Some Like It Hoax:

Automated Fake News Detection in Social Networks





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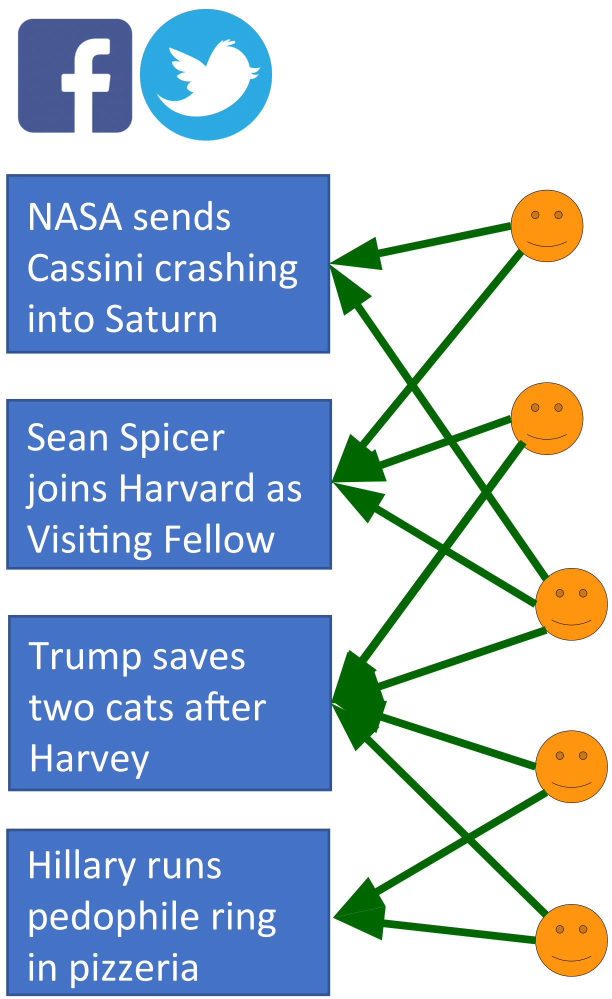
News spread through social networks...

...and some of them are fake

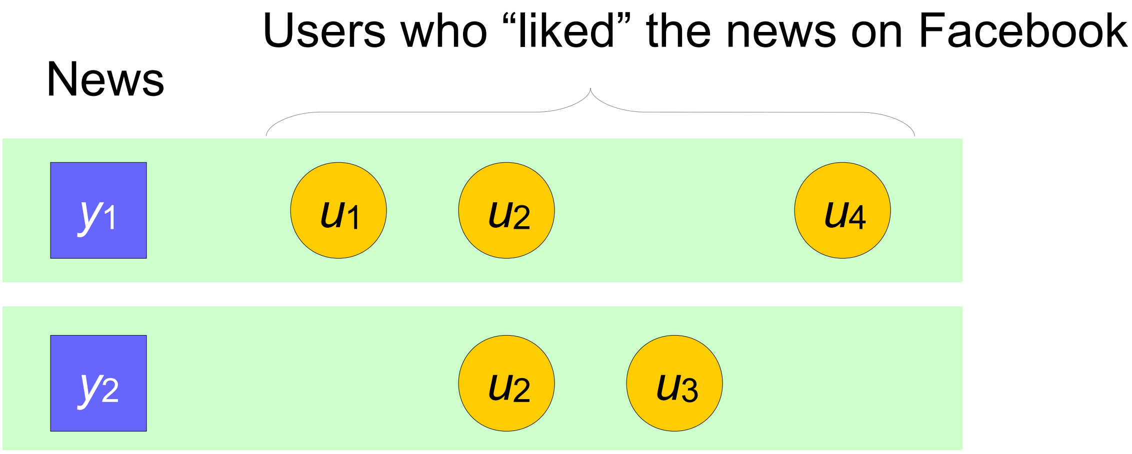


Can we identify fake news automatically?

- Text analysis is hard: many fake news read like real ones.
- Can we use social signals instead?
- Can we identify fake news on the basis of the users who share/like them?

