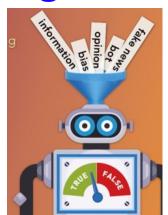
# The Magnitude of Truth: On Using Magnitude Estimation for Truthfulness Assessment in Fact-Checking

#### **Stefano Mizzaro**

Truth is in the Eyes of the Machines Amsterdam, 9/5/2025





#### Ack

This research has been partially supported by project PRIN 2022
 "MoT – The Measure of Truth: An Evaluation-Centered Machine-Human Hybrid Framework for Assessing Information
 Truthfulness" - Codice n. 20227F2ZN3 CUP n. G53D23002800006

 "Finanziato dall'Unione Europea – Next-Generation EU – PNRR M4 C2 I1.1" RS Mizzaro



#### Outline

- Intro
- Crowdsourcing for fact-checking
- Truthfulness Scales and Magnitude estimation

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- Crowdsourcing for fact-checking
- Truthfulness Scales and Magnitude estimation

#### Aims

- Our overall approach → Fact-checking, we use crowdsourcing
- A bit of the story → Many people, many papers
- Focus on truth scales → Magnitude Estimation

#### The team

- Isabelle Augenstein
- Francesco Bombassei De Bona
- Davide Ceolin
- Alessandro Checco
- Vincenzo Della Mea
- Gianluca Demartini
- Massimiliano De Luise
- Tim Draws
- Shaoyang Fan
- David La Barbera
- Joel Mackenzie

- Eddy Maddalena
- Beatrice Portelli
- Yunke Qu
- Kevin Roitero
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- Michael Soprano
- Damiano Spina
- Denis Eduard Tapu
- Dustin Wright
- Arkaitz Zubiaga

#### The team

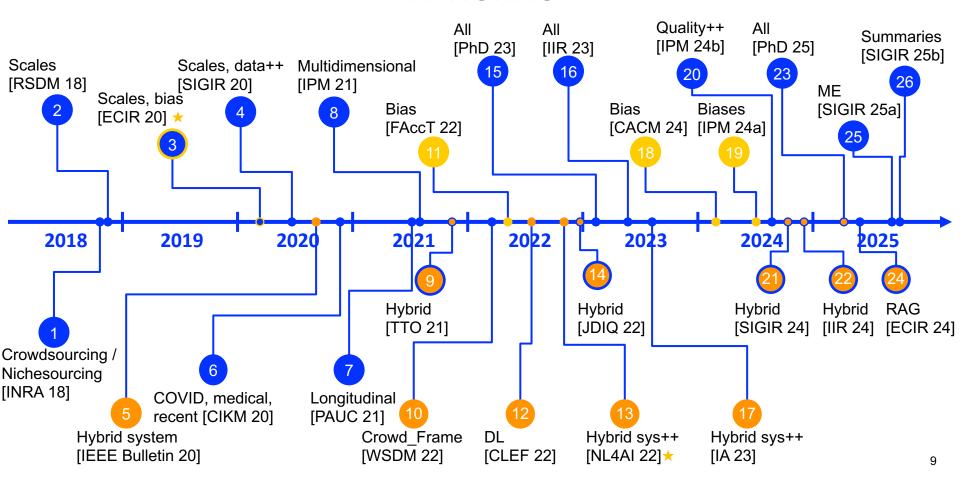
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## Many people, many papers

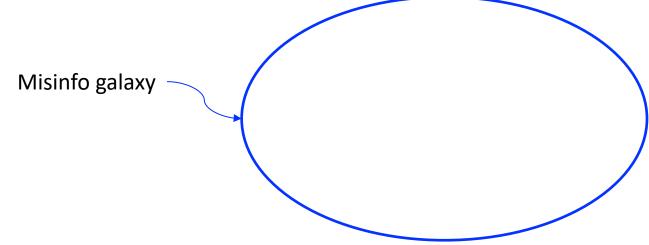
- The gang has been working!
- 7-8 years, 22 people  $\rightarrow$  26 papers
  - (at least)
- How to present them?

#### Timeline



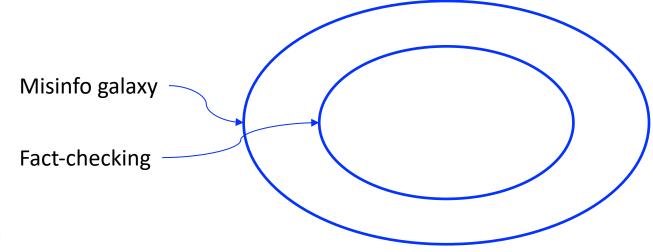
#### Misinformation

- Misinformation & Disinformation are spreading
- Need for researchers and society to find countermeasures



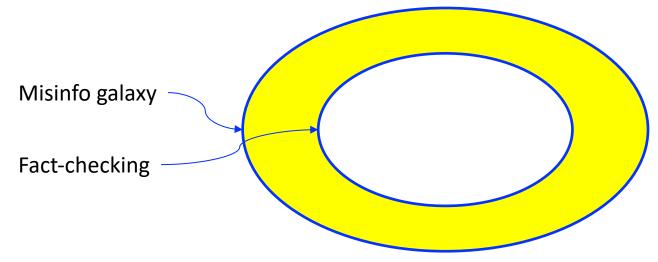
## Fact-checking

- The process aimed at determining if a claim/info/news/etc. is true or not
- Rather complex process
  - Experts, follow a protocol, seek evidence, discuss, reach a verdict



## Beyond Fact-checking

- Of course there's much more
  - E.g., how the fake news spread when compared to the true ones?
  - Echo chambers
  - Filter bubbles
  - Etc.



#### Truthfulness assessment

- We focus on "Is this true or not?"
- And on how to answer that question
- Usually done by experts
- A lot of research on using Al
- We use crowdsourcing

Misinfo galaxy

Fact-checking

Truthfulness assessment

#### Outline

- Intro
- Crowdsourcing for fact-checking
- Truthfulness Scales and Magnitude estimation

#### **Crowdsourcing?**

Crowdsourcing

文A 45 languages ~

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From Wikipedia, the free encyclopedia

"Crowd work" redirects here. For the performing arts term, see audience participation.



This article is written like a personal reflection, personal essay, or argumentative essay that states a Wikipedia editor's personal feelings or presents an original argument about a topic. Please help improve it by rewriting it in an encyclopedic style. (September 2022) (Learn how and when to remove this message)

Crowdsourcing involves a large group of dispersed participants contributing or producing goods or services—including ideas, votes, micro-tasks, and finances—for payment or as volunteers. Contemporary crowdsourcing often involves digital platforms to attract and divide work between participants to achieve a cumulative result. Crowdsourcing is not limited to online activity, however, and there are various historical examples of crowdsourcing. The word crowdsourcing is a portmanteau of "crowd" and "outsourcing". [1][2][3] In contrast to outsourcing, crowdsourcing usually involves less specific and more public groups of participants. [4][5][6]



## Crowdsourcing – Definition

- "taking a task traditionally performed by an employee or contractor, and outsourcing it to an undefined, generally large group of people or community in the form of an open call"
- [http://en.wikipedia.org/wiki/Crowdsourcing]

## Crowdsourcing – Definition

- "The practice of obtaining needed services, ideas, or content by soliciting contributions from a large group of people and especially from the online community rather than from traditional employees or suppliers"
- [Merriam-Webster]

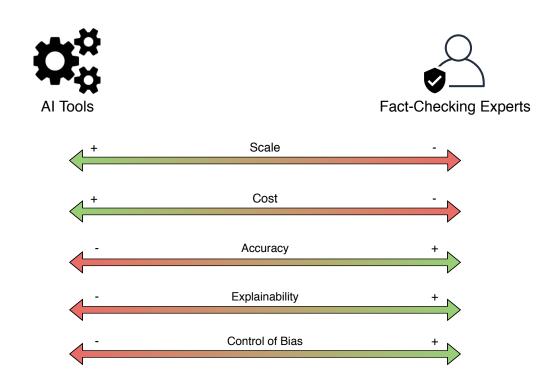
## Crowdsourcing – Definition

- "Simply defined, crowdsourcing represents the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call. This can take the form of peer-production (when the job is performed collaboratively), but is also open undertaken by sole individuals. The crucial prerequisite is the use of the open call format and the large network of potential laborers."
- [Howe, 2006]

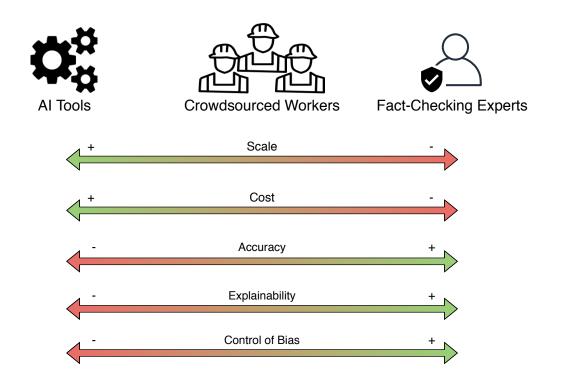
## Motivation / Justification

- So, we propose to crowdsource truthfulness assessment
- Does it make sense, and why?
  - In principle

