Combating Disinformation on Social Media and Its Challenges

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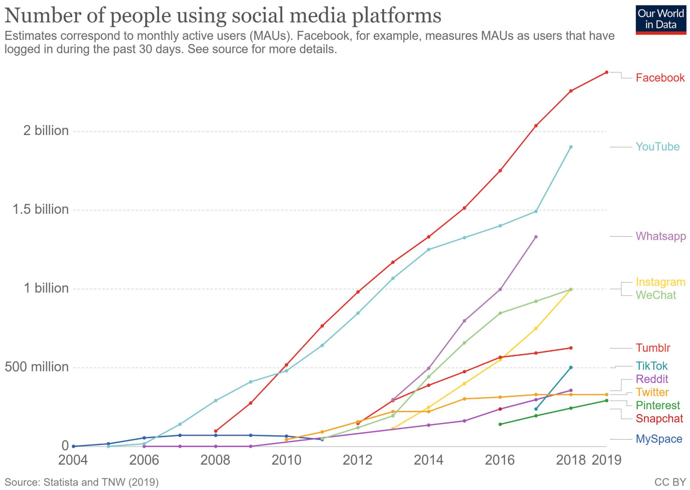
Spot "Fake News"

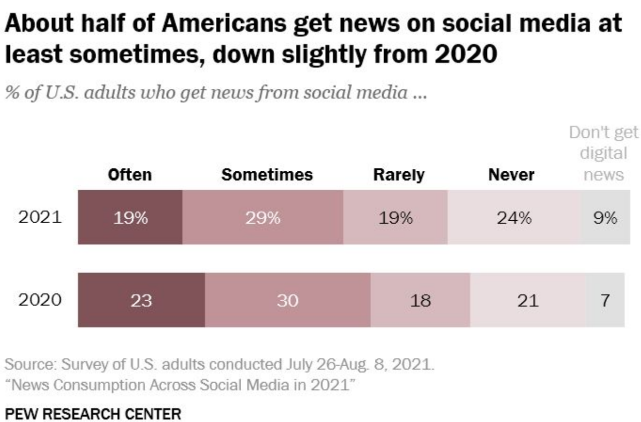
It's true: AI is the engine that pushes "fake news" out to the masses, but Google, Microsoft, and grassroots effort Fake News Challenge are using AI (machine learning and natural language processing) to assess the truth of articles automatically. Due to the trillions of posts, Facebook must monitor and the impossibility of manually doing it, the company also uses artificial intelligence to find words and patterns that could indicate fake news. Other tools that rely on AI to analyze content include Spike, Snopes, Hoaxy, and more.

Social Media for Information Sharing

- People are increasingly using social media for information sharing, social networking, etc

- 67% of Americans get news on social media





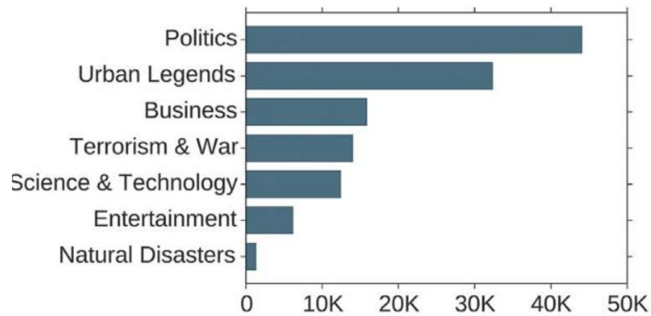
https://www.pewresearch.org/journalism/2021/09/20/news-consumption-across-social-media-in-2021/

Disinformation Is Rampant on Social Media

- ***Disinformation*** is false information with a bad intention aiming to mislead the public
- ***Fake news*** is news with intentionally false information

World Health Organization

Managing the COVID-19 infodemic: Promoting healthy behaviours and mitigating the harm from misinformation and disinformation



[1] A public health research agenda for managing infodemics: Methods and results of the first WHO infodemiology conference, JIMR Infodemiology, 2021.
[2] Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. Science, 359(6380), 1146-1151.

