Towards Robust Crowd Computations

Alan Mislove Northeastern University

Motivation

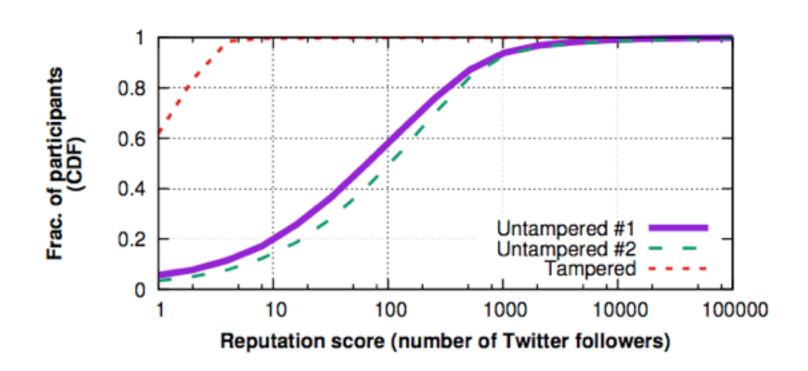
Sybil attacks on crow computation systems: An attacker create fake identities and manipulate the aggregate opinion of the crowd (e.g., rating of business on Yelp, # of followers in Twitter)

Existing approach to detect individual Sybil identities has a **fundamental limitation**: Adaptive attacker can create hard-to-detect Sybil identities

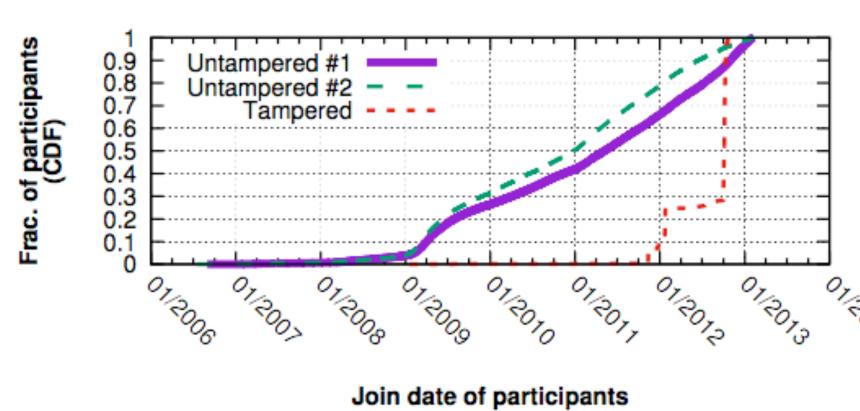
We developed **Stamper**, which detects a tampered computation robustly

Key Insights

1. Sybil identities as a group, **tend to skew** towards low reputation scores (e.g., number of Twitter followers)



2. Sybil identities can't change the **past history** (e.g., join date)



Focus on the **group** of sybil identities and **unforgeable timestamps** of activities

Stamper Algorithm

Goal: Detect whether a given large crowd computation was tempered by Sybil identities or not

Algorithm:

(1) Compare distributions of reputation scores (e.g., # of friends in a crowd or join dates) using Kullback-Leibler (KL) divergence (i.e., all vs. target sets)

$$\mathsf{KLD}(\mathsf{P},\mathsf{Q}) = \sum_{i=1}^r \left(\log(\frac{\mathsf{P}(i)}{\mathsf{Q}(i)}) \mathsf{P}(i) + \log(\frac{\mathsf{Q}(i)}{\mathsf{P}(i)}) \mathsf{Q}(i) \right)$$

(2) If KLD(P, Q) < ϵ , it means that two distributions are similar (i.e., target sets are NOT tampered) (3) If KLD(P, Q) > ϵ , it means that two distributions are very different (i.e., target sets are tampered)

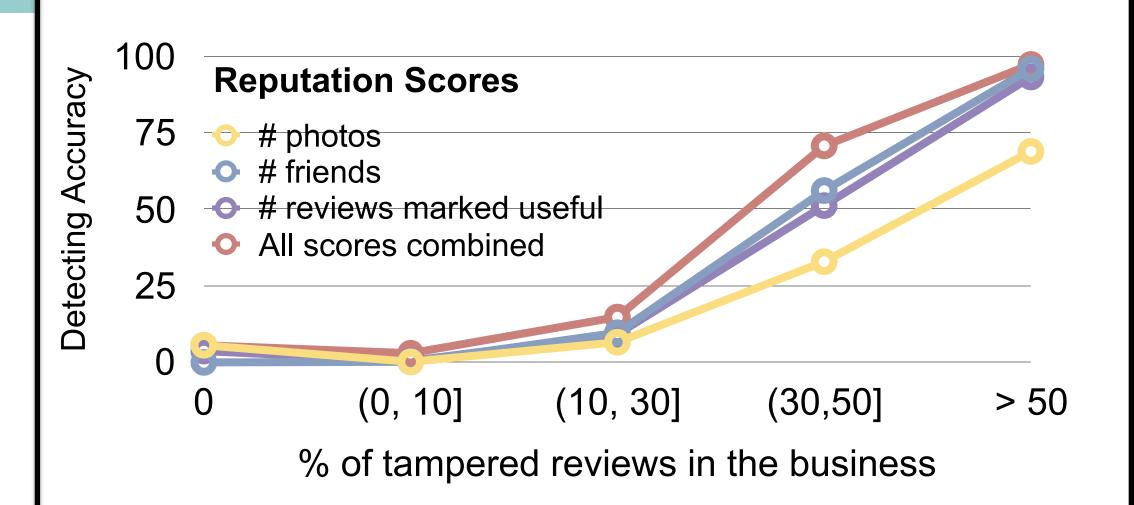
Evaluation

Case 1: Yelp Review Tampering on Business

Goal: Find the business with highly tampered reviews

| Data | Numbers |
|--|---------|
| # of all business | 3,579 |
| # of tampered reviews | 195,825 |
| # of business not having tampered reviews* | 54 |

*Each business has different portion of tampered reviews



Stamper can detect most of the highly tampered (> 50%) business while having low false positive rate (only 3%)

Case 2: Twitter Follower Tampering

Goal: Find the Twitter accounts having tampered followers

| Data | Numbers |
|--|---------|
| # of users | 69,409 |
| # of users not having tampered followers* | 30,000 |
| # of found Sybil accounts from Stamper using <i>join dates</i> distribution** | 620 |

*These accounts are verified from Twitter

**We manually investigated the accounts to see whether they are Sybil or not

Output

Unforgeable timestamp is an effective measure to detect tampering

Join date of participants

Conclusion

- Stamper can detect tampered computation (by Sybil)
- Key insight is focus on (1) large statistical samples (groups) of Sybil and (2) unforgeable timestamp information
- Stamper can raise the bar for defense against adaptive attackers and detect regardless of attacker strategy

Interested in meeting the PIs? Attach post-it note below!



