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Towards Crowdsourcing Tasks for Accurate Misinformation Detection

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Crowdsourcing in Factchecking Can it be done?

Crowdsourced Factchecking

There is a role for crowdsourcing in factchecking but (so far) it's not factchecking

Can crowdsourcing scale fact-checking up, up, up? Probably not, and here's Why NiemanLab

"We foolishly thought that harnessing the crowd was going to require fewer human resources, when in fact it required, at least at the micro level, more."

By MEVAN BABAKAR June 6, 2018, 9:42 a.m.

The fact-checking process is highly complex and not amenable to crowdsourcing.

Tradeoff between coverage, complexity and speed.

- Spotting: biased upvoting, long tail ignored
- Finding primary sources: crowd tends to find secondary sources
- Synthesize conclusions & writeup: demotivates participants when high quality required

WikiTribune



WikiTribune was a news wiki where volunteers wrote and curated articles about widely publicised news by proof-reading, fact-checking, suggesting possible changes, and adding sources from other, usually long established outlets. Wikipedia

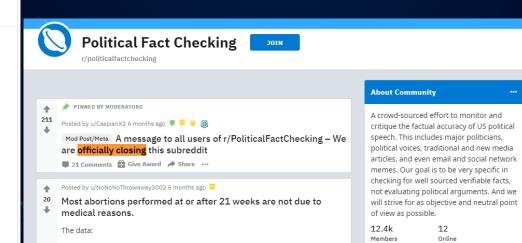
Date launched: April 25, 2017

Type of site: Online newspaper

Headquarters: London

Available in: Spanish Language

Owner: Jimmy Wales







Can we find a sweetspot?

Misinformation Detection:

- does this document contain inaccurate claims?
- If so, which claims and what evidence is there against them?

O. If we automate the process...

Extracting sentences

Spotting claims

Match them to primary sources or evidence

Even if not perfectly...

1. Can we derive simple crowdsourcing tasks?

Long primary sources or evidence leading to them are difficult to find

Better to work at smallest level possible: sentence/claim?

This may also limit bias as context is removed

2. Can we improve the system?

Use the feedback to detect errors of initial system

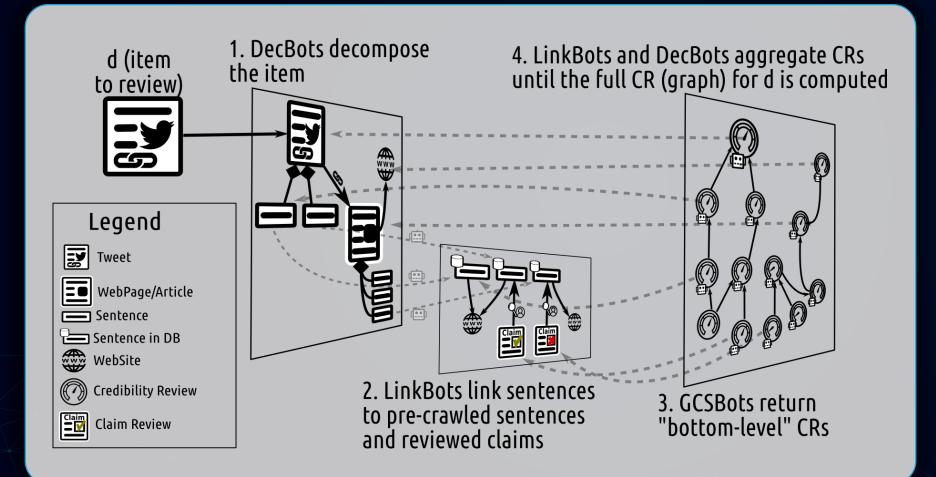
Use feedback to obtain improved system

Go to step 0.





Linked Credibility Reviews acred



Result: Review Graph

Main Review with:

- credibility rating & confidence
- links to sub reviews and eventually evidence

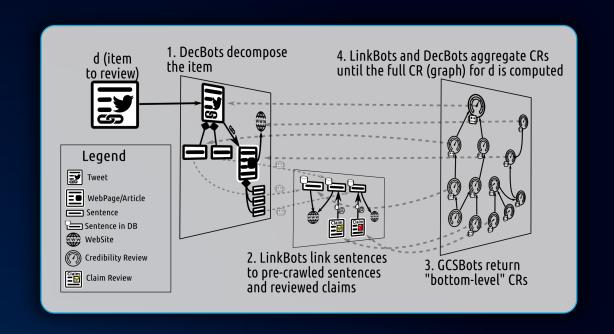
Can be rendered as a label (e.g. "not credible")

See main conference presentation for conceptual and data model





Steps use Deep Learning models, implemented as finetuned RoBERTa instances



Checkworthiness

Is a Sentence a verifiable claim?

