

Computational Solutions against Fake News: Al vs. DB Approaches

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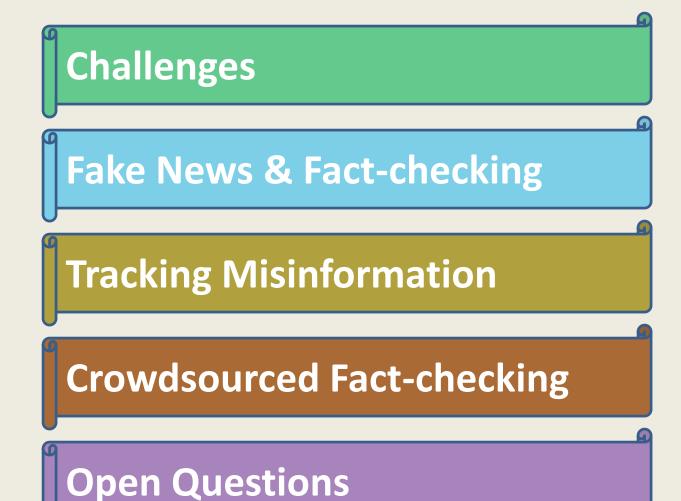
Hassan & Lee

AAAI 2018



Part 3. DB Approaches

Outline



Available Datasets

- ASU FakeNewsNet: https://github.com/KaiDMML/FakeNewsNet
- PHEME rumor: https://goo.gl/5JXAXt
- NewsVerification: https://goo.gl/jDZJpS
- BuzzFeedNews: https://goo.gl/TUnw2K
- LIAR: https://goo.gl/wkNYhv
- BS Detector: https://github.com/bs-detector/bs-detector/bs-detector/
- FakeNewsSites: https://www.kaggle.com/mrisdal/fake-news/data

 There are no agreed upon bench-mark datasets for the fake news detection problem. [Shu et al., 2017]

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BS Detector¹: This dataset is collected from a browser extension called BS detector developed for checking news veracity. It searches all links on a given web-page for references to unreliable sources by checking against a manually complied list of domains. The labels are the outputs of BS detector, rather than human annotators.

1. https://www.kaggle.com/mrisdal/fake-news

 There are no agreed upon bench-mark datasets for the fake news detection problem. [Shu et al., 2017]

LIAR¹: This dataset is collected from fact-checking website PolitiFact through its API. It includes 12,836 human-labeled short statements. The labels for news truthfulness are fine-grained multiple classes: pants-fire, false, barely-true, half-true, mostly true, and true.

1. https://www.cs.ucsb.edu/william/data/liar_dataset.zip

 There are no agreed upon bench-mark datasets for the fake news detection problem. [Shu et al., 2017]

CREDBANK¹: This is a large scale crowdsourced dataset of approximately 60 million tweets. All the tweets are broken down to be related to over 1,000 news events, with each event assessed for credibility by 30 annotators from Amazon Mechanical Turk

1. http://compsocial.github.io/CREDBANK-data/

Comparison of Fake News Detection Datasets

Features	News Content		Social Context		
Dataset	Linguistic	Visual	$\mathbf{U}\mathbf{ser}$	\mathbf{Post}	Network
BuzzFeedNews	✓				
LIAR	✓				
BS Detector	✓				
CREDBANK	✓		✓	✓	✓

FakeNewsNet¹

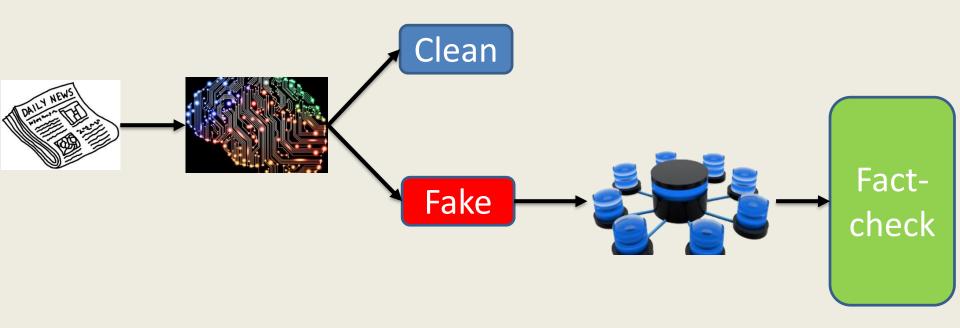
To address the disadvantages of existing fake news detection datasets, [Shu et al., 2017] have an ongoing project to develop a usable dataset for fake news detection on social media. This dataset includes all mentioned news content and social context features with reliable ground truth fake news labels.