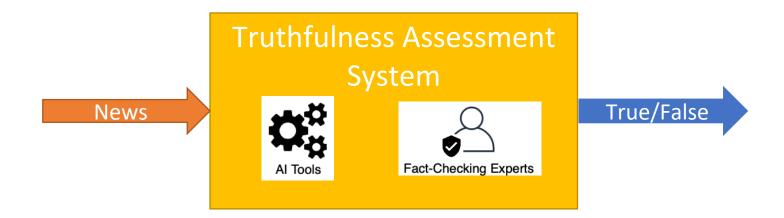
## Al vs. Experts

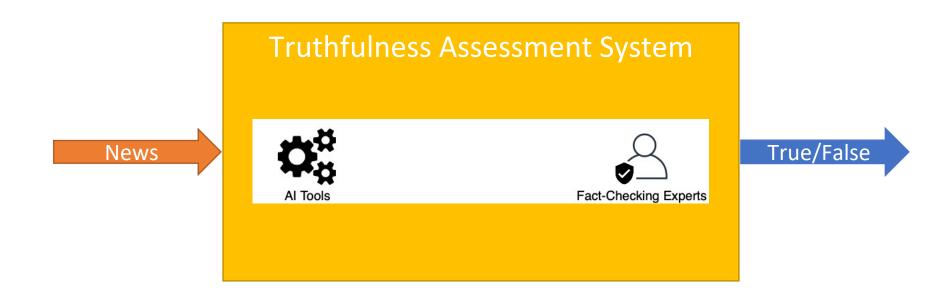


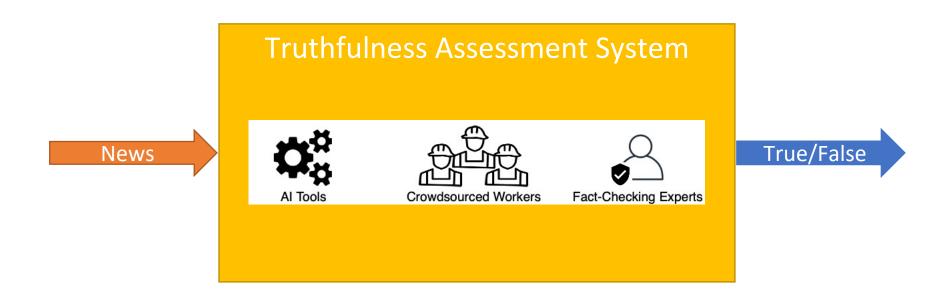
## Al vs. Crowd vs. Experts

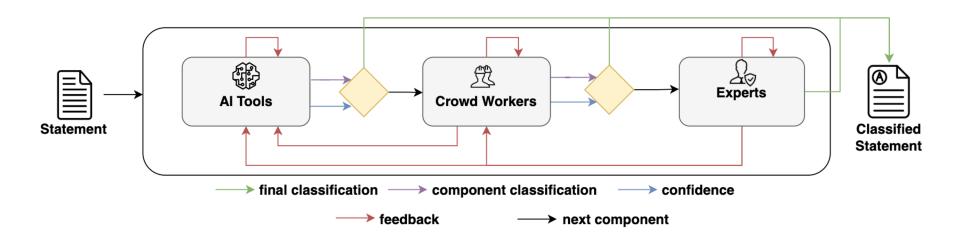


#### AI + Experts









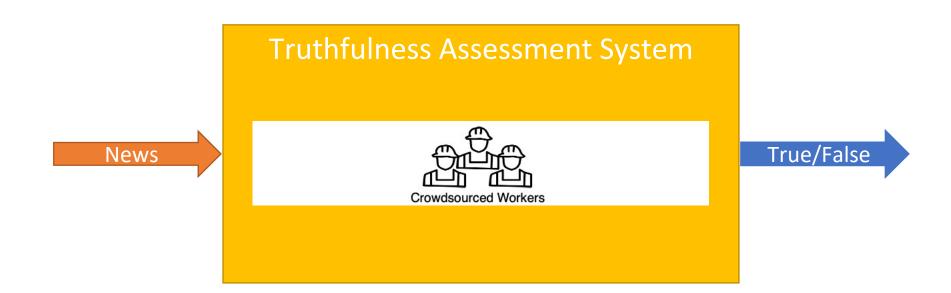
#### After the panel

- I did not plan to spend too much time on this but after the panel...
- "It is impossible to reach all the users that have been reached by misinformation if platforms do not cooperate" [Giovanni]
- Well, it is impossible anyway given that we do not have enough fact-chekers!

#### AI + Experts

- Stage 1: Al
  - Output: Truthfulness value + Confidence
  - (+ more: explanations...)
- Stage 2 (if low Confidence): Experts
  - Output: Truthfulness value + Confidence
  - (+ more: explanations, motivations, ...)

- Stage 1: Al
  - Output: Truthfulness value + Confidence
  - (+ more: explanations...)
- Stage 2 (if low Confidence): Crowd
  - Output: Truthfulness value + Confidence
  - (+ more: explanations, motivations, ...)
- Stage 3 (if low Confidence): Experts
  - Output: Truthfulness value + Confidence
  - (+ more: explanations, motivations, ...)



#### Main RQ

- Can crowdsourcing work?
- Can the crowd be put in the right conditions to assess truthfulness?

## Overall approach

- We take some statements, with ground truth
- We ask crowd workers to assess the truthfulness
  - In a sort of "controlled" situation
- We compute agreement with ground truth

(several variations / versions)

## Experimental design (one version)

- Crowdsourcing platform:
  - Amazon's Mechanical Turk
  - Prolific
- Each worker judges the truthfulness of 8 (6 + 2) statements
  - (randomization to avoid bias)
- Redundancy
  - Each statement judged by 10 workers
- Quality checks:
  - 2 statements are equal for all workers: one clearly true and one clearly false
  - Time, Actions
  - **-** ...

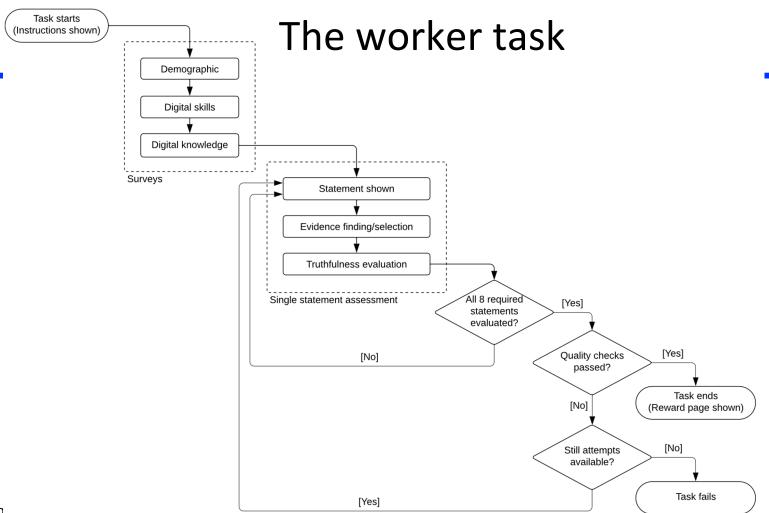
## Experimental design (one version)

#### Datasets

- Politifact (<a href="https://www.politifact.com">https://www.politifact.com</a>)
- (But not only)

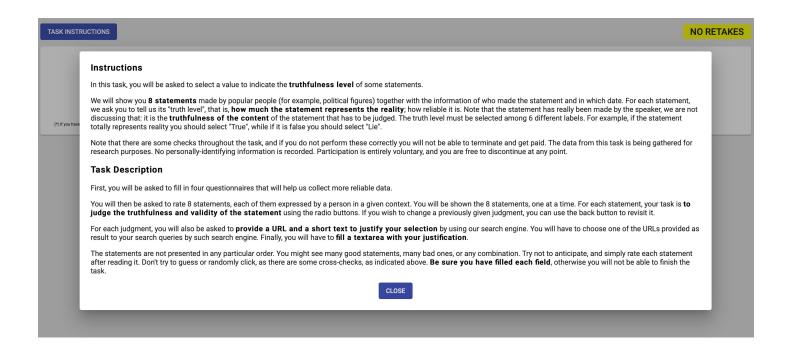


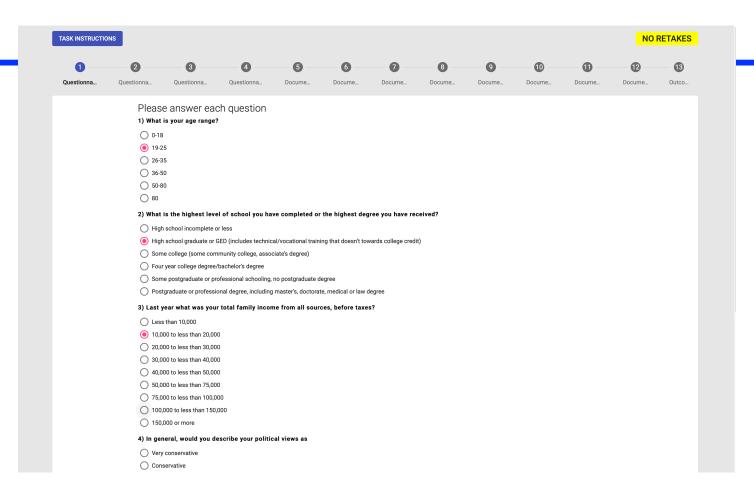
- In total
  - 120 statements, 20 for each Politifact category (+ the two for quality check)
  - 120 / 6 \* 10 = 200 workers, each expressing 8 assessments, 1,600 assessments in total
- We also ask for evidence
  - Custom search engine to avoid workers finding Politifact pages with evidence



