

You Are How You Click



Clickstream Analysis for Sybil Detection

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Sybils in Online Social Networks

- Sybil (*sibɪl*): fake identities controlled by attackers
 - Friendship is a pre-cursor to other malicious activities
 - Does not include benign fakes (secondary accounts)



- Large Sybil populations*

facebook 14.3 Million Sybils (August, 2012)

twitter 20 Million Sybils (April, 2013)

Sybil Attack: a Serious Threat

- Social spam
 - Advertisement, **malware**, **phishing**



- Steal user information 



spies used Facebook to steal Nato chiefs' details

Taliban uses sexy Facebook profiles to lure troops into giving away military secrets

- Sybil-based political lobbying efforts 

Fake Twitter Accounts? Obama's Political Group Pushes Gun Control

Ericka Andersen | February 26, 2013 at 10:45 am | (19)  Like

Russian Twitter political protests 'swamped by spam'



Sybil Defense: Cat-and-Mouse Game



The image shows a screenshot of a Facebook profile for Amandeep Kaur. The profile includes a cover photo, a profile picture, and various sections such as 'Work and Education', 'Philosophy', 'Religious Views', 'Political Views', 'Favorite Quotations', and 'Arts and Entertainment'. The 'Work and Education' section lists 'NIKEID' as an employer. The 'Religious Views' section shows a Sikh symbol. The 'Political Views' section shows 'I hate Politics'. The 'Favorite Quotations' section shows 'god'. The 'Arts and Entertainment' section shows music by Shakira, Sade, and Sade Song.



Attackers

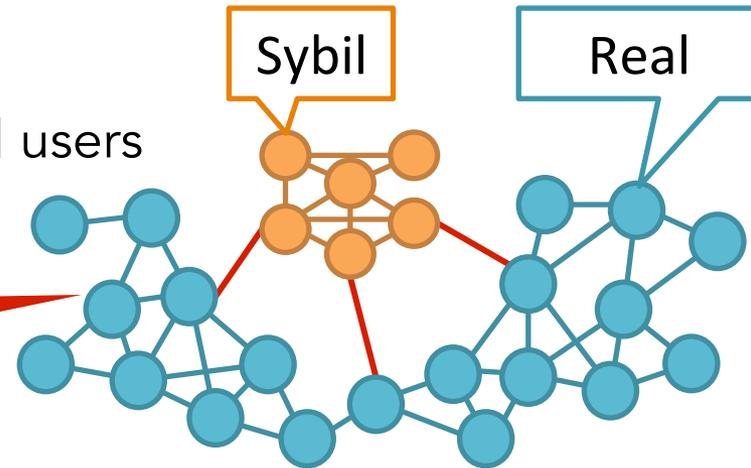
Crowdsourcing CAPTCHA solving
• [USENIX'10]

Realistic profile generation
• Complete bio info, profile pic
[WWW'12]

Graph-based Sybil Detectors

- A key assumption
 - Sybils have difficulty “friending” normal users
 - Sybils form tight-knit **communities**

Is This True?



- Measuring Sybils in **Renren** social network [IMC'11]
 - Ground-truth 560K Sybils collected over 3 years
 - Most Sybils befriend real users, integrate into real-user communities
 - Most Sybils don't befriend other Sybils

Sybils don't need to form communities!

NEW

Sybil Detection Without Graphs

- Sybil detection with **static profiles analysis** [NDSS'13]
 - Leverage human intuition to detect fake profiles (crowdsourcing)
 - Successful user-study shows it scales well with high accuracy
- Profile-based detection has limitations
 - Some profiles are easy to mimic (e.g. CEO profile )
 - Information can be found online
- **A new direction:** look at what users do!
 - How users browse/click social network pages
 - Build user behavior models using clickstreams



Clickstreams and User Behaviors

- Clickstream: a list of server-side user-generated events
 - E.g. profile load, link follow, photo browse, friend invite

UserID	Event Generated	Timestamp
345678	Send Friend Request_23908	1303022295242
214567	Visit Profile_12344	1300784205886
...

