"

black-and-white fallacy • Francis said these words: Everyone is guilty for the good he could have done and did not do ... If we do not oppose evil, we tacitly feed it.

thought-terminating cliches • I do not really see any problems there. Marx is the President whataboutism • President Trump —who himself avoided national military service in the 1960's—keeps beating the war drums over North Korea

reductio ad hitlerum • "Vichy journalism," a term which now fits so much of the mainstream media. It collaborates in the same way that the Vichy government in France collaborated with the Nazis.

red herring • It describes the tsunami of vindictive personal abuse that has been heaped upon Julian from well-known journalists, many claiming liberal credentials. The Guardian, which used to consider itself the most enlightened newspaper in the country, has probably been the worst.

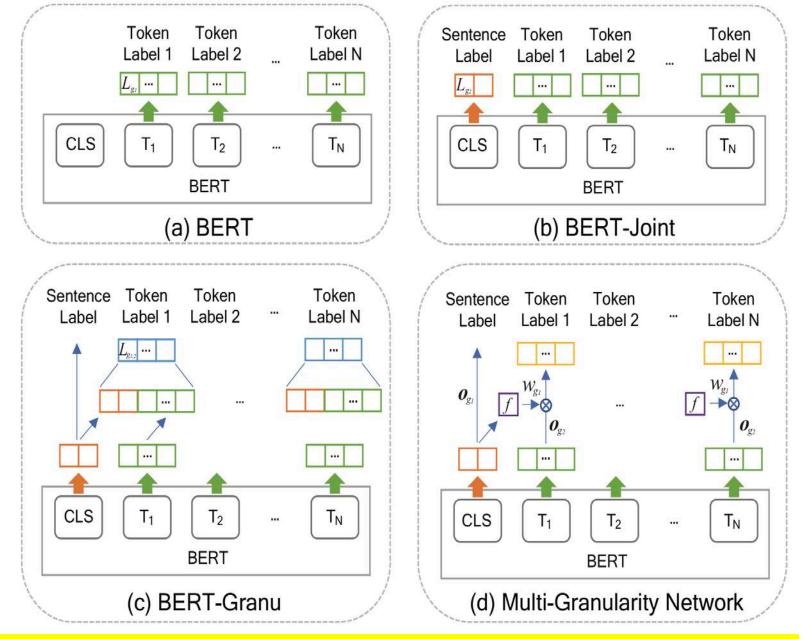
bandwagon • He tweeted, "EU no longer considers #Hamas a terrorist group. Time for US to do same." obfusc., int. vagueness, confusion • The cardinal's office maintains that rather than saying "yes," there is a possibility of liturgical "blessing" of gay unions, he answered the question in a more subtle way without giving an explicit "yes."

straw man • "Take it seriously, but with a large grain of salt." Which is just Allen's more nuanced way of saying: "Don't believe it."

# Propagandistic News Outlets and Number of Articles

News Outlet	#	News Outlet	#
Freedom Outpost	133	The Remnant Magazine	14
Frontpage Magazine	56	Breaking911	11
shtfplan.com	55	truthuncensored.net	8
Lew Rockwell	26	The Washington Standard	6
vdare.com	20	www.unz.com	5
remnantnewspaper.com	19	www.clashdaily.com	1
Personal Liberty	18		

Propaganda Technique	inst	avg. length
loaded language	2,547	$23.70 \pm 25.30$
name calling, labeling	1,294	$26.10 \pm 19.88$
repetition	767	$16.90 \pm 18.92$
exaggeration, minimization	571	$45.36 \pm 35.55$
doubt	562	$123.21 \pm 97.65$
appeal to fear/prejudice	367	$93.56 \pm 74.59$
flag-waving	330	$61.88 \pm 68.61$
causal oversimplification	233	$121.03 \pm 71.66$
slogans	172	$25.30 \pm 13.49$
appeal to authority	169	$131.23 \pm 123.2$
black-and-white fallacy	134	$98.42 \pm 73.66$
thought-terminating cliches	95	$34.85 \pm 29.28$
whataboutism	76	$120.93 \pm 69.62$
reductio ad hitlerum	66	$94.58 \pm 64.16$
red herring	48	$63.79 \pm 61.63$
bandwagon	17	$100.29 \pm 97.05$
obfusc., int. vagueness, confusion	n 17	$107.88 \pm 86.74$
straw man	15	$79.13 \pm 50.72$
all	7,485	$46.99 \pm 61.45$