- Source
- Headline
- Body
- Image
 - 1. https://github.com/KaiDMML/FakeNewsNet

Fake News & Fact-checking

Fake News & Fact-checking

Machine learning is good at finding patterns. All
can raise the flag. But to check it's veracity, we
need to check against a knowledge base.



Linking Multiple Data sources.





Enter Your Own Text



2016 U.S. Presidential Debates



Hansard: Parliament of Australia

ClaimBuster API



ClaimBuster Slackbot





The math: Procedural vote Fri nite got 50 yeas. Graham & Flake were noes. Likely to be yeas. that's 52. 5 Dems were yeas Fri: Donnelly, Heitkamp, Manchin, Jones, McCaskill. McConnell is technically a yea. So that's 53. Still need 7 Dems. Look at moderate Dems who are up this fall

2 1

[→

Jan 21, 2018

ClaimBuster Retweeted



In 2013 I worked w/Susan Collins as 1 of 14 senators (7 dems & 7 repubs) who led the effort to end the last shutdown. That group has gotten together again (w/some new members)& we've been working for past 2 days to find bipartisan solution. Making progress. Heading to Capitol now

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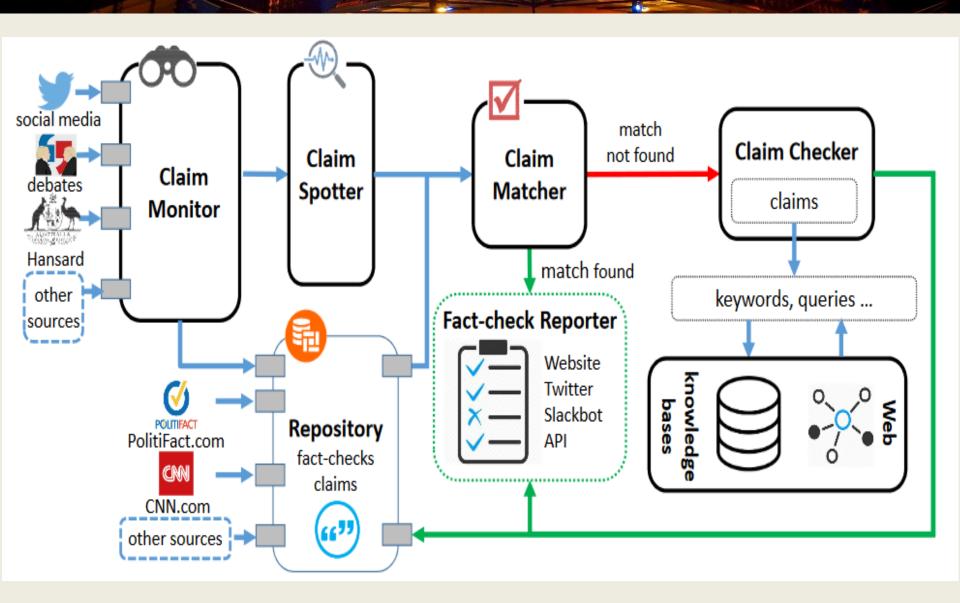
http://idir.uta.edu/claimbuster

[Hassan et al., 2017a, Hassan et al., 2017b]

ClaimBuster^{1,2,3} Demo Time

- 1. Go to http://idir.uta.edu/claimbuster
- 2. Claim Spotter
 - 1. Any text
 - 2. 2016 U.S. Presidential Election
 - 3. Social media [Twitter]
 - 4. Hansard
- 3. Fact-Checker
 - 1. Knowledge base [Wolfram Alpha, Google, Freebase]
 - 2. Search Engines
 - 3. Fact-checking Platforms

ClaimBuster System Architecture



ClaimBuster: Fact to Question

Fact: The capital of Louisiana is New Orleans.