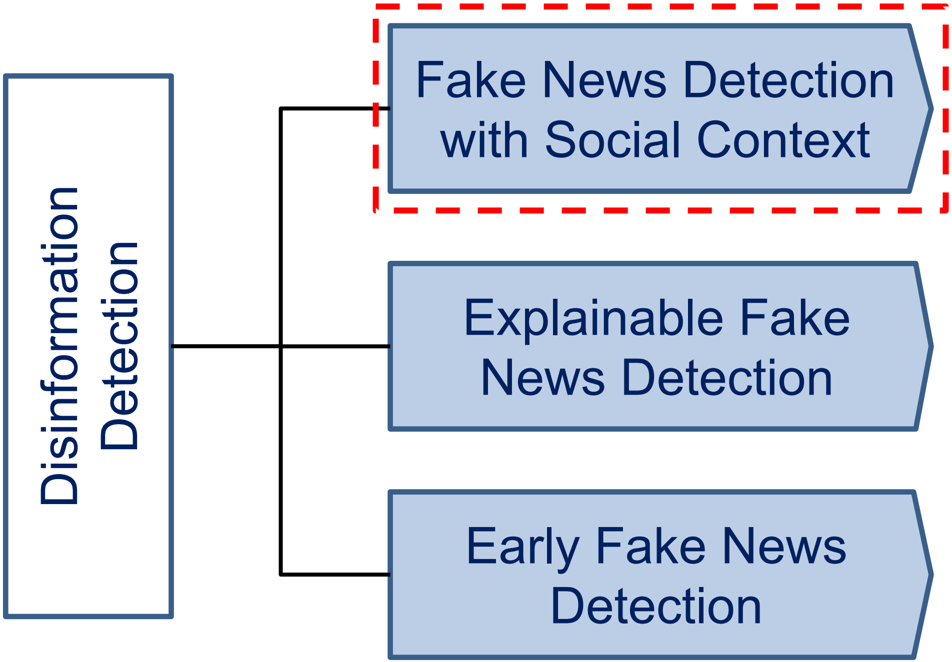
Studying Fake News

- Humans are **susceptible** to fake news
  - ***Limited resources***: time, information, and expertise
  - ***Confirmation Bias***: people tend to believe information when it confirms their pre-existing knowledge

- Fake news can have **detrimental societal effects**
  - ***Misleading*** people to false information
  - ***Changing*** the way people respond to true news
  - ***Weakening*** public trust in governments and journalism

Why It Is So Challenging

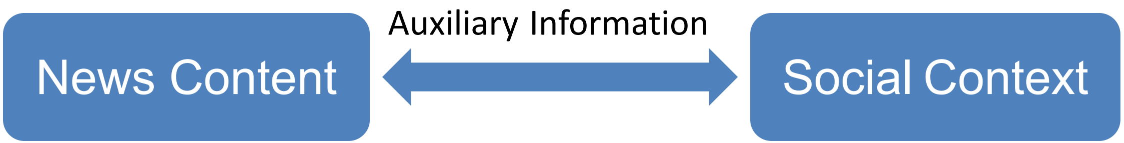
- *Fake news detection* is not just another competition
  - A competition gives a dataset with ground truth and shows who can fare best
- Fake news detection is complex in many dimensions
- We discuss some imperative challenges
  - Detection, Explainability, and Data



Kai Shu, Suhang Wang, and Huan Liu. ``Beyond News Content: The Role of Social Context for Fake News Detection". WSDM 2019, February 11-15, 2019. Melbourne, Australia.

Motivation

- It is **difficult** to differentiate fake news from real news using **only** news content
- **Social context** provides rich auxiliary information beyond news content

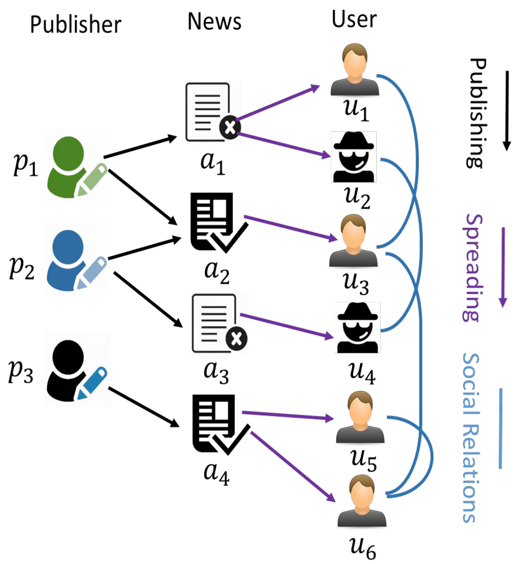


→ What are the ***actors*** and ***their relations*** in social context?