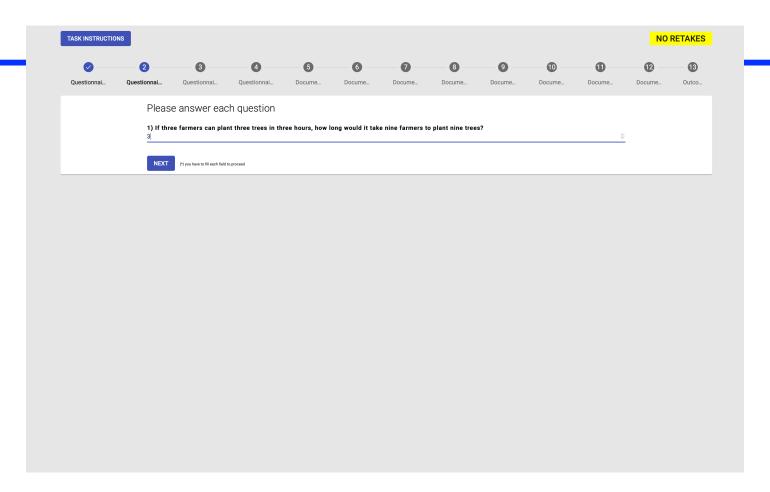
The Mag

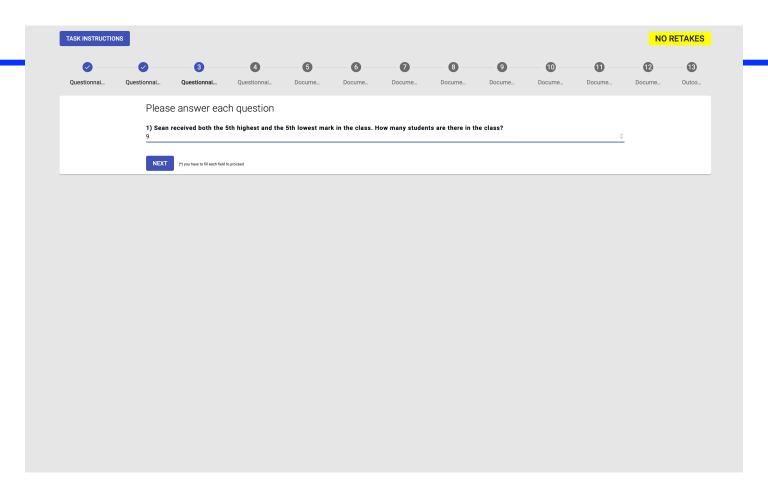
#### Screenshots – What the workers are doing

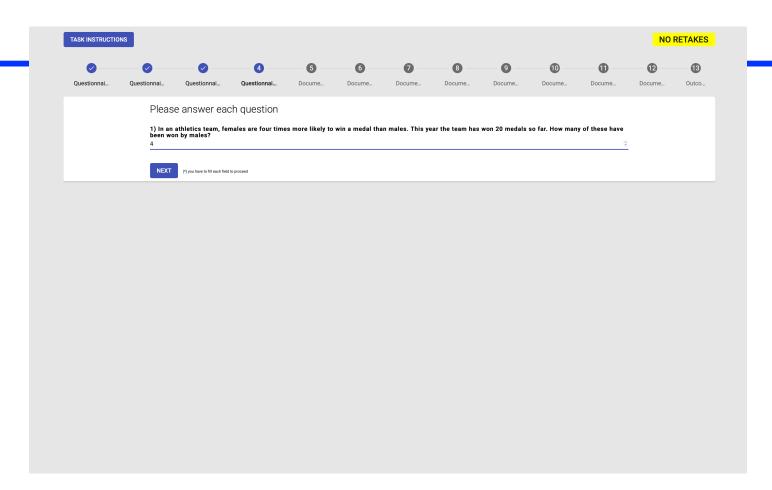


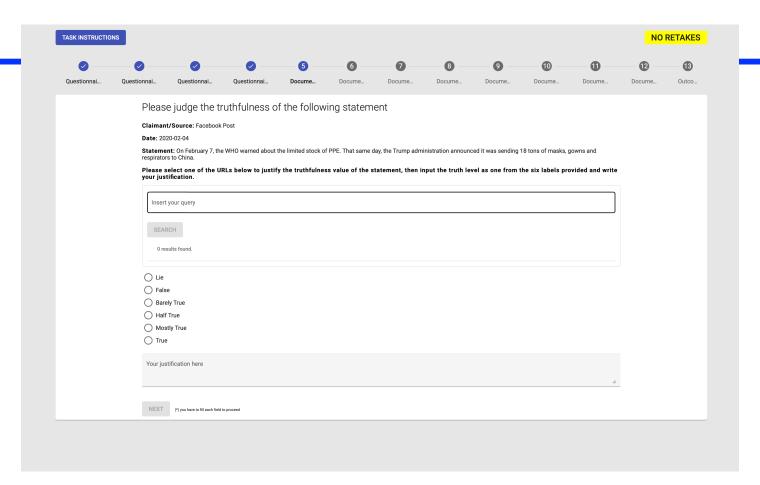


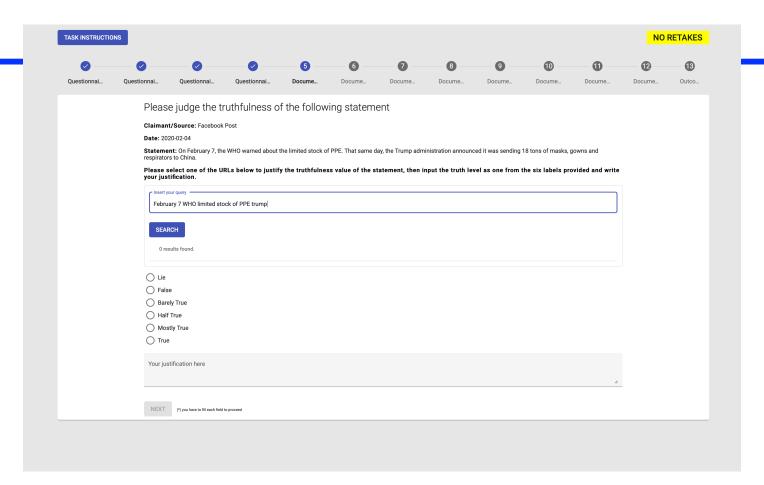
Some postgraduate or professional schooling, no postgraduate degree	
Postgraduate or professional degree, including master's, doctorate, medical or law degree	
3) Last year what was your total family income from all sources, before taxes?	
O Less than 10,000	
<ul><li>10,000 to less than 20,000</li></ul>	
O 20,000 to less than 30,000	
O 30,000 to less than 40,000	
○ 40,000 to less than 50,000	
O 50,000 to less than 75,000	
75,000 to less than 100,000	
O 100,000 to less than 150,000	
○ 150,000 or more	
4) In general, would you describe your political views as	
O Very conservative	
○ Conservative	
○ Moderate	
○ Liberal	
Very liberal	
5) In politics today, do you consider yourself a	
O Republican	
O Democrat	
Independent	
Osmething else	
6) Should the U.S. build a wall along the southern border?	
○ Agree	
Disagree	
○ No opinion either way	
7) Should the government increase environmental regulations to prevent climate change?	
O Disagree	
O No opinion either way	
NEXT (*) you have to fill each field to proceed	

