

Automated Fact-Checking

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What is fact-checking?

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Examples of claims:

- News reports
- Statements made in political/other public debates
- Social media content — viral content, rumours
- Fake news — journalistic content designed to mislead

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Rumours in Twitter tweets

Oh my god is this real? RT @AP: Breaking: Two Explosions in the White House and Barack Obama is injured
Is this real or hacked? RT @AP: Breaking: Two Explosions in the White House and Barack Obama is injured
Is this legit? RT @AP: Breaking: Two Explosions in the White House and Barack Obama is injured

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News headlines

Nigerian professor solves 150 year old maths problem – 2015 BBC interview with Nigerian professor claiming to have solved the Riemann hypothesis

Fact-checking today

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Two challenges:

- ① Too much information to process — unbacked claims are easy to make but hard to confirm/refute in our “big data” age.
- ② Social media enables anyone to create content with massive reach. Need methods to cope with this new channel of information to manage negative effects of misinformation (hysteria, dishonest mass influence of election outcomes, etc.).

Fact-checking today

Example:



Automated fact-checking

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- Detection and ranking of claims
- Detection of rumours trending in social media
- Automated checking of simple claims — “Einstein was born in Ulm”, “The Danube flows through Serbia”, “Obama is a Muslim”.

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Various aspects/subtasks:

- Detection and ranking of claims
- Detection of rumours trending in social media
- Automated checking of simple claims — “Einstein was born in Ulm”, “The Danube flows through Serbia”, “Obama is a Muslim”.
- Formulating more sophisticated mathematical models — checking more complicated claims (numerical/quantitative/dates etc.), finding counterarguments, reverse-engineering vague claims to make them more precise. . .

Claim detection and ranking

Hassan et al. [1, 2]

ClaimBuster (<http://idir-server2.uta.edu/claimbuster/>) scores sentences based on how “checkworthy” they are.

- Supervised learning — train a classifier to classify statements as “nonfactual statements”, “unimportant factual statements” and “important factual statements”.
- Use Platt scaling to obtain a probability score that a given sentence is an important factual statement.



Claim detection and ranking

Least Check-worthy $\geq 0.1 \geq 0.2 \geq 0.3 \geq 0.4 \geq 0.5 \geq 0.6 \geq 0.7 \geq 0.8 \geq 0.9 \geq 1.0$ Most Check-worthy

0.76 Donald Trump : It's -- the premiums are going up 60 percent, 70 percent, 80 percent.

0.76 Hillary Clinton : When my husband was president, we went from a \$300 billion deficit to a \$200 billion surplus and we were actually on the path to eliminating the national debt.

0.72 Chris Wallace : Mr. Trump, even conservative economists who have looked at your plan say that the numbers don't add up, that your idea, and you've talked about 25 million jobs created, 4 percent...

0.72 Hillary Clinton : They have 4 million American citizen children, 15 million people.

0.72 Hillary Clinton : ... the fact is, he's going to advocate for the largest tax cuts we've ever seen, three times more than the tax cuts under the Bush administration.

0.70 Donald Trump : We're up to \$20 trillion.

0.69 Donald Trump : I pass factories that were thriving 20, 25 years ago, and because of the bill that her husband signed and she blessed 100 percent, it is just horrible what's happened to these people in these communities.

0.66 Chris Wallace : Secretary Clinton, I want to pursue your plan, because in many ways it is similar to the Obama stimulus plan in 2009, which has led to the slowest GDP growth since 1949.

are definitely...

0.20 Hillary Clinton : What kind of rights will Americans have?

0.20 Donald Trump : That's right.

0.20 Donald Trump : We're going to have trade, but we're going -- we're going to terminate it, we're going to make a great trade deal.

0.20 Donald Trump : Which is a big mistake.

0.20 Donald Trump : Our inner cities are a disaster.

0.20 Hillary Clinton : And it really is up to all of us to make that true, now and in the future, and particularly for our children and our grandchildren.

0.20 Hillary Clinton : I have made the cause of children and families really my life's work.

0.20 Donald Trump : They feel we have to have strong borders.

0.20 Hillary Clinton : So I think we could strike a deal and make it very clear to the Russians and the Syrians that this was something that we believe was in the best interests of the people on the ground in Syria, it would help us with our fight against ISIS.

0.20 Donald Trump : They will have a conservative bent.

Text from transcript of 2016 Third US presidential debate.

Automatic rumour detection

Zhao, Resnick and Mei [3]

Rumour: *“a controversial and fact-checkable statement”*.

