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**Research**

# SocialWatch: Detection of Online Service Abuse via Large-Scale Social Graphs

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# Arms Race between Attackers and Defenders

- ▶ Malicious accounts in Hotmail
  - **Attacker-created** accounts
  - **Hijacked** accounts
  - Attackers are constantly **evolving** with counter-strategies
- ▶ The power of social graph
  - Capture both **local** and **global** graph features
  - Hard for attackers to manipulate the overall graph pattern
- ▶ Challenges
  - Hijacked accounts have mixed behaviors
  - Incomplete graph – unknown among external accounts
  - Large graph scale requires efficient parallel algorithms

# Our Contributions

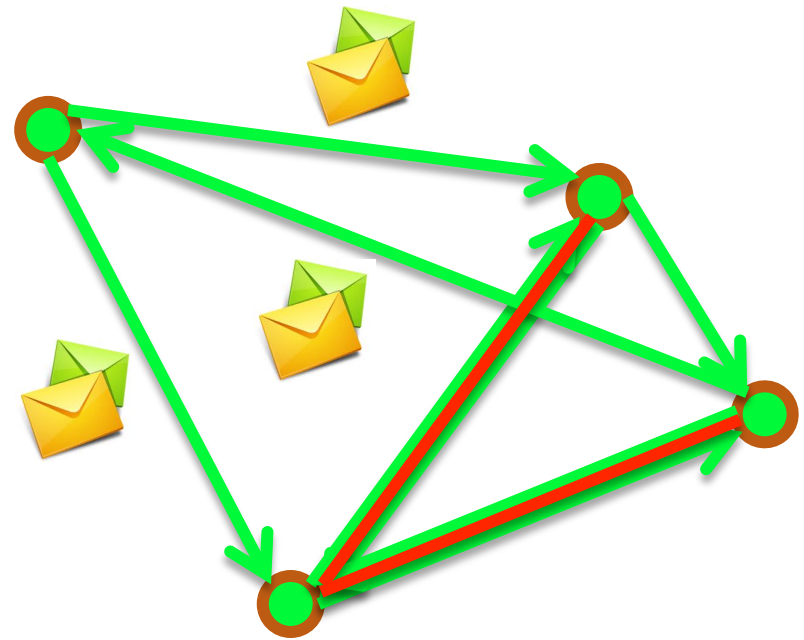
- ▶ Detection methodology – **local** and **global** social graph features for detection
- ▶ Implementation – demonstrate **practicality** and **scalability** for large-scale social graphs
- ▶ Evaluation – use a **real-world** data set with large scale and long duration



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Hotmail®

# Social Graph for Hotmail

- ▶ Vertex
  - Email account
- ▶ Edge
  - Directed
    - Send/receive emails
  - Undirected
    - Friendship

