

Crowd-sensing with Polarized Sources

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Presented by
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IEEE DCROSS 2014



Humans as Sensors



Egypt Unrest



Fukushima Disaster



Sandy Gas Outage



Crimea Annexation



Syria Chemical Attack



Twitter

Facebook

Google+

Instagram

Flickr

Credibility
Estimation

Anomaly
Detection

Timeline
Reconstruction

...



Binary Sensor Model

- Assume that each observation is either **True** or **False**
 - **True** means independently observable events.

Flights halted at airport in east Ukrainian city of Donetsk after armed separatists demand withdrawal of troops bbc.in/1nKCMIB ◉

← Reply ↻ Retweet ★ Favorite ... More

After Hurricane Irene hit Puerto Rico, the streets were so flooded that a shark managed to swim in a street. yfrog.com/kly3ljjj ◉

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12:04 AM - 25 Aug 2011

- Some observations are neither True nor False, representing Non-Factual claims.
 - May be slogans or emotions or opinions.

America doesn't learn. Another mass shooting. This time in California. A person should never be able to buy that many bullets [#massShooting](#)

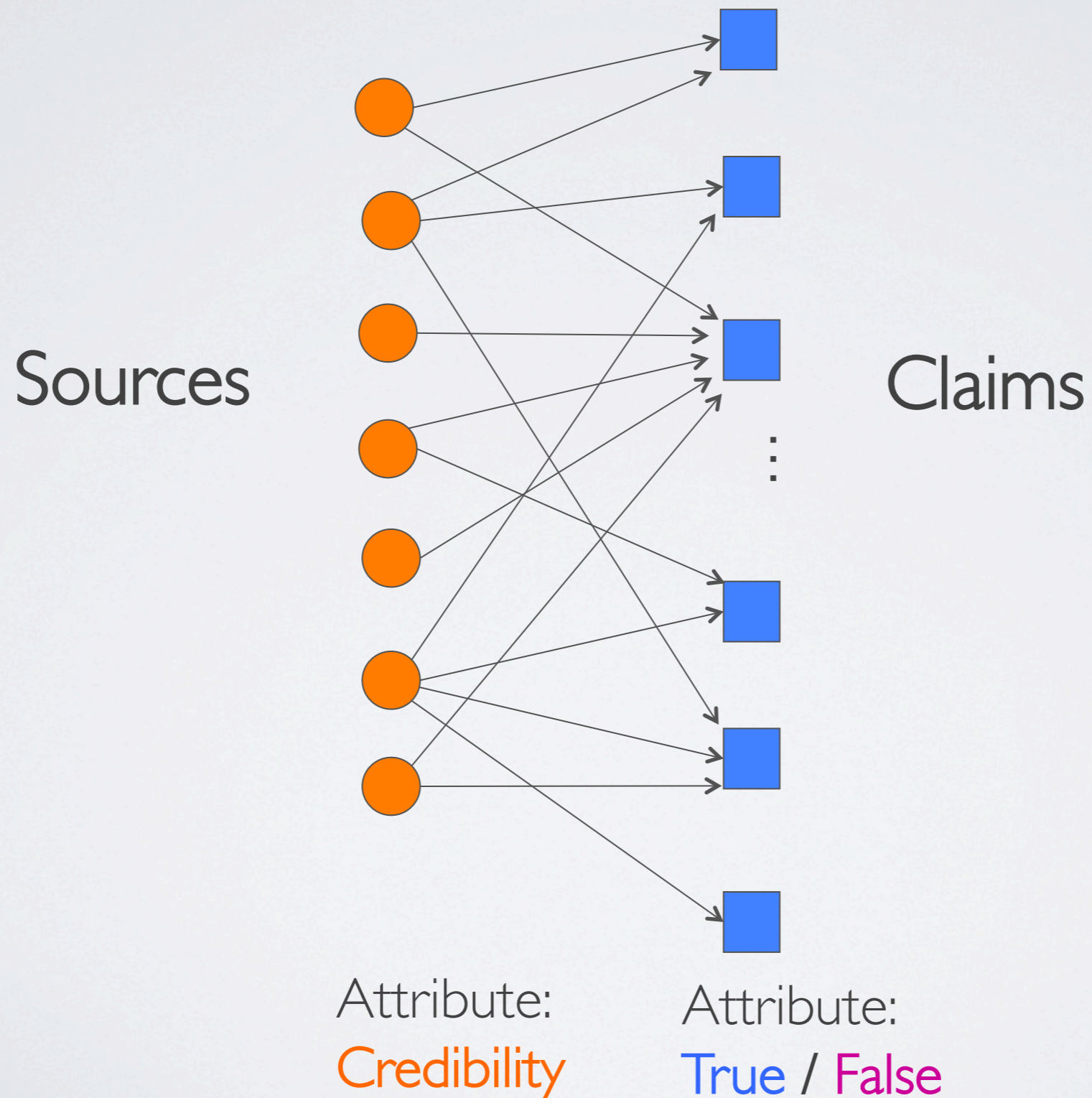
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Anyone else think that Steve jobs missed a trick by not calling the battery charge on an iPhone "apple juice" ???

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Source Claim Network





State of the Art

- Independent Sources, Independent Claims IPSN 2012
 - On Truth Discovery in Social Sensing
- Confidence Bounds SECON 2012
 - On scalability and robustness limitations of real and asymptotic confidence bounds in social sensing
- Admission Control INSS 2012
 - On Diversifying Source Selection in Social Sensing
- Conflicting Claims RTSS 2013
 - Exploitation of Physical Constraints for Reliable Social Sensing
- Non-independent Sources IPSN 2014
 - Using Humans as Sensors: An Estimation Theoretic Perspective
- Polarized Sources DCOSS 2014
 - This paper



Case Study: Egypt 2013

- Event: 2013 Uprising regarding former Egyptian President Mohamed Morsi
- Crawler starting July 2013, and continued for more than four months.
- 17 GB of tweets collected. 600K were “English” containing the word “Morsi”, which belonged to 173K cascades of different claims / observations.
- The largest 1000 cascades were manually annotated as being **Pro-Morsi** or **Anti-Morsi** or **Neither**
 - Accounted for 44K sources and 95K tweets



Pro Claims



Mahmoud M. Abuelnass
@MAbuelnass



 Follow

#EGYPT

#Morsi supporters denied right amid reports of arrests and beating

#Military_Coup

facebook.com/photo.php?fbid... 

 Reply  Retweet  Favorite  More

RETWEETS

2



2:44 AM - 19 Jul 2013



BBC Breaking News
@bbcnews_ticker



 Follow

Egyptian police fire tear gas to disperse supporters of ousted President Mohammed Morsi, reports say bbc.in/17maf3 

 Reply  Retweet  Favorite  More

RETWEET

1



8:10 AM - 13 Aug 2013



Anti Claims

 **ArabIdolNews**
@Arabidolnews Follow

#RT " @DrBassemYoussef Helicopter footage of Anti Morsi protests, very impressive youtube.com/watch?v=Vux_-v... ... "

Reply Retweet Favorite More

RETWEETS 2 FAVORITES 5

5:48 AM - 2 Jul 2013

 **Khaled Abol Naga** ✓
@kalnaga Follow

Amnesty International | Egypt: Evidence points to torture carried out by Morsi supporters amnesty.org/en/for-media/p...

Reply Retweet Favorite More

RETWEETS 60 FAVORITES 21

2:09 PM - 18 Aug 2013



Neither





BBC Breaking News ✓

@BBCBreaking



Follow

PHOTO: Supporters of ousted President Morsi (left) and supporters of the army (right) in Cairo bbc.in/16jb0K5 
pic.twitter.com/j9GnkBfoJH 

Reply Retweet Favorite More



RETWEETS 370 FAVORITES 73



11:56 AM - 26 Jul 2013

Flag media



TavernKeepers

@TavernKeepers



Follow

Our two part series on [#Benghazi](#). Was it a botched kidnapping? Were [#Morsi](#) [#Obama](#) involved? The Blind Sheik?
tavernkeepers.com/benghazi-murde... 
[#LNYHBT](#)