→ How to ***model*** social context to help detect fake news?

News, Actors, and Their Relations

- A typical news ecosystem with social context
  - **Entities**: publishers, news pieces, and social media users
  - **Relations**: publishing, spreading, and social relations



Modeling Social Context

- **Goal**: learn the news representations from the **heterogeneous network** for fake news prediction
- Jointly embedding news content and social context

$$
\begin{aligned}
\min_{\mathbf{D},\mathbf{U},\mathbf{V},\mathbf{T}\geq 0,\mathbf{p},\mathbf{q}} \; & \|\mathbf{X} - \mathbf{D}\mathbf{V}^T\|_F^2 && \text{Content Embedding} \\
+ \; & \alpha\|\mathbf{Y} \odot (\mathbf{A} - \mathbf{U}\mathbf{T}\mathbf{U}^T)\|_F^2 && \text{User-User Embedding} \\
+ \; & \beta \mathrm{tr}(\mathbf{H}^T \mathbf{L} \mathbf{H}) && \text{User-News Embedding} \\
+ \; & \gamma\|\mathbf{e} \odot (\bar{\mathbf{B}}\mathbf{D}\mathbf{q} - \mathbf{o})\|_2^2 && \text{Publisher-New Embedding} \\
+ \; & \eta\|\mathbf{D}_L \mathbf{p} - \mathbf{y}_L\|_2^2 + \lambda R && \text{Fake News Classifier}
\end{aligned}
$$

Social Context

How Unique is FakeNewsNet

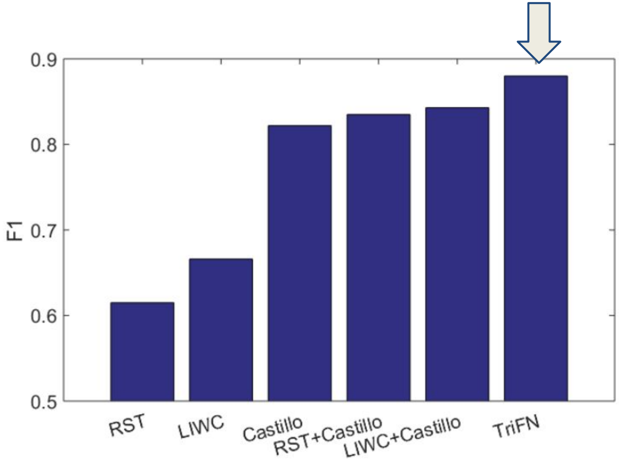
- **FakeNewsNet**: A comprehensive data repository that contains **news contents**, **social context**, and **spatiotemporal information**

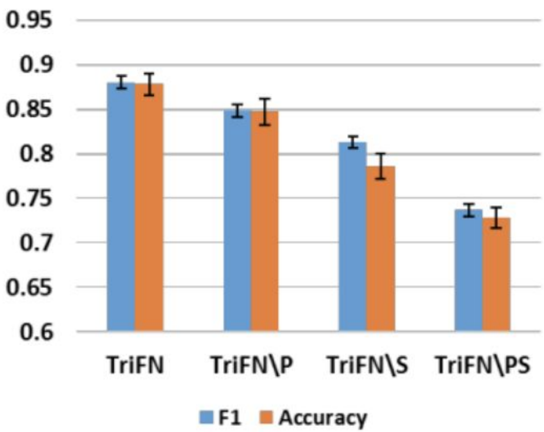
Features / Dataset	News Content		Social Context				Spatiotemporal Information	
	Linguistic	*Visual*	*User*	*Post*	*Response*	*Network*	*Spatial*	*Temporal*
BuzzFeedNews	✓							
LIAR	✓							
BS Detector	✓							
CREDBANK	✓		✓	✓			✓	✓
BuzzFace	✓			✓	✓			✓
FacebookHoax	✓		✓	✓	✓			
FakeNewsNet	✓	✓	✓	✓	✓	✓	✓	✓