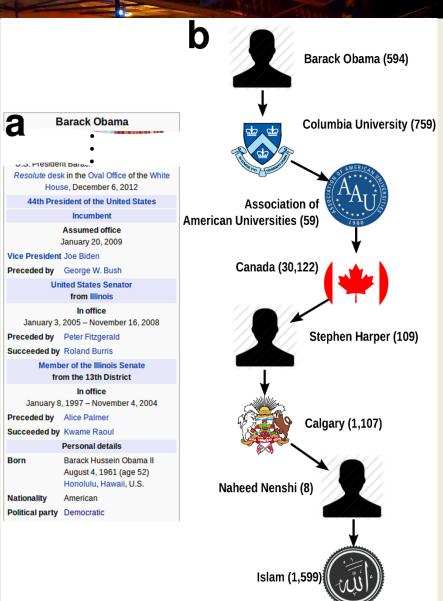
Question:

- What is the capital of Louisiana?
- What is New Orleans?
- Is the capital of Louisiana New Orleans?

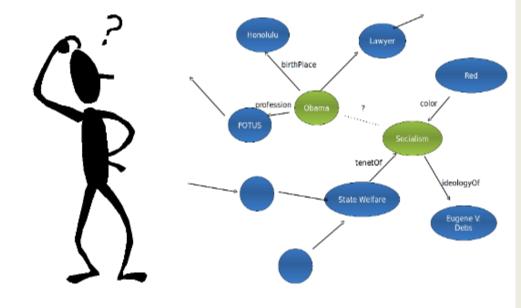
Knowledge Network Approach

- Create a knowledge graph from Wikipedia.
- Veracity of a subjectpredicate-object statement → finding a path between subject and object entities.

[Ciampaglia et al., 2015]

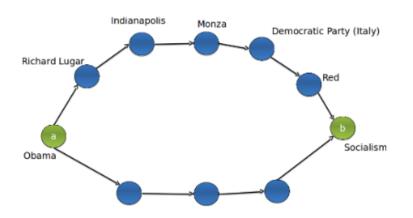


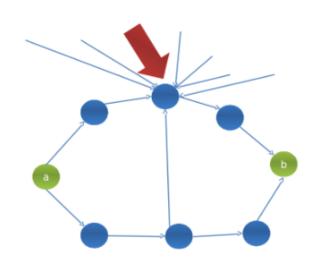
- Amount of "work" needed to resolve a novel statement
- On a network: how hard it is to find a path between two nodes
- Graph closure



