

# CatchSync: Catching Synchronized Behavior in Large Directed Graphs



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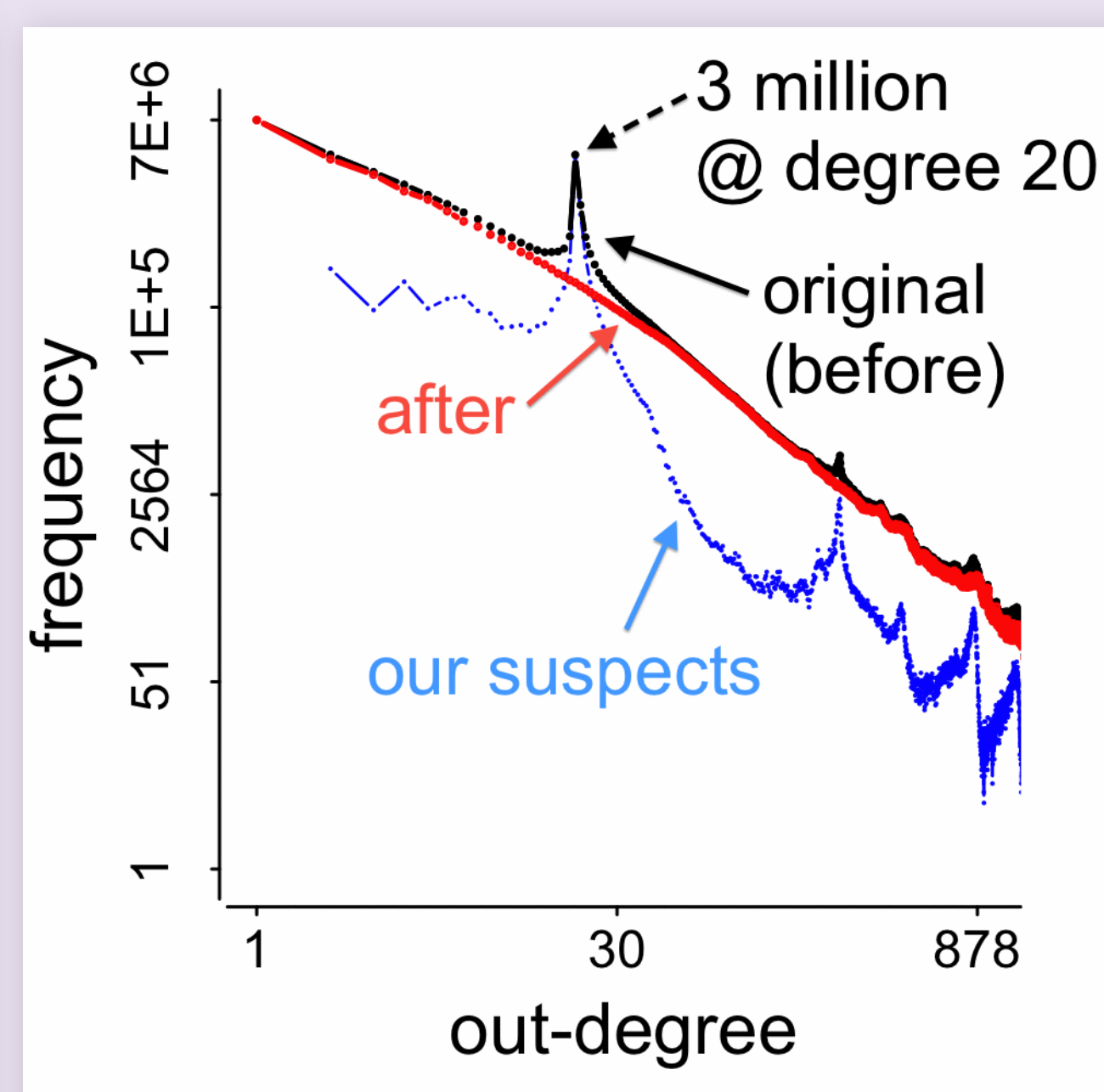
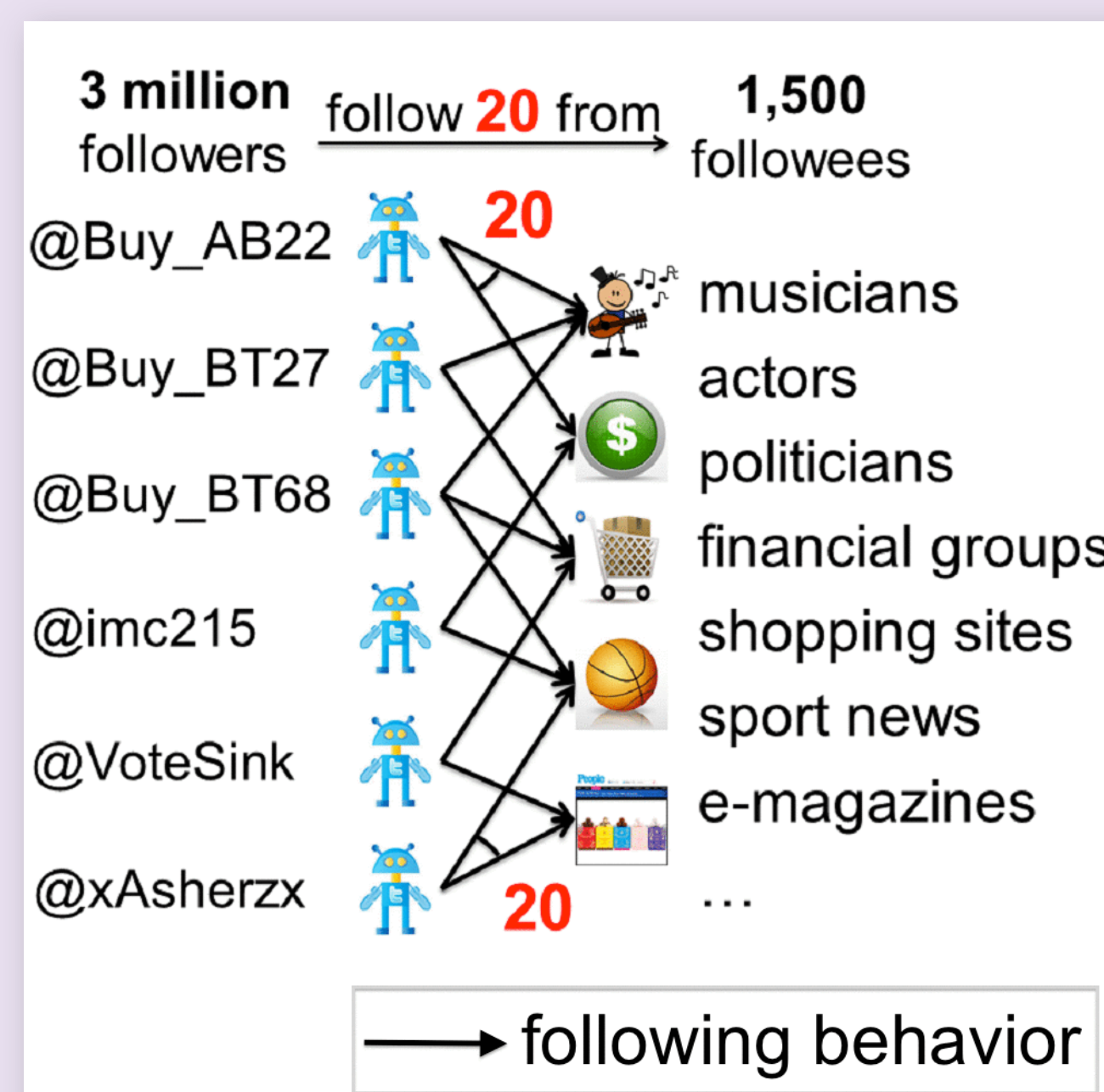
## Zombie Followers in “Who-Follows-Whom” Networks