https://github.com/KaiDMML/FakeNewsNet

Experimental Evaluation

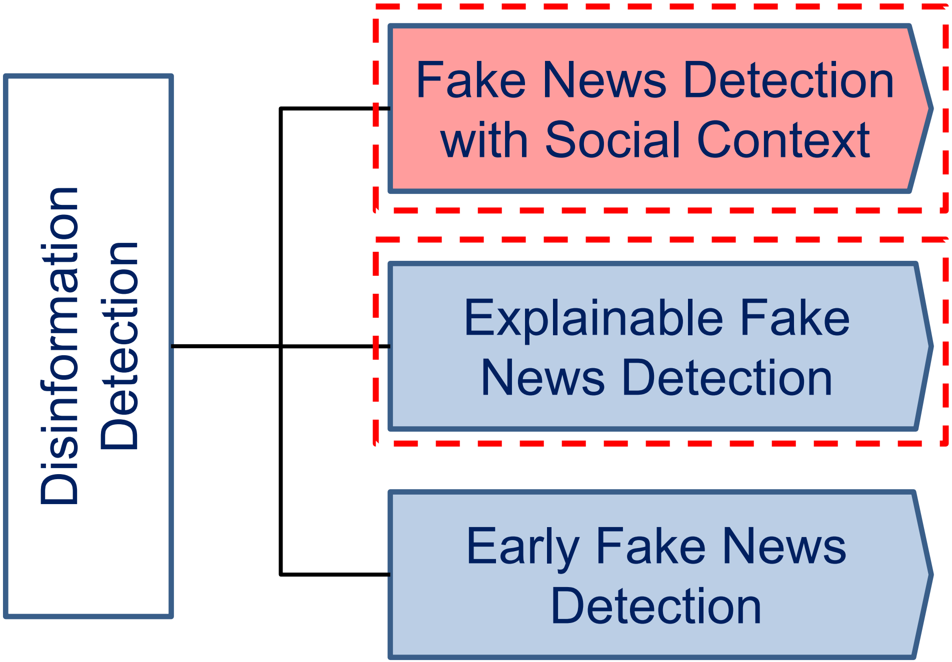
- The proposed model can achieve **best** performance in detecting fake news consistently
- It is necessary to model **both** news contents and social context because they contain complementary information





Summary

- ***Social context*** information brings ***additional*** signals to fake news detection
- It is important to capture the ***relations*** among publishers, news pieces, and users to detect fake news
- The proposed framework is ***effective*** to model ***tri-relationships*** through heterogeneous network embedding



Kai Shu, Limeng Cui, Suhang Wang, Dongwon Lee, and Huan Liu. ``dEFEND: Explainable Fake News Detection", KDD 2019, August 4-8, 2019. Anchorage, Alaska.

Motivation

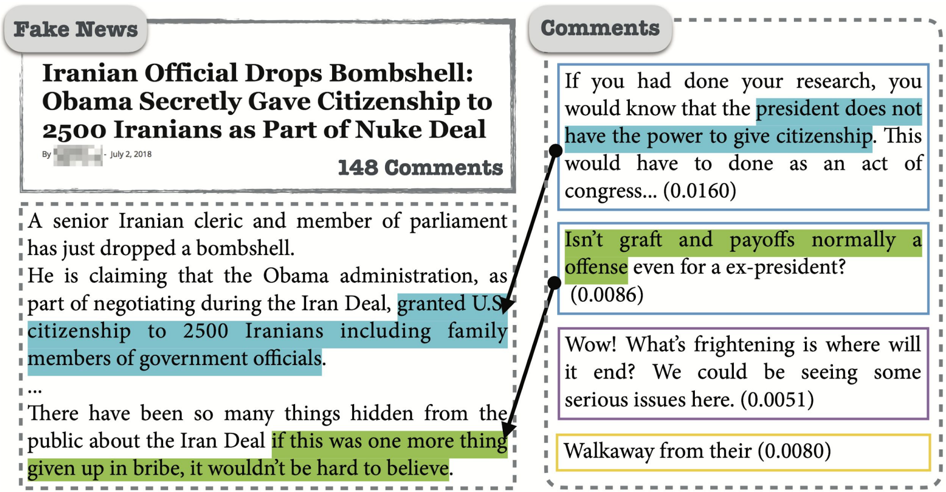
- **Goal**: detecting fake news and explaining why it is detected as fake
  - Provide insights and knowledge to domain experts
  - Explainable features from noisy auxiliary information can further help detection performance

→ Would ***comments*** be helpful to explain and detect fake news?