http://cns.iu.edu/docs/netscitalks/2014.10.13-Talk-GiovanniCiampaglia.pdf

Distance function

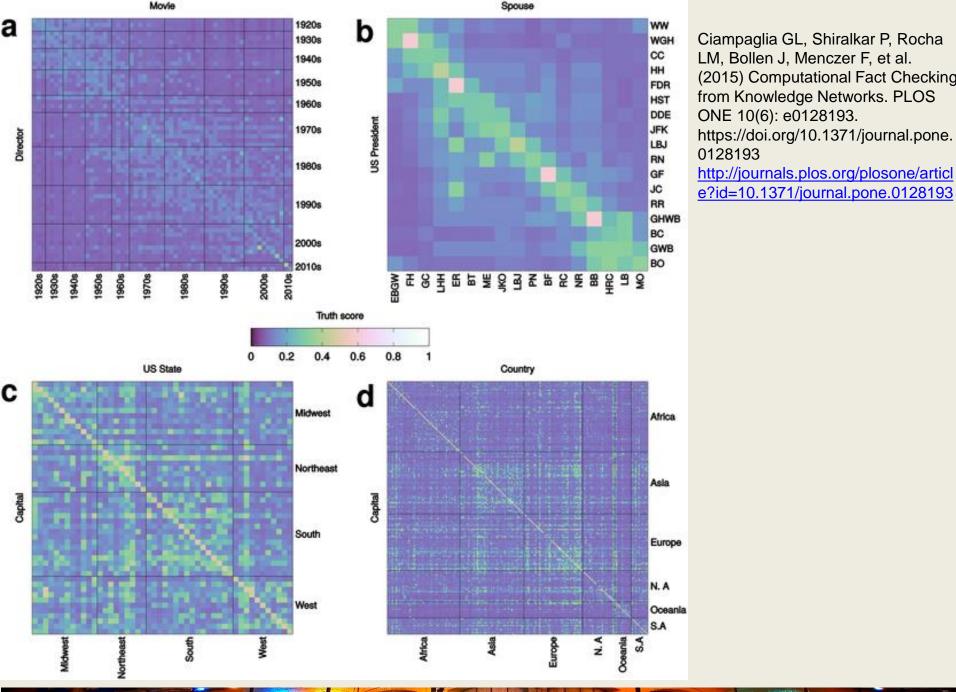




$$\mathcal{W}_{u}(P_{s,o}) = \mathcal{W}_{u}\left(v_{1}\dots v_{n}\right) = \left\{\begin{array}{ll} 1 & \text{if } n=2\\ \phi\left(\min_{i=2}^{n-1}\left\{\log\left(k\left(v_{i}\right)\right)\right)\right\} & \text{if } n>2 \end{array}\right.$$

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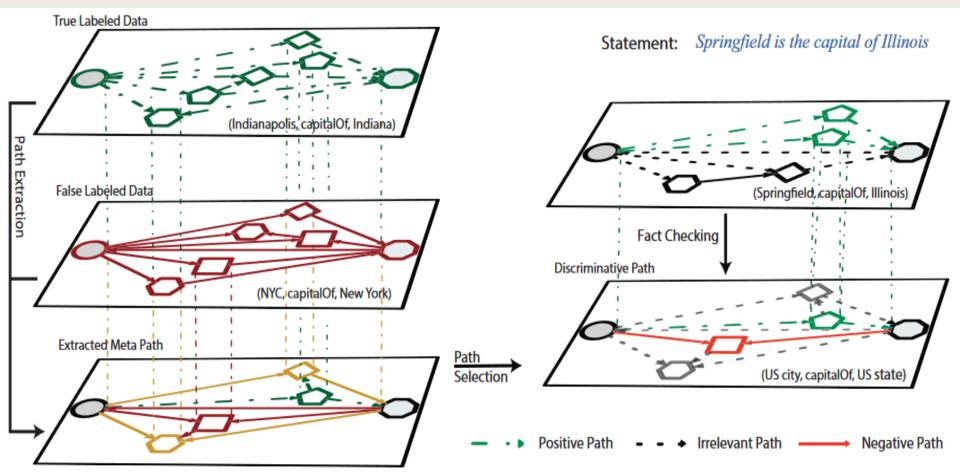


Ciampaglia GL, Shiralkar P, Rocha LM, Bollen J, Menczer F, et al. (2015) Computational Fact Checking from Knowledge Networks. PLOS ONE 10(6): e0128193. https://doi.org/10.1371/journal.pone. 0128193

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Knowledge Network Approach

 Views this problem as a link-prediction task in a knowledge graph. [Shi et al., 2015]



Finding Stream in Knowledge Graph

Fact checking as a Minimum Cost Maximum Flow Problem [Shiralkar et al., 2017]