Finedtuned on 7.5K samples from CBD (8.7K), Clef'20 Task1 (637) and claims for which a ClaimReview exists (4.6K)

0.85 weighted F1 on Clef'19 test (7K) 0.95 weighted F1 on CB2020 (100)

Semantic Sentence Similarity

How similar are 2 sentences?

Finetuned on STS-B train(5.7K)

0.83 pearson correlation on STS-B dev (1.5K)

Stance Detection

Confirm similarity and provide polarity

Finetuned on FNC-1 train (50K)

92% accuracy on FNC-1 test (25K)

If you have the right data, these models perform really well







FakeNewsNet (Politifact)

420 fake + 528 real webpages/articles Classes: fake, real



coinform250

250 tweets Classes: credible, mostly credible, uncertain, not credible, not verifiable



coinform4550 "train"

400 tweets
Balanced co-inform classes
"Silver" labels (automatically mapped from ClaimReviews using MisinfoMe)

| System | Accuracy | Precision | Recall | F1 |
|-----------------------------|----------|-----------|--------|-------|
| acred | 0.586 | 0.499 | 0.823 | 0.622 |
| \mathtt{acred}^+ | 0.716 | 0.674 | 0.601 | 0.713 |
| CNN | 0.629 | 0.807 | 0.456 | 0.583 |
| $\overline{\mathrm{SAF/S}}$ | 0.654 | 0.600 | 0.789 | 0.681 |

| credible | 2 | 0 | 3 | 5 | 0 | 4 | -40 |
|-------------|---|---|----|----|---|----|------|
| ≈cred | 3 | 0 | 35 | 8 | 0 | 4 | - 30 |
| uncertain | 6 | 0 | 41 | 34 | 7 | 22 | |
| ¬verifiable | 2 | 0 | 4 | 4 | 0 | 5 | - 20 |
| ≈¬cred | 0 | 0 | 0 | 0 | 0 | 0 | -10 |
| ¬credible | 7 | 0 | 11 | 21 | 0 | 23 | |
| | | | | | | | - 0 |

| | | | | | _ | | |
|---|----|----|----|----|----|---|------|
| credible | 18 | 2 | 9 | 37 | 14 | 0 | - 40 |
| ≈cred | 2 | 22 | 3 | 5 | 1 | 0 | |
| uncertain | 4 | 1 | 27 | 35 | 13 | 0 | - 30 |
| ¬verifiable | 10 | 2 | 20 | 30 | 18 | 0 | -20 |
| ¬credible | 6 | 0 | 5 | 47 | 22 | 0 | -10 |
| check_me | 0 | 0 | 0 | 0 | 0 | 0 | - 0 |
| credible cred incertain credible thet he -0 | | | | | | | |
| ree " unce weith creek heer" | | | | | | | |

72% accuracy

27% accuracy

33% accuracy





Feasible! but time-consuming when finding cause



Possible causes

- Dataset issue: e.g. insufficient content, mislabeled
- Selected non-claim as least credible sentence
- Incorrect semantic similarity + stance leads to:
 - incorrect linking to evidence, or
 - over/underestimating confidence in link
- Incorrect confidence affects aggregation
- Type of evidence: Website Review vs ClaimReview



Example from fakeNewsNet real as "not credible" (sample of 26)

77% (20) cases involving stance

But expecting 92% accuracy!