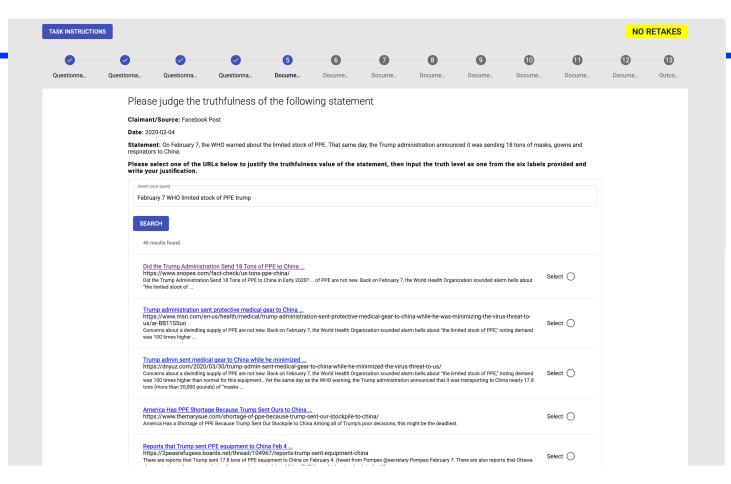


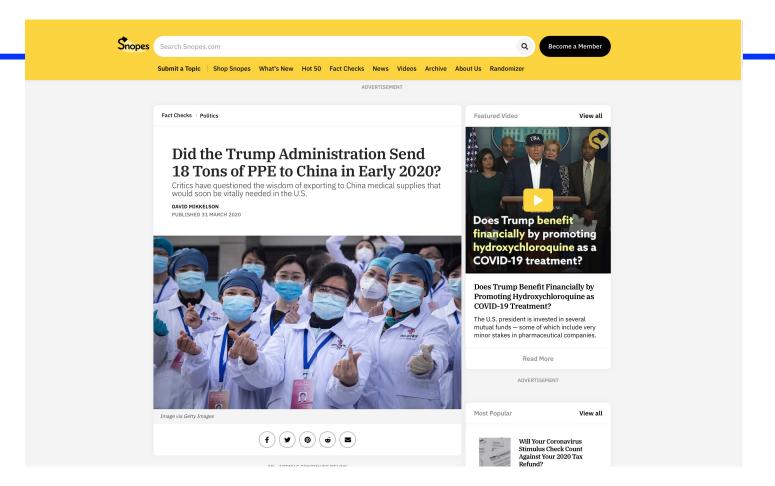


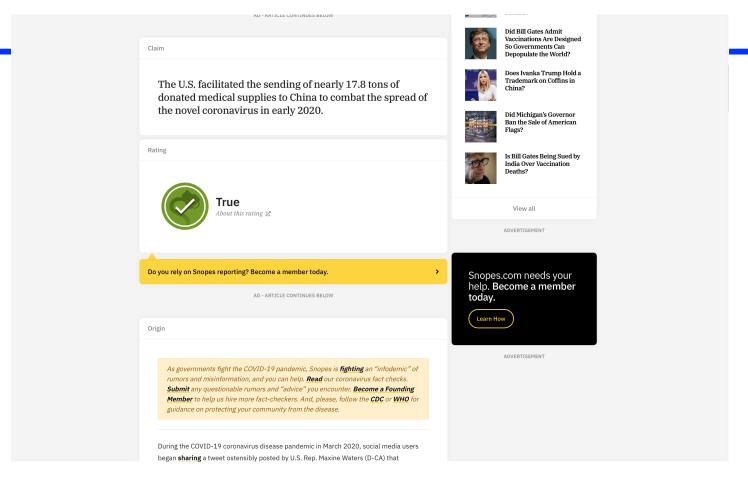


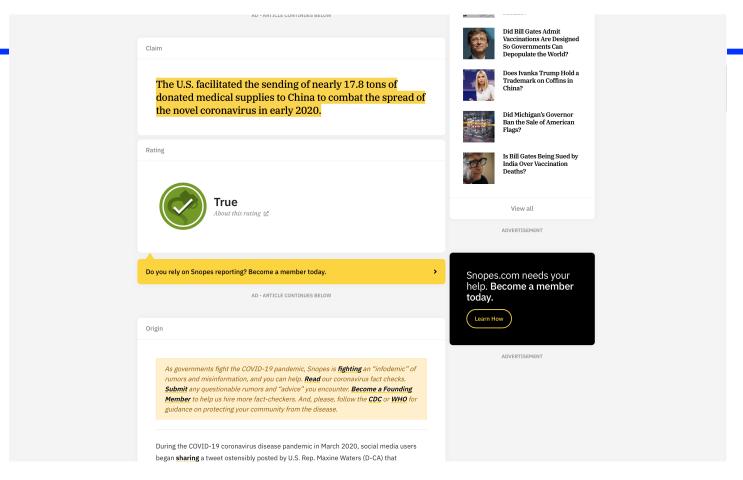


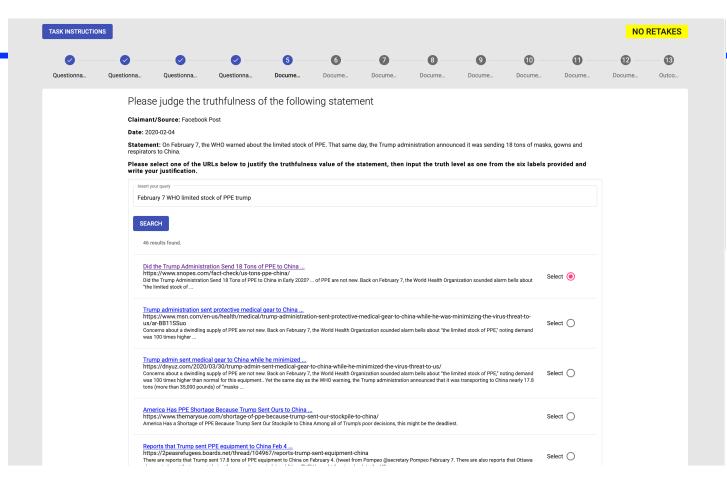


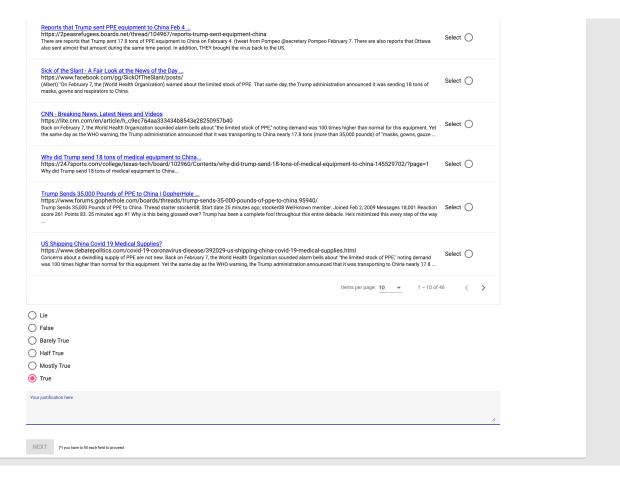


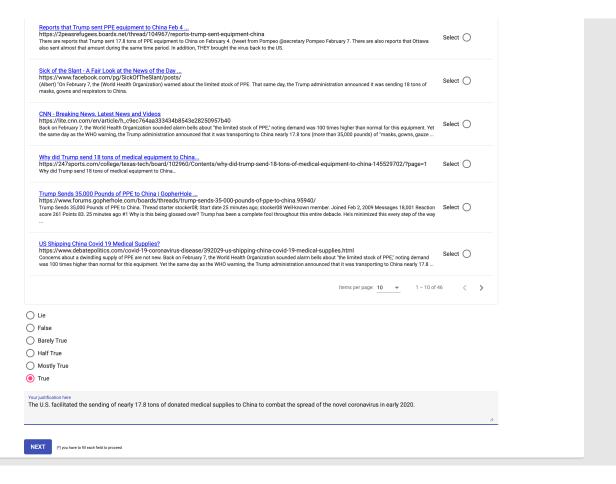


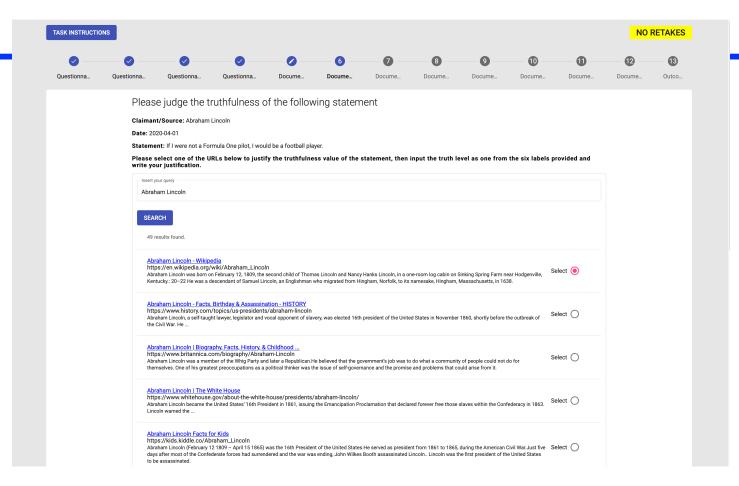


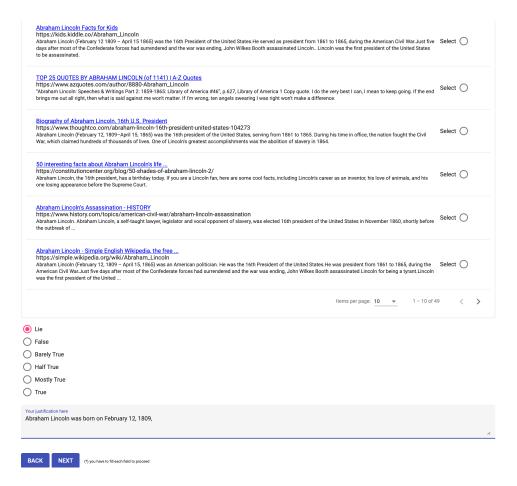






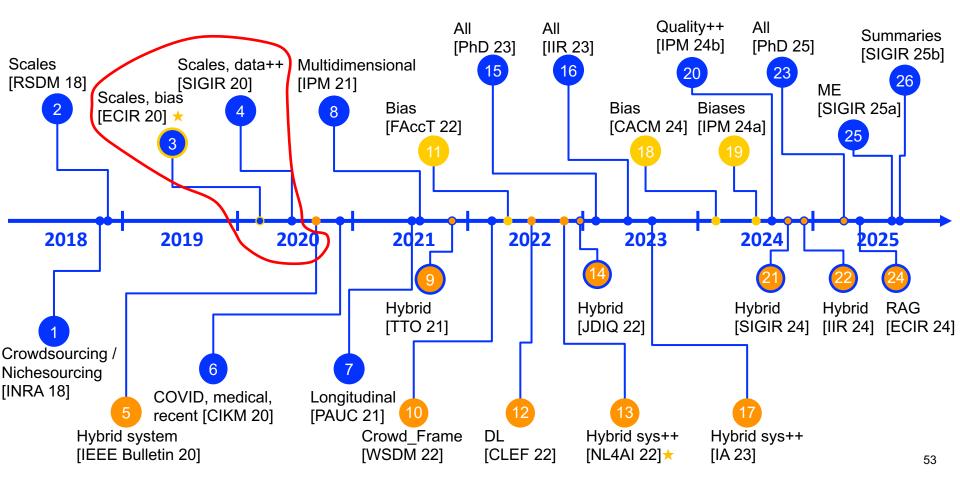




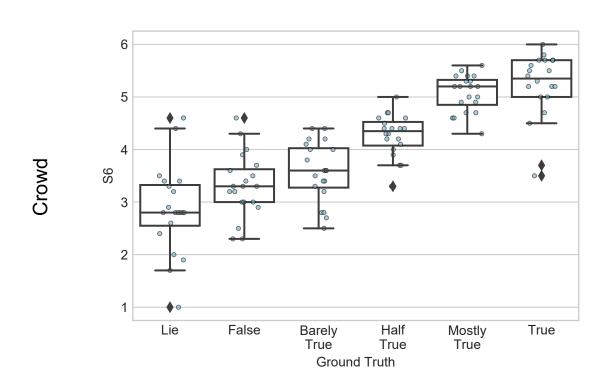


## Now, does it work?

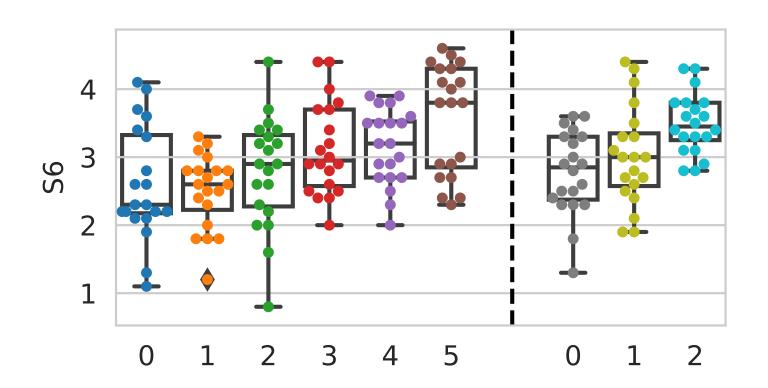
#### Timeline



## Agreement with Ground truth 3. [ECIR 2020]



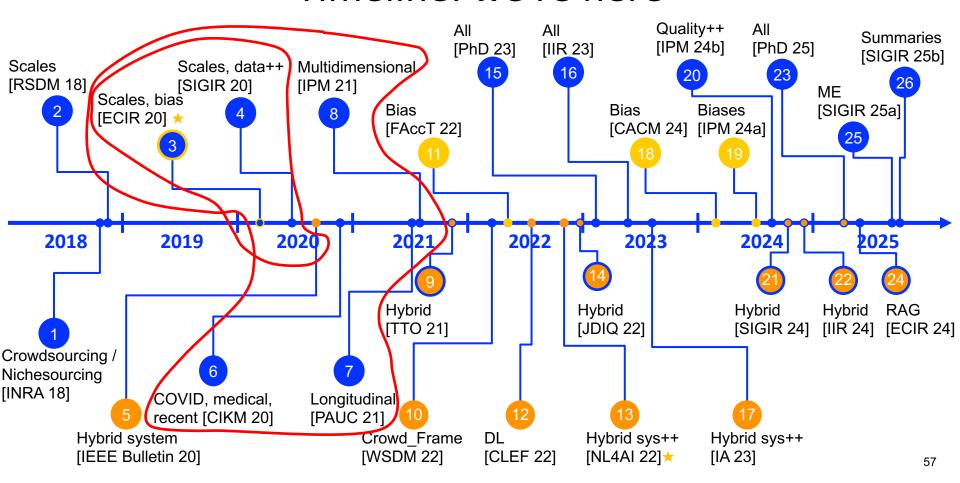
## Another result 4. [SIGIR 2020]



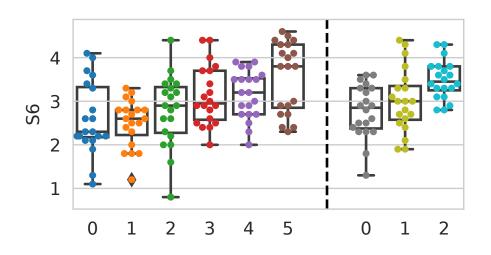
#### What we told ourselves

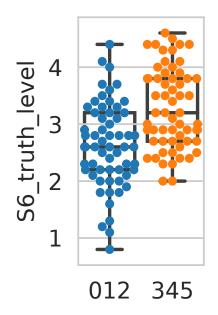
- "Increasing medians"... bla bla bla ... "there is a signal" ... bla bla bla ...
- Yes we published some papers
- And some more in the following years
  - Multidimensional scale
  - COVID-related statements (medical, recent, sensitive)
  - Longitudinal
  - **-** ...

#### Timeline: we're here



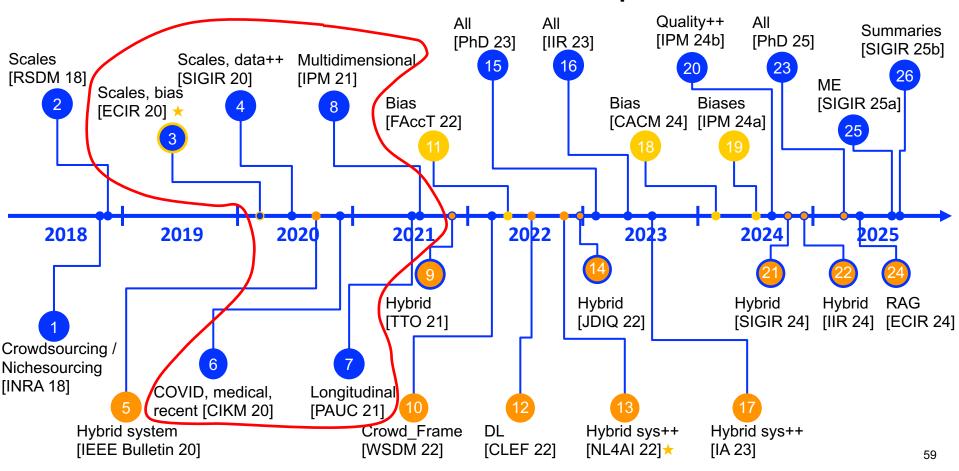
### The sad truth





Binary accuracy: 0.6

## We. Did. Not. Stop.



## Motivation: Does crowdsourcing actually work?

Study	Binary Accuracy