*Who are they? What do they do?*

- Fraudsters are paid to make certain accounts seem more legitimate or famous through giving them many additional followers.
- They are often required to perform some tasks (e.g., follow the same group of users) together.

*Deviations on out-degree distribution*

- 3 million Twitter zombie followers create a spike at degree 20.
- CatchSync** restores normal (power-law-like and smooth) patterns.



## Suspicious Following Behavior Patterns

**Synchronized:** they have extremely similar behavior pattern.

**Abnormal:** their behavior patterns are different from the majority.

*Feature space [HITS, Kleinberg et al., 1999]*

Followee	<b>In-degree</b>	<b>Authority:</b> high-quality celebrities/idols
Follower	<b>Out-degree</b>	<b>Hub:</b> containing links to famous idols

Example:

User X: a zombie follower

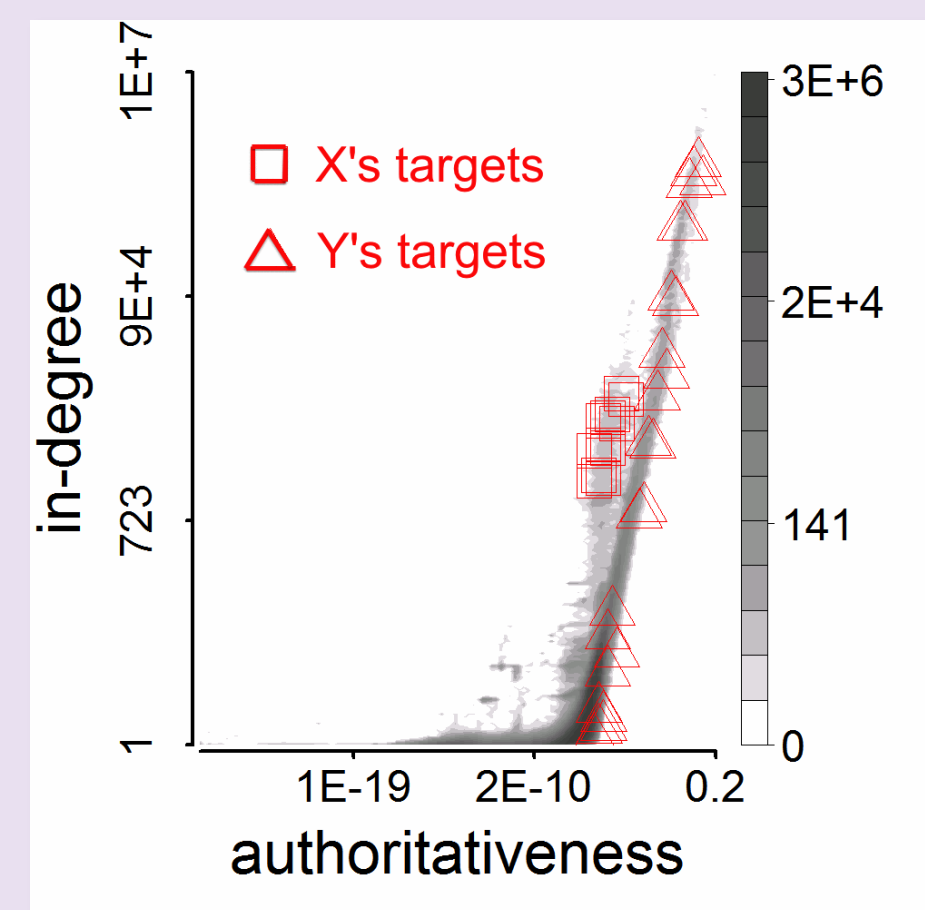
User Y: an honest account

(1) Out-degree values are the same: 20.

(2) X's hub ( $4.7 \times 10^{-7}$ ) << Y's hub ( $1.6 \times 10^{-4}$ )

(3) X's and Y's targets (followees):

- X's targets are too similar and very strange.



## Synchronicity and Normality

**Synchronicity:** similarity between X's targets.

$$\text{sync}(u) = \frac{\sum_{(v,v') \in \mathcal{F}(u) \times \mathcal{F}(u)} \mathbf{p}(v) \cdot \mathbf{p}(v')}{d(u) \times d(u)}$$

**Normality:** similarity between X's targets and other nodes.

$$\text{norm}(u) = \frac{\sum_{(v,v') \in \mathcal{F}(u) \times \mathcal{U}} \mathbf{p}(v) \cdot \mathbf{p}(v')}{d(u) \times N}$$

\* Features in vector **p**: (1) each source/target node; (2) structural features like centrality, eigenvectors; (3) side information like dates of birth, names.