- Intuition: Sybil users act differently from normal users
 - **Goal-oriented**: concentrate on specific actions
 - **Time-limited**: fast event generation (small inter-arrival time)

Analyze ground-truth clickstreams for Sybil detection

Outline

- Motivation
- Clickstream Similarity Graph
 - Ground-truth Dataset
 - Modeling User Clickstreams
 - Generating Behavioral Clusters
- Real-time Sybil Detection

Ground-truth Dataset

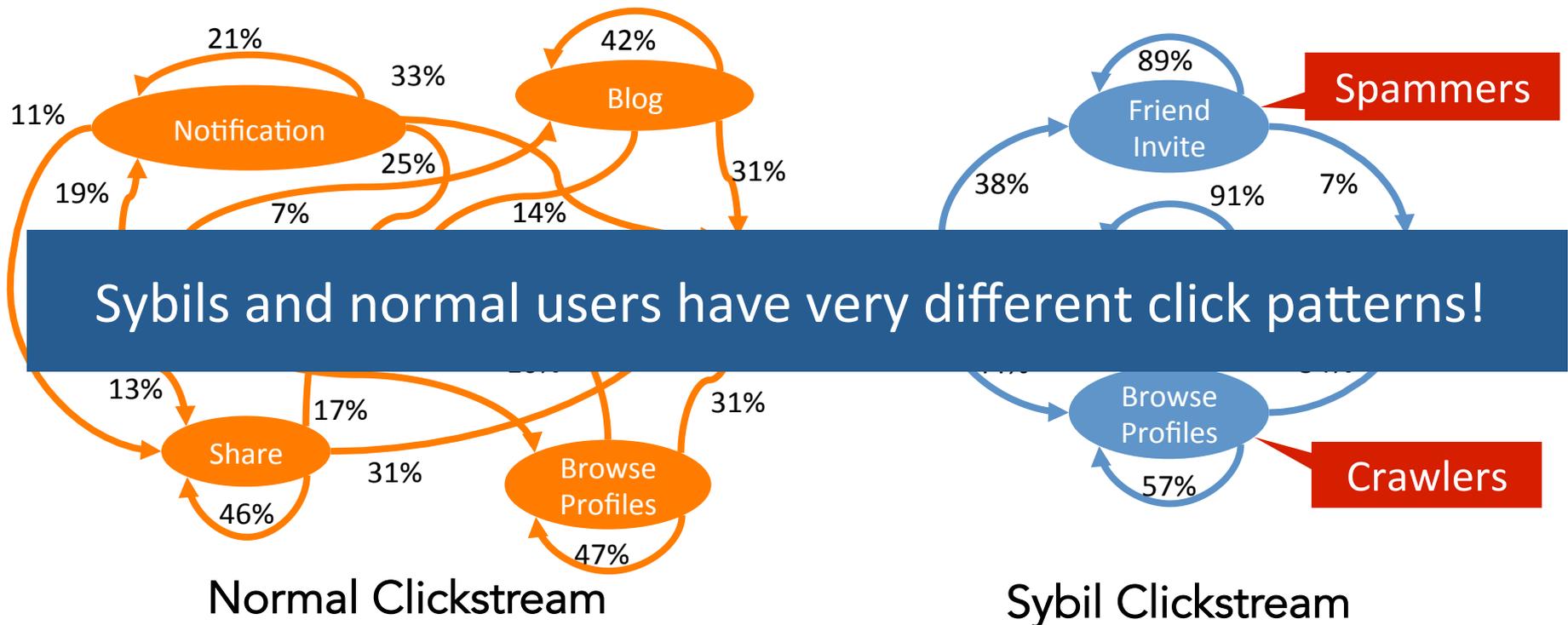
- Renren Social Network
 - A large online social network in China (280M+ users)
 - Chinese Facebook
- Ground-truth
 - Ground-truth provided by Renren’s security team
 - 16K users, clickstreams over two months in 2011, 6.8M clicks



Dataset	Users	Sessions	Clicks	Date (2011)
Sybil	9,994	113,595	1,008,031	Feb.28-Apr.30
Normal	5,998	467,179	5,856,941	Mar.31-Apr.30

