

2017

Deception Detection & Rumor Debunking

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Citation of this paper:

Rubin, Victoria L., "Deception Detection & Rumor Debunking" (2017). *FIMS Presentations*. 45.
<https://ir.lib.uwo.ca/fimpspres/45>

Deception Detection & Rumor Debunking

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Goals of the Talk

I'll divide my 10-minute talk into **2 parts**:

(1) Deception Detection and (2) Rumor Debunking, as the title suggests, and I will argue for **the need of hybrid methods** (in a combination of the two).

My main goal here is to point researchers interested in social media research towards these 2 exciting fields.

I predict that such technologies (with more R&D, as they mature) will **become indispensable** in our attention-economy.

Content producers are rushed to be first in the news stream, and social media consumers simply don't have **time or energy to verify content that is pushed at them**.

Part 1.

Deception



Photo by Nicole Mason, unsplash.com

a message
knowingly and intentionally transmitted
to foster a **false belief or conclusion**

Buller & Burgoon (1996) in *Communication Theory*
Zhou et al. (2004) in *Group Decision and Negotiation*

an intentional control of information
in a **technologically mediated environment**

Hancock (2012) in *Oxford Handbook of Internet Psychology*

Detection

Human Ability To Detect Deception



55–58% success rate

Frank et al. 2004;
Kraut, 1980; Vrij, 2000

54% mean accuracy

DePaulo et al., 1997

Social Psychology & Communications Studies

Detection

Recently proven possible

at ~74% accuracy with Natural
Language Processing

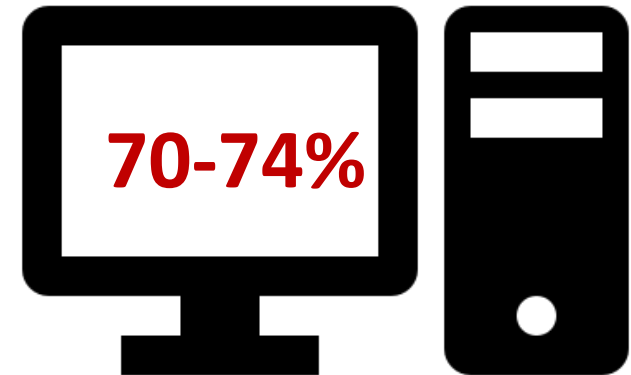
Zhou et al., 2004

at ~70% with Machine Learning

Mihalcea & Strapparava, 2009

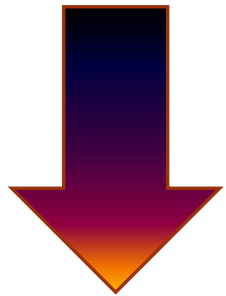
**Automated
Deception
Detection**

70-74%



PATTERNS IN PREDICTORS EXIST, BUT NO CLEAR CONSENSUS. VARIATIONS BY CONTEXTS.

Verbal Cues for Automated Deception Detection

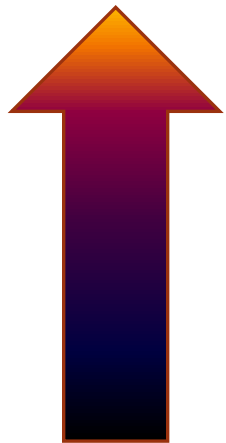


Deceivers:

self-references
detailed answers



Larker & Zakolyukina (2010)
featured in *The Economist*



indirect statements
negative emotions

Hancock et al. (2008) in *Discourse Processes*

sense-based word

Granhag et al. (2004) in *Legal & Criminological Psych.*

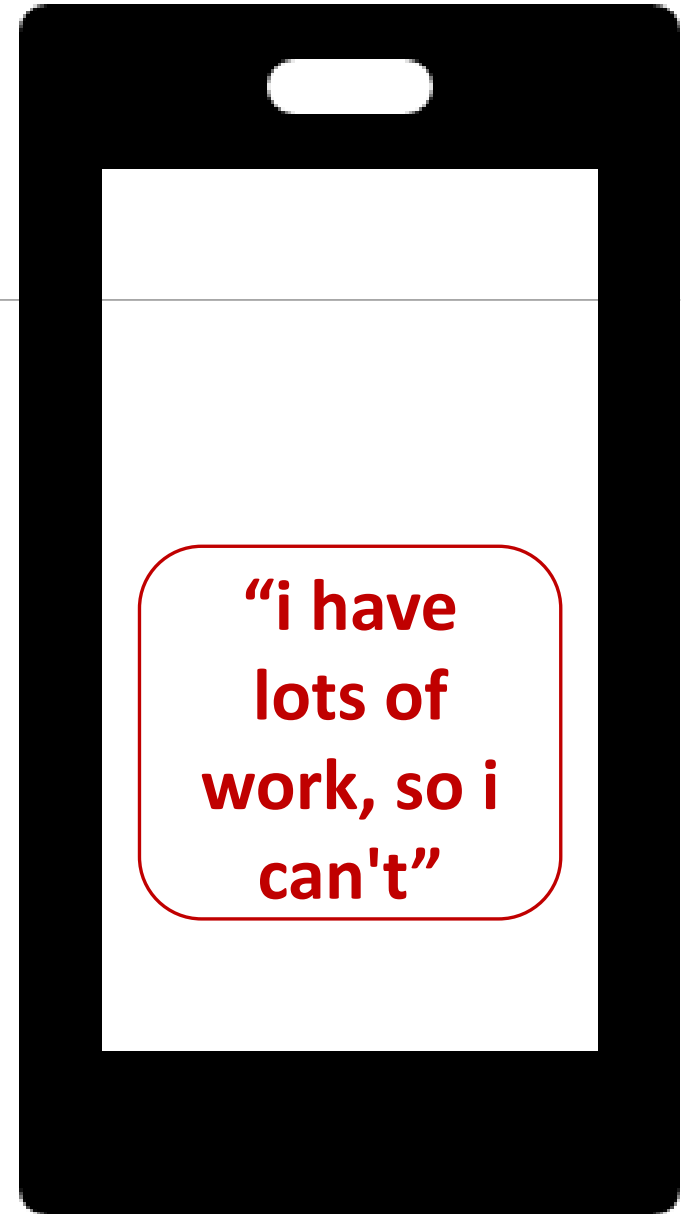
*Are there cues of
deception
in social media?*