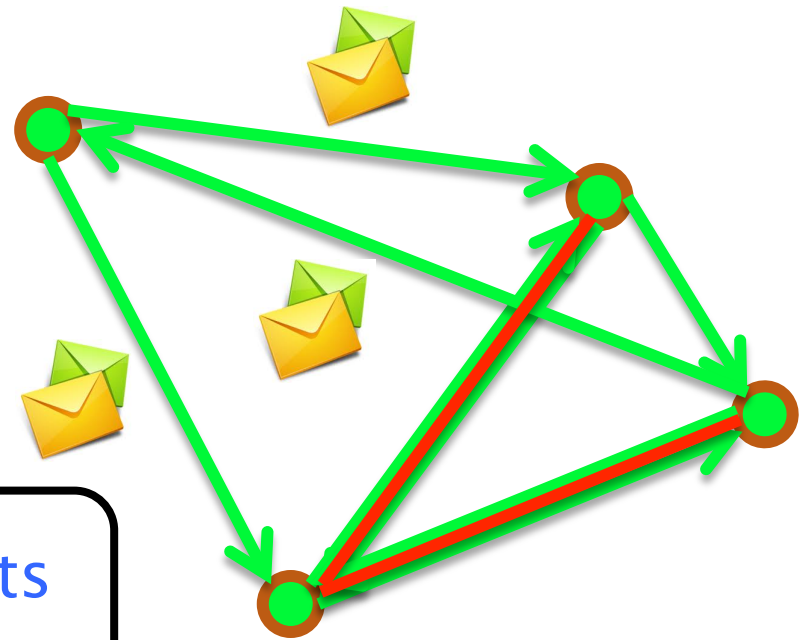




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# Social Graph for Hotmail

- ▶ Vertex
  - Email account (**680 million**)
- ▶ Edge
  - Directed (**5.7 billion**)
    - Send/receive emails
  - Undirected (**440 million**)
    - Friendship

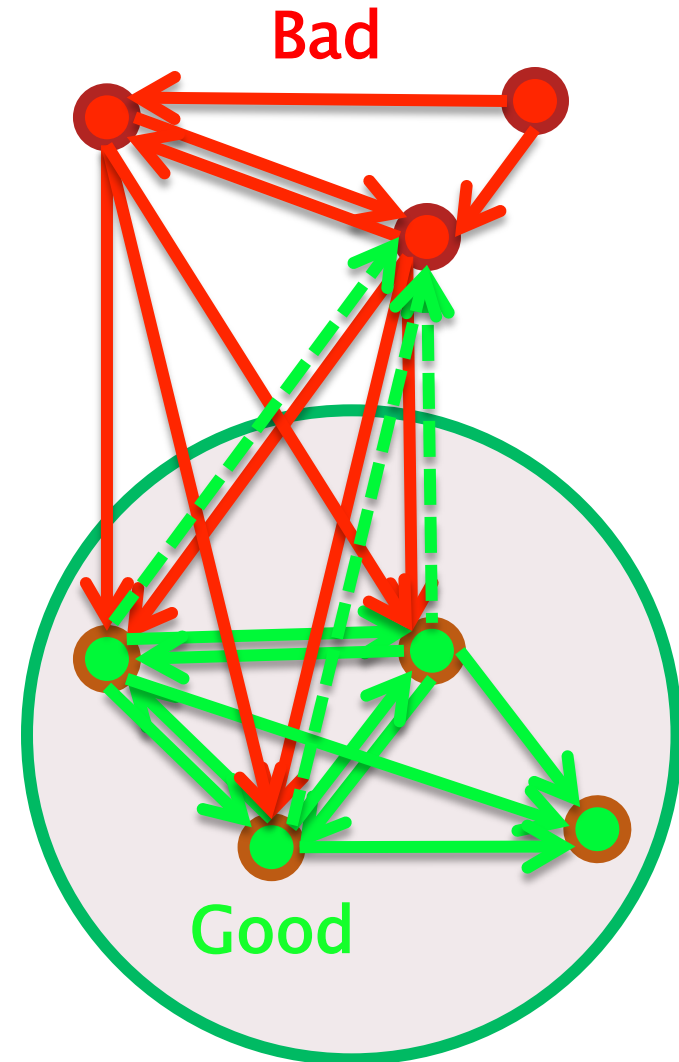


Sampled Hotmail user accounts  
from 10/2007 to 04/2010

# Intuitions in Leveraging Social Graphs

- ▶ Good users send emails to other good users
- ▶ Sending emails to bad users is suspicious
- ▶ Difficult for bad users to enter good users' community