Basic Analysis: Click Transitions

- Normal users use many social network features
- Sybils focus on a few actions (e.g. friend invite, browse profiles)

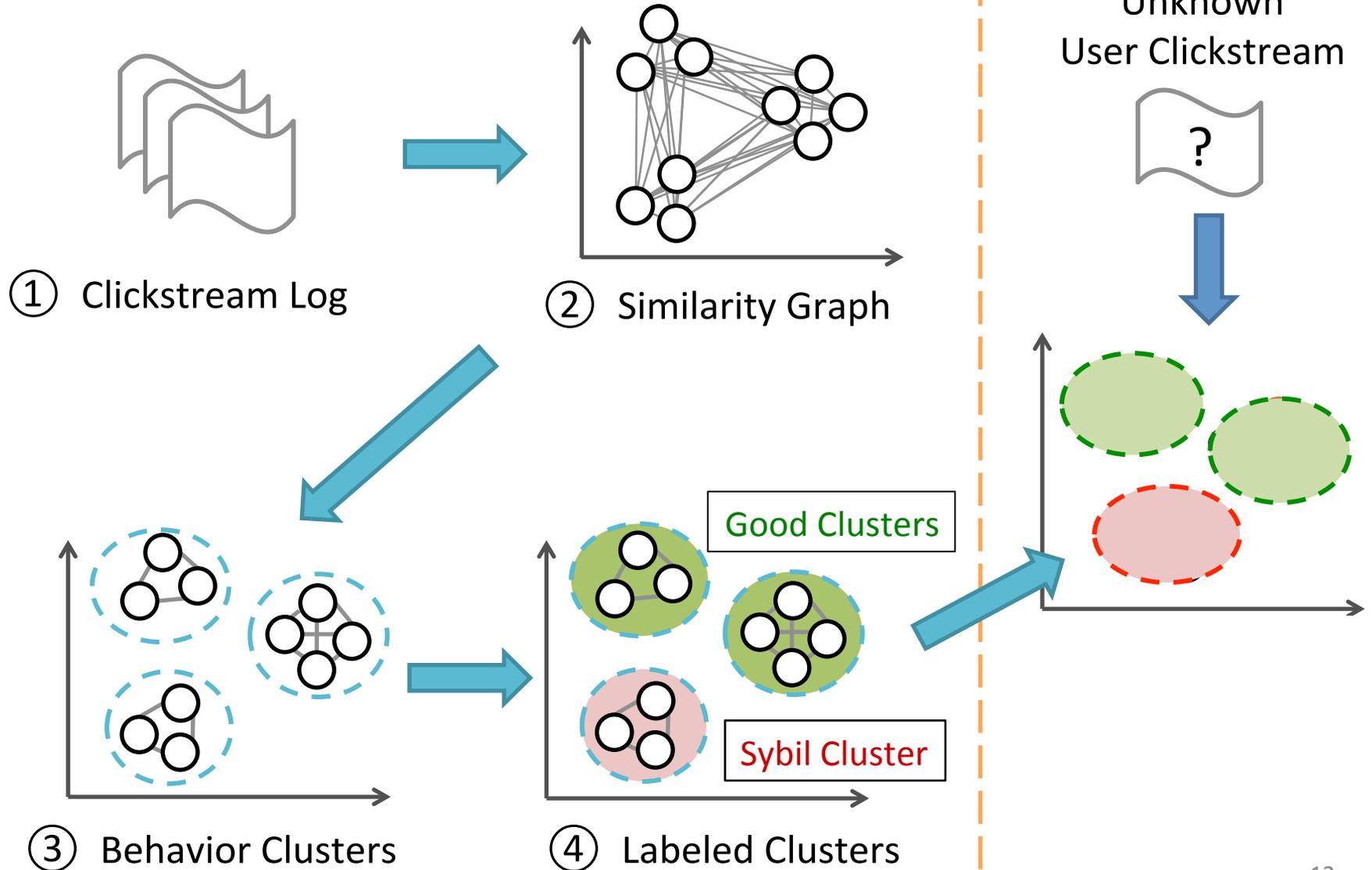


Identifying Sybils From Normal Users

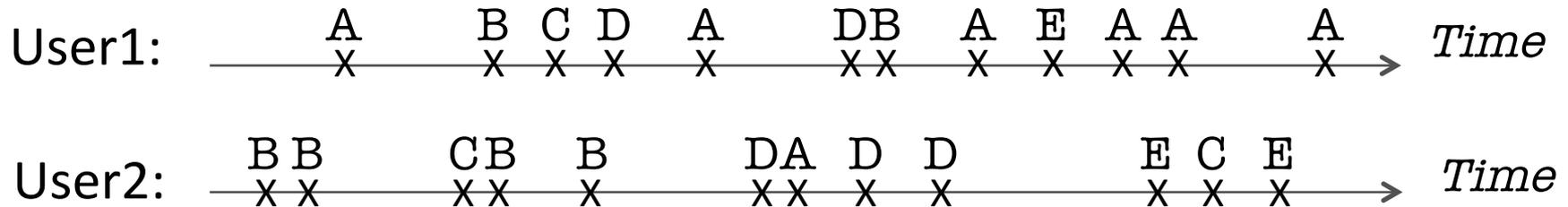
- Goal: quantify the differences in user behaviors
 - Measure the similarity between user clickstreams
- Approach: map user's clickstreams to a **similarity graph**
 - Clickstreams are nodes
 - Edge-weights indicate the similarity of two clickstreams
- Clusters in the similarity graph capture user behaviors
 - Each cluster represents certain type of click/behavior pattern
 - Hypothesis: Sybils and normal users fall into different clusters

Model Training