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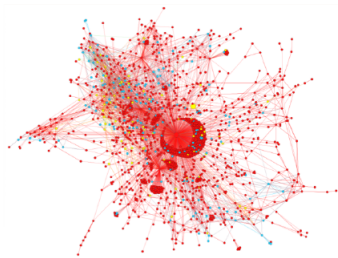
Automatically detecting if an individual tweet contains a rumour is difficult.

Instead, classify *clusters* of tweets containing a given rumour based on how many of them contain **enquiry signals**, i.e. tweets containing statements like “really?” or “what?”

Automatic rumour detection

- ➊ **Identify signal tweets** containing predefined enquiry signal strings.
- ➋ **Cluster signal tweets** into clusters of similar content.
- ➌ **Determine the common text/topic** of the signal clusters.
- ➍ **Capture all non-signal tweets** (i.e. those that contain the same topic but do not contain enquiry signals) and merge them into signal clusters to form candidate rumour clusters.
- ➎ Using statistical features **rank candidate rumour clusters** by the likelihood that their topic is a rumour.

Automatic rumour detection



White House explosion rumour. Red, yellow and blue nodes: tweets spreading, correcting and questioning the rumour.

Left: 60 seconds after the source there were already sufficient enquiry nodes.

Right: After the rumour went viral.

Automated checking of simple claims

Ciampaglia et al. [4], Shi and Wenginger [5]

Consider *relational claims*, i.e. claims linking two entities via some relation.

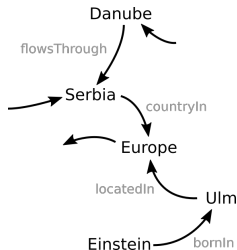
Einstein $\xrightarrow{\text{was born in}}$ Ulm

The Danube $\xrightarrow{\text{flows through}}$ Serbia

Barack Obama $\xrightarrow[\text{(has religion)}]{\text{is a}}$ Muslim

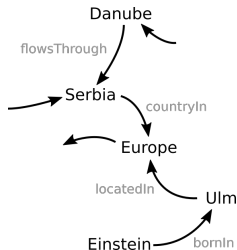
Automated checking of simple claims

- Form a **knowledge graph** from a collection of true relational triples. (Nodes are entities, edges are relation predicates.)



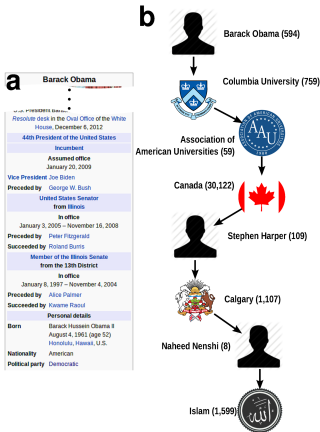
Automated checking of simple claims

- Form a **knowledge graph** from a collection of true relational triples. (Nodes are entities, edges are relation predicates.)



- Determining the truth of a new relational claim can be modeled by various graph problems, e.g. link prediction, path mining, path weight optimization...

Is Obama a Muslim?



(a) Knowledge graph defined from Wikipedia infobox data. Weight $W(P)$ of a path P between two nodes decreases with the degree of intermediate nodes.

(b) The path between “Barack Obama” and “Islam” with greatest weight passes through the “Canada” node which has large degree. The path thus has low weight, indicating low support for the statement “Obama is a Muslim”.

(Ciampaglia et al. [4])

More sophisticated fact-checking frameworks

Wu et al. [6]

More complex claims:

“...adoptions went up 65 to 70 percent...[during 1996–2001 compared to 1990–1995]”

“Jim Marshall [US Democratic politician] voted the same as Republican leaders 65 percent of the time”

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- Often vague — can we reverse-engineer to make them more precise?

More sophisticated fact-checking frameworks

A very high-level overview:

- The numerical/date data in claims can be thought of as parameters that can be perturbed.
- Varying these parameters yield statements with different truth scores, in this way we obtain a function surface of the truth score against the parameters.
- Optimizing over the function lets us determine how “robust” a claim is, reverse-engineer imprecise claims, find counterarguments etc.

References

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- [3] Zhao, Resnick and Mei. *Enquiring Minds: Early Detection of Rumours in Social Media from Enquiry Posts*. 2015.
- [4] Ciampaglia, Shiralkar, Rocha, Bollen, Menczer and Flammini. *Computational Fact Checking from Knowledge Networks*. 2015.
- [5] Shi and Wenginger. *Discriminative Predicate Path Mining for Fact Checking in Knowledge Graphs*. 2016.
- [6] Wu, Agarwal, Li, Yang and Yu. *Toward Computational Fact-Checking*. 2014.