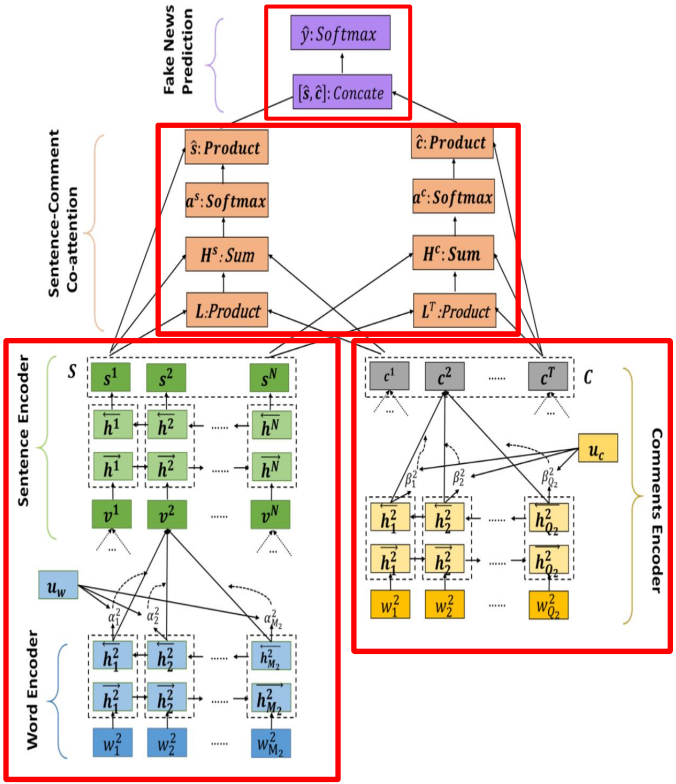
→ How to ***model*** content-comment relations for explainable fake news detection?

Contents, Comments, and Their Relations

- News contents and user comments are **inherently related** and provided important cues for explanation and detection
  - News contents may contain false information
  - User comments have rich information from the crowd such as opinions, stances, and sentiment



dEFEND explains why it is detected as fake



- Learn news sentence representations through a hierarchical attention network
- Encode comment representations through a word-level attention network
- Select top explainable sentences and comments through a co-attention network
- Detect fake news with concatenated sentence and comment representations

Detection Performance

- User comments based methods are slightly more **effective** than news content based methods
- dEFEND performs the **best** among the methods using both news content and user comments

User comments

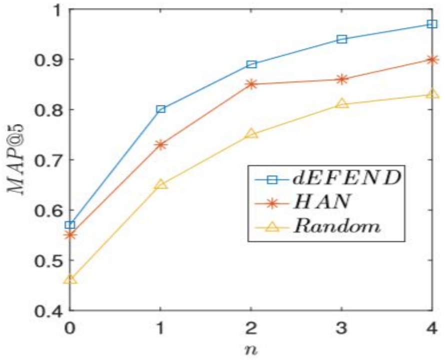
Datasets	Metric	RST	LIWC	text-CNN	HAN	TCNN-URG	HPA-BLSTM	CSI	dEFEND
PolitiFact	Accuracy	0.607	0.769	0.653	0.837	0.712	0.846	0.827	**0.904**
	Precision	0.625	0.843	0.678	0.824	0.711	0.894	0.847	**0.902**
	Recall	0.523	0.794	0.863	0.896	0.941	0.868	0.897	**0.956**
	F1	0.569	0.818	0.760	0.860	0.810	0.881	0.871	**0.928**
GossipCop	Accuracy	0.531	0.736	0.739	0.742	0.736	0.753	0.772	**0.808**
	Precision	0.534	**0.756**	0.707	0.655	0.715	0.684	0.732	0.729
	Recall	0.492	0.461	0.477	0.689	0.521	0.662	0.638	**0.782**
	F1	0.512	0.572	0.569	0.672	0.603	0.673	0.682	**0.755**