3. [ECIR 2020]	0.841 (*)
4. [SIGIR 2020]	0.627
8. [IPM 2021]	0.571
11. [FAccT 2022]	0.580

## Motivation: Does crowdsourcing actually work?

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Allen, J., Arechar, A. A., Pennycook, G., & Rand, D. G. (2021). Scaling up fact-checking using the wisdom of crowds. *Science Advances*, 7(36), eabf4393. https://doi.org/10.1126/sciadv.abf4393

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Allen et al. (Science Advances 2021)	0.826	
Hu et al. (Al Open 2022)	[0.531 - 0.904]	Al

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(\*) But the Politifact evidence was easily retrievable...

#### Real motivation!

Study	Binary Accuracy	Method
3. [ECIR 2020]	0.841 (*)	
4. [SIGIR 2020]	0.627	
8. [IPM 2021]	0.571	Crowd
11. [FAccT 2022]	0.580	
Allen et al. (Science Advances 2021)	0.826	
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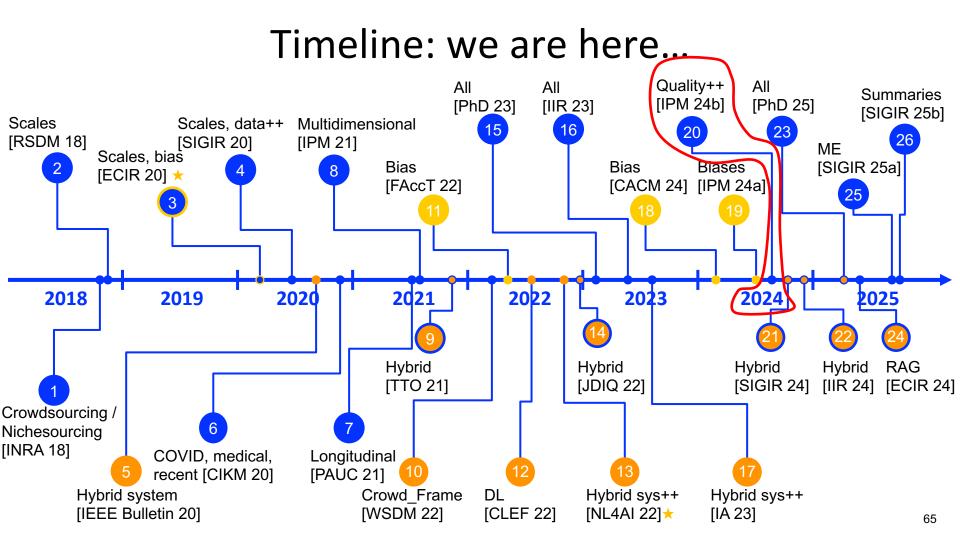
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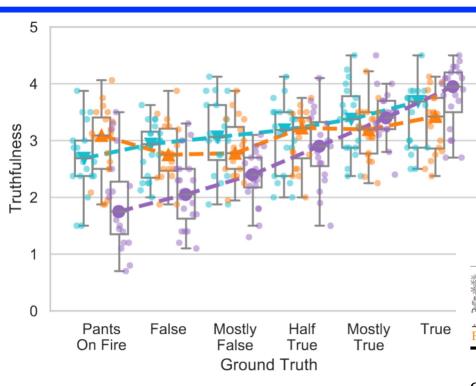
## **Improvements**

- Better crowd
  - Amazon's Mechanical Turk → Prolific
- Better instructions
  - Rewording, shortening, more direct
- Better UI
  - Some small improvements

(even after 5+ years of re-doing the same experiments!)



