

KDD Workshop 2021: Argumentatively Phony? Detecting Misinformation via Argument Mining

Muheng Yan, Yu-Ru Lin, Diane J. Litman
School of Computing and Information
University of Pittsburgh

Fighting Misinformation by Identifying it

Misinformation is false or inaccurate information, commonly intended to deceive.

It is a threat to people's properties, trusts, health -- and even lives in the past year of the COVID pandemic.

CDC admits that “fully vaccinated” Americans are super-spreaders carrying deadly variants and high viral loads

Sunday, August 01, 2021 by: Ethan Huff

Tags: badhealth, badmedicine, badscience, CDC, contagious, coronavirus, COVID, Delta Variant, infections, mass vaccination, outbreak, pandemic, Plandemic, shedding, spike protein, spread, super spreaders, transmission, vaccine wars, vaccines

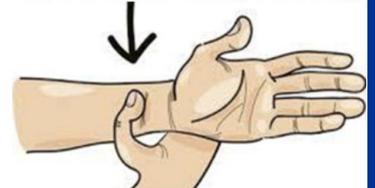
(Natural News) It is official: The biggest public health threat right now are “fully vaccinated” people, whom the U.S. Centers for Disease Control and Prevention (CDC) **now warns** are super-spreaders polluting society with Wuhan coronavirus (Covid-19) “variants.”

Nothing the CDC did this past year helped bring the “case” count down, nor did the agency save any lives. To the contrary, by pushing face masks and Fauci Flu shots, the CDC *took* people's lives, all the while depriving the public of information about how to support their immune systems naturally.

We tried to tell everyone and were ridiculed repeatedly. To give him credit, so did former President Donald Trump, who early on revealed that existing off-patent medications like ivermectin and hydroxychloroquine (HCQ) would have done the job without the need for medical fascism and injections.

Unfortunately, Trump decided to go all-in with the deep state by proudly taking ownership of “Operation Warp Speed.” Since that time, the former president has been aggressively

How To Entirely Empty Your Bowels Every Morning



Learn [THIS] Simple Trick

A pseudo-science news article reporting the latest wave of COVID-19 Delta Variant

Fact-checking: A Way to Identify Misinformation

“Fact-checking is a process that seeks to verify sometimes factual information, in order to promote the veracity and correctness of reporting.”

-- Wikipedia



Why is Fact-checking Hard?

Nothing the CDC did this past year helped bring the “case” count down, nor did the agency save any lives. To the contrary, by pushing face masks and Fauci Flu shots, the CDC *took* people’s lives, all the while depriving the public of information about how to support their immune systems naturally.



For example, to identify the above paragraph as misinformation, one would need deep investigation on what CDC has done in the past year, and how vaccines and masks saved people’s lives instead of took.

One need to ***exhaust*** facts to counter an accusation like the example, which is nearly impossible.

Why is Fact-checking Hard?

1. Fact-checking requires huge human resources with expertise in journalism to scale up
2. Fact-checking requires specific domain background knowledge
3. Fact-checking can “backfire”: present contrast facts to mis-believers may reinforce their false beliefs (Meinert et al.)*

How can we help normal people to spot non-credible information?

**Our idea: promote and assist
reason-checking through AI**

Reason-checking: An Alternative way

Any Proof?

Nothing the CDC did this past year helped bring the “case” count down, nor did the agency save any lives. To the contrary, by pushing face masks and Fauci Flu shots, the CDC *took* people’s lives, all the while depriving the public of information about how to support their immune systems naturally.