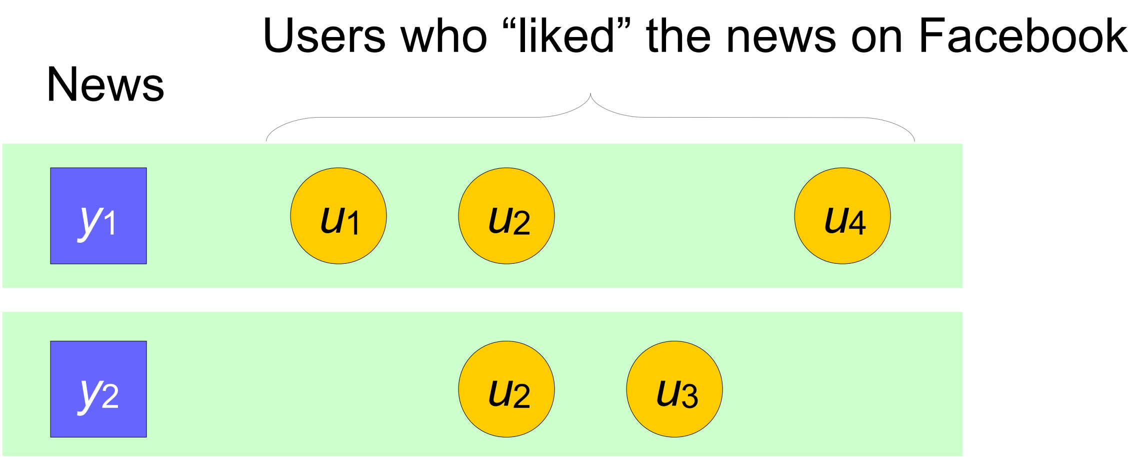
→ We answer in the affirmative, introducing techniques that can be shown to work with high accuracy

Technique 1: Logistic Regression



- Users who liked news articles are the “features”

Technique 1: Logistic Regression



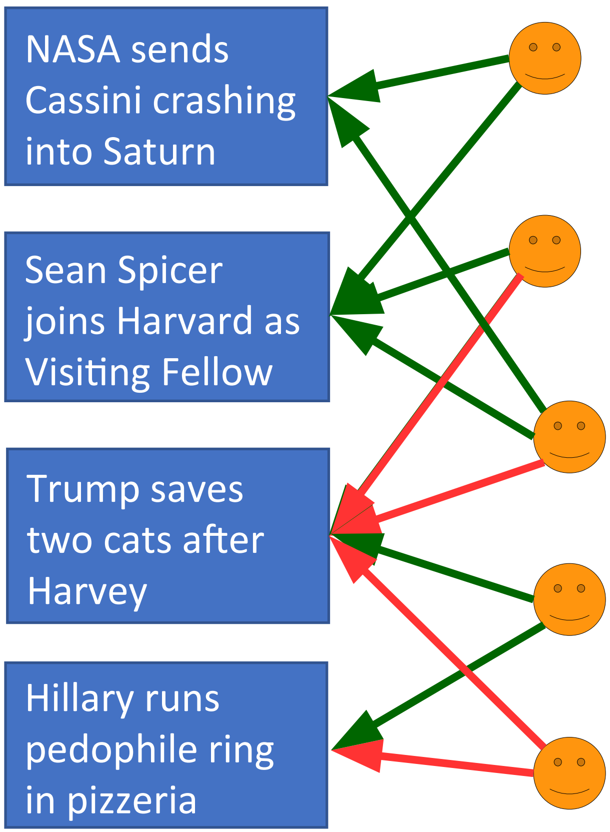
- Users who liked news articles are the “features”
- Logistic regression:

$$logit(y_1) = w_1 \cdot 1 + w_2 \cdot 1 + w_3 \cdot 0 + w_4 \cdot 1$$

$$logit(y_2) = w_1 \cdot 0 + w_2 \cdot 1 + w_3 \cdot 0 + w_4 \cdot 0$$

Train on news of known True/Fake value, and compute the user coefficients $w_1, w_2, \ldots, w_n$. Use the coefficients to classify other news.

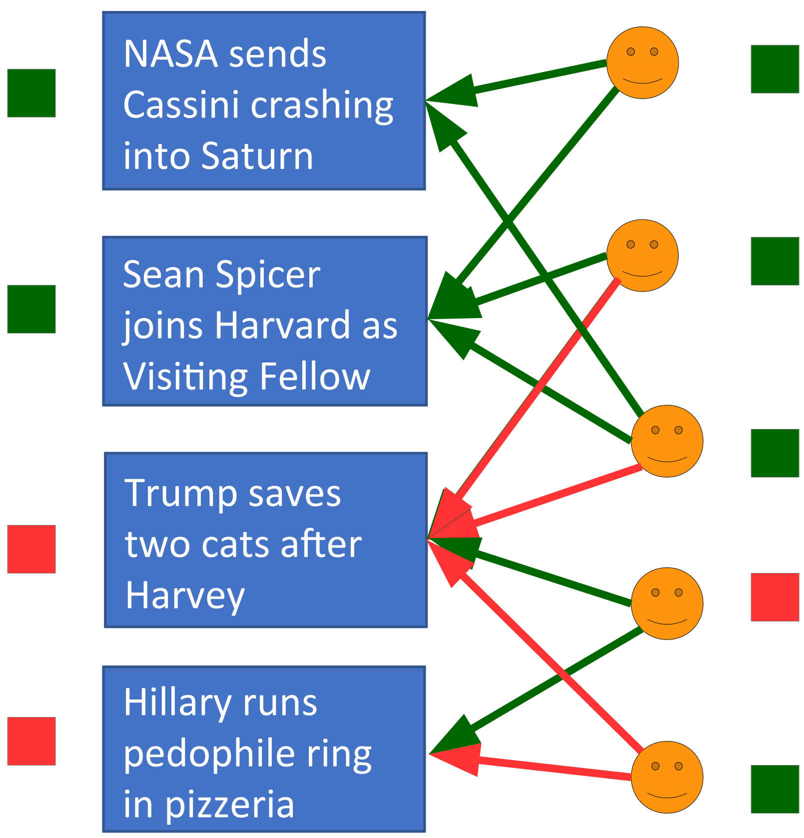
Technique 2: Harmonic Crowdsourcing



In boolean crowdsourcing:

- Users vote yes/no

Technique 2: Harmonic Crowdsourcing



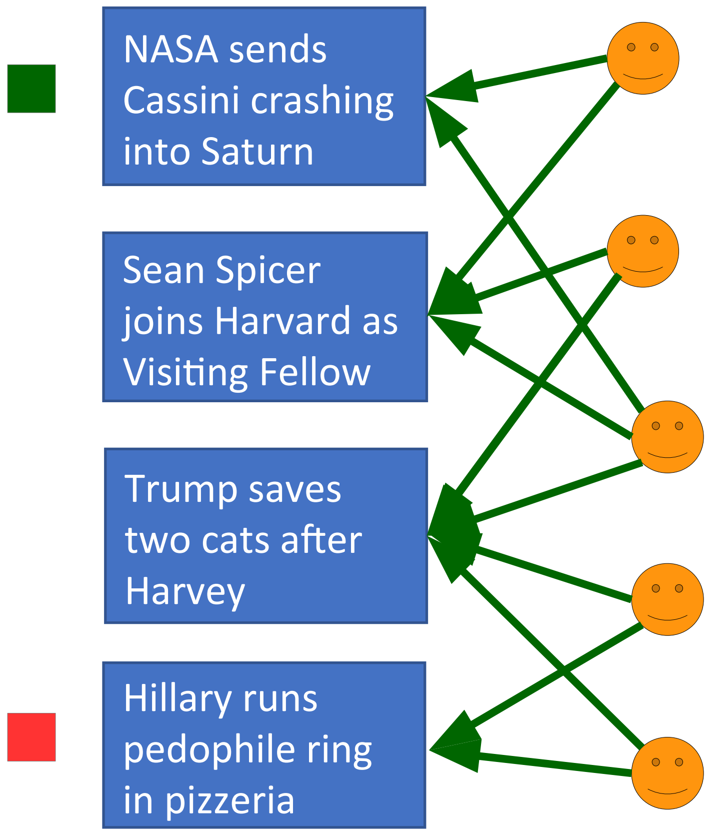
In boolean crowdsourcing:

- Users vote yes/no

The algorithms compare the votes, and reconstruct:

- Items → True, False
- Users → Truthful, Liar

Technique 2: Harmonic Crowdsourcing



In our application:

- Users vote yes (like / share)
- The algorithms starts from a ground truth

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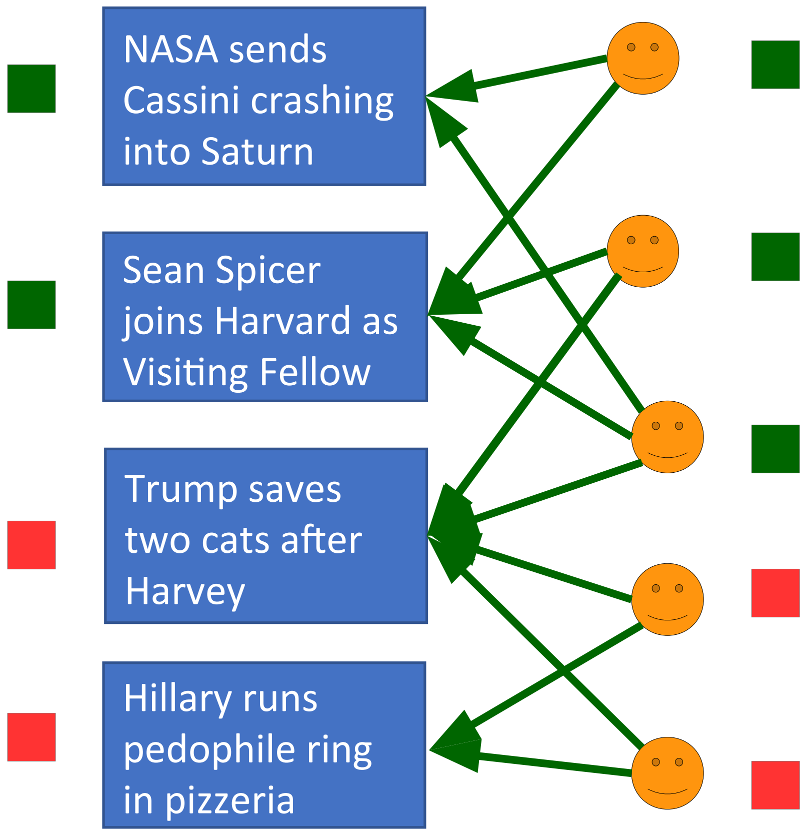