## (Better) Results!



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journal homepage: www.elsevier.com/locate/ipm





#### Crowdsourced Fact-checking: Does It Actually Work?

David La Barbera <sup>a,\*</sup>, Eddy Maddalena <sup>a</sup>, Michael Soprano <sup>a</sup>, Kevin Roitero <sup>a</sup>, Gianluca Demartini <sup>b</sup>, Davide Ceolin <sup>c</sup>, Damiano Spina <sup>d</sup>, Stefano Mizzaro <sup>a</sup>

The Magnitude of Truth - Stefano Mizzaro

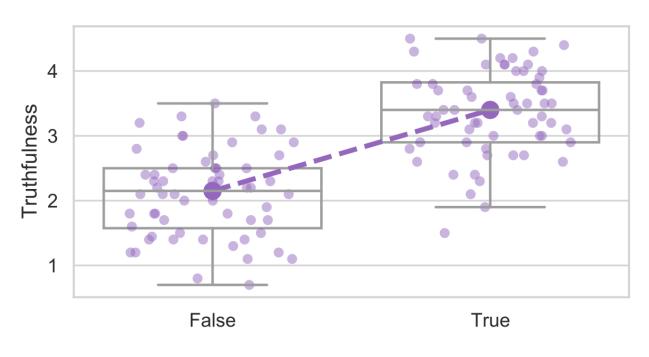
a University Of Udine, Via Delle Scienze 206, Udine, Italy

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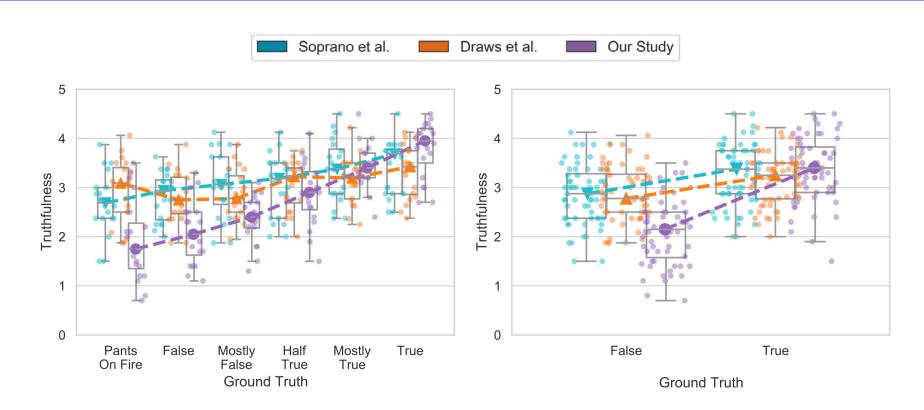
d RMIT University, 124 La Trobe St, Melbourne, Australia

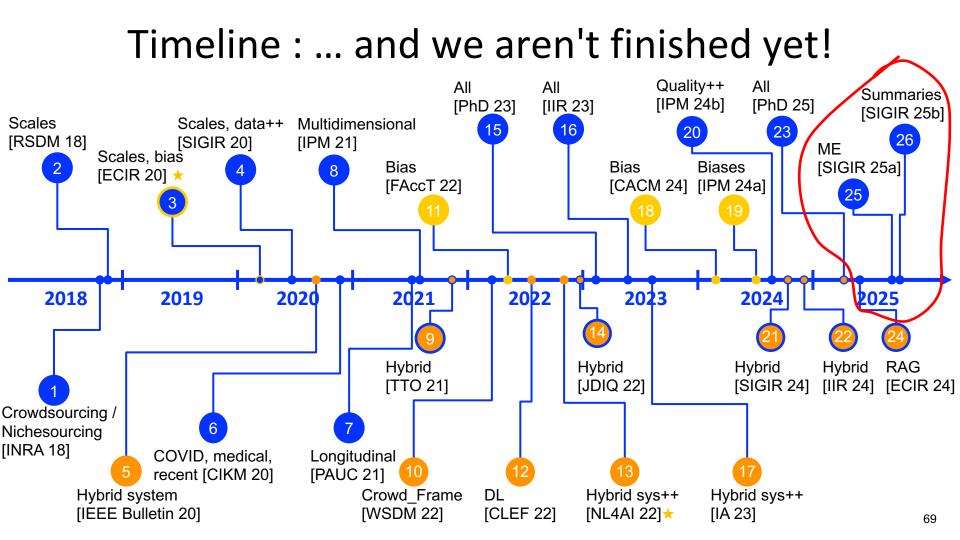
# Aaaaaah, 0.8



**Ground Truth** 

# Aaaaaah, 0.8





### Outline

- Intro
- Crowdsourcing for fact-checking
- Truthfulness Scales and Magnitude estimation

## How to express truthfulness?

In technical terms, which scale to use?

## Binary scale

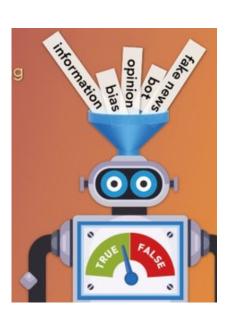
- Traditional solution: binary scale
- Binary truthfulness







**False** 



# Non-binary scales

- 3-levels scale
  - True
  - Neither false not true
  - False







# Non-binary scales

- 4-levels scale
  - Completely false
  - More false than true
  - More true than false
  - Completely true









# It's not just categories

- 4-level ordinal category scale
  - Completely false
  - More false than true
  - More true than false
  - Completely true









450ml (15 fl oz)



# It's not just ranking

- 4-level ordinal category scale
  - Completely false
  - More false than true
  - More true than false
  - Completely true









### Also IRL

- Politifact: <a href="https://www.politifact.com">https://www.politifact.com</a>
- 6 levels scale

















The Poynter Institute

### Subtle differences

2 (n) levels	3 (n) ordered levels
Binary (n-ary) classification	Ordinal classification
All errors are equal	Misclassifying in the adjacent category is a smaller error than misclassifying in the next one - False - Neither true nor false - True
Standard metrics (F1, Accuracy)	No standard metrics

### No standard metrics?!

- Accuracy
  - Assumes all errors are equal!
- MSE, RMSE, MAE, ...?
  - Assume equally spaced categories!
- CEM!?
  - (but that's for another talk)

#### An Effectiveness Metric for Ordinal Classification: Formal Properties and Experimental Results

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### 0, 1, 2, 3, 4, 5?

 0
 1
 2
 3
 4
 5

 0
 1
 3
 5
 7
 8

 0
 1
 10
 100
 1000
 10000



(more later on this)

### We even tried 100 levels

101 actually

Session 3A: Bias and Fairness

SIGIR '20, July 25-30, 2020, Virtual Event, China

# Can The Crowd Identify Misinformation Objectively? The Effects of Judgment Scale and Assessor's Background

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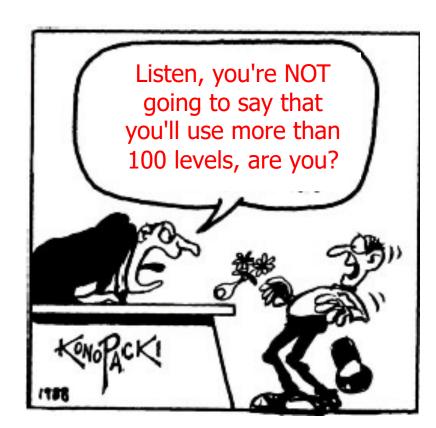
Shaoyang Fan fsysean@gmail.com The University of Queensland Brisbane, Australia

Gianluca Demartini demartini@acm.org The University of Queensland Brisbane, Australia

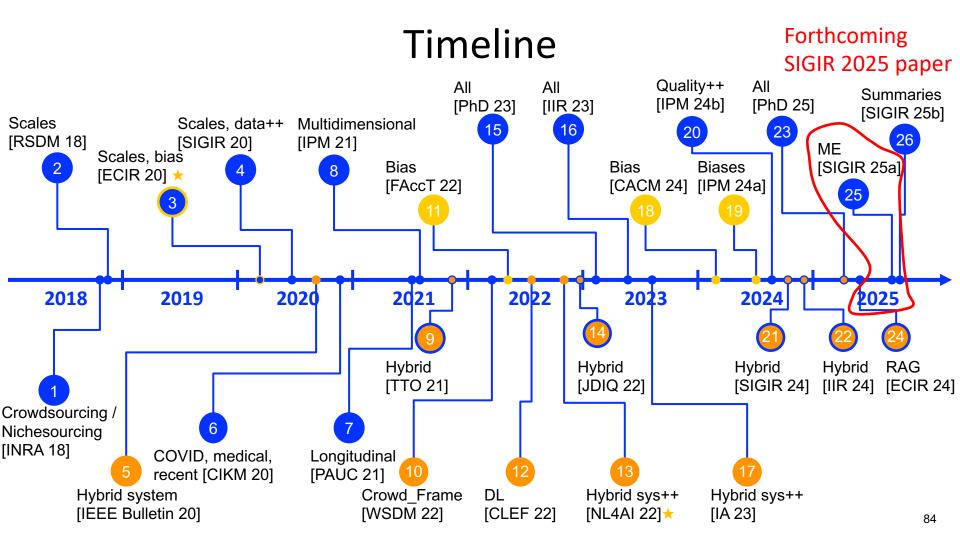
The Magnitude of Trut

### Even more?!

- So,
  - **2**
  - **3**
  - **4**
  - **5**
  - **6**
  - **•** 101
- Even more!?



### Yes. More than 101.

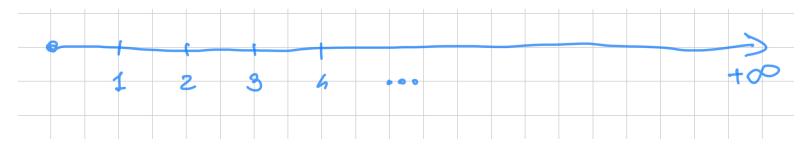


# Magnitude Estimation (ME)

- A psychophysical scaling technique for measuring perception
- Stimuli at different levels of intensity are presented to an observer
- The intensity of each stimulus is rated by the assignment of a number, depending on the perceived intensity
  - "Given a stimulus, assign it a number (whole o fraction)"
- Developed by Stanley Stevens at Harvard in 1950s

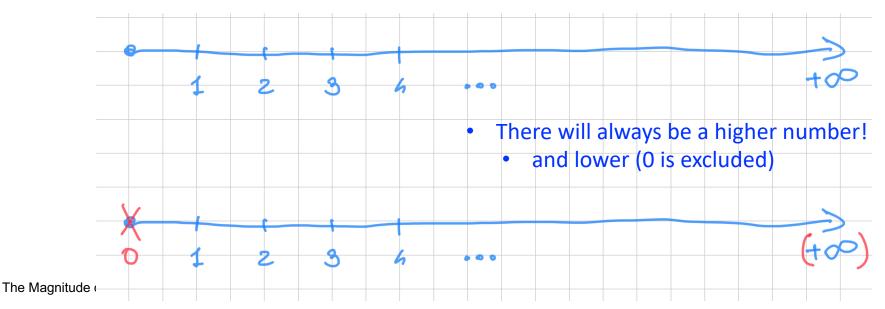
# Magnitude Estimation (ME)...