Giovanni Da San Martino, Seunghak Yu, Alberto Barrón-Cedeño, Rostislav Petrov, Preslav Nakov *Fine-Grained Analysis of Propaganda in News Articles.* EMNLP 2019

## Results: Fragment-Level

Model		Spans		Full Task		
Model	P	R	$F_1$	P	R	$F_1$
BERT	39.57	36.42	37.90	21.48	21.39	21.39
Joint	39.26	35.48	37.25	20.11	19.74	19.92
Granu	43.08	33.98	37.93	23.85	20.14	21.80
Multi-Gran	ularity					
ReLU	43.29	34.74	38.28	23.98	20.33	21.82
Sigmoid	44.12	35.01	38.98	24.42	21.05	22.58

Results: Sentence-Level

Model	Precision	Recall	F1
All-Propaganda	23.92	1.00	38.61
BERT	63.20	53.16	57.74
BERT-Granu	62.80	55.24	58.76
<b>BERT-Joint</b>	62.84	55.46	58.91
MGN Sigmoid	62.27	59.56	60.71
MGN ReLU	60.41	61.58	60.98



- Long press release: https://www.datasciencesociety.net/ global-datathon-aims-at-detecting-theuse-of-propaganda-in-the-news/
- Summary: <a href="https://www.datasciencesociety.net/">https://www.datasciencesociety.net/</a> <a href="hack-news-datathon/">hack-news-datathon/</a>
- Detailed description: https://www.datasciencesociety.net/ hack-news-datathon-case-propagandadetection/
- Leaderboard: https://www.datasciencesociety.net/ events/hack-the-news-datathon-2019/ leaderboard/

**RULES/DATES** 

REGISTER

**RESULTS** 

**ORGANISERS EMNLP-IJCNLP 2019** 

Team Page

https://propaganda.qcri.org/nlp4if-shared-task/



# SemEval-2020

International Workshop on Semantic Evaluation

Sponsored by SIGLEX

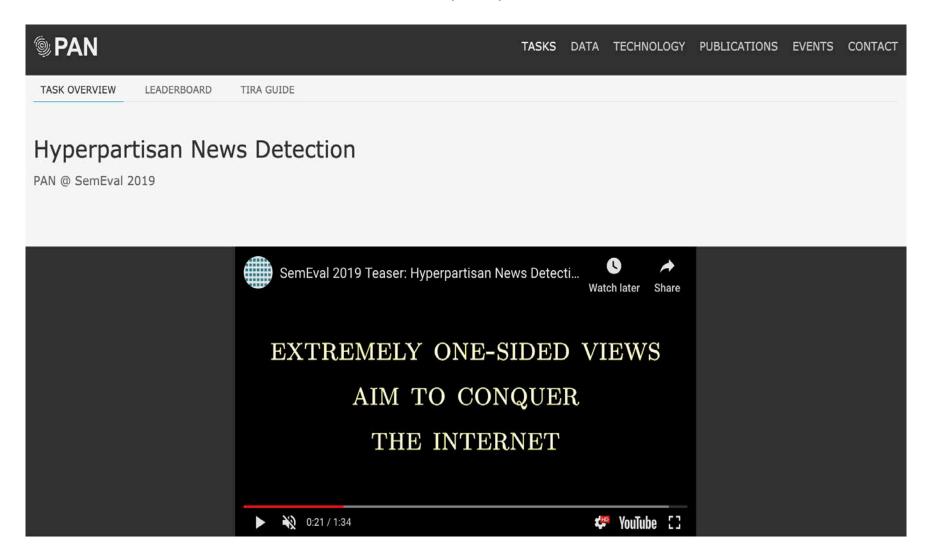
http://alt.qcri.org/semeval2020/index.php?id=tasks

#### **Tasks**

We are pleased to announce the following tasks in SemEval-2020.