Detection

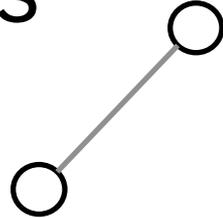


Capturing User Clickstreams



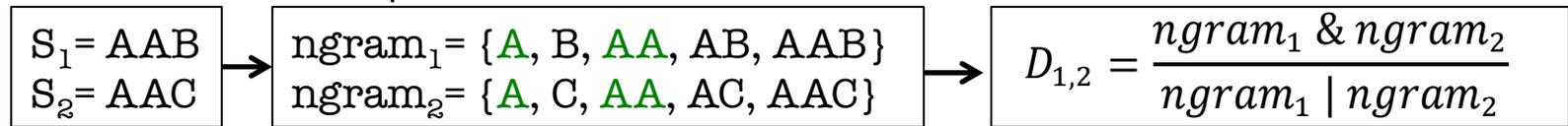
- 1. Click Sequence Model:** order of click events
 - e.g. ABCDA ...
- 2. Time-based Model:** sequence of inter-arrival time
 - e.g. $\{t_1, t_2, t_3, \dots\}$
- 3. Complete Model:** sequence of click events with time
 - e.g. $A(t_1)B(t_2)C(t_3)D(t_4)A \dots$

Clickstream Similarity Functions

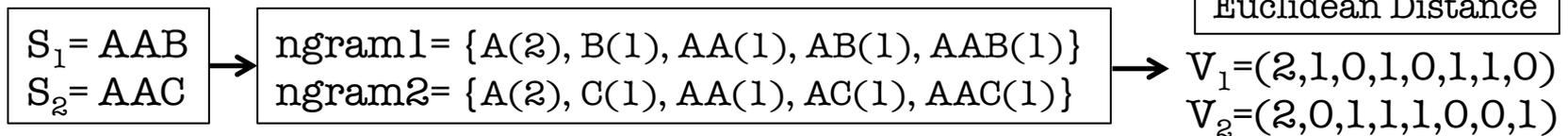


- Similarity of sequences

- Common subsequence



- Common subsequence **with counts**

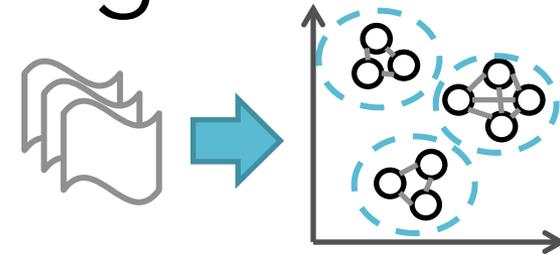


- Adding "time" to the sequence

- Bucketize inter-arrival time, encode time into the sequence
- Apply the same sequence similarity function