- Unlimited (≠ "category scale with many categories")
  - either ]- $\infty$ , + $\infty$ [ or
  - **■** ]0, +∞[ (we used this one)



# Magnitude Estimation (ME)...

- Unlimited (≠ "category scale with many categories")
  - either ]- $\infty$ , + $\infty$ [ or
  - **■** ]0, +∞[ (we used this one)



### ME used for

- Initially for physical stimuli, such as:
  - brightness of a light
  - frequency of a sound
  - etc.
- These have an underlying measurable quantity
- Also applied to stimuli that are not physically quantifiable, such as:
  - levels of pain or emotional stress (medicine)
  - severity of crimes, appropriateness of punishments (law)
  - importance of Swedish monarchs (sociology)
  - wine tasting
  - usability of an interface (HCI)
  - judging grammaticality of sentences (linguistics)
  - relevance assessments

### ME

- Leads to ratio scale: ratios of the assigned numbers is what's important
  - If one item is assigned a 50, and another 10, then it can be inferred that the former is 5 times more ... than the latter
  - Supports all mathematical operations, and parametric statistical analysis
- ME truthfulness assessment should be more precise than binary or ordinal assessments
  - The granularity of the scale is chosen by the assessor, and not constrained by pre-determined levels
  - Assessors cannot run out of categories

### Issues with ME

- My "inner scale" is different from yours
- Cultural background might affect which numbers are used
  - E.g., school marks over 0–10 (in Italy) vs. A–F vs. 0–100 vs. ...
  - Round number tendency (prefer 20 to 21)
- Using ME for truthfulness assessment?
  - "A claim more true (false) than an already absolutely true (false) one?!"
- It. Can't. Work.
  - But we tried! (and we are the first!)

### RQs

- Can the crowd express reliable truthfulness assessments using ME?
- Are there any advantages to do so?

### Comparison with S6

- Experimental design identical to a previous study
  - 20. [IPM 2024b]
  - Apart from the scale: we had used Politifact 6-level scale (S6 from now on)
- We knew it worked



- (actually, many studies)
- We can compare ME with S6 <sup>9</sup>



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#### Crowdsourced Fact-checking: Does It Actually Work?

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d RMIT University, 124 La Trobe St. Melbourne, Australia

### Normalization

- S6 values were converted into [0, 5]
  - (yes, more on that later)
- Each ME value is normalized into [0, 5]
  - Using the max & min values by each worker

$$\alpha_{\text{norm}} = \frac{\alpha - \min(A_w)}{\max(A_w) - \min(A_w)} \cdot 5$$

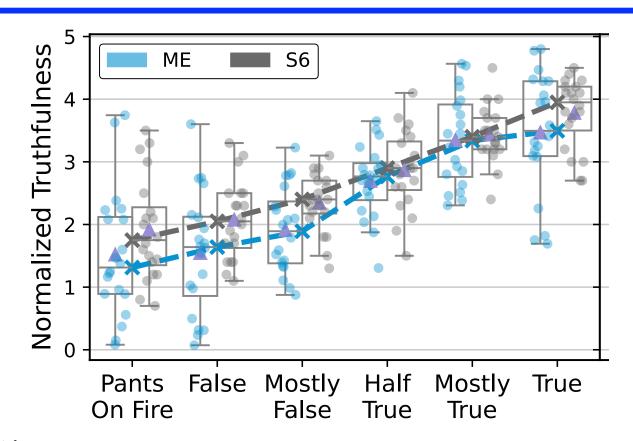
### Aggregation

- 10 individual scores → 1 aggregated score
- We tried several alternatives
  - Weighted mean resulted more effective

Table 2: Comparison of aggregation functions across effectiveness measures.

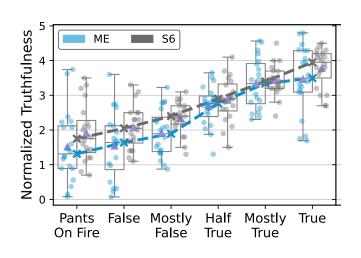
	Accuracy <sub>2</sub>	Accuracy <sub>3</sub>	Accuracy <sub>6</sub>	External	Pairwise <sub>2</sub>	Pairwise <sub>3</sub>	Pairwise <sub>6</sub>	MAE	MSE
wmean	0.80	0.60	0.32	0.63	0.89	0.83	0.79	0.97	1.59
median	0.73	0.59	0.28	0.67	0.87	0.82	0.78	1.02	1.73
mean	0.75	0.57	0.29	0.53	0.86	0.82	0.77	1.07	1.78
gmean	0.57	0.41	0.21	-0.15	0.26	0.25	0.24	2.10	7.06

### ME vs. S6 & ground truth



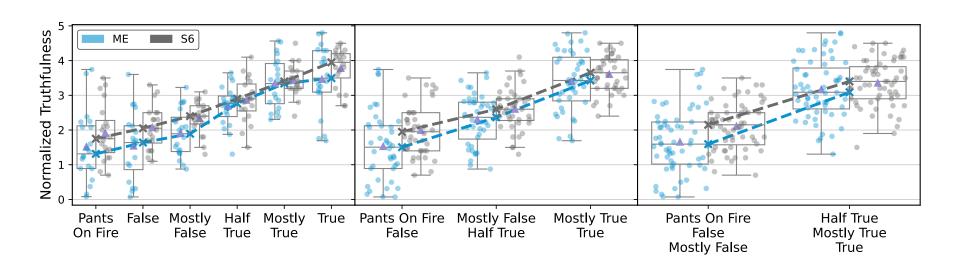
The Magnitude of Truth - Stef

### ME vs. S6 & ground truth



- ME: increasing medians/means
- ME vs. S6: similar trends
  - ME lower for low truthfulness values, but lower also for high truthfulness value

## ME vs. S6 & ground truth



### ME vs. S6: numbers

	Individual		
Measure	<b>S</b> <sub>6</sub>	ME	
Accuracy <sub>2</sub>	0.65	0.63	
Accuracy <sub>3</sub>	0.51	$0.46^\dagger$	
Accuracy <sub>6</sub>	0.29	$0.24^{\ddagger}$	
MAE	1.35	$1.66^{\ddagger}$	
MSE	3.45	$4.83^{\ddagger}$	
Pairwise <sub>2</sub>	0.61	0.63	
Pairwise <sub>3</sub>	0.58	0.61	
Pairwise <sub>6</sub>	0.56	0.58	
External	0.39	0.34	
Internal	0.29	$0.15^{\ddagger}$	

Remember Ordinal Classification? No metric works, but we use all of them

### ME vs. S6: numbers

	Individual		Aggreg	ated
Measure	S <sub>6</sub>	ME	<b>S</b> <sub>6</sub>	ME
Accuracy <sub>2</sub>	0.65	0.63	0.83	0.80
Accuracy <sub>3</sub>	0.51	$0.46^{\dagger}$	0.60	0.60
Accuracy <sub>6</sub>	0.29	$0.24^{\ddagger}$	0.37	0.32
MAE	1.35	$1.66^{\ddagger}$	0.97	0.97
MSE	3.45	$4.83^{\ddagger}$	1.48	1.59
Pairwise <sub>2</sub>	0.61	0.63	0.89	0.89
Pairwise <sub>3</sub>	0.58	0.61	0.85	$0.83^{\ddagger}$
Pairwise <sub>6</sub>	0.56	0.58	0.81	$0.79^{\ddagger}$
External	0.39	0.34	0.61	0.63*
Internal	0.29	$0.15^{\ddagger}$	0.22	$0.10^{*}$

Remember Ordinal
Classification? No
metric works, but
we use all of them

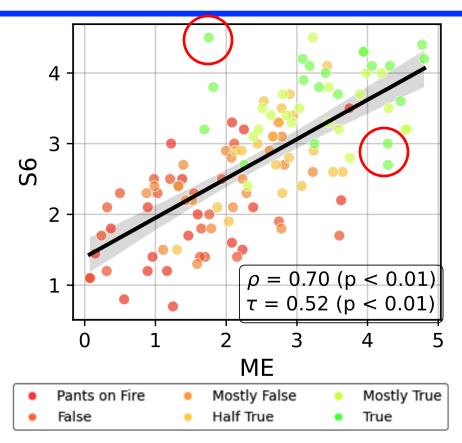
### First result

- ME allows to gather reliable truthfulness assessments
- No evidence that ME is worse than S6

# Beyond ME vs. S6

- Can ME tell us something that S6 can not?
- Possible, ME is more fine-grained
- Is the additional information useful?
- Yes, in two ways

### 1. Complementarity



- If ME and S6 were equivalent, dots would be on the diagonal
  - They are not
  - (ME covers more [0,5])
- → Combination of ME and S6?

# 2. Perception of truthfulness values

- **0**, 1, 2, 3, 4, 5?
- Actually, no.