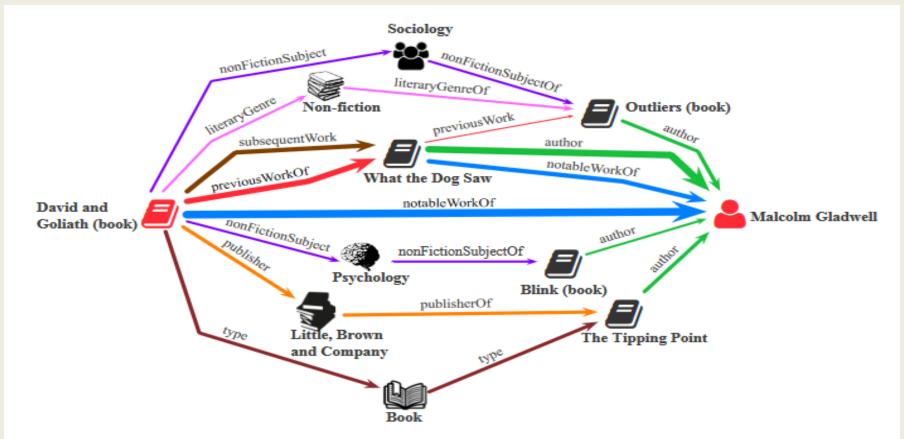
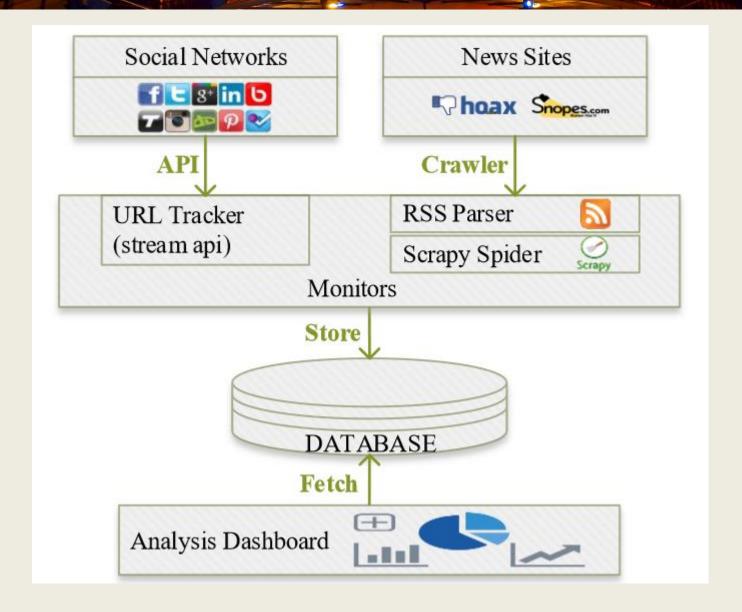


Fig. 1. The best paths identified by Knowledge Stream for the triple (David and Goliath (book), author, Malcolm Gladwell). The width of an edge is roughly proportional to the flow of knowledge through it.

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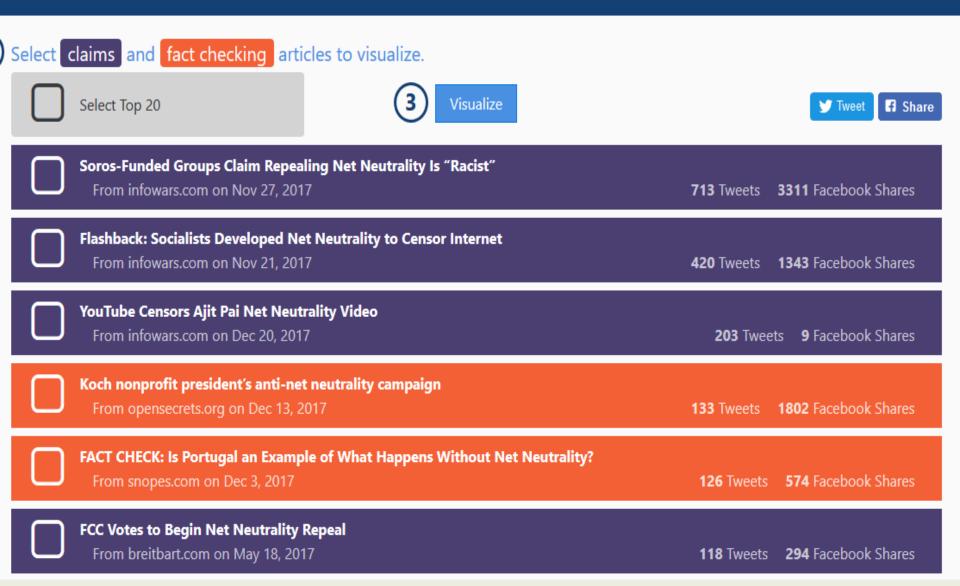
Monitoring Facts and Tracking Misinformation

Hoaxy System Architecture [Shao et al., 2016]