Reply Retweet Favorite More

RETWEET 1 FAVORITE 1



8:01 PM - 5 Nov 2013



semprecontro

@semprecontro



Follow

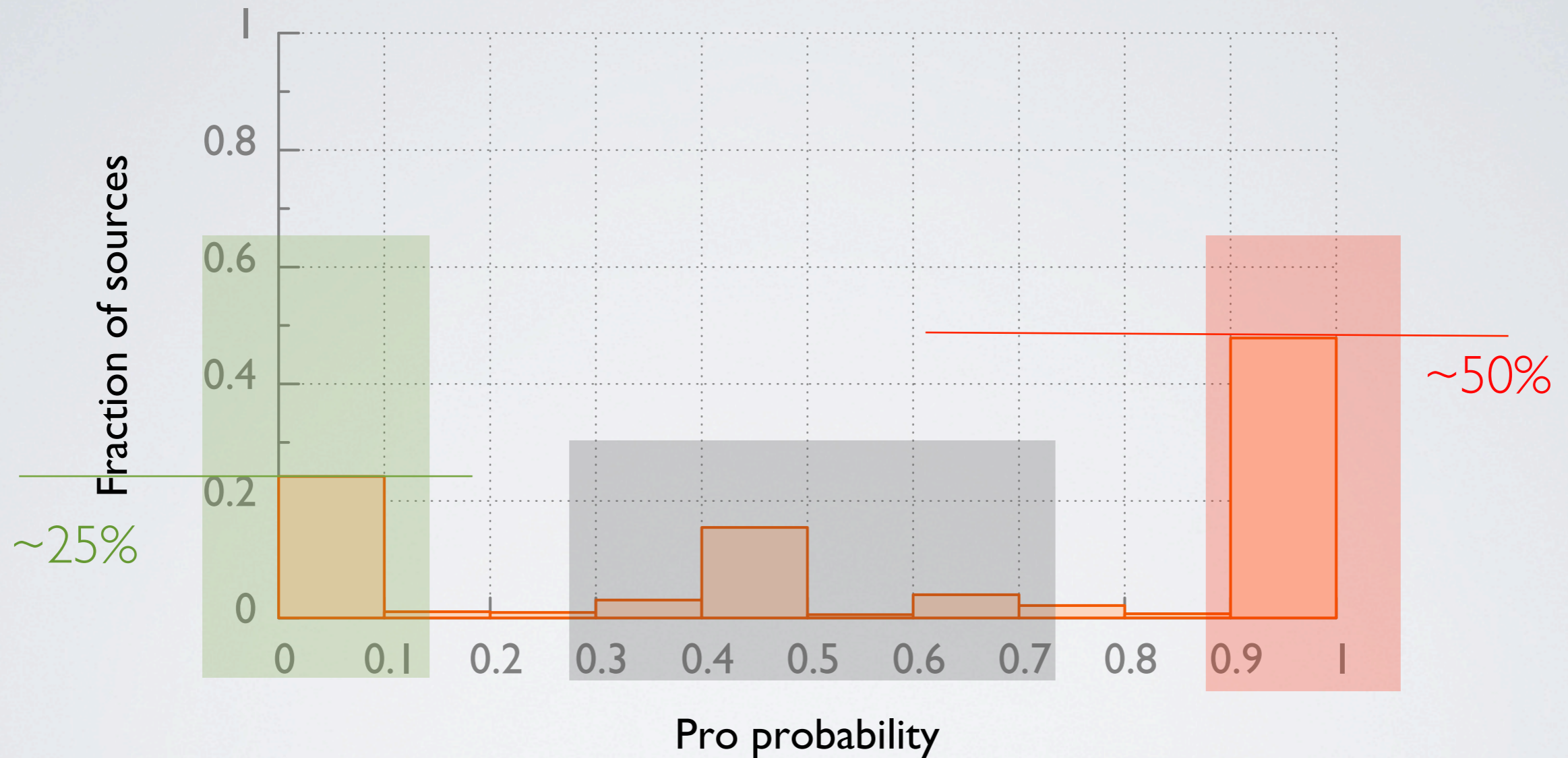
[#Syrian](#) refugees living in Egypt get swept up by turmoil following Morsi's ouster | Fox News" (fxn.ws/18fYHQS )

Reply Retweet Favorite More

3:02 AM - 15 Jul 2013



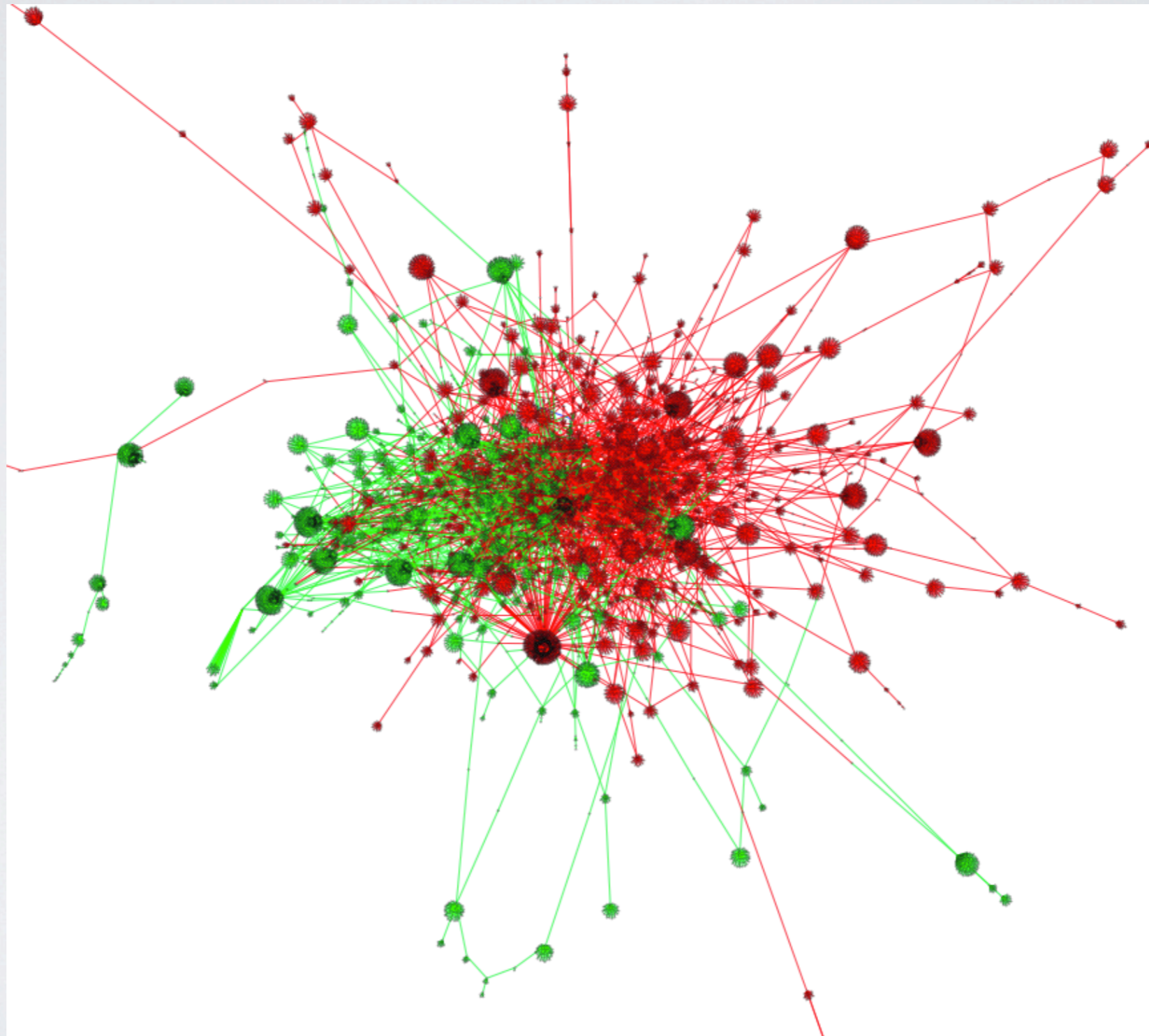
Degree of Polarization



- Some users are highly polarized, and mostly forwards tweets favoring camp they belong to (**Pro** or **Anti**)
- Some users are neutral



Social Propagation Network



— Anti network

— Pro network



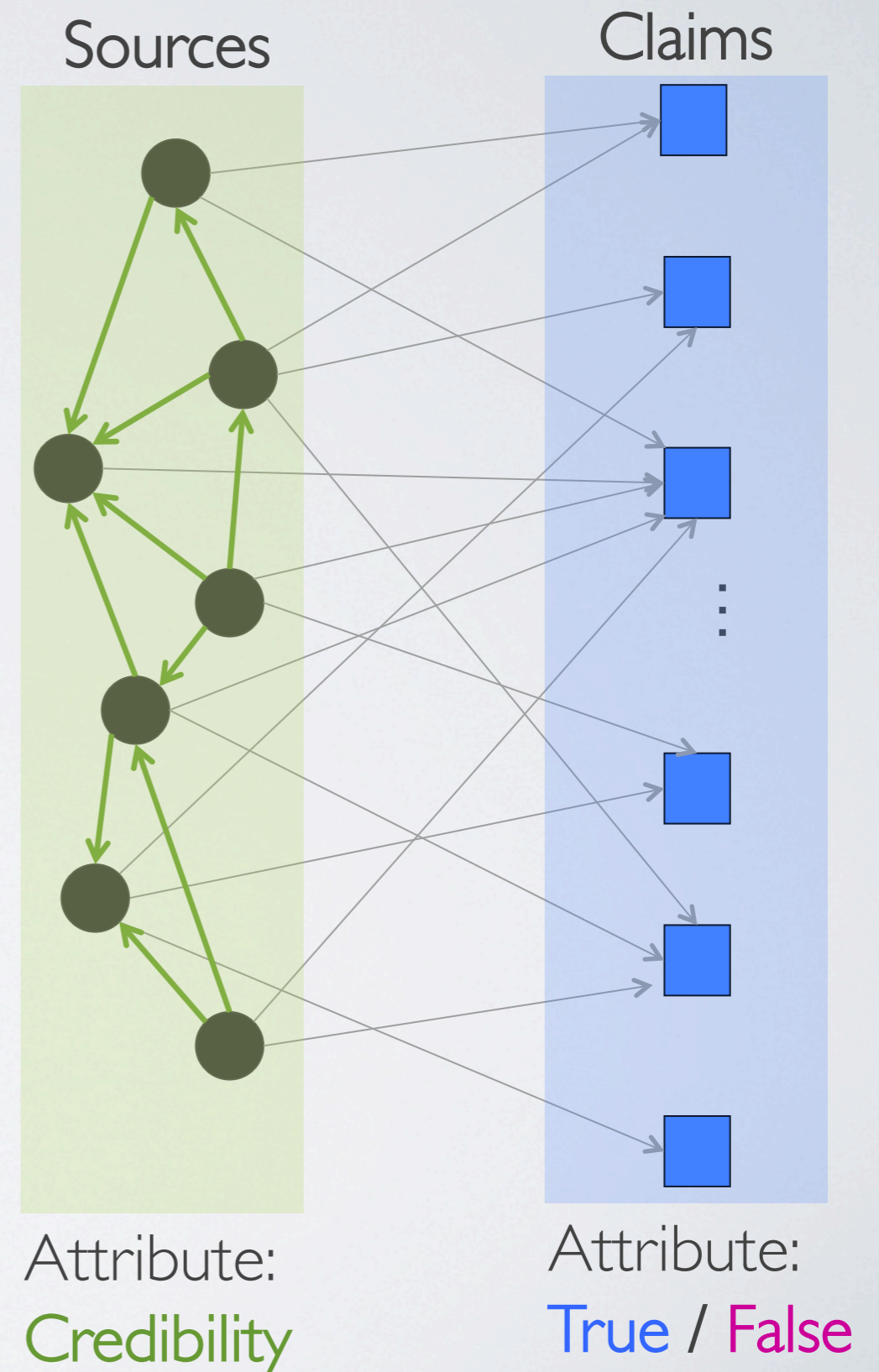
Effect of Polarization

- When sources are biased towards a topic, their observation errors on that topic are more correlated.
 - When they do not share a bias, errors are independent.
 - Corroboration among correlated sources carry less statistical weight than when they are independent.
- Polarity unaware algorithm improperly computes the correlation between sources.