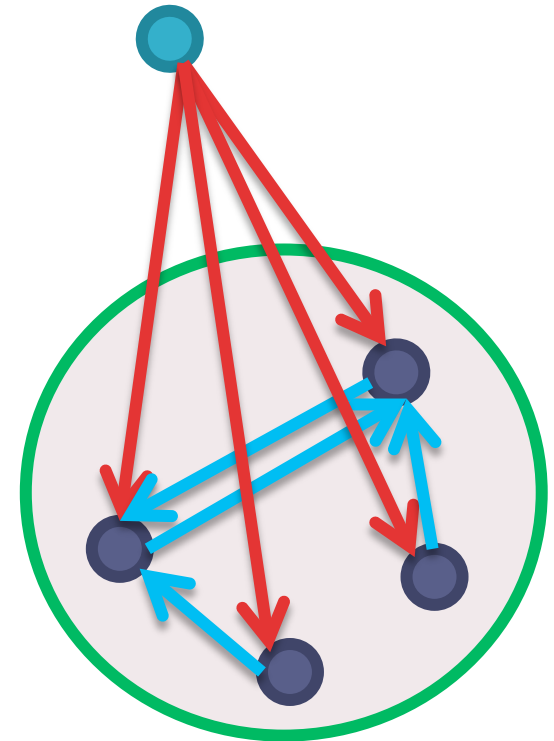
Degree and PageRank based detection



# Intuitions in Leveraging Social Graphs

- ▶ Recipient sets of good users are more connected than those of bad users

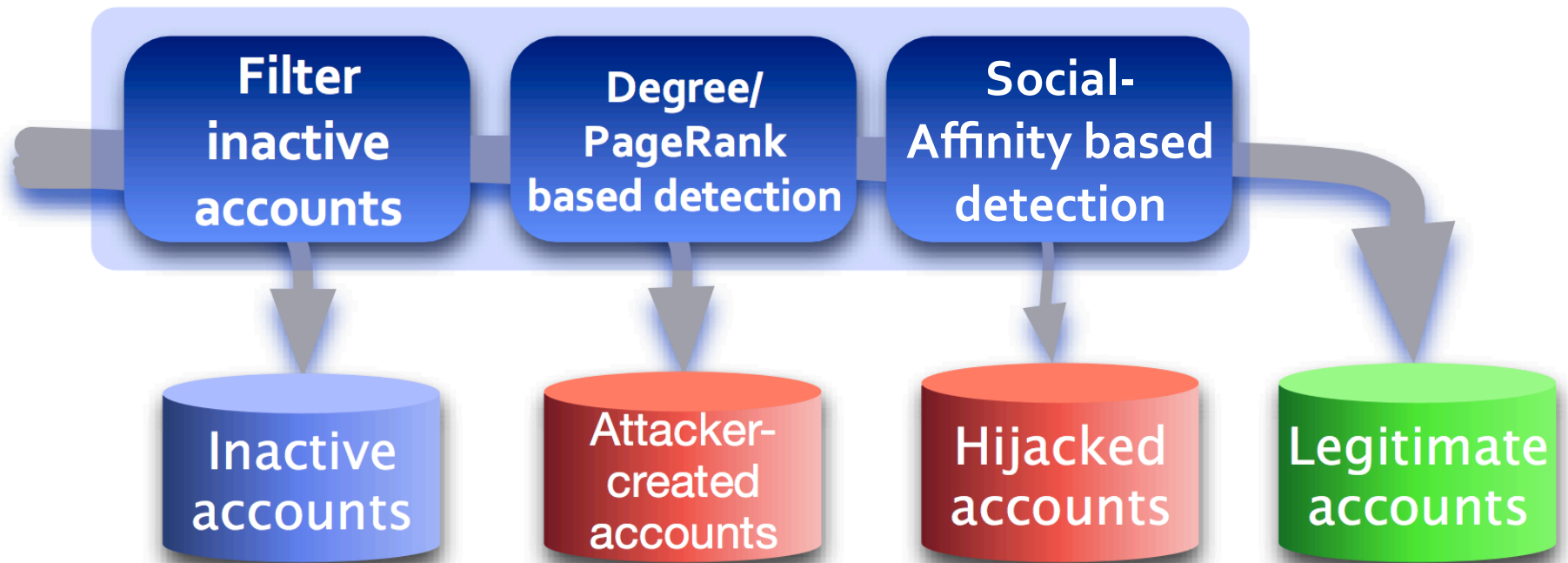
Social-affinity based detection



Recipient set



# Design of SocialWatch





# Detecting Attacker-created Accounts

## ▶ Social features

- Degree – a **local** graph feature that captures the **sending/receiving** behavior of an account
- PageRank – a **global** graph feature that calculates the weight of a node on the overall graph