**Theorem** For any distribution, there is a parabolic lower limit in the synchronicity-normality plot.

$$s_{\min} = (-Mn^2 + 2n - s_b)/(1 - Ms_b)$$

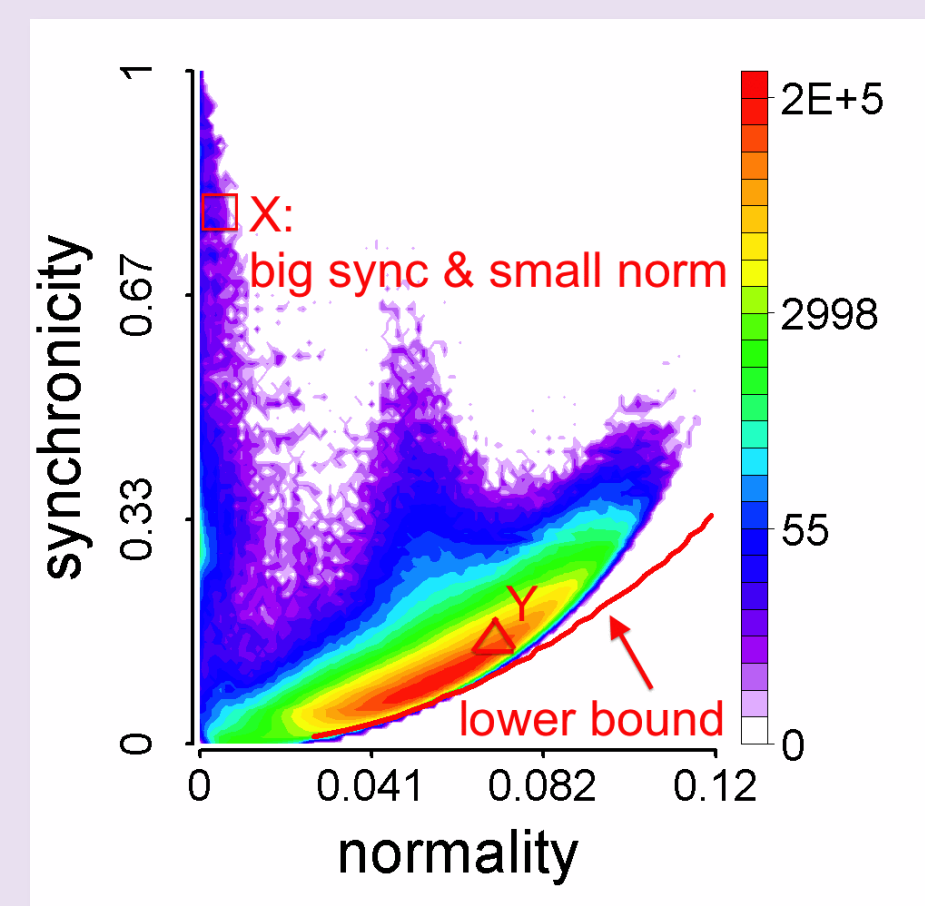
Proof. It is based on Lagrange multipliers.

- X has much **bigger synchronicity** and **smaller normality** than Y (from majority).

**CatchSync Algorithm:** (1) feature space;

(2) sync and norm; (3) outlier detection.