News Content

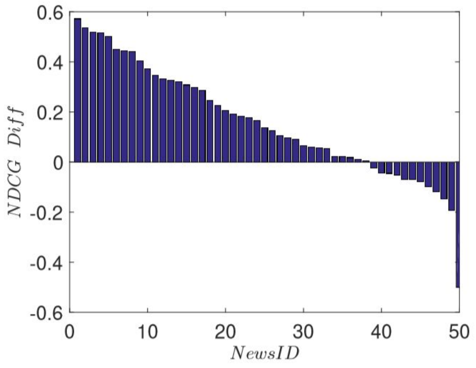
News Content + User comments

Explainability Performance

- ***Contents***: dEFEND can achieve better performance to capture check-worthy sentences

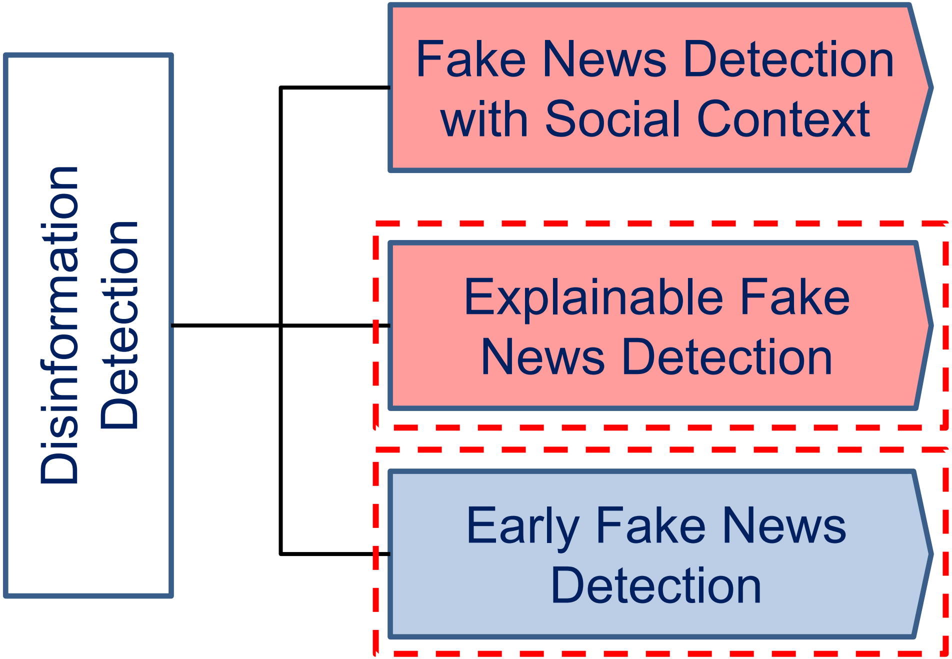


- ***Comments***: dEFEND can better discover explainable comments than baselines



Summary

- We study a **new** problem of explainable fake news detection
- dEFEND can **Identify** explainable news sentences and user comments for understanding why news is detected as fake
- dEFEND **achieves high accuracy** in comparison with the state-of-the-art fake news detection methods



Kai Shu, Guoqing Zheng, Yichuan Li, Subhabrata Mukherjee, Ahmed Awadallah, Scott Ruston, and Huan Liu. ``Early Detection of Fake News with Multi-source Weak Social Supervision", ECML-PKDD 2020, September 14-18, 2020. Ghent, Belgium.

Early Fake News Detection

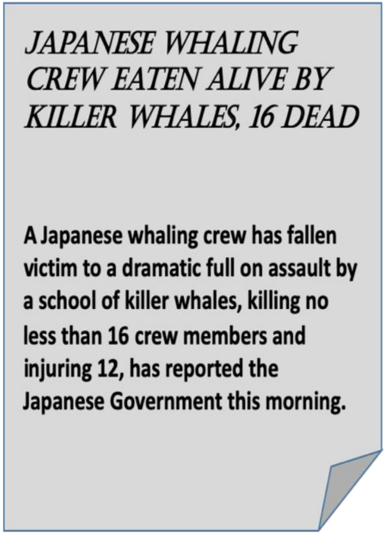
- Fake news can spread farther, faster, deeper, and more widely than true news
- **Goal**: detect fake news at an **early** stage with limited labeled data

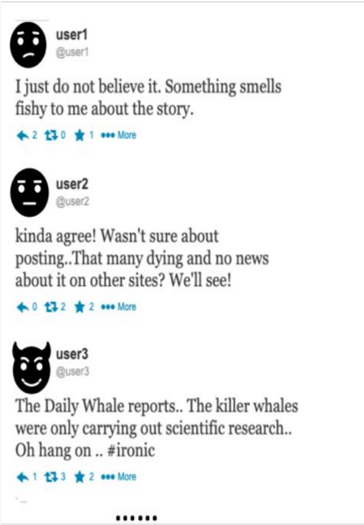
→ Would ***social engagements*** be helpful to detect fake news early?