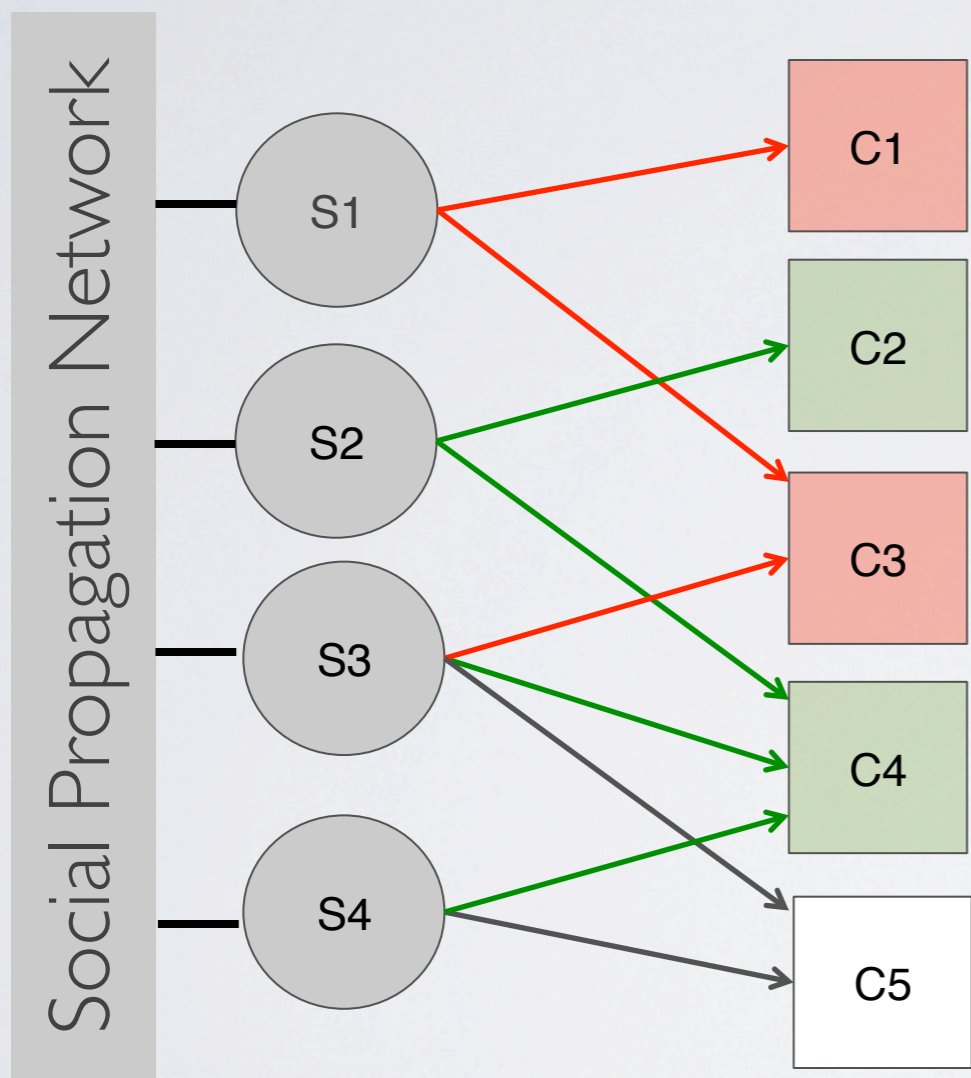
Polarity-aware Fact Finder

- Computes the latent networks from pro, anti, and neutral claims (SIGMETRICS 2012)
- Uses each network to estimate correlated errors in a manner that depends on content type.
- Accounts for correlation in credibility analysis.

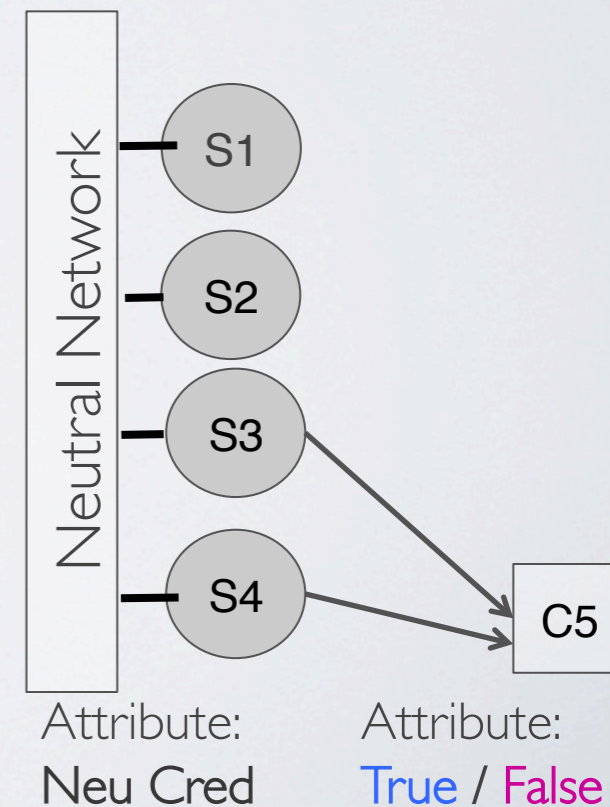
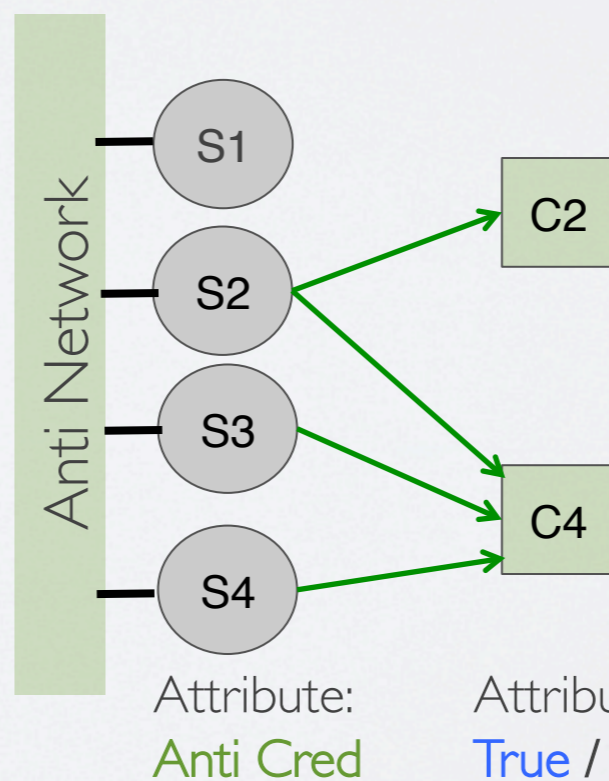
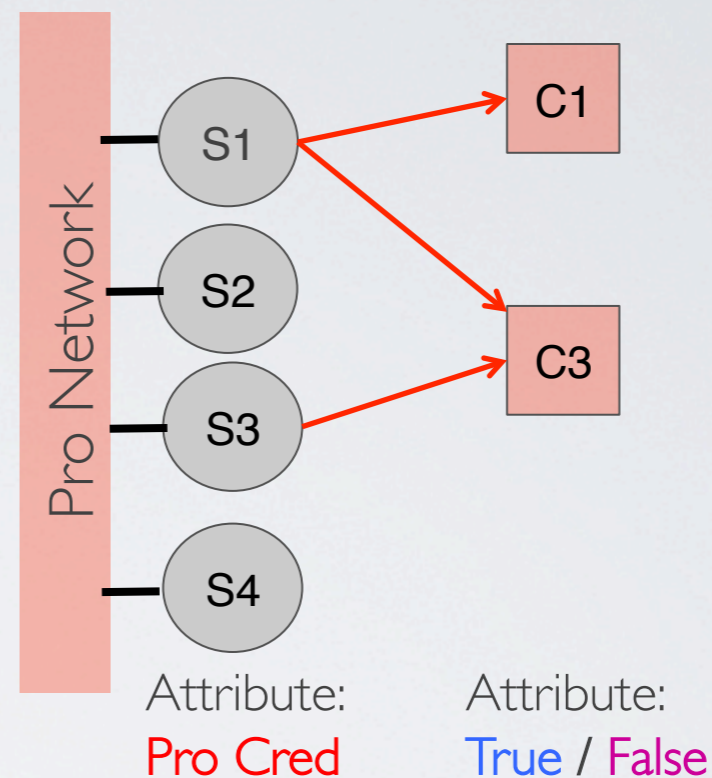




Polarity-aware Fact Finder



Original Problem





Evaluation

	Input	Combined	Polarized
Pro Claims	199	147	128
Anti Claims	109	88	76
Neutral Claims	692	543	496



Evaluation

	Set A	Set B
Definition	Polarized Exclusive	Combined Exclusive
Total	38	116
Factual	26	82
Non-factual (0)	12	34
True (1)	25	72
False (-1)	1	10
False Claims	2.6 %	8.6 %
Factual True	96 %	88 %