**Complexity analysis:** O(E) – scalable.

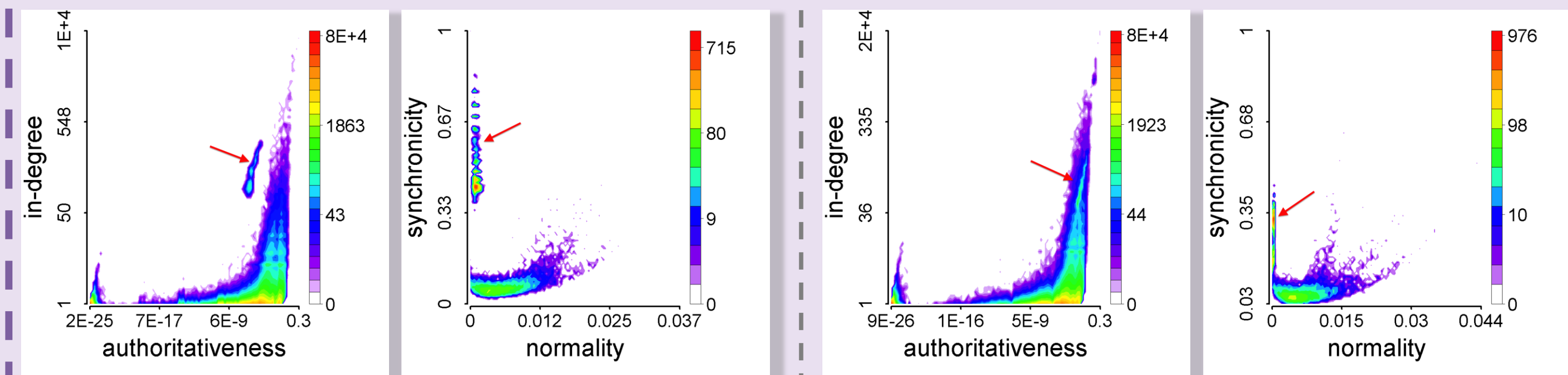


## Experimental Results on Synthetic Data

*Injection on random power law graph*

- $3M^2 + 5$  groups (16K sources  $\times$  1.6K targets,  $8K \times 800, \dots, 1K \times 100$ ).
- Camouflage:** 10% more **RAND**om users; 50% top **POP**ular idols.