→ How to ***learn from*** weak social supervision for early fake news detection?

Weak Social Supervision (WSS) Can Help

- User engagements in social media provide **different** sources to derive **weak social supervision**
  - ***Sentiment***: conflicting sentiments indicate high probability of fake news
  - ***Bias and Credibility***: more biased and less credible users are more likely to share fake news

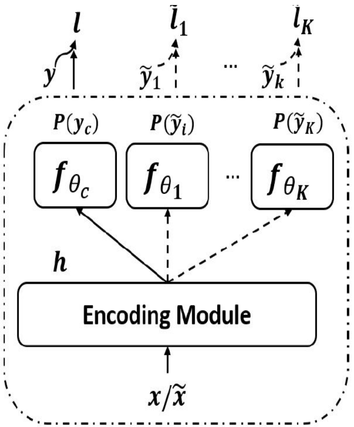




Learning with Multi-Sources of WSS

- **Goal**: **jointly** learn the **correlation** and **distinction** from clean and weak labels
  - ***Shared encoder*** for representation learning
  - ***Separate functions*** for mapping representations to clean or weak labels

$$\mathcal{L} = \min_{\theta_E,\theta_c,\theta_1,\ldots,\theta_k} \overbrace{\mathbb{E}_{(x,y)\in\mathcal{D}}\ell(y, f_{\theta_c}(h_{\theta_E}(x)))}^{\text{clean labels}} + \underbrace{\sum_{k=1}^{K} \mathbb{E}_{(x,\tilde{y})\in\tilde{\mathcal{D}}^{(k)}} \overset{\text{label weight function}}{\boxed{\omega_\alpha(h_{\theta_E}(x),\tilde{y})}} \ell(\tilde{y}, f_{\theta_k}(h_{\theta_E}(x)))}_{\text{weak labels from K sources}}$$



Experimental Evaluation

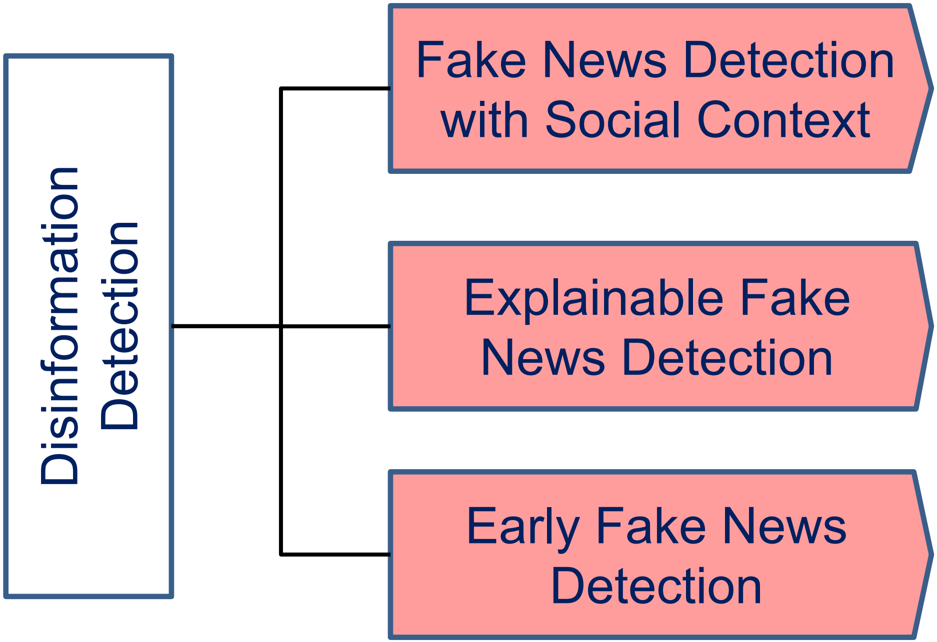
- In general, our model **MWSS** achieves the **best** performance consistently
- Training only on **clean** data performs **better** than only on **weak** data
- MWSS with **multiple** weak sources achieves **better** performance compared to that of a **single** weak source