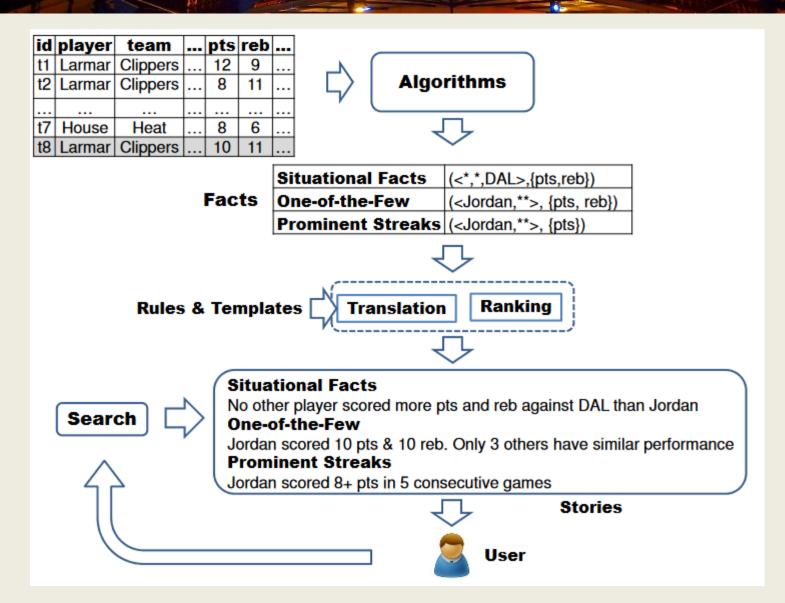
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https://hoaxy.iuni.iu.edu

FactWatcher [Hassan et al., 2014]

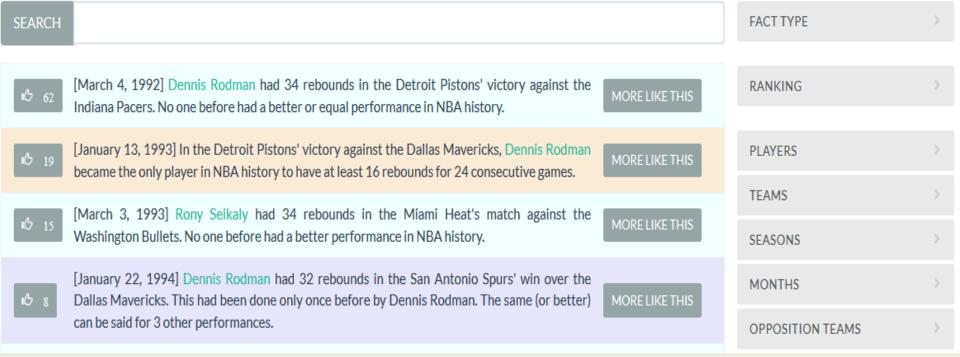




»LIVE UPDATE

[February 20, 1998] Antonio Davis had 12 rebounds, and 2 blocks in the Indiana Pacers' win over the Orlando Magic. This had been done only 6 times before by Antonio Davis. The same (or better) can be said for 18 other performances.

SHOW GRAPHS



http://idir.uta.edu/factwatcher/

TwitterTrail [Metaxas et al., 2015]

Web-based interactive tool that uses an algorithm to measure the trustworthiness of a tweet.

- Who broke the story and when?
- How is the story spreading?
- Who are the main actors of the event?
- How are the communities self-describing?

http://www.twittertrails.com/

Crowdsourced Fact-checking



https://reporterslab.org/fact-checking/

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Why fact-checking sites close?

- "Fact-checking is time consuming and therefore expensive." - Nicolas Patte
- Tied to offer impartial service; eschew partisan funding sources.
- Less scalable and more labor intensive.
- Funding is often tied to election cycle.

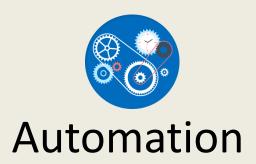
https://www.poynter.org/news/why-do-fact-checking-sites-close-and-how-can-new-ones-avoid-fate

What's a sustainable model for fact-checking?

- I don't know :)
- But, we question ourselves, is the following combination sustainable?







What role does Crowd play in fact-checking?

Average fact-checking time is about 7 days.