In our application:

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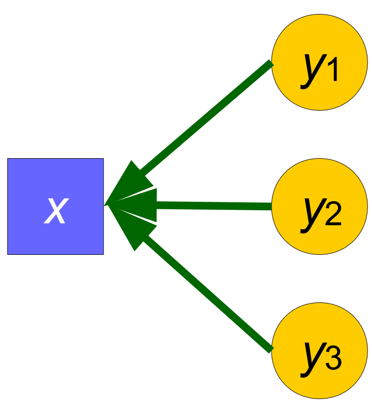
The algorithm computes:

- Items → True, False
- Users → Truthful, Liar

We use the "harmonic crowdsourcing" of [de Alfaro, Polychronopoulos HCOMP 2015]: simple, robust, scalable, and almost optimal.

Technique 2: Harmonic Crowdsourcing

- Model the truth of each node x (a user, or a news item) with a beta distribution *beta*(α_x, β_x), where:
  - α_x is the "positive" evidence for the truth of x.
  - β_x the "negative" evidence for the truth of x.
- The node x has truth $\sim$*beta*(α_x, β_x) with average value $\alpha_x / (\alpha_x + \beta_x)$
- Valuation propagation:



$$\alpha_x = \kappa + \sum_i \{ y_i - \tfrac{1}{2} \mid y_i > \tfrac{1}{2} \}$$

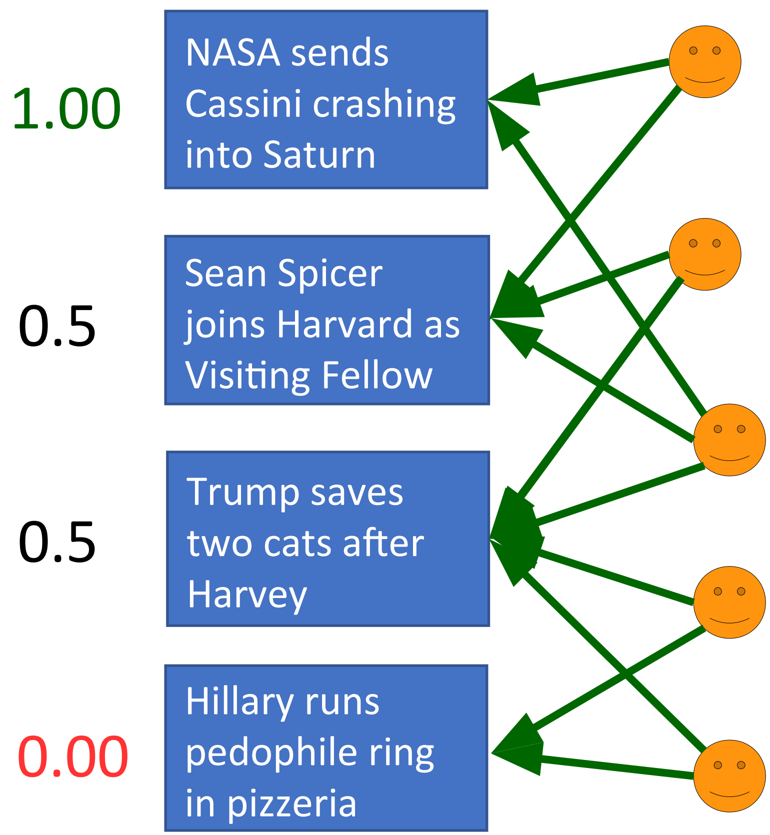
$$\beta_x = \kappa + \sum_i \{ \tfrac{1}{2} - y_i \mid y_i < \tfrac{1}{2} \}$$

$$x = \alpha_x / (\alpha_x + \beta_x)$$

κ : inertia of null belief.

Technique 2: Harmonic Crowdsourcing

Propagation:



Label ground truth with 1, 0; the rest with 0.5

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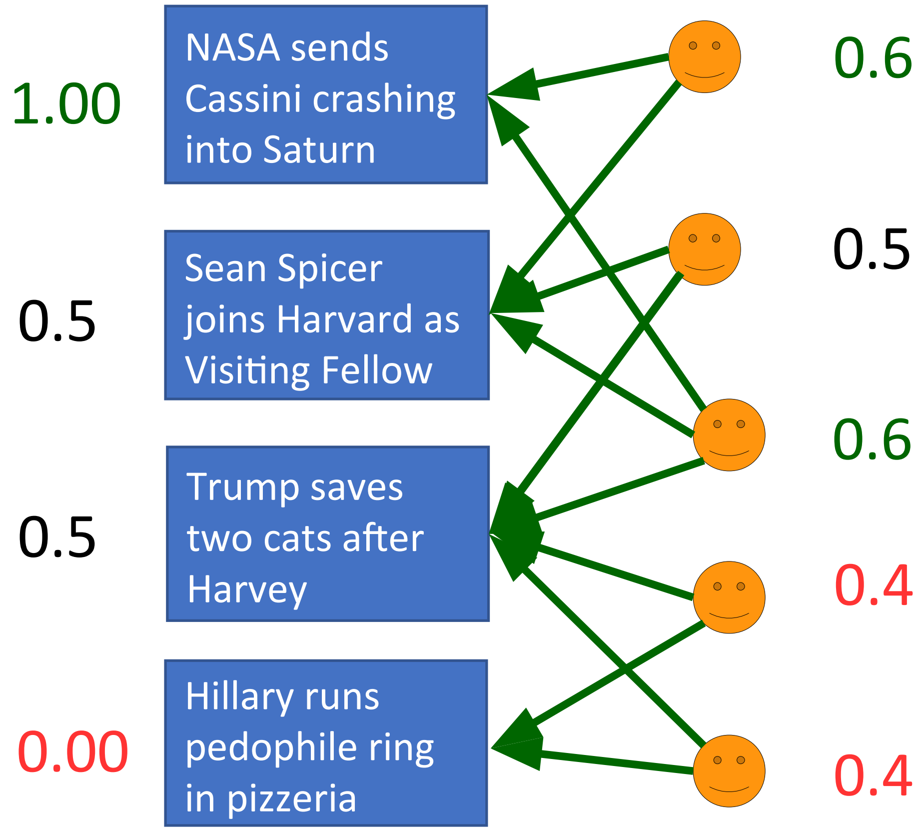
Propagation:



Iterate: items → users

Technique 2: Harmonic Crowdsourcing

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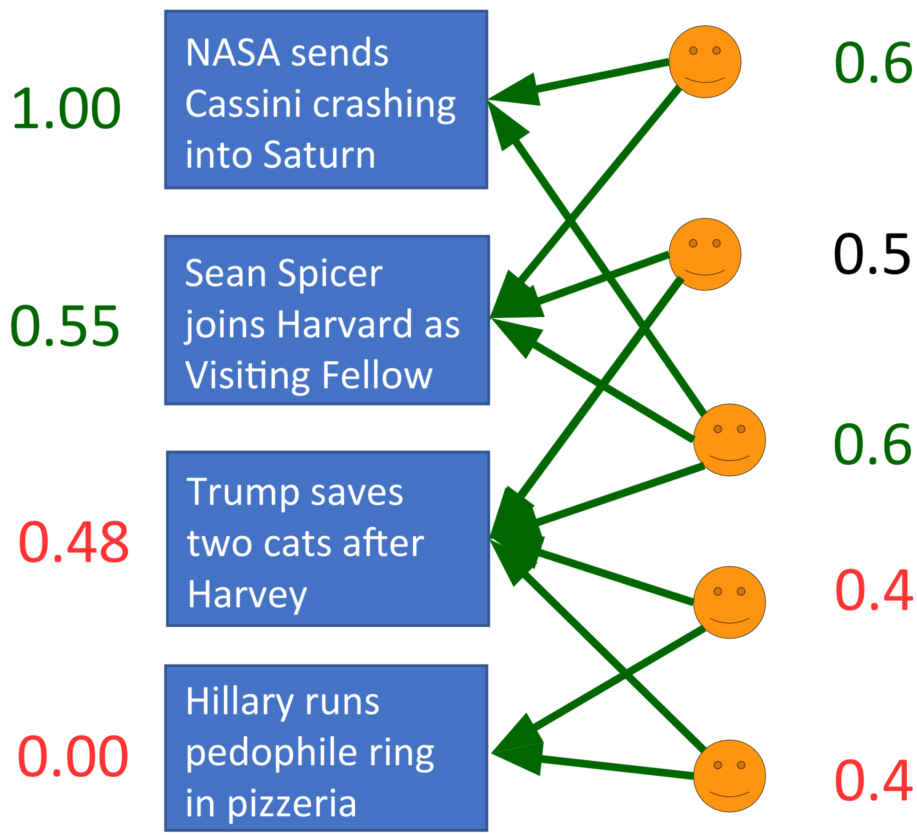