Clickstream Clustering

- Similarity graph (fully-connected)
 - Nodes: user's clickstreams
 - Edges: weighted by the **similarity score** of two users' clickstreams
- Clustering similar clickstreams together
 - Minimum edge weight cut
 - Graph partitioning using METIS
- Perform clustering on ground-truth data
 - **Complete model** produces very accurate behavior clusters
 - 3% false negatives and 1% false positives



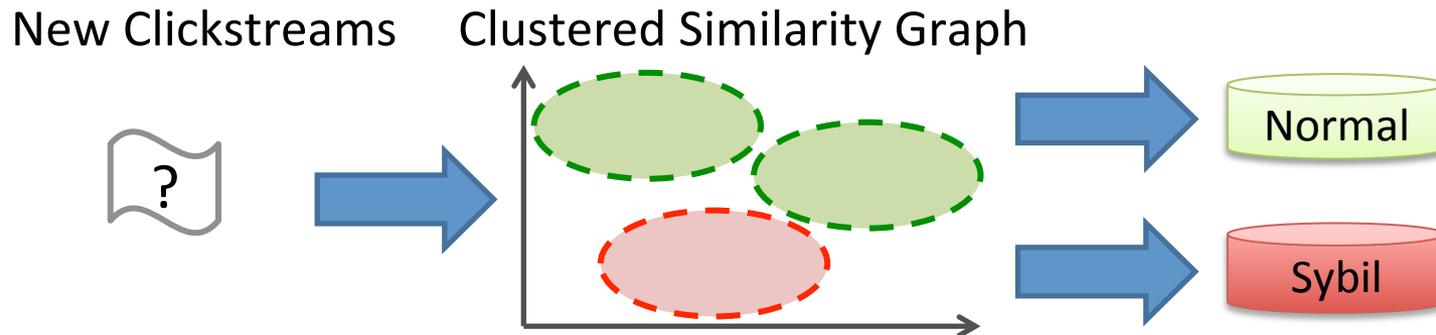
Sybils in normal clusters

Normal users in Sybil clusters

Outline

- Motivation
- Clickstream Similarity Graph
- Real-time Sybil Detection
 - Sybil Detection Using Similarity Graph
 - Unsupervised Approach