150

111

91

78

68

51

40

politifact.com

nytimes.com

youtube.com

factcheck.org

whitehouse.gov

washingtonpost.com

reddit.com

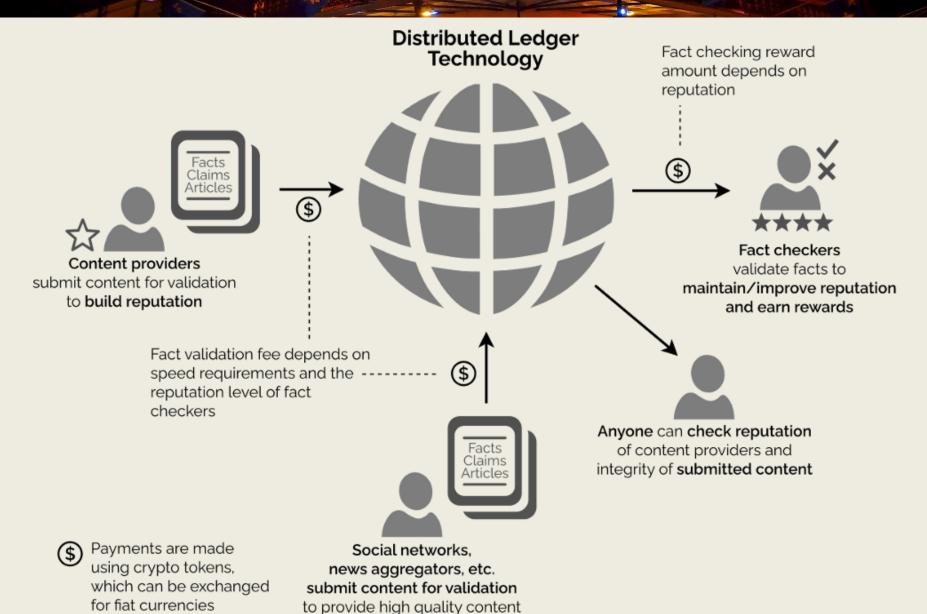
Action	# Comments	Percentage	Flair	Avg. # Factual Evidence	Avg. # Opinion/Judgment		
Provide Argument	1942	69.56	Mostly True	3.22	1.83		
Post Irrelevant	402	14.40	Half True	3.17	1.67		
Seek Clarification	355	12.71	Confirmed	3.10	1.56		
Assign Flair	141	5.05	False	2.89	2.59		
Check Verifiability	48	1.72	Mostly False	2.75	1.86		
			Partisan Bias	2.73	1.90		
Domain	# Citations		Please Verify	2.59	2.40		
wikipedia.org	298		Unverifiable	2.38	3.33		

Hassan et al., 2017c

Q4: How Automation can help scaling-up?

- Ranking fact-check request by their checkworthiness.
 - ClaimBuster
- Argument Classification
 - Classes: Based on evidence (E), Evidence lacking opinion/judgement (O)
 - Average Accuracy: 82.2% (+/- 0.17%)
- Stance Detection
- Comments Ranking
- Soliciting arguments from users based on expertise

4Fact.org



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Part 4. Postlude

Organizations and Industries

- PolitiFact [www.politifact.com]
- FullFact [www.fullfact.org]
- Factcheck [www.factcheck.org]
- Snopes.com
- Reddit #politicalfactchecking

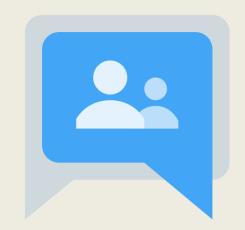
- Factmata [https://factmata.com]
- Newscheck [http://www.newscheck.com/]
- 4facts [http://4facts.org/]

Connect with other researchers.

Slack group of Misinfocon [https://misinfocon.slack.com/]



- Google Groups "Combating Fake
 News: The Science of
 Misinformation"
 https://groups.google.com/group/fakenewssci
- The Credibility Coalition
 https://meedan.com/credibility-coalition/





Future Direction

- Unified Knowledge Base + Credibility
 - Knowledge base from fact-checks
- Natural Language to Query Formulation
- Question Answering System
 - Aggregation
- Query Similarity

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