Methods	GossipCop		PolitiFact	
	F1	Accuracy	F1	Accuracy
TCNN-URG (Clean)	0.76	0.74	0.77	0.78
EANN (Clean)	0.77	0.74	0.78	0.81
CNN (Clean)	0.74	0.73	0.72	0.72
CNN (Weak)	0.73	0.65	0.33	0.60
CNN (Clean+Weak)	0.76	0.74	0.73	0.72
CNN-*Snorkel* (Clean+Weak)	0.76	0.75	0.78	0.73
CNN-*L2R* (Clean+Weak)	0.77	0.74	0.79	0.78
CNN-MWSS (Clean+Weak)	**0.79**	**0.77**	**0.82**	**0.82**

Dataset	Sentiment	Bias	Credibility	All Sources
GossipCop	0.75/0.69	0.78/0.75	0.77/0.73	0.79/0.77
PolitiFact	0.75/0.75	0.77/0.77	0.75/0.73	0.78/0.75

Summary

- A **novel** problem of early fake news detection with weak social supervision
- MWSS can **jointly** model **little** labeled data and **multi-source** of weak labels for early fake news detection
- Different sources of weak social supervision contain **complementary** information



Detection

Explainability

Data

Some Lessons Learned

- Fake news detection is difficult
  - A moving target
- Data is key
  - Impractical to label data at scale
- Early detection is critical
  - Data-driven approaches are limited

Some Open Issues

- Online disinformation and its offline impact
  - Causal analysis of online disinformation to offline real-world effects
  - Impact estimation over time and across platforms
- Trustworthy AI for combating disinformation
  - Explainability and transparency
  - Mitigating bias of marginalized groups
  - Robust modeling to defend against adversaries
- Beyond text-focused disinformation
  - Multi-modality: text, images, videos, etc
  - Neural-generated: e.g., deepfakes

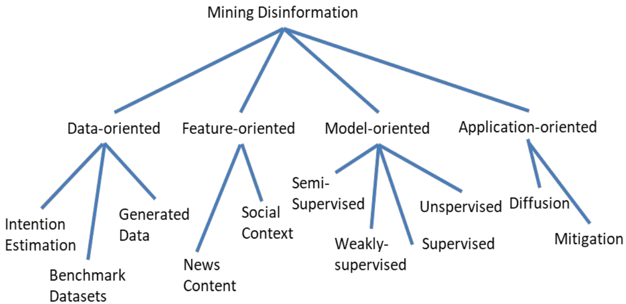
Seeking Interdisciplinary Illumination

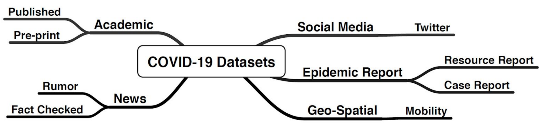
- Learning from **social theories** for computational approaches
  - When labeled data is limited

- Explaining computational results to benefit social scientists
  - Where domain expertise is desired

- Can social media intelligence play a role in understanding human behaviors?

Thank You All



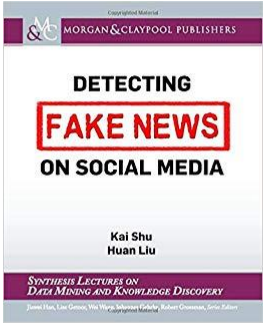


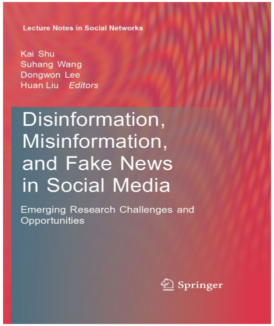
https://github.com/bigheiniu/awesome-coronavirus19-dataset

https://www.fake-news-tutorial.com/

AIM — Top ML Projects To Fight Fake News Fatigue During COVID-19

DIGITAL INFORMATION WORLD — Artificial Intelligence Can Possibly Detect Fake News In A Better Way By Analyzing User Interaction





KDnuggets™ Top Stories Last Week — A Quick Guide to Fake News Detection on Social Media

DATA SKEPTIC — Algorithmatic Detection of Fake News

datanami — AI Squares Off Against Fake News

Psychology Today — What is Fake News? Is Debate Worth the Effort?

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