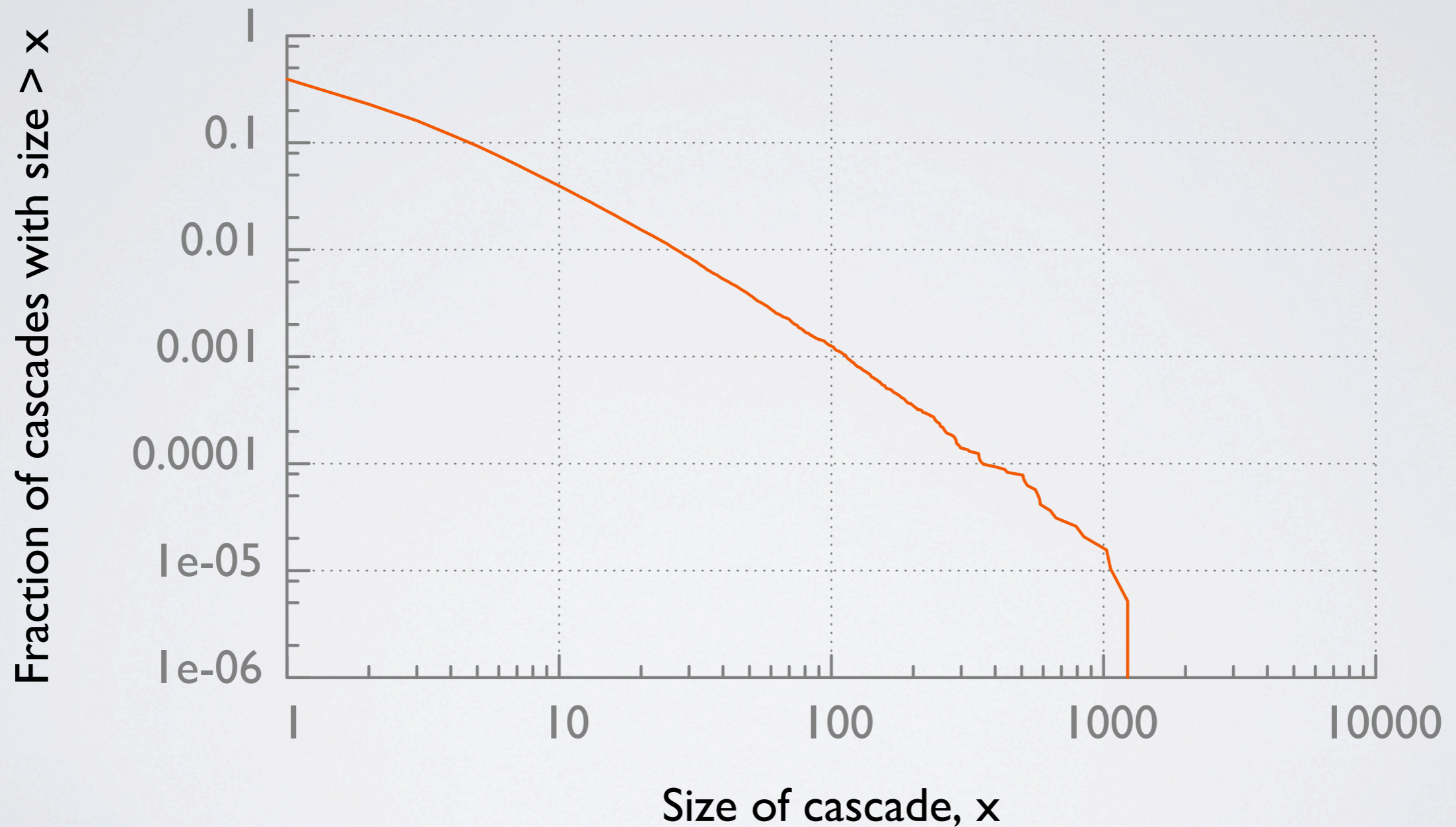


Conclusion

- Separation of claims by polarity prevents estimation of false dependencies between neutral sources.
- Probability of error reduced by **factor of three** for the factual claims.
- More than **18%** improvement in overall Quality of Information.
- Easily extensible to incorporate ML or NLP analysis which may improve the fact-finding performance.
- Idea of polarities can be extended to “topics” with arbitrary relations and hierarchy.
- Did not consider adversarial sources.



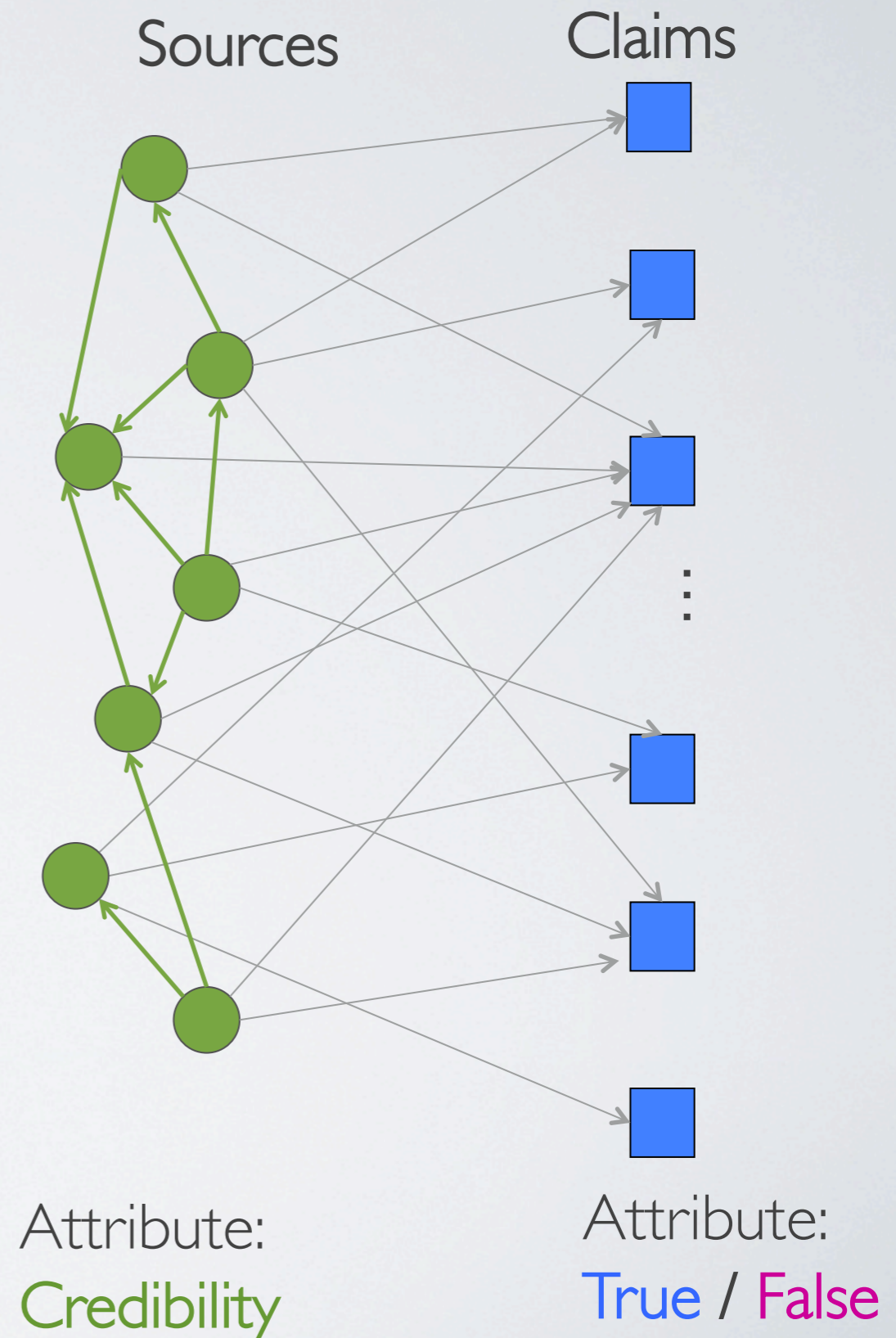
Why Largest Cascades?





