On Sybil Classification in Online Social Network Using Only OSN Structural Features

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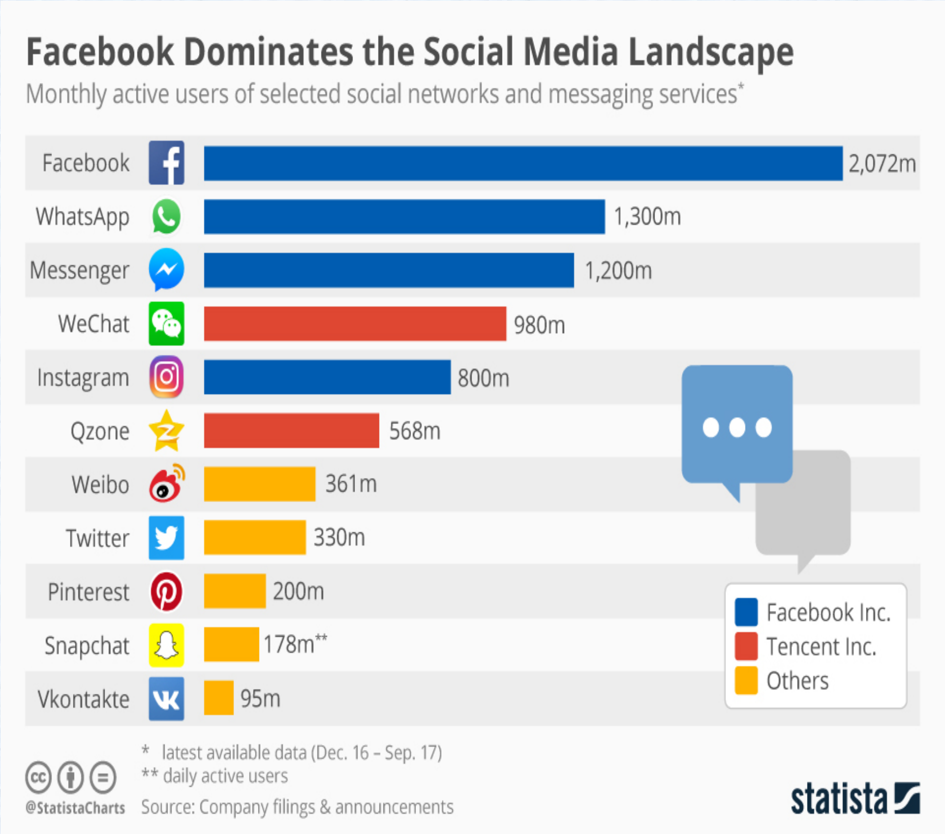
Online Social Network

- Preferred way to connect peoples
- Open platform: Anyone can join
- Some users can be fake or malicious
  - Sybils



Fake accounts (Sybils)

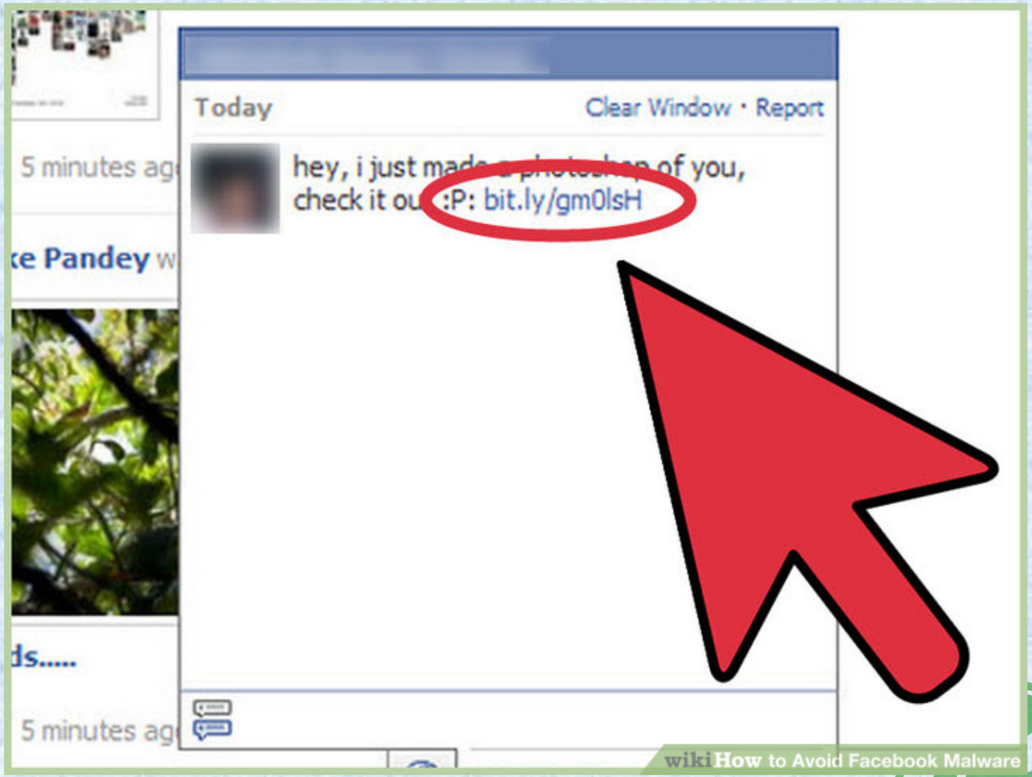
Sybils are for sale on the underground market

Fake accounts (Sybils)

Why are sybils so harmful ?