~~Learn [THIS] Simple Tri~~

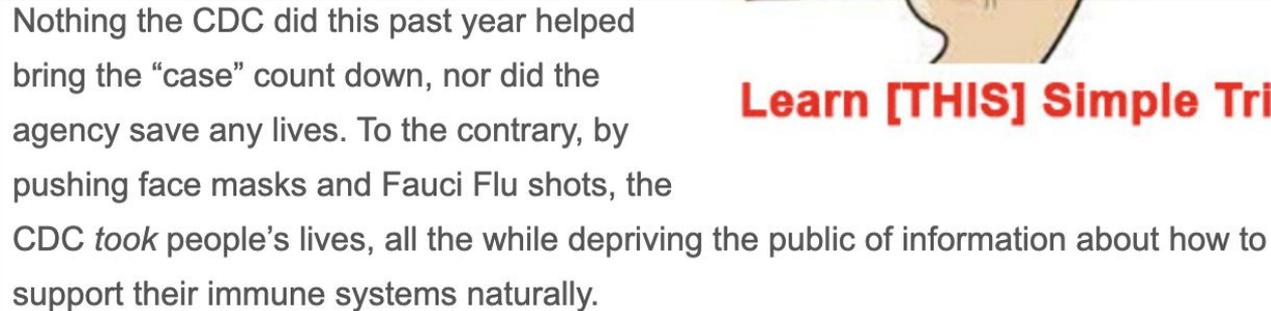
How did the vaccine and masks “take people’s lives”? And how did the information is deprived?

Alternatively, we may logically identify the misinformation by exploiting its reasoning failures.

With the same example, one can criticize its logic as its assertions are not supported at all.

Argumentation: What is it and How it Helps

Sentences serve (as the elementary unit of argumentation, named as “Argumentation Discourse Unit”, ADU) for certain purpose when constructing discourses in news article. The functionality of sentences are linked by argumentation logic.

A screenshot of a news article snippet. The text is black on a white background. A yellow highlight box surrounds the sentence: "Nothing the CDC did this past year helped bring the 'case' count down, nor did the agency save any lives. To the contrary, by pushing face masks and Fauci Flu shots, the CDC took people's lives, all the while depriving the public of information about how to support their immune systems naturally." To the right of the highlighted text, there is a yellow speech bubble icon and the text "Learn [THIS] Simple Trick" in red.

Nothing the CDC did this past year helped bring the “case” count down, nor did the agency save any lives. To the contrary, by pushing face masks and Fauci Flu shots, the CDC *took* people’s lives, all the while depriving the public of information about how to support their immune systems naturally.

In the example, both of the sentences are **assumptions**, which are the opinions of the article author that needs supporting (Al-Khatib et al.).

Roles of ADUs in Digital News

There are other types of roles (Al-Khatib et al.):

- **Anecdote**: personal experience
- **Statistics**: results of quantitative analysis
- **Testimony**: proposition from specified sources

These 3 roles can support the “assumption”. Other roles that are rare:

- **Common ground**: widely accepted truth
- **Other**: non-argumentative sentences, e.g. “happy new year”

Guess Which is Non-credible, without argumentation

(A)

CNN ' s Oliver Darcy reports that the Biden administration is reaching out to news organizations to make sure to include context in their reporting about COVID - 19 .

One Biden official told Darcy , “ The media ' s coverage doesn ' t match the moment . It has been hyperbolic and frankly irresponsible in a way that hardens vaccine hesitancy . The biggest problem we have is unvaccinated people getting and spreading the virus . ”

Want an example of how it ' s done ? Check out this clip from CNN ' s Jake Tapper , who used facts and numbers to say , “ Less than . 001 % of those fully vaccinated have experienced a fatal breakthrough case . Less than . 004 % of those fully vaccinated had to be hospitalized . In other words , the vaccines work . The vaccines remain the best way to protect yourselves from this virus . Period . Full stop . ”

(B)

Even when Wuhan coronavirus (Covid - 19) case numbers were plummeting between April 24 and June 27 of last year , most major media outlets were still pumping out nonsense about “ rising cases ” and new “ surges ” and “ waves ” of the virus that never actually panned out as real .

Consequently , a CBS News poll found from last June found that most Americans , at least those who watch television , were scared to death of the Chinese virus and felt as though the “ fight ” to contain it was going badly .