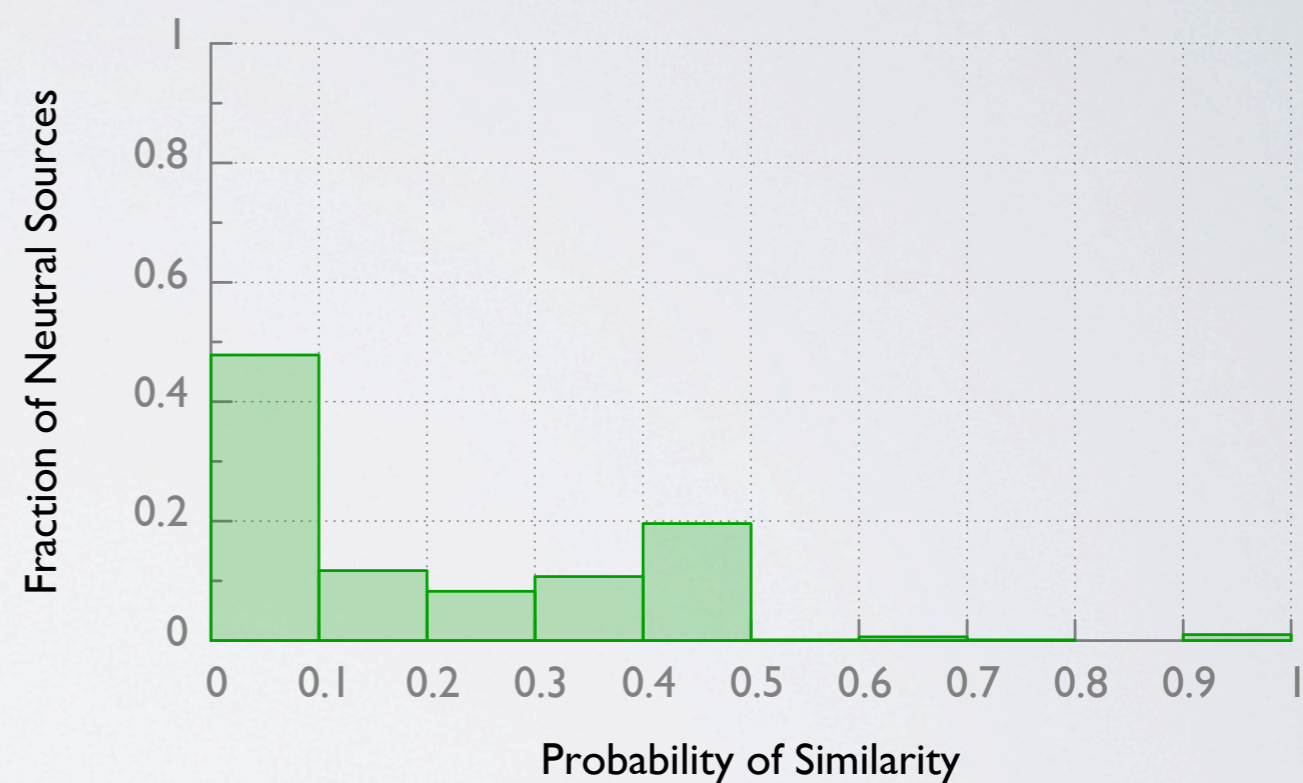
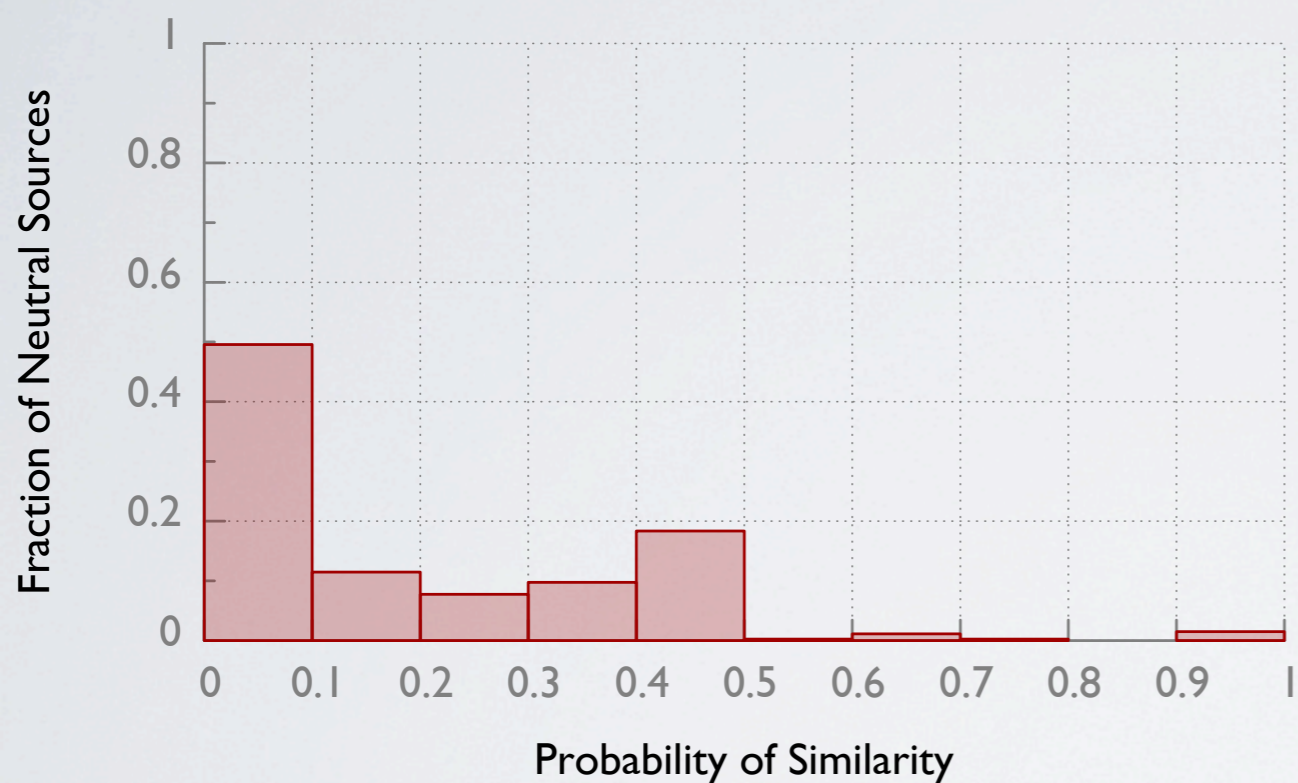
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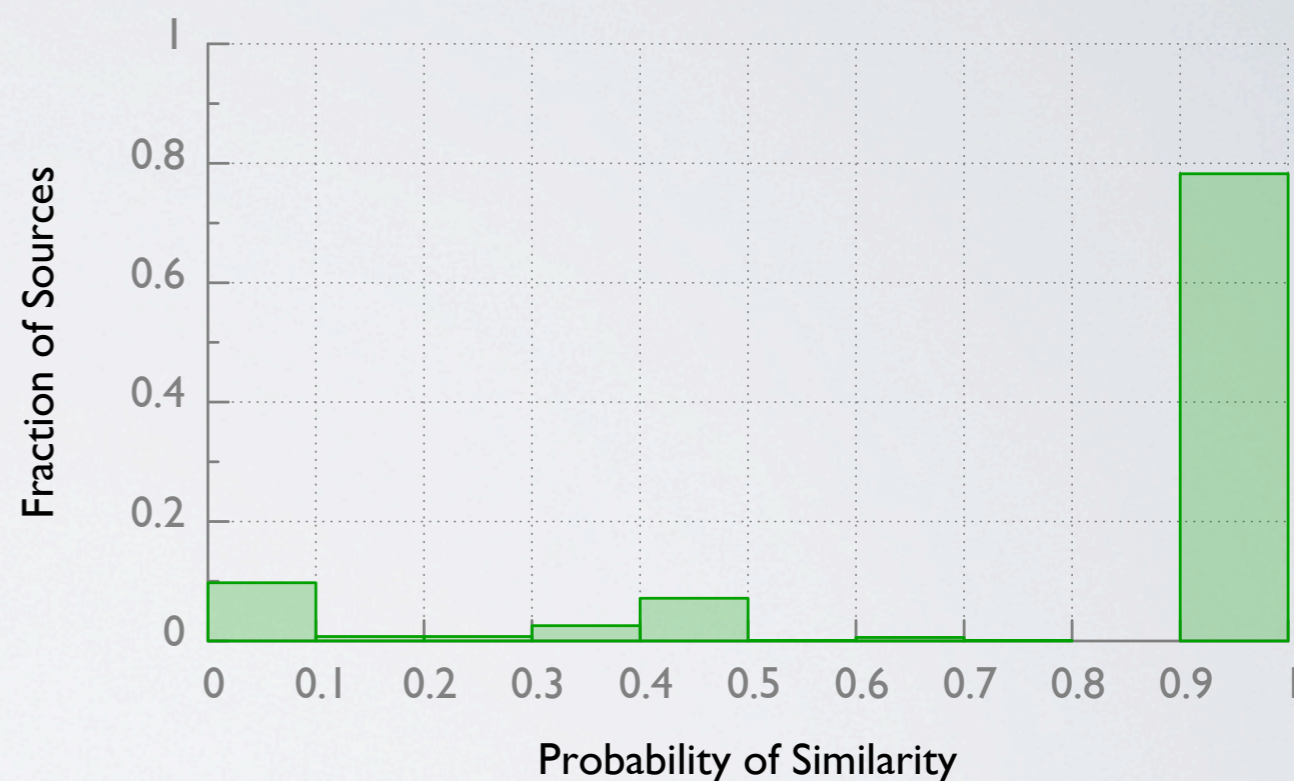
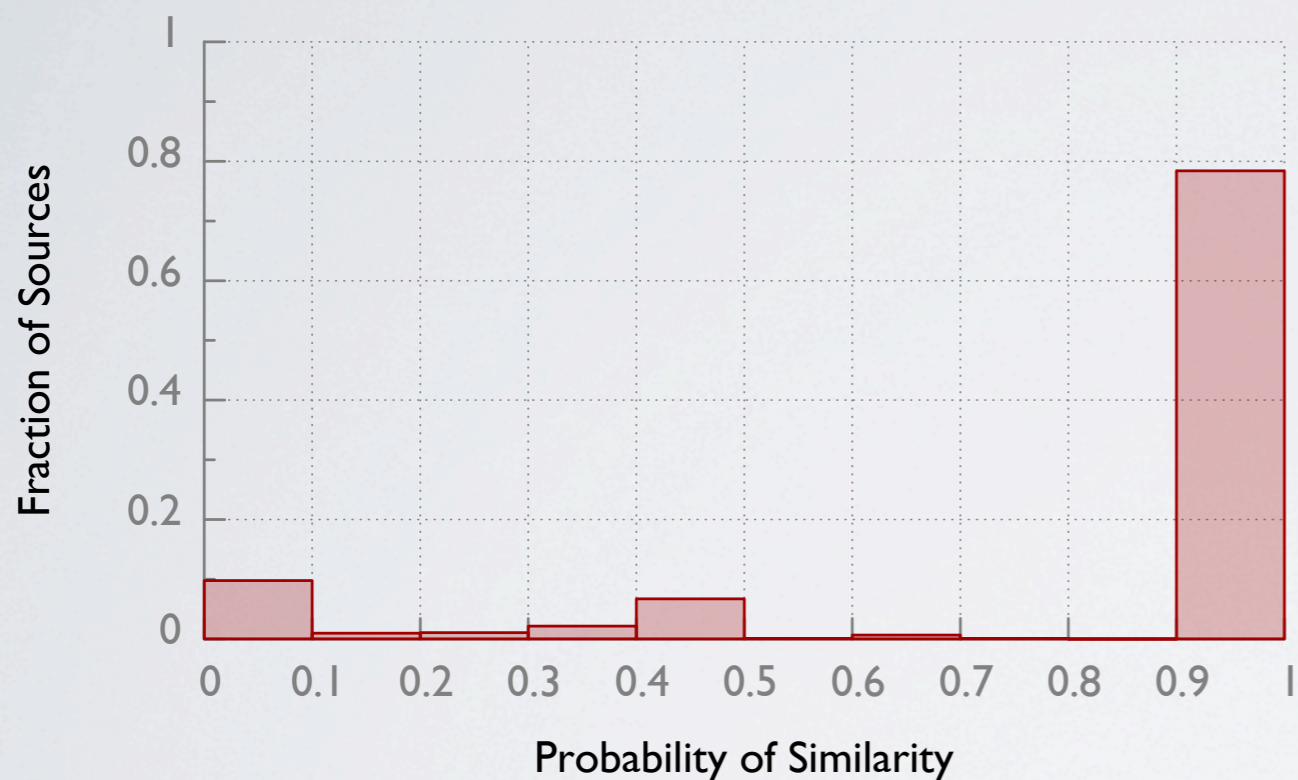
Effect of Polarization