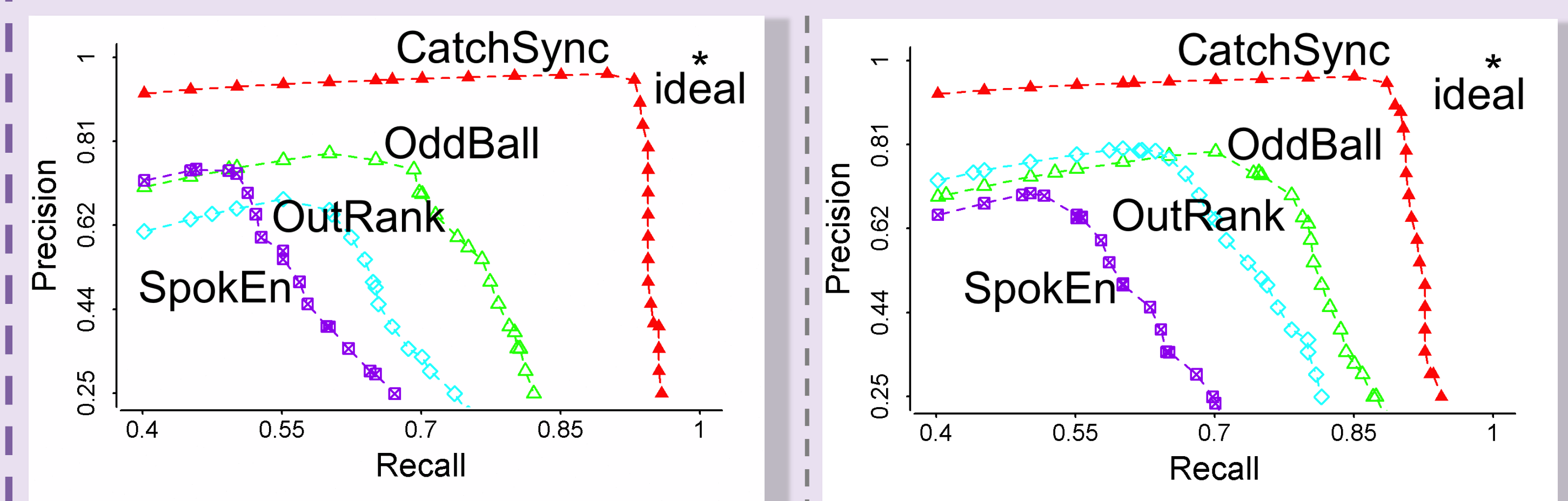
*Synchronicity-normality plots*



*Accuracy on 3M, 3M-RAND and 3M-POP*

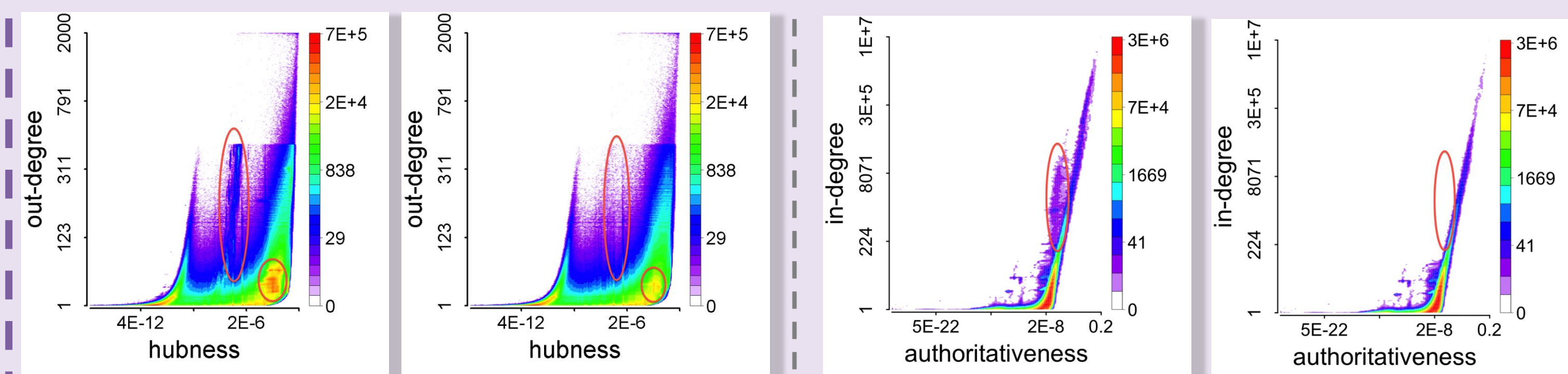
Synthetic graph	SYNTH-3M	SYNTH-3M-RAND	SYNTH-3M-POP
Camouflage ( $d_{\text{camou}}$ )	None (0)	10%	50%
CATCHSYNC	<b>0.956</b>	<b>0.910</b>	<b>0.764</b>
ODDBALL	0.755	0.702	0.525
OUTRANK	0.725	0.678	0.516
SPOKEN	0.677	0.586	0.470