Detection in a Nutshell

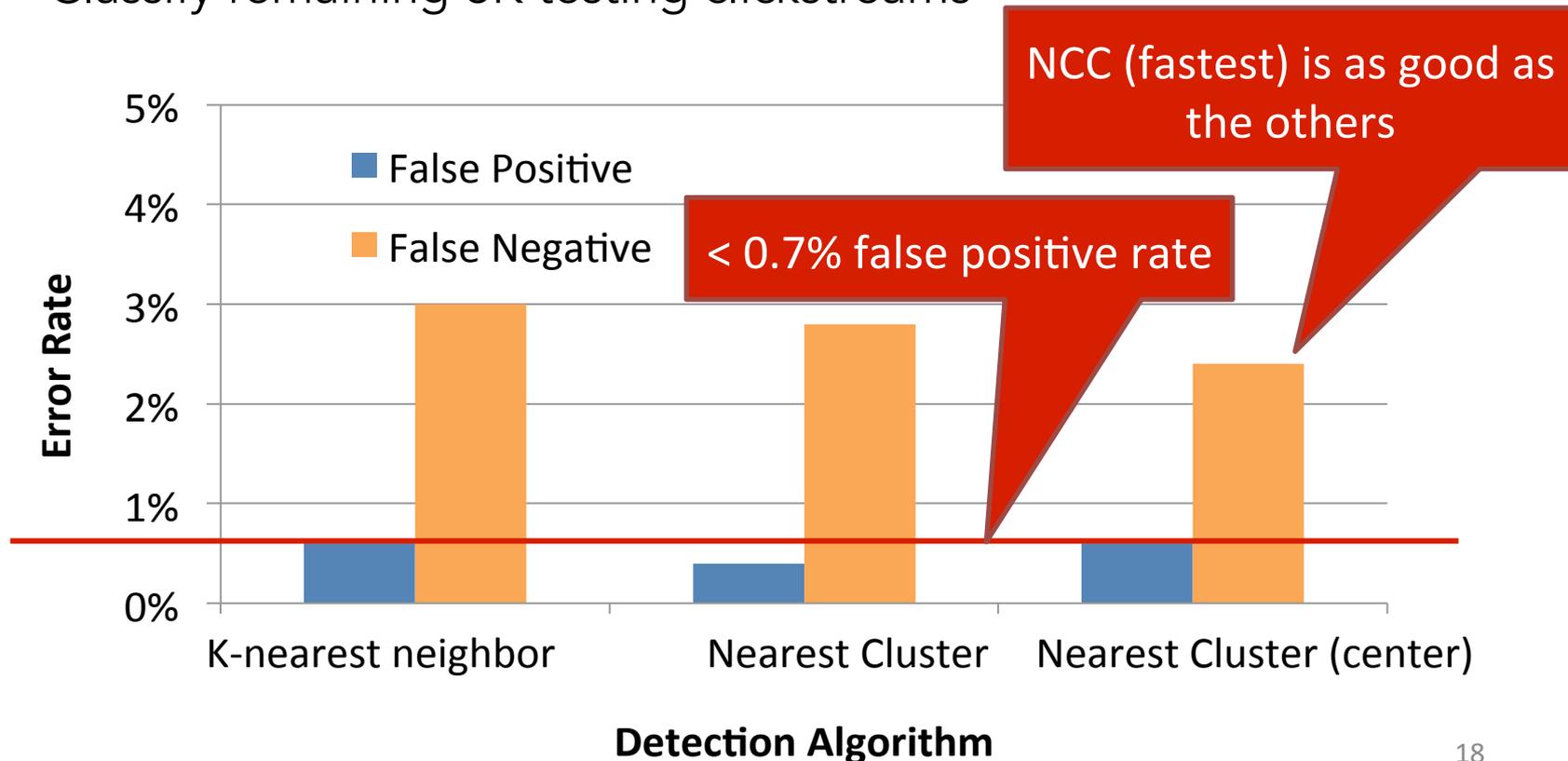


- Sybil detection methodology
 - Assign the unclassified clickstream to the “nearest” cluster
 - If the nearest cluster is a Sybil cluster, then the user is a Sybil
- Assigning clickstreams to clusters
 - K nearest neighbor (KNN)
 - Nearest cluster (NC)
 - Nearest cluster with **center** (NCC)

Fastest, scalable

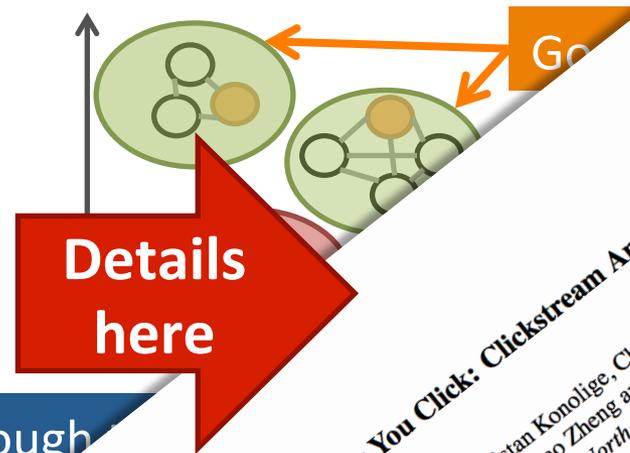
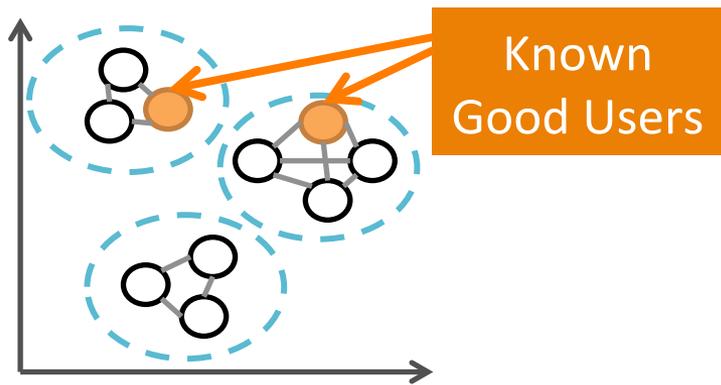
Detection Evaluation