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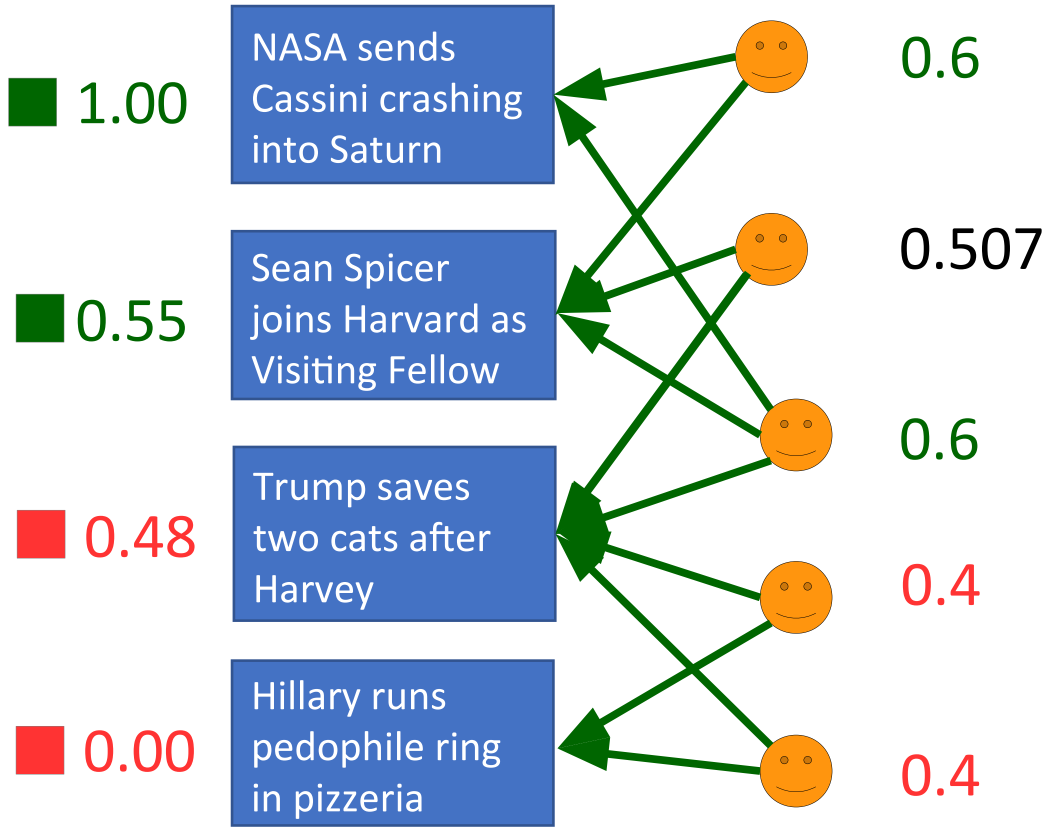
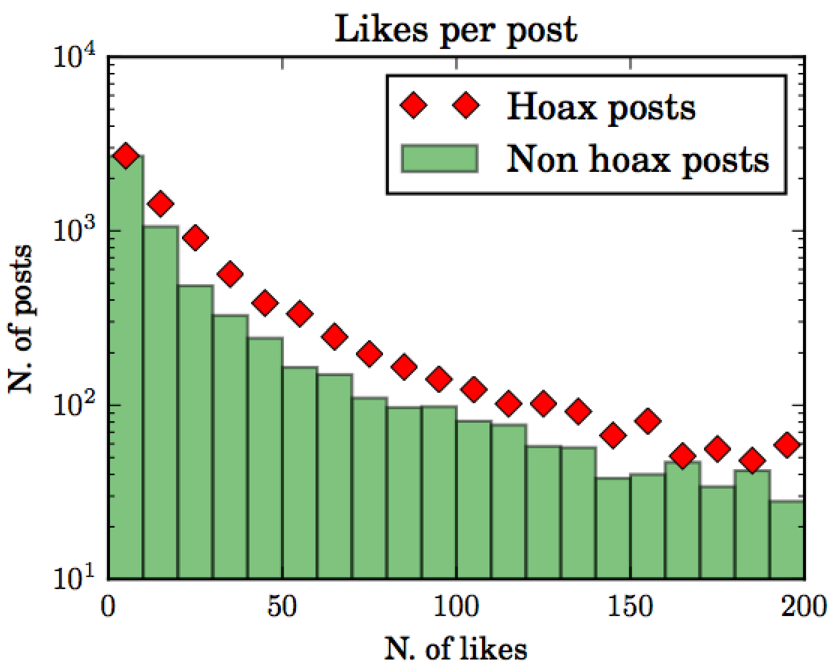
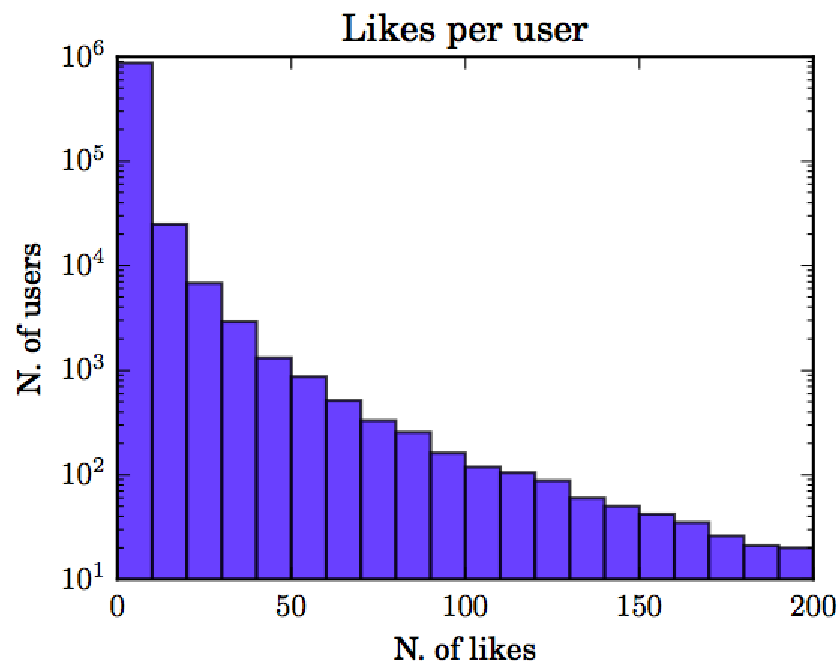