#### Related PAN Task at SemEval

https://pan.webis.de/semeval19/semeval19-web/



# The Role of Education

# Finland is winning the war on fake news. What it's learned may be crucial to Western democracy

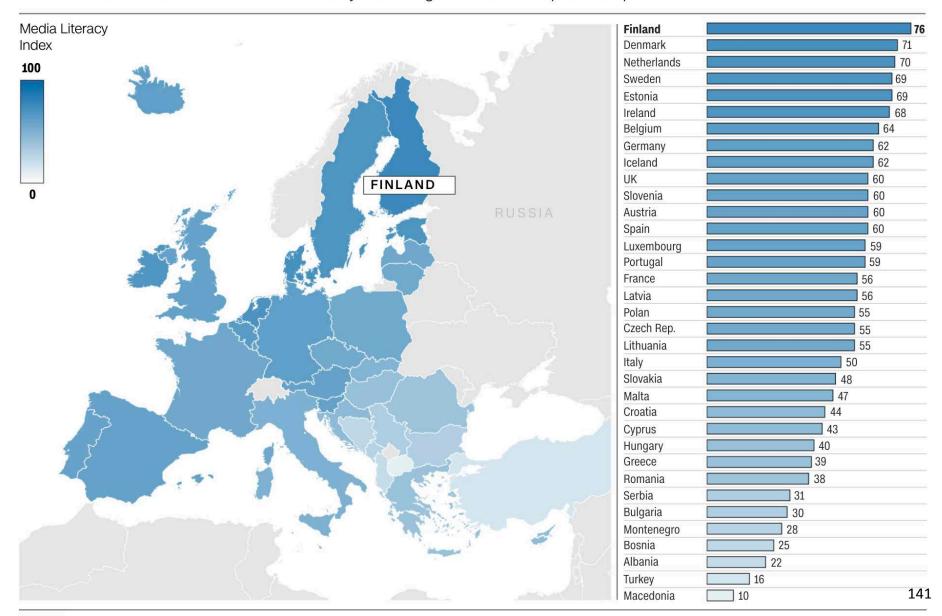
By Eliza Mackintosh, CNN Video by Edward Kiernan, CNN

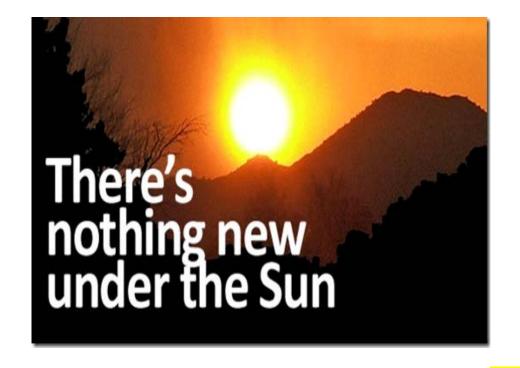
https://edition.cnn.com/interactive/ 2019/05/europe/finland-fake-news-intl/



#### **Media literacy across Europe**

Finland ranked first out of 35 countries in a study measuring resilience to the post-truth phenomenon





"Propaganda becomes ineffective the moment we are aware of it."

Joseph Goebbels (1897-1945)

# The Tanbih Project

## Tanbih: News Aggregator



Show stance, bias, propaganda in the news.

Promote different viewpoints, engage users.

Limit the effect of disinformation.