The non polarized algorithm confuses the dependency of the neutral sources



Effect of Polarization



Dependency of the strongly polarized sources are correctly determined by both polarized and non-polarized algorithms



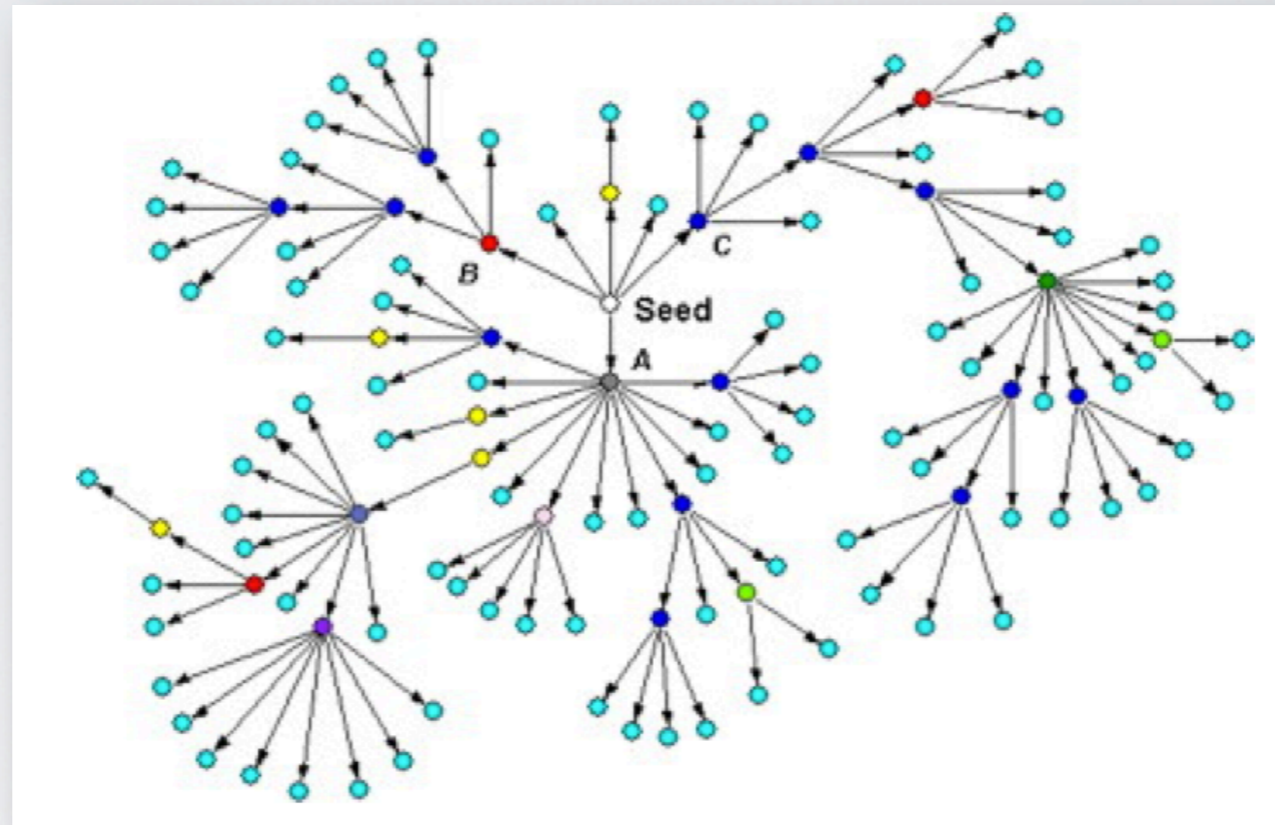
Evaluation

	Input	Combined	Polarized
Pro Claims	199	147	128
Anti Claims	109	88	76
Neutral Claims	692	543	496
Total	1000	778	700

- 662 output claims were common to both algorithms

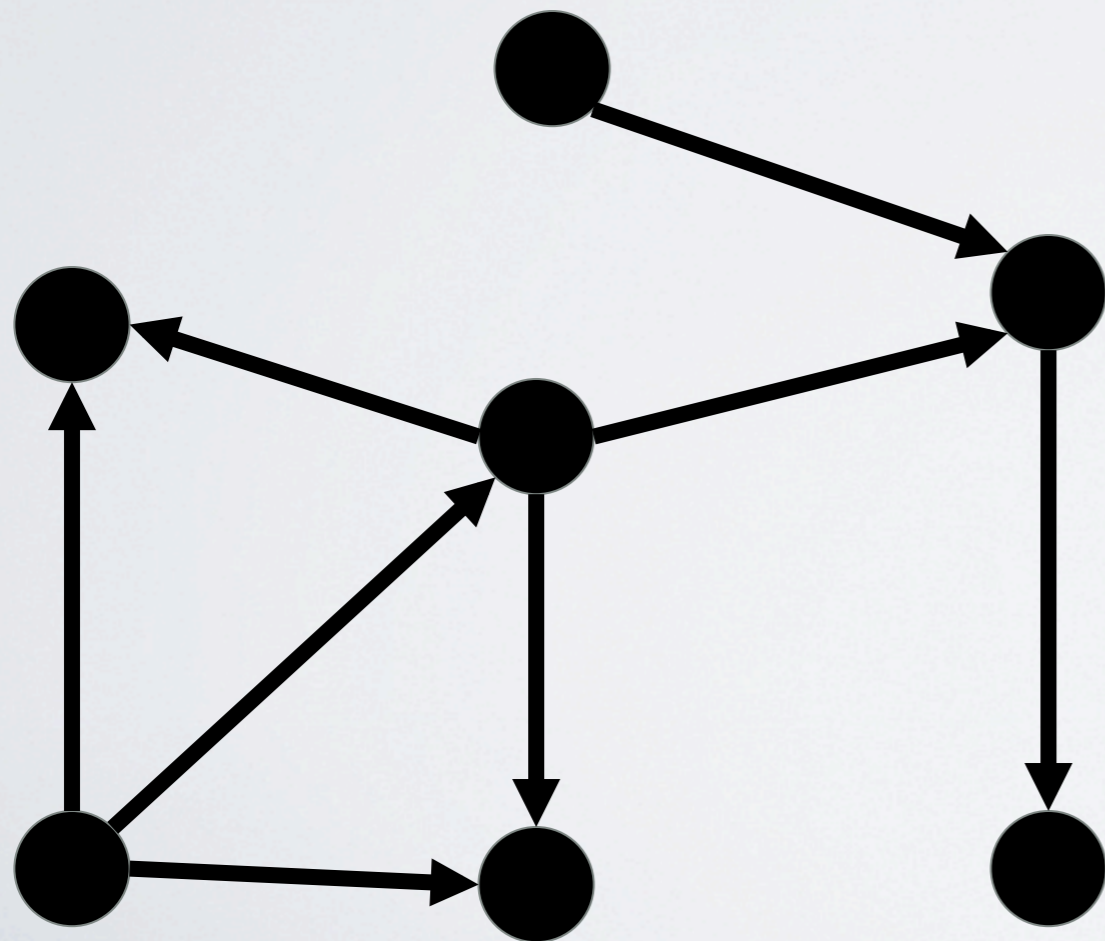
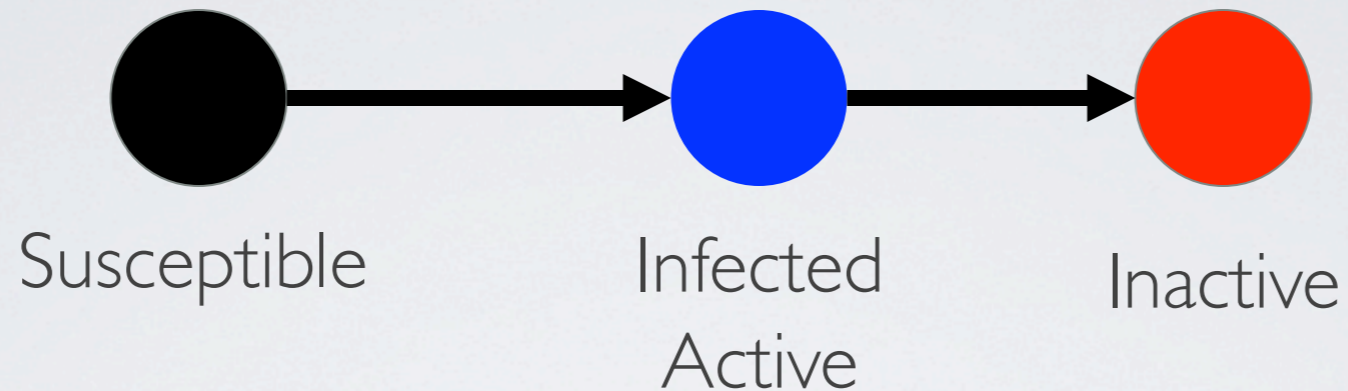
Epidemic Propagation

- Nodes get infected, infect other nodes, and the process continues resulting in a propagation graph.