This poll , ironically enough , was used to churn out more “ bad ” news about how the United States was collapsing under the weight of a virus that almost nobody was observing in real life beyond their screens .

Study Goal

This study is to:

1. Investigate how effective the argumentation mining methods are on fake news articles
2. Investigate whether the argumentation information will **computationally** benefit the identification of misinformation

Method Overview

When getting input texts of news articles, our method will:

1. Find the Argumentation Discourse Units (ADU) and their spans in the text
2. Incorporate the sequential information of argumentation in a fake news classifier, and make the predictions

Dataset:

- We collect the social media shared digital news articles during Jan - May, 2020, and categorize them into credible/non-credible articles based on a curated news website list [1]
- 87340 articles collected, 62551 (71.6%) of them are credible

Mining Arguments from Texts

In Natural Language Processing, Argumentation Mining is formed as a sequence tagging problem in Begin-Inside-Outside (BIO) scheme:

For each token in a text, decide whether the token is the beginning (B), inside (I) of a type of Argument Discourse Unit (ADU) span (in our case, there are 6 major categories including assumption, anecdote, testimony, statistics, common-ground, other), or outside (O) of any ADU span.

Tagging Argumentation Discourse Units

We use the Webis-16 dataset (300 articles labeled with ADU spans) to train a ADU tagger with BERT, with additional validation in misinformation articles.

Below we show the F1 for each type of the tags:

		B-AS	I-AS	B-AN	I-AN	B-ST	I-ST	B-TS	I-TS	B-CG	I-CG	O	Macro
<i>Webis-16 Editorial dataset</i>	F1	0.656	0.675	0.552	0.639	0.581	0.670	0.218	0.663	0.000	0.000	0.724	0.489
<i>fake news dataset</i> All Articles	F1	0.534	0.695	0.594	0.692	0.594	0.680	0.151	0.556	0.000	0.000	0.803	0.476
<i>fake news dataset</i> Credible Articles	F1	0.131	0.687	0.614	0.718	0.581	0.697	0.110	0.570	0.000	0.000	0.821	0.448
<i>fake news dataset</i> Fake Articles	F1	0.575	0.694	0.588	0.684	0.577	0.650	0.139	0.545	0.000	0.000	0.798	0.477

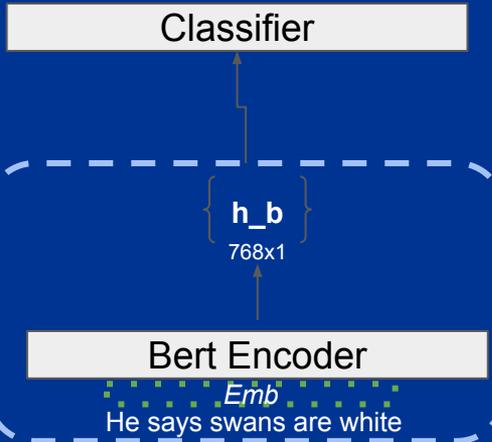
How we Incorporate ADUs in Misinformation Classification

We build a baseline misinformation classifier with BERT.