Iterate: items → users … fixpoint is soon reached.

The Dataset

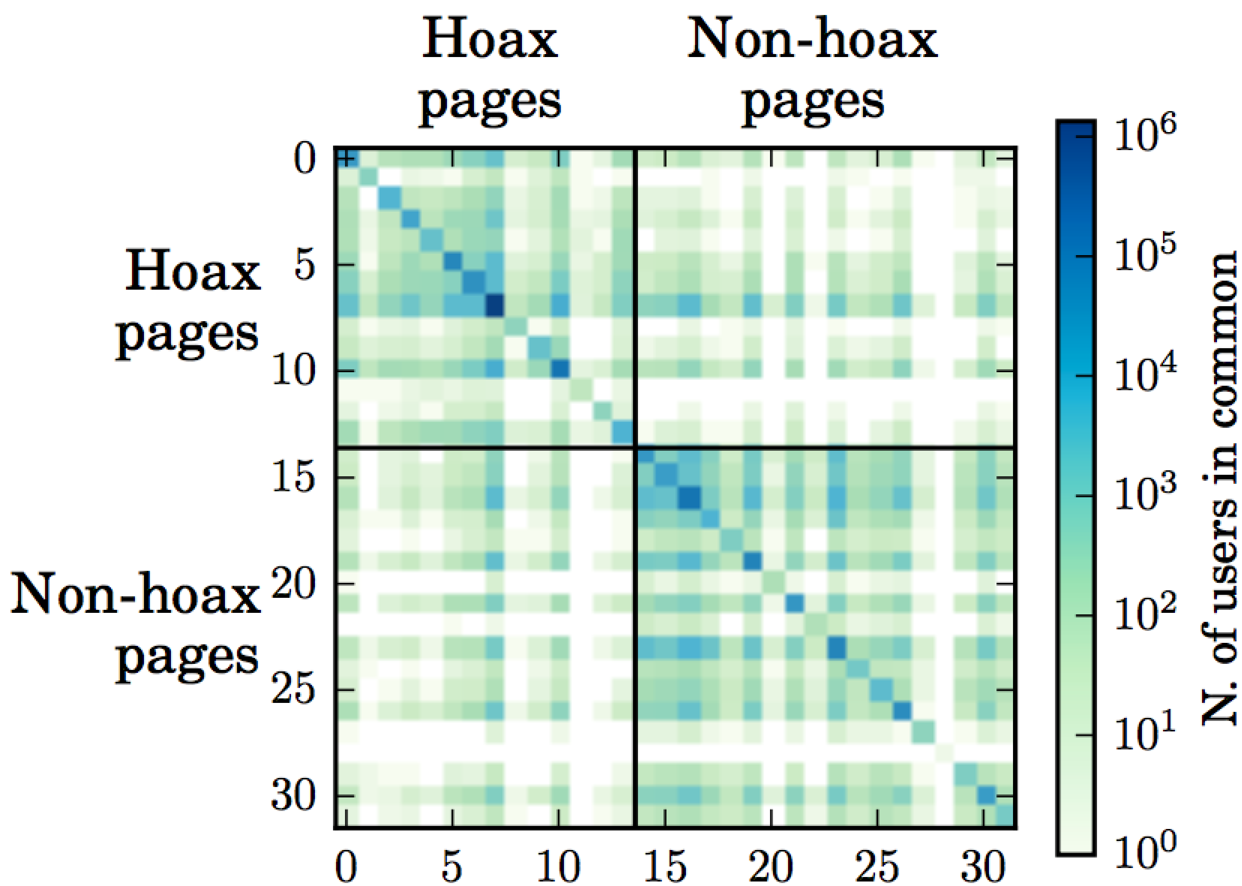
- All posts in a set of Facebook pages from Jul 1-Dec 31, 2015 on science vs. conspiracy.
- The pages are from [Science vs Conspiracy: Collective Narratives in the Age of Misinformation. Bessi et al, PLOS ONE, 2105]