- Inverse Problem*: **Given the observation of infections, find the structure.**

Standard Independent Cascade Model*

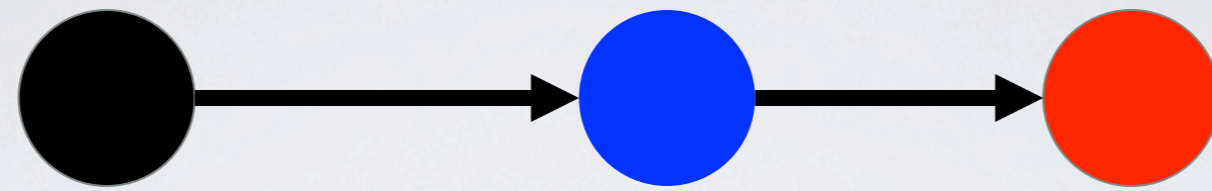


- Proceed in discrete step
- Initial seeds random with probability p_{init}
- i infect j with p_{ij}
- Active node inactive after one step

* Proposed by Goldenberg, Libai, and Muller, "Talk of the Network: A complex systems look at the underlying process of word-of-mouth. Marketing Letters 2001. Also appears in Kempe, Kleinberg, and Tardos "Maximizing the spread of influence through a social network, KDD 03

• Illustrative example taken from author's presentation

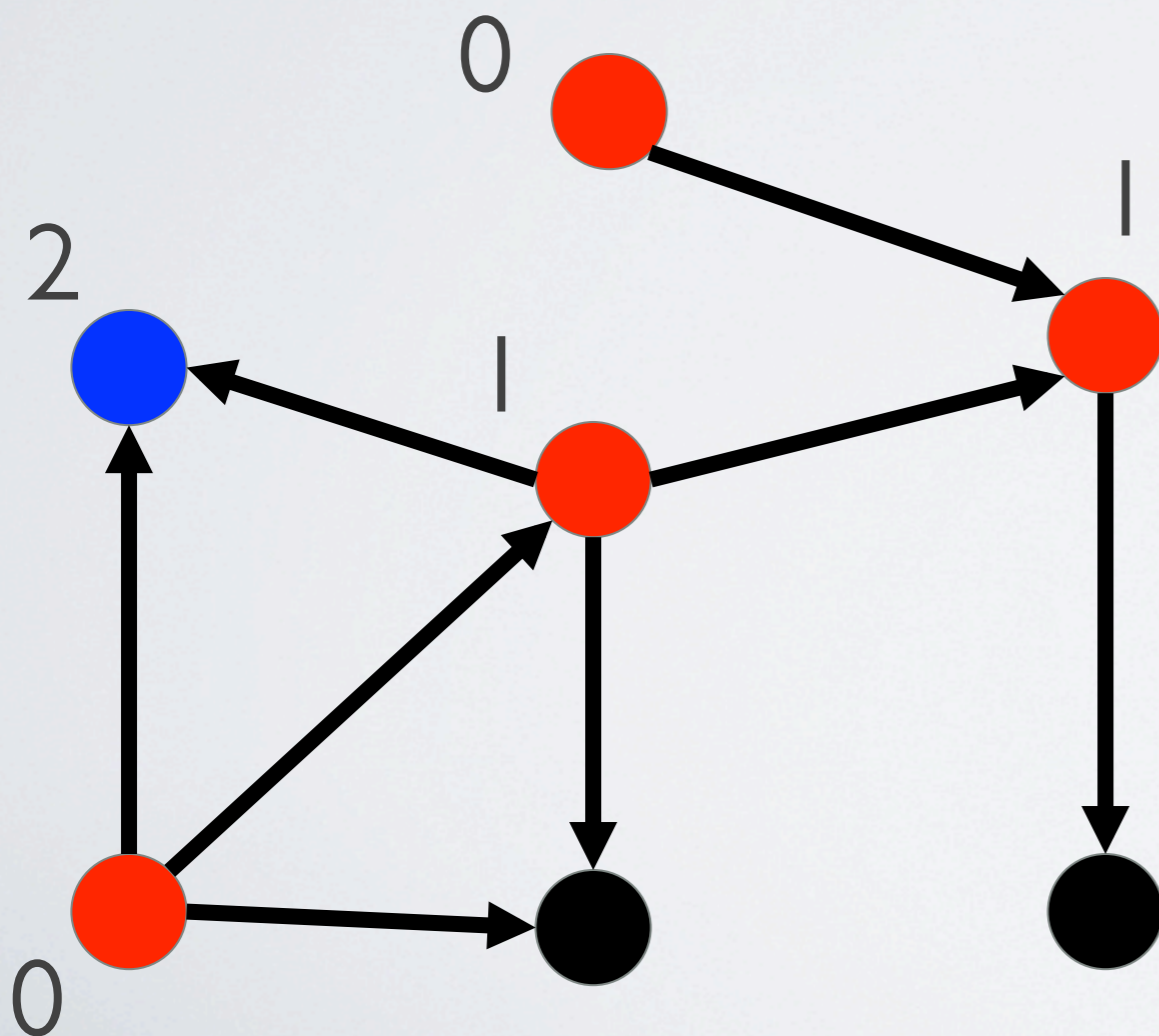
Standard Independent Cascade Model



Susceptible

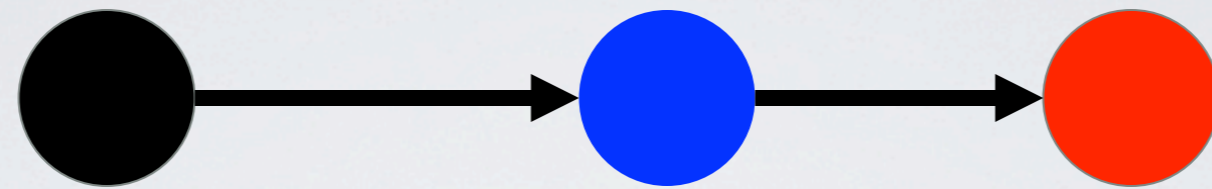
Infected
Active

Inactive



- Proceed in discrete step
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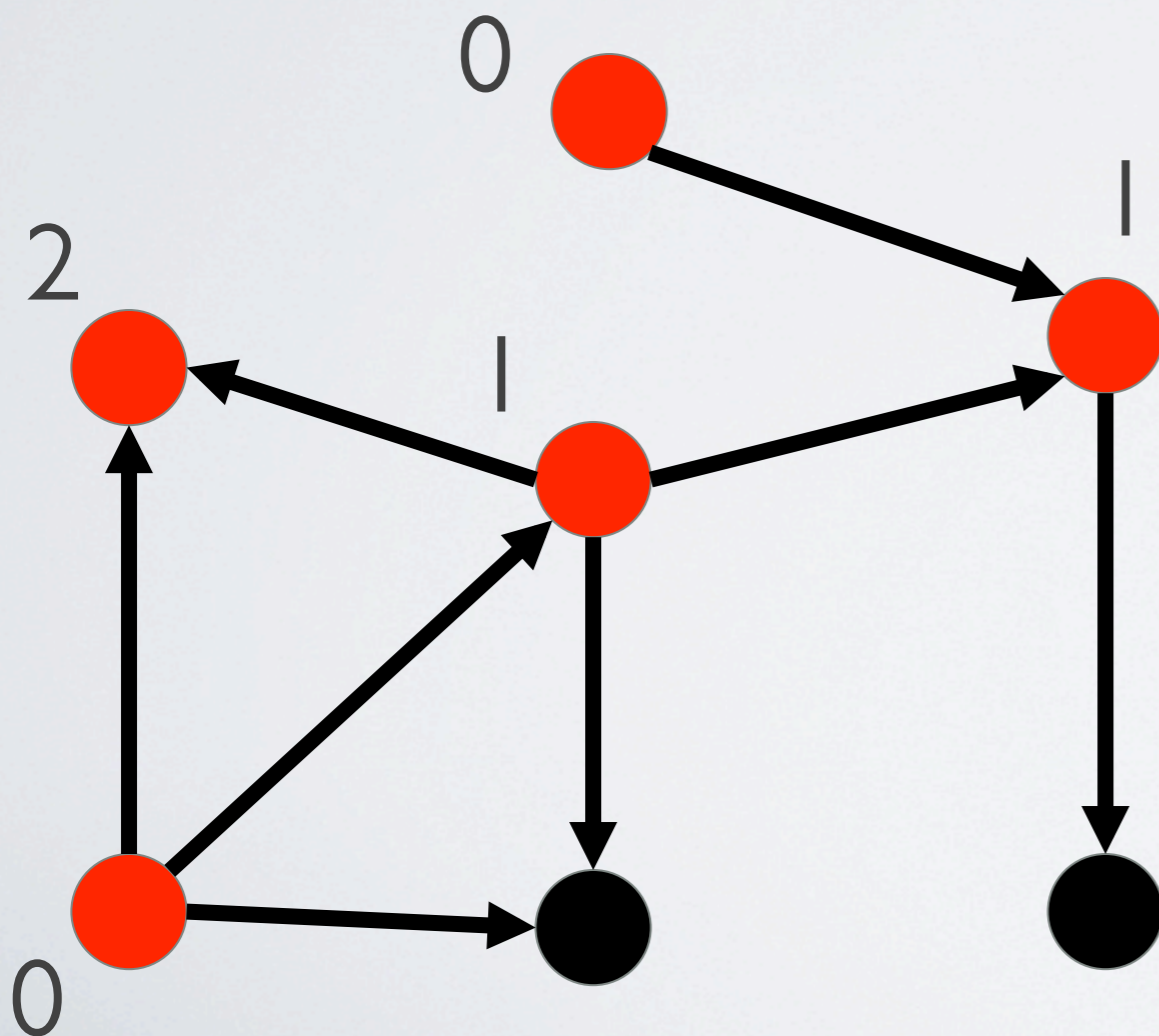
Standard Independent Cascade Model