## ▶ Detection methods

- Identify aggressive spamming accounts with high out degrees and low response rates
- Identify less aggressive spamming accounts using the badness-goodness PageRank ratio

# Computing Goodness / Badness PageRank Score

- ▶ Goodness score
  - PageRank value in the directed social graph
- ▶ Badness score
  - PageRank value in the **reversed** directed social graph
- ▶ Adjust edge **weights** based on email exchange patterns
  - Propagate more “goodness” to “good” users and more “badness” to “bad” users

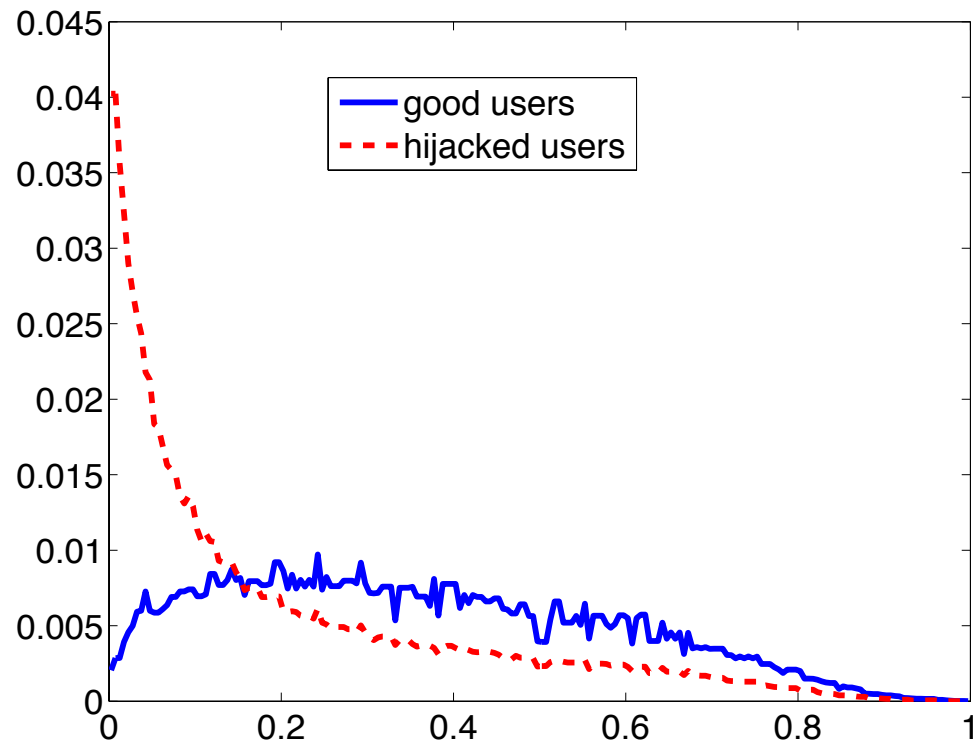
# Computing Social-Affinity Features

## ▶ Intuition

- Recipients of legitimate users tend to have more direct connectivity

## ▶ Recipient connectivity $r$

- The fraction of socially connected recipients



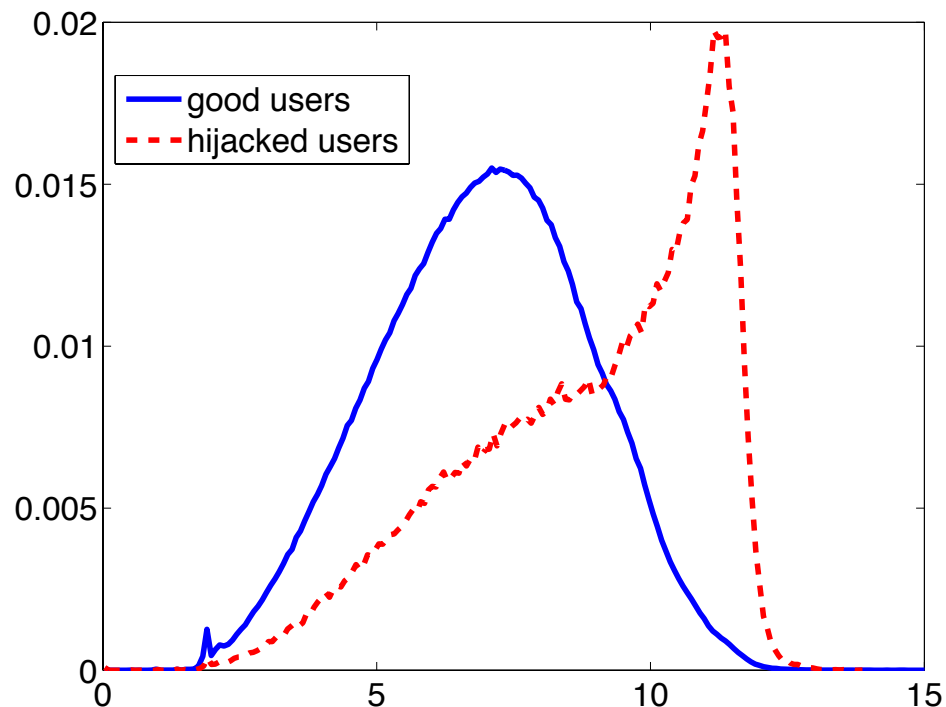
# Computing Social-Affinity Features

## ▶ Intuition

- Recipients of legitimate users tend to have closer social distance

## ▶ Social distance $l$

- The mean of all pairwise social distances between any two users in the recipient set



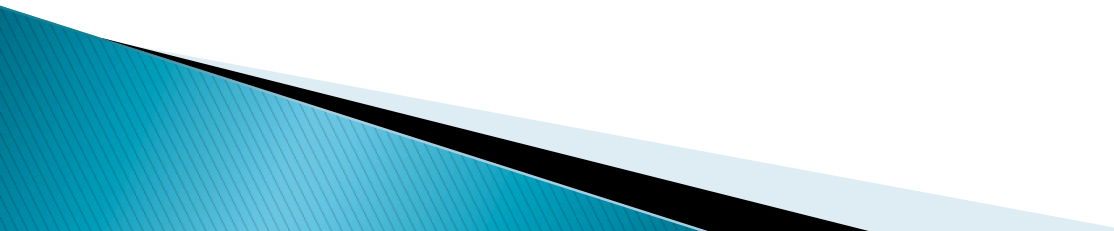
# Detecting Hijacked Accounts

- ▶ Detection **without known** hijacked accounts
  - **One-tailed hypothesis testing** to detect hijacked accounts
  - Given a significance level, compute a threshold along each feature dimension based on data
  - Classify as hijacked if one of its feature values violates the computed threshold
- ▶ Detection **with known** hijacked accounts
  - Use a **Bayesian decision framework** to detect additional hijacked accounts using with training data

# Implementation and Evaluation

- ▶ SocialWatch is implemented using **DryadLINQ** and processes data **in parallel** on a **240-** machine cluster
- ▶ SocialWatch detects **57 million** attacker-created accounts, with a **0.8%** false detection rate and a **0.6%** false negative rate
- ▶ At a false detection rate of 2%, SocialWatch identifies **2 million** hijacked accounts, **1.2 million** were not detected previously

# Conclusions

- ▶ SocialWatch is an online service protection framework, that uses **social connectivity** features to detect **attacker-created** accounts and **hijacked** accounts at a large scale
  - ▶ SocialWatch is **practically deployable** and **scalable** using parallel algorithms
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*Thank you!*



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