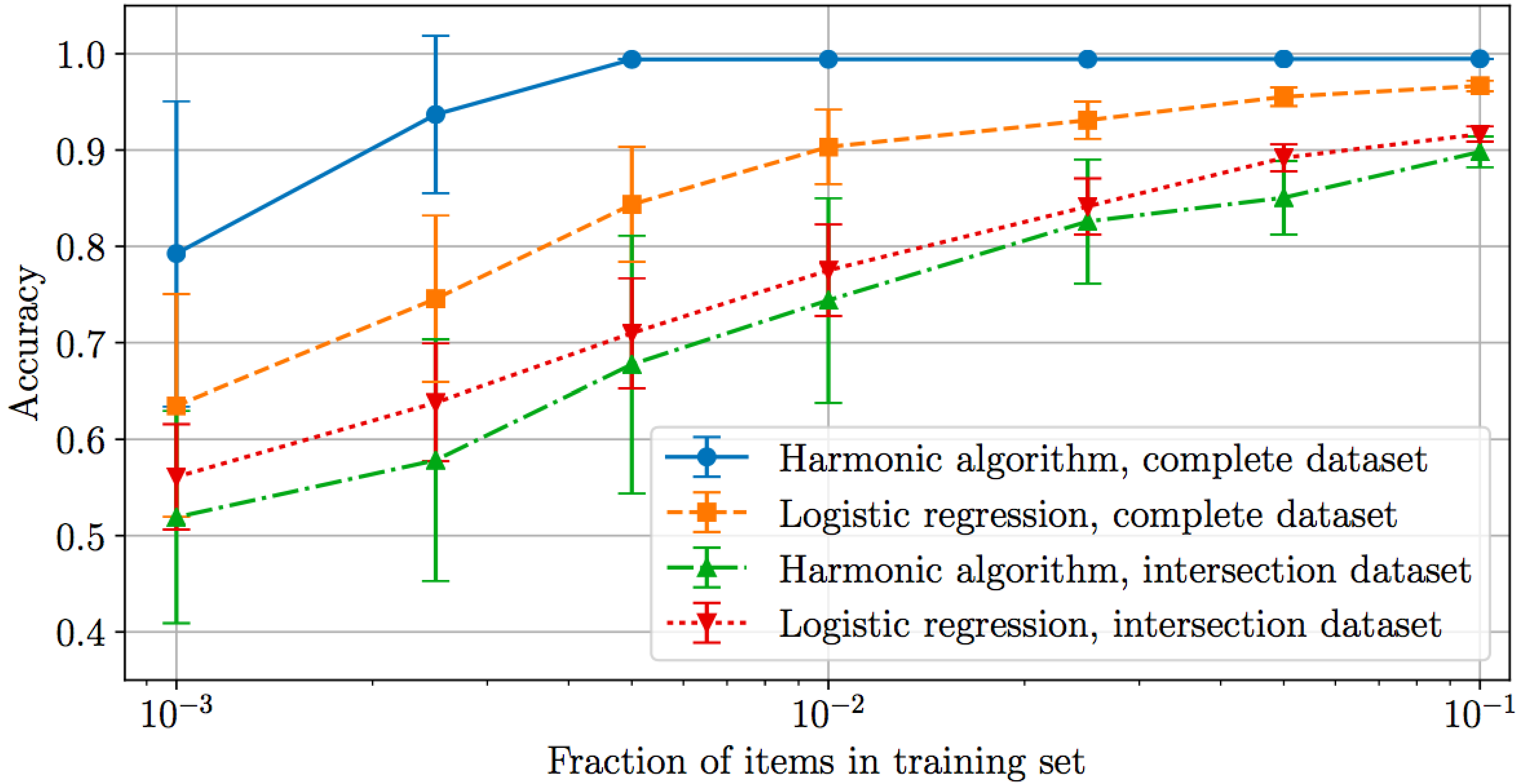


We consider two sub-datastes:

- **Complete dataset:** 15,500 posts, 909,236 users, 2.3M likes
- **Intersection dataset:** only the users who liked *both* hoax and non-hoax posts: 10,520 posts, 14,149 users, 118k likes.



Results



Accuracy
1.0
0.9
0.8
0.7
0.6
0.5
0.4
10^{-3}
10^{-2}
10^{-1}
Fraction of items in training set
Harmonic algorithm, complete dataset
Logistic regression, complete dataset
Harmonic algorithm, intersection dataset
Logistic regression, intersection dataset

Conclusions

- Our emphasis is in obtaining high accuracy with as small as possible a training set.
  - Labeling even a small percentage of the daily news by hand is a large task, so the smaller the labeled fraction required, the better.
- We obtain an accuracy of 99% even when < 0.5% of the dataset is used for training.
  - The harmonic algorithm is very efficient in spreading knowledge across the “likers” graph.
- Even on the artificial *intersection* dataset, consisting only of people who liked both hoax and non-hoax posts, the accuracy is high: 90% with 10% in training set, ~75% with 1% in training set.