Susceptible

Infected
Active

Inactive

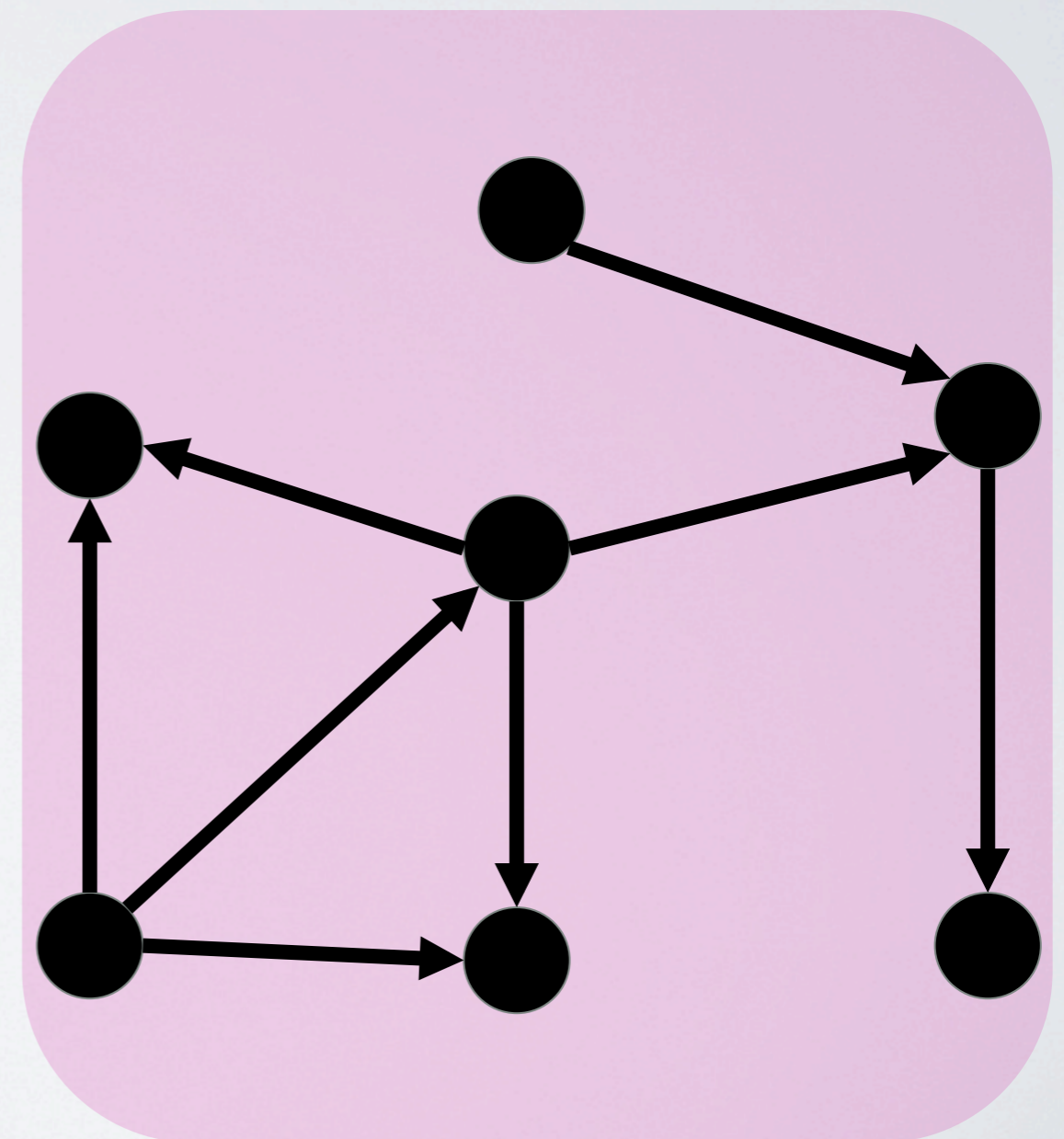
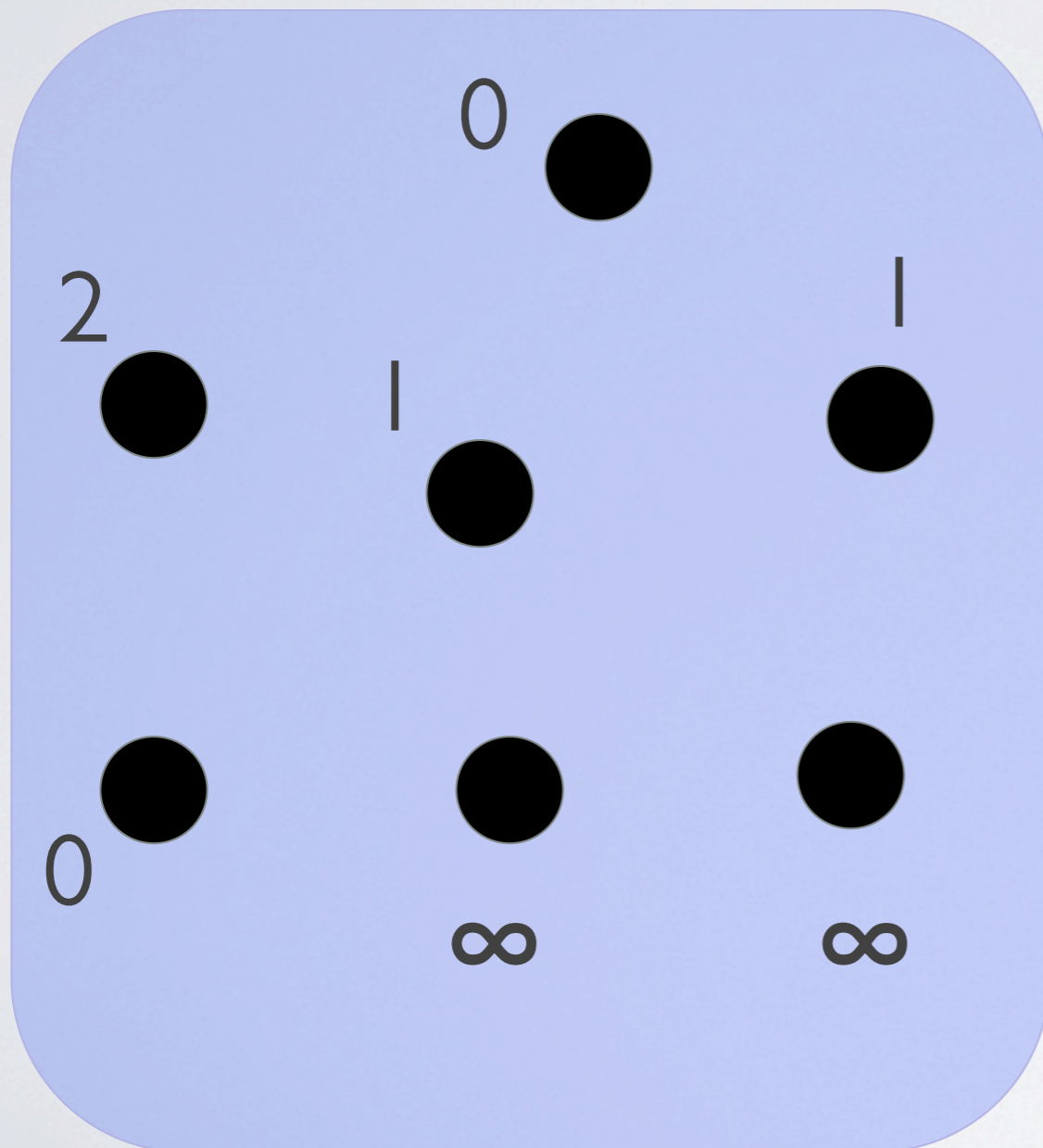


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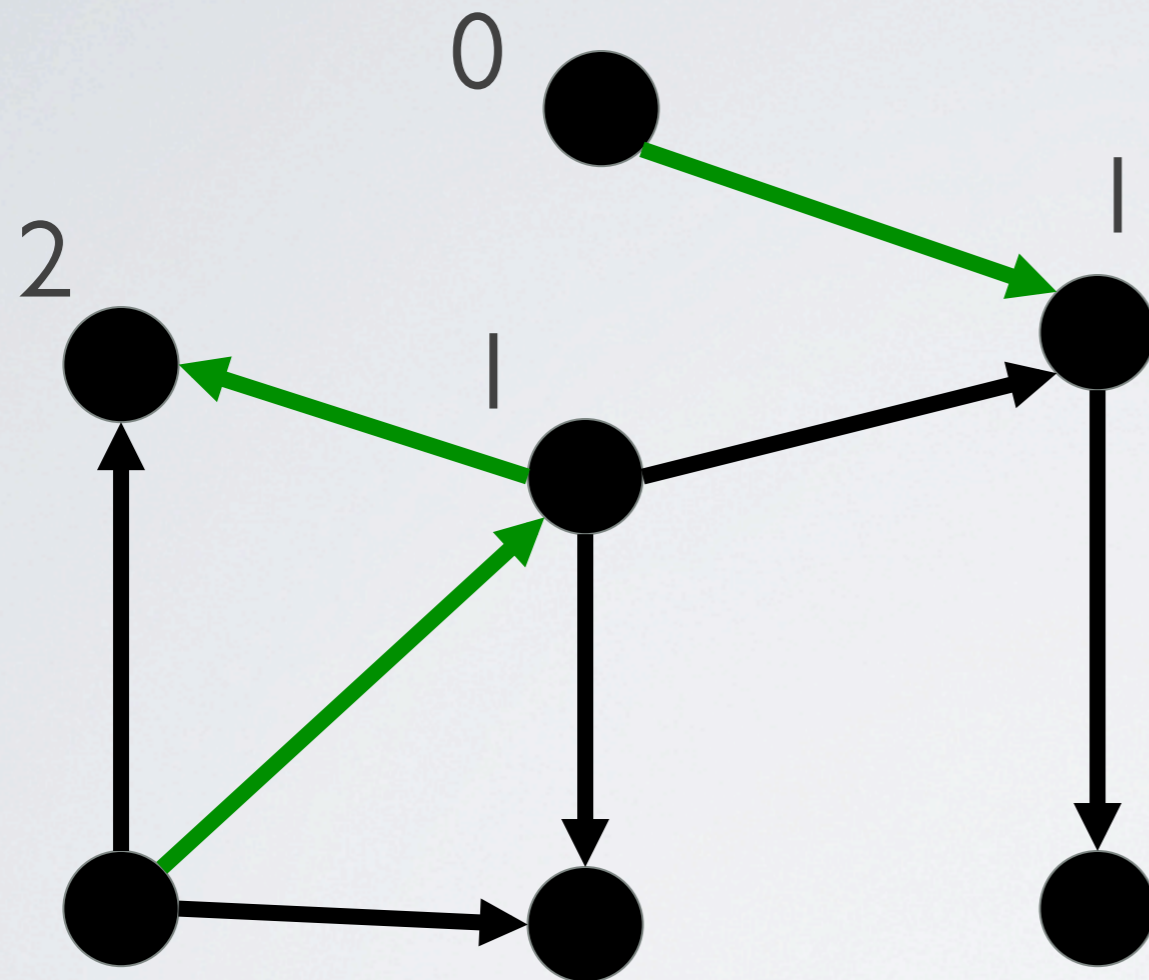
Structure Learning Problem

Given node activation times

Find network structure



Structure Learning Problem



The example cascade had no evidence of the black edges. Hence, one cascade is not sufficient to learn the structure.

Q: How many cascades necessary?

Q: Given the cascades, how to find the structure?