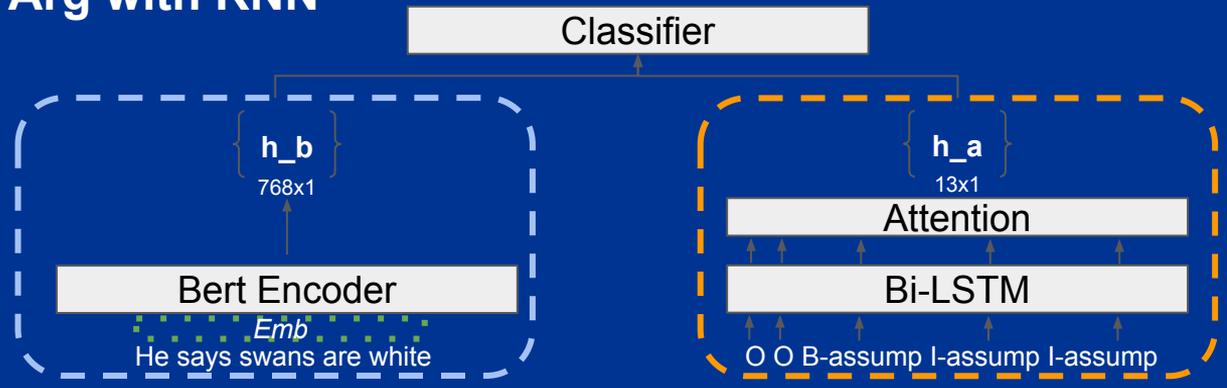
On top of it, we use two ways to incorporate the argumentation information in the model:

1. **[Non-Linear Combination]** Represent the ADU tags as a sequential embedding, and add the embedding to the semantic embedding
2. **[Concatenation]** Use a standalone recursive neural network to represent the ADU tag sequences, and merge the representation with the BERT hidden layer

BERT

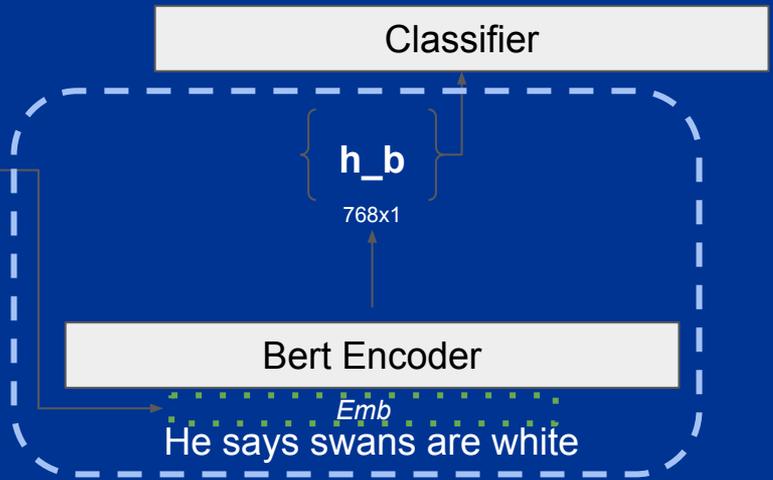


Arg with RNN



Arg as Embedding

Input	[CLS]	my	dog	is	cute	[SEP]	he	likes	play	#ing	[SEP]
Token Embeddings	$E_{[CLS]}$	E_{my}	E_{dog}	E_{is}	E_{cute}	$E_{[SEP]}$	E_{he}	E_{likes}	E_{play}	$E_{\#ing}$	$E_{[SEP]}$
Segment Embeddings	E_A	E_A	E_A	E_A	E_A	E_A	E_B	E_B	E_B	E_B	E_B
Position Embeddings	E_0	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}
Arg Embeddings		B	I	I	I	...					



Experiment Ablations

Factor of Topic

The topic of articles may be correlated with the veracity of the articles. Also the topic may influence the efficiency of the model utilizing the sequential argumentation patterns.

Hence we run a topic model on the corpus, and found 15 topics by the elbow rule. We name the topics by top keywords, and manually categorized them into 4 topic clusters: 1) COVID's impact on life (57270 articles); 2) Authorities' Response (5436); 3) Travel and Lockdown (10331); and 4) Science/Medicare of COVID-19 (14303)

Experiment Ablations

Factor of Model Architecture

We create 4 ablation conditions for the model variants:

1. Argumentation Baseline: LSTM with Argumentation Tags
2. Language Model Baseline: BERT with Binary Classification Layer
3. BERT + Argumentation LSTM
4. BERT + Argumentation as Embedding