#### **Highlights:**

- Disinformation-aware news aggregator
- Media profiles: can fact-check the news before they were even written
- Fine-grained propaganda analysis: adversarial attacks are very hard
- Focus on MENA: media, events, languages

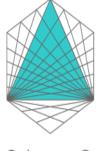
## **Collaborations**







ST. KLIMENT OHRIDSKI



Data Science Society





عضو في مؤسسة قطر Member of Qatar Foundation



Carnegie Mellon University Qatar





UNIVERSITY OF TEXAS ARLINGTON



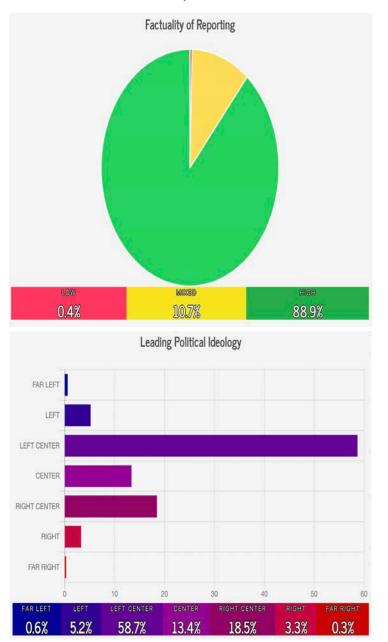
Associated Press



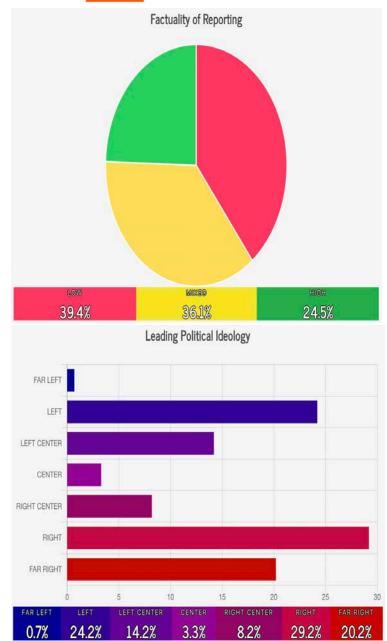


# Tanbih: App

# The New York Times







1 of 2

BUSINESS POLITICS TECH & SCI



"We're OK" says British colleague of eight climbers feared dead in India





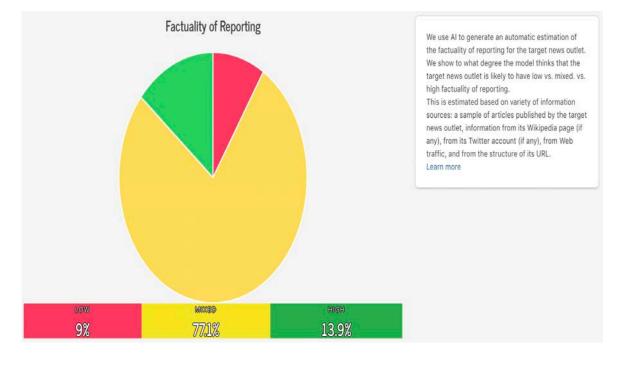
'Nothing Short of Madness': Netanyahu Accused of Trying to Turn Israel Into Iran

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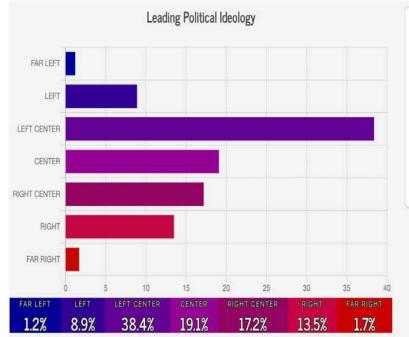
MIDDLEEAST

1 of 2





Try Tanbih: http://www.tanbih.org



We use AI to generate an automatic estimation of the leading political ideology for the target news

We show to what degree the model thinks that the target news outlet is likely to be extreme left vs. left vs. left-center vs. center vs. right-center vs. right vs. extreme right.

This is estimated based on variety of information sources: a sample of articles published by the target news outlet, information from its Wikipedia page (if any), from its Twitter account (if any), from Web traffic, and from the structure of its URL.

Learn more



Try Tanbih: http://www.tanbih.org

This work is part of the Tanbih project, developed in collaboration between the QCRI and MIT-CSAIL, with the aim to limit the effect of "fake news", propaganda and media bias by making users aware of what they are reading.

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