*Photo by Eric Pickersgill, www.removed.social/, *The NY Review of Books**

'Butler Lies' in Texting

manage or avoid social interactions



Part 2.

Rumors

Unverified assertions... spread over time from node to node in a network.

Vosoughi (2015), MIT PhD Thesis

Harmful. Why?

Undesirable responses:

defamation, protests, destruction of properties, spread of fear or hate, euphoria, or stock market fluctuations.

Matthews (2013), Time



Photo by Ben White, unsplash.com

Figure 3. Verification Feature for Rumor Debunking on Twitter (Liu et al., 2015).

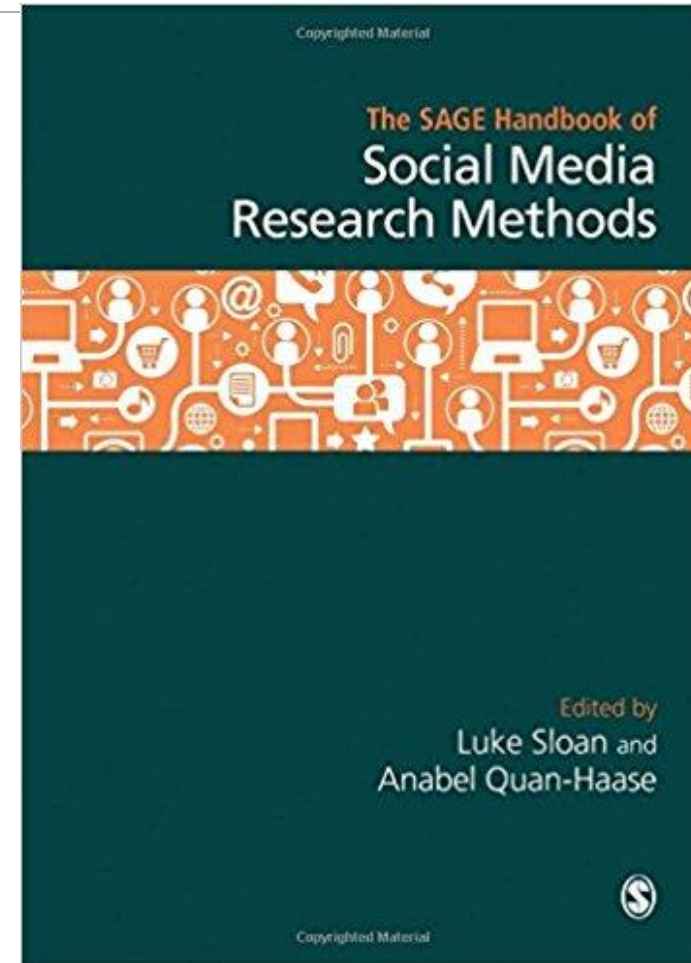
The six proposed categories of verification features largely based on insights from journalists.

CATEGORY	FEATURE NAME
SOURCE CREDIBILITY	Is trusted/satirical news account Has trusted/satirical news url Profile has url from top domains Client application name
SOURCE IDENTITY	Profile has person name Profile has location Profile includes profession information
SOURCE DIVERSITY	Has multiple news/non-news urls after dedup Deduped tweets' text is dissimilar
SOURCE LOCATION & WITNESS	If tweet location matches event location If profile location matches event location Has witness phrases, i.e., "I see" and "I hear"
MSG. BELIEF	Is support, negation, question or neutrality
EVENT PROPAGATION	Event Topic Retweet, mention, hashtag h-index Max reply/retweet graph4 size/depth

(Liu et al, 2015, Reuters)

Final Thoughts...

- ✓ Hybrid approaches are needed
- ✓ More R&D needed based on social media data.
- ✓ Detailed R&D overview (Chapter 21).
- ✓ Come to my talk on the News Verification Suite
@ CAIS Wed May 31 @ 2.



Thank you! Questions? Ideas?



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References upon request and in the book chapter.

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