Performance Gain from Incorporating Argumentation

- Reason-checking performance is no worse than “fact-checking” -- the performance increased by 1-2%
- RNN for Argumentation sequence is better in general condition

Train On	Test On	Arg-LSTM (no BERT)	BERT	Arg-emb	Arg-LSTM
Impact	Impact	0.700	0.892	0.879	0.918
	Travel	0.629	0.884	0.863	0.871
	Medicare	0.674	0.892	0.855	0.895
	Authority	0.626	0.866	0.882	0.903
Travel	Impact	0.629	0.876	0.876	0.884
	Travel	0.676	0.897	0.895	0.892
	Medicare	0.626	0.861	0.861	0.868
	Authority	0.553	0.903	0.887	0.892
Medicare	Impact	0.668	0.863	0.863	0.855
	Travel	0.624	0.847	0.863	0.858
	Medicare	0.697	0.884	0.897	0.887
	Authority	0.632	0.884	0.884	0.879
Authority	Impact	0.684	0.871	0.874	0.882
	Travel	0.639	0.855	0.874	0.816
	Medicare	0.637	0.868	0.874	0.850
	Authority	0.668	0.908	0.934	0.921
All	All	0.670	0.918	0.897	0.927
	Impact	0.700	0.916	0.882	0.921
	Travel	0.645	0.897	0.882	0.926
	Medicare	0.674	0.918	0.905	0.921
	Authority	0.663	0.937	0.921	0.942

How Argumentation can Help

There are differences between credible/misinformation news on how they organize paragraphs. For example, in reporting “media reported numbers scare people”:

(A) CNN 's Oliver Darcy reports that the Biden administration is reaching out to news organizations to make sure to include context in their reporting about COVID - 19 .
One Biden official told Darcy , “ The media 's coverage doesn ' t match the moment . It has been hyperbolic and frankly irresponsible in a way that hardens vaccine hesitancy . The biggest problem we have is unvaccinated people getting and spreading the virus . ”
Want an example of how it 's done ? Check out this clip from CNN 's Jake Tapper , who used facts and numbers to say , “ Less than . 001 % of those fully vaccinated have experienced a fatal breakthrough case . Less than . 004 % of those fully vaccinated had to be hospitalized . In other words , the vaccines work . The vaccines remain the best way to protect yourselves from this virus . Period . Full stop . ”

(B) Even when Wuhan coronavirus (Covid - 19) case numbers were plummeting between April 24 and June 27 of last year , most major media outlets were still pumping out nonsense about “ rising cases ” and new “ surges ” and “ waves ” of the virus that never actually panned out as real .
Consequently , a CBS News poll found from last June found that most Americans , at least those who watch television , were scared to death of the Chinese virus and felt as though the “ fight ” to contain it was going badly .
This poll , ironically enough , was used to churn out more “ bad ” news about how the United States was collapsing under the weight of a virus that almost nobody was observing in real life beyond their screens .

Assumption

Statistics

common-ground anecdote statistics assumption other testimony O

Can you guess which one is from a credible source?

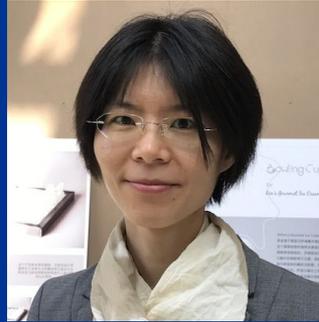
Future Direction

1. Improving the argumentation modelling (tagging) with more annotated data
2. Incorporate our technique in an intelligent interface design with other linguistic cues
 - Better way to present argumentation knowledge
 - Design of the interface with user study

Thank You!



Muheng Yan
muheng.yan@pitt.edu



Yu-Ru Lin
yurulin@pitt.edu



Diane J. Litman
dlitman@pitt.edu

This study is funded by:



Our Lab:



Computational Social Dynamics Lab

<https://picsolab.github.io/>