- Split 12K clickstreams into training and testing datasets
 - Train initial clusters with 3K Sybil + 3K normal users
 - Classify remaining 6K testing clickstreams



(Semi) unsupervised Approach

- What if we don't have a big ground-truth dataset?
 - Need a method to label clusters
- Use a (small) set of known-good users to **color** clusters
 - Adding known users to existing clusters
 - Clusters that contain good users are "good" clusters



- 400 random good users are enough
- For unknown dataset, add good
- Still achieve high detection acc

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online content such as f
ware and spam on soci
Sybil-based politica
Recent work h
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sumption
users.

Real-world Experiments

- Deploy system prototypes onto social networks
 - Shipped our prototype code to Renren and LinkedIn
 - All user data remained on-site



- Scanned 40K ground-truth user's clickstreams
- Flagged 200 previous unknown Sybils



- Scanned 1M user's clickstreams
- Flagged 22K suspicious users
- Identified a new attack

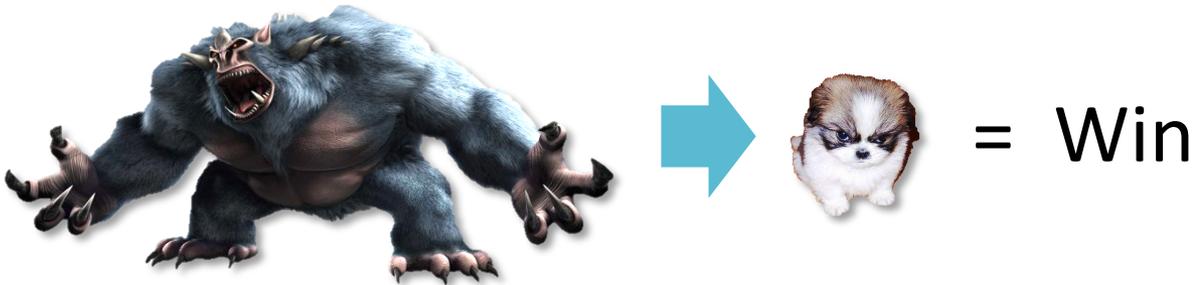
"Image" Spammers

- Embed spam content in images
- Easy to evade text/URL based detectors

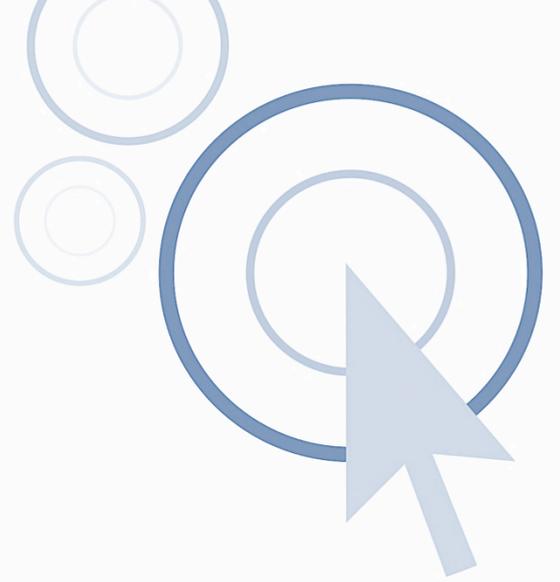


Evasion and Challenges

- In order to evade our system, Sybils may ...
 - Slow down their click speed
 - Generate “normal” actions as cover traffic



- Practical challenges
 - How to update behavior clusters over time (incrementally)?
 - How to integrate with other existing detection techniques? (e.g. profile, content based detectors)



Thank You!

Questions?