*Precision-recall on 3M-RAND and 3M-POP*



## Experimental Results on Twitter and Tencent Weibo Data

*Restore normal patterns in feature space/distributions*



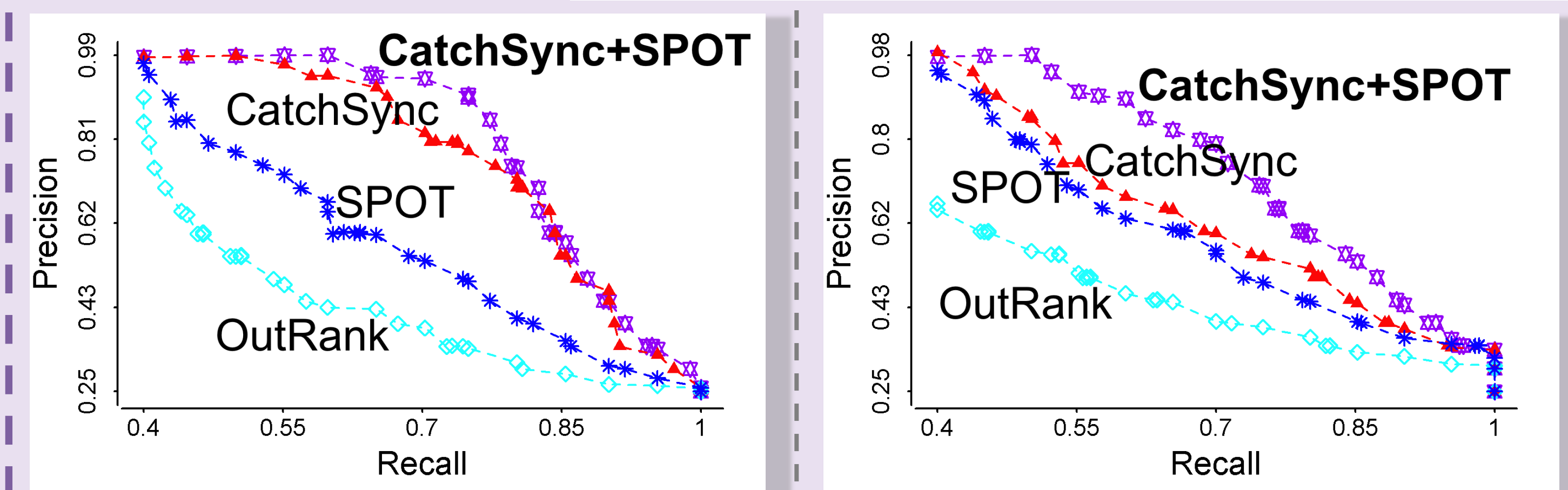
*Accuracy, precision and recall on fraudsters*

SPOT: content-based

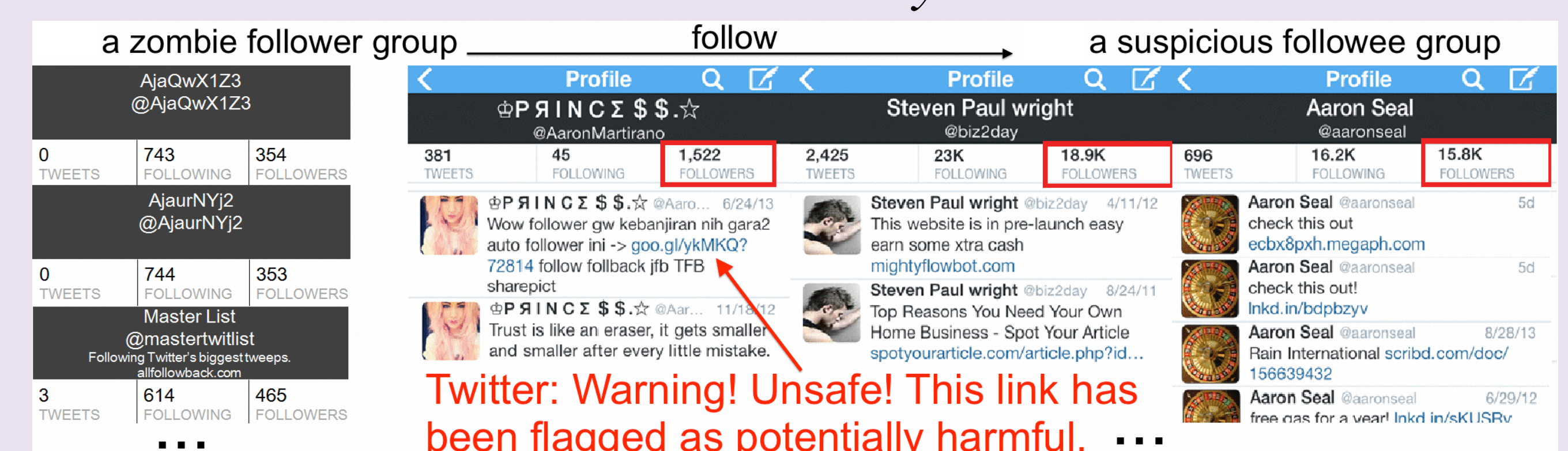
CatchSync: graph-based

**CatchSync OR(+) SPOT**

	TWITTERSG	WEIBOSG
CATCHSYNC	0.751	0.694
OUTRANK	0.412	0.377
SPOT	0.597	0.653
CATCHSYNC+SPOT	<b>0.813</b>	<b>0.785</b>



*Case Study*



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