- 50% (13) stance is overestimated (agree/disagree instead of discuss or unrelated)
- 27% (7) correct stance (unrelated), but not reduced confidence enough



In general

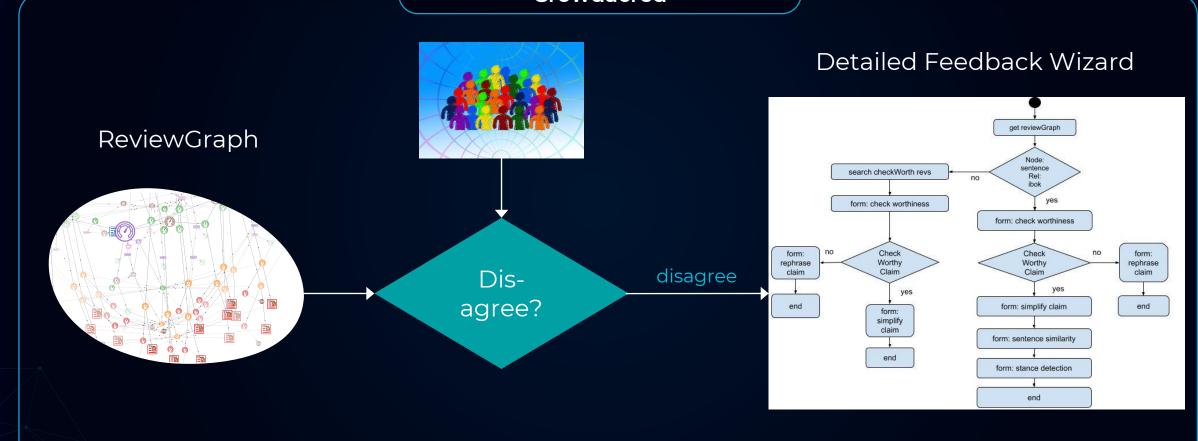
BERT based models great at coarse level, but struggle with specific domains and entities. Can we fix this with additional domain specific samples?

We need a "gold" label to know that we made a mistake and to assess its severity and possible causes.



Crowdacred Overview

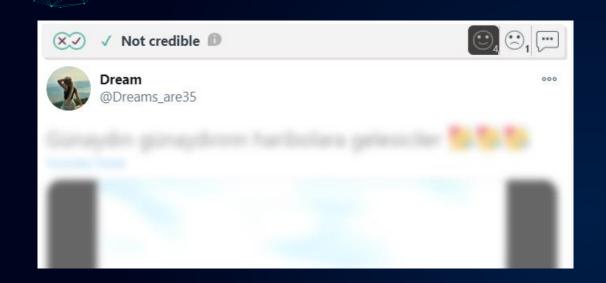
Crowdacred





Dis/agreement

Tweet + Label (explanation optional)



Can we reach consensus?

- At least n (dis)agreements for tweet/label
- At least d:a ratio

Currently collecting ratings for 400 tweets in coinform4550_train using Co-inform Browser Plugin



Crowdacred

Detailed feedback wizard

Check Worthiness Task

Help us to detect if a sentence contains a factual claim

Do you think the following sentence contains a factual claim?

care, this Care, the Care, this Care, the Car

Yes, but no

Do you think the

 Before Roe care, this co

Simplified Clair In the US, befo Sentence Similarity Task

Help us to detect how similar are two sentences

Choose one of the options that describes the semantic similarity grade between the following pair of sentences.

- "The so-called 'heartbeat' law outlaws abortion before most women even know that they're pregnant. This is one of the most restrictive anti-abortion laws in our country."
- Before Roe v. Wade, thousands of women died every year and because of extreme attacks on safe, legal abortion care, this could happen again right here in America
- on different topics
- on not equivalent, but are on the same topic
- not equivalent, but share some details
- oroughly equivalent, but some important information differs/missing
- o mostly equivalent, but some unimportant details differ
- o completely equivalent, as they mean the same thing

Stance Detection Task

Help us to better understand the relation between two sentences

Choose one of the options that describes the relation between the following sentences.

- · "The so-called 'heartbeat' law outlaws abortion before most women even know that they're pregnant. This is one of the most restrictive anti-abortion laws in our country."
- efore Roe v. Wade, thousands of women died every year and because of extreme attacks on safe, legal abortion care, this could happen again right here in America
- agree with each other
- disagree with each other
- discuss the same issue
- are unrelated













Dis/agreement phase seems to converge

Useful for identifying errors What to do with "debatable" cases? How many "agree" cases are lucky?



Detailed Feedback Wizard

Now able to:

- Prune Review Graph to focus on relevant steps/sub reviews
- Generate simple tasks to get feedback and generate new datasamples



Open Questions

How to combine detailed feedback from different users? How many new data samples do we need to improve RoBERTa models? Will improvements generalise?