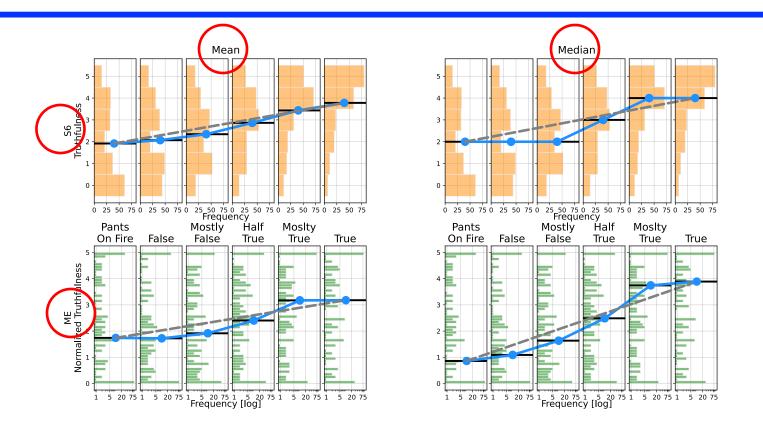








### Distributions of individual normalized values



### Remember 0, 1, 2, 3, 4, 5?

- Pants On Fire ~ False
- Superlinear increase
  - False → Mostly False → Half True → Mostly True
- Mostly True ~ True
- Maybe 0, 0.5. 1.8, 3.1, 4.5, 5?!
  - (even with an "official" scale)
- And maybe the middle of the scale is around Half True
  - Steepest increase







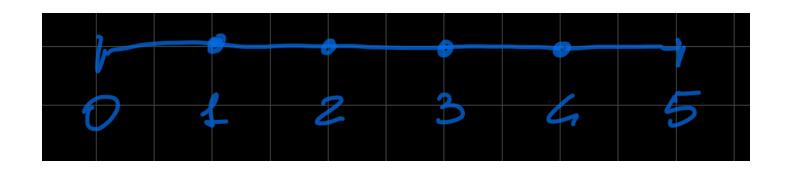




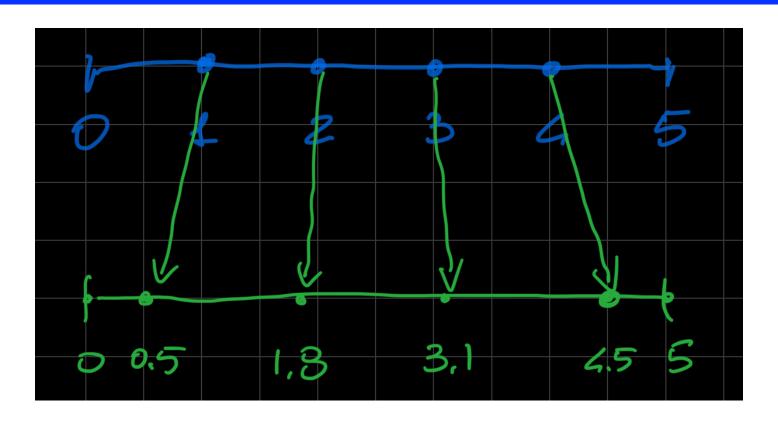


- Less than 1
- More than 1
- Less than 1

# From this...



# ... to something like this



# So, Magnitude Estimation

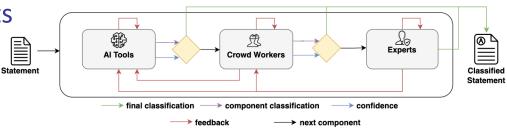
- In terms of accuracy, we couldn't find any compelling reason to prefer S6 to ME
  - (ok, ok, neither the other way around)
- But, ME did provide more information
  - It appears that workers judge differently
  - Useful indication on the scale used by Politifact

#### Conclusions & Lessons learned

- Lesson 1. Crowdsourcing is a viable alternative (?)
  - Is 0.8 enough?! 🖥
- Lesson 2. Improvements are always possible
  - Hard work is needed
  - "Live. Die. Repeat." → "Try. Fail. Repeat."
- Lesson 3. Magnitude Estimation can be used
  - Even though it looked crazy

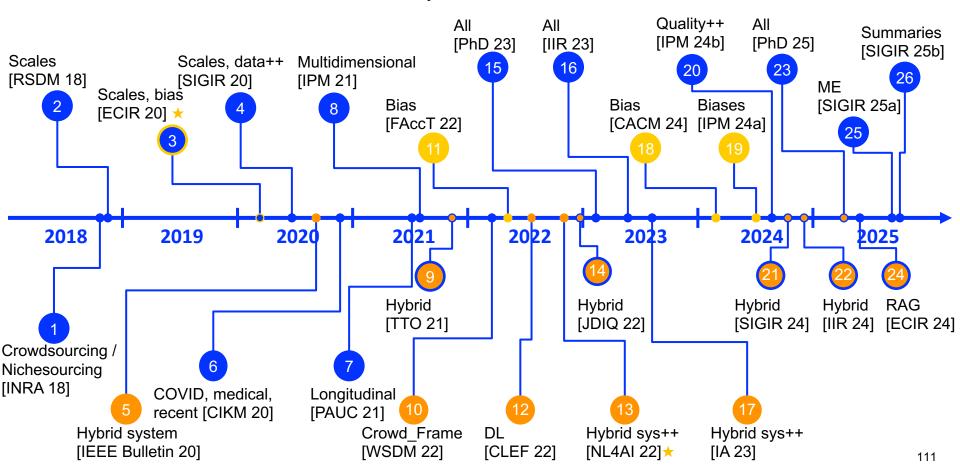
#### **Future**

- Changes/Improvement to the task
  - E.g., workers interacting?
- Combination AI / Crowd / Experts
  - Al, Gen Al, LLMs, ...
  - So far inconclusive evidence
  - E.g., Confidence seems not useful
- Deep fakes (video, multimedia)
  - (First preliminary results: we are doomed! 🚱)
- Summary of evidence: → [SIGIR 2025b]
- Metrics for ordinal classification



# Timeline, a last time 💝





## Biblio – Our papers, grouped

#### Several similar experiments

- 1. Crowdsourcing vs. Nichesourcing [INRA 2018]
- 2. Scales [RDSM 2018]
- 3. Initial, a few data, worker background, scales, bias [ECIR 2020] ★
- 4. More data, scales [SIGIR 2020]
- 6. COVID-19: medical, recent news [CIKM 2020]
- 7. Longitudinal: [PAUC 2021]
- 8. Multidimensional: Measure more aspects [IPM 2021]
- 20. Quality > (Prolific, UI, ...) [IPM 2024b]
- 25. ME [SIGIR 2025a]
- 26. Summaries [SIGIR 2025b]

#### Implementation – Hybrid system

- 5. First proposal [Bulletin 2020]
- 10. Crowd Frame [WSDM 2022]
- 12. Deep Learning [CLEF 2022]
- 13. System description [NL4AI2022] \*
- 17. Hybrid system ++ [IA 2023]

#### Hybrid approaches Crowd + LLMs

- 9. First experiments [TTO 2021]
- 14. Hybrid [JDIQ 2022]
- 21. Hybrid++ [SIGIR 2024]
- 22. Hybrid [IIR 2024]
- 24. RAG [ECIR 2025]

#### Bias

- 11. Bias [FAccT 2022]
- 18. Bias management [CACM 2023]
- 19. Biases in Fact-checking [IPM 2024a]

#### All

- 15. PhD Thesis Soprano [PhD 2023]
- 16. Summary [IIR 2023]
- 23. PhD Thesis La Barbera [PhD 2025]

(details in next slides)

### 1. [INRA 2018]

- E. Maddalena, D. Ceolin, S. Mizzaro. "Multidimensional News Quality: A Comparison of Crowdsourcing and Nichesourcing."
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### 3. [ECIR 2020]

- D. La Barbera, K. Roitero, G. Demartini, S. Mizzaro, D. Spina.
   Crowdsourcing Truthfulness: The Impact of Judgment Scale and Assessor Bias. Advances in Information Retrieval - 42nd European Conference on IR Research, ECIR 2020. 207-214
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https://www.youtube.com/watch?v=9wFFMcplvjk



#### ECIR 2020 @ecir2020 · 1g

#ECIR2020 Best **Short** Paper **Award** goes to "Crowdsourcing Truthfulness; The Impact of Judgment Sca Je and Assessor Bias" authored by

David la Barbera, Kevin Roitero, Damiano Spina, Stefano Mizzaro, Gianluca Demartini. Congratulations!!





### 4. [SIGIR 2020]

K. Roitero, M. Soprano, S. Fan, D. Spina, S. Mizzaro, G. Demartini. Can The Crowd Identify Misinformation Objectively? The Effects of Judgment Scale and Assessor's Background. Proceedings of the 43st International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2020). Xi'an, China (Online). July 25-30, 2020, <a href="https://doi.org/10.1145/3397271.3401112">https://doi.org/10.1145/3397271.3401112</a>

Video:

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- https://www.damianospina.com/publication/demartini-2020human/demartini-2020-human.pdf

### 6. [CIKM 2020]

- K. Roitero, M. Soprano, B. Portelli, D. Spina, V. Della Mea, G. Serra, S. Mizzaro, G. Demartini. The COVID-19 Infodemic: Can the Crowd Judge Recent Misinformation Objectively?, Proceedings of the 29th ACM International Conference on Information and Knowledge Management (CIKM 2020). Galway, Ireland (Online). October 19-23, 2020, <a href="https://doi.org/10.1145/3340531.3412048">https://doi.org/10.1145/3340531.3412048</a>
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- https://truthandtrustonline.com/wpcontent/uploads/2021/11/TTO\_2021\_proceedings.pdf#page=52

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#### 11. [FAccT 2022]

- T. Draws, D. La Barbera, M. Soprano, K. Roitero, D. Ceolin, A. Checco, S. Mizzaro. 2022. The Effects of Crowd Worker Biases in Fact-Checking Tasks. In 2022 ACM Conference on Fairness, Accountability, and Transparency (FAccT '22), June 21–24, 2022, Seoul, Republic of Korea. ACM, New York, NY, USA, 17 pages.
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- http://sag.art.uniroma2.it/NL4AI/wpcontent/uploads/2022/11/paper4.pdf







Associazione Italiana per l'Intelligenza Artificiale

## CERTIFICATE

FOR BEST PAPER

NL4AI 2022

This certificate is proudly awarded by

David La Barbera, Kevin Roitero and Stefano Mizzaro
"A Hybrid Human-In-The-Loop Framework for Fact Checking"



Chairs

Debora Nozza, Lucia Passaro, Marco Polignano

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  - (I was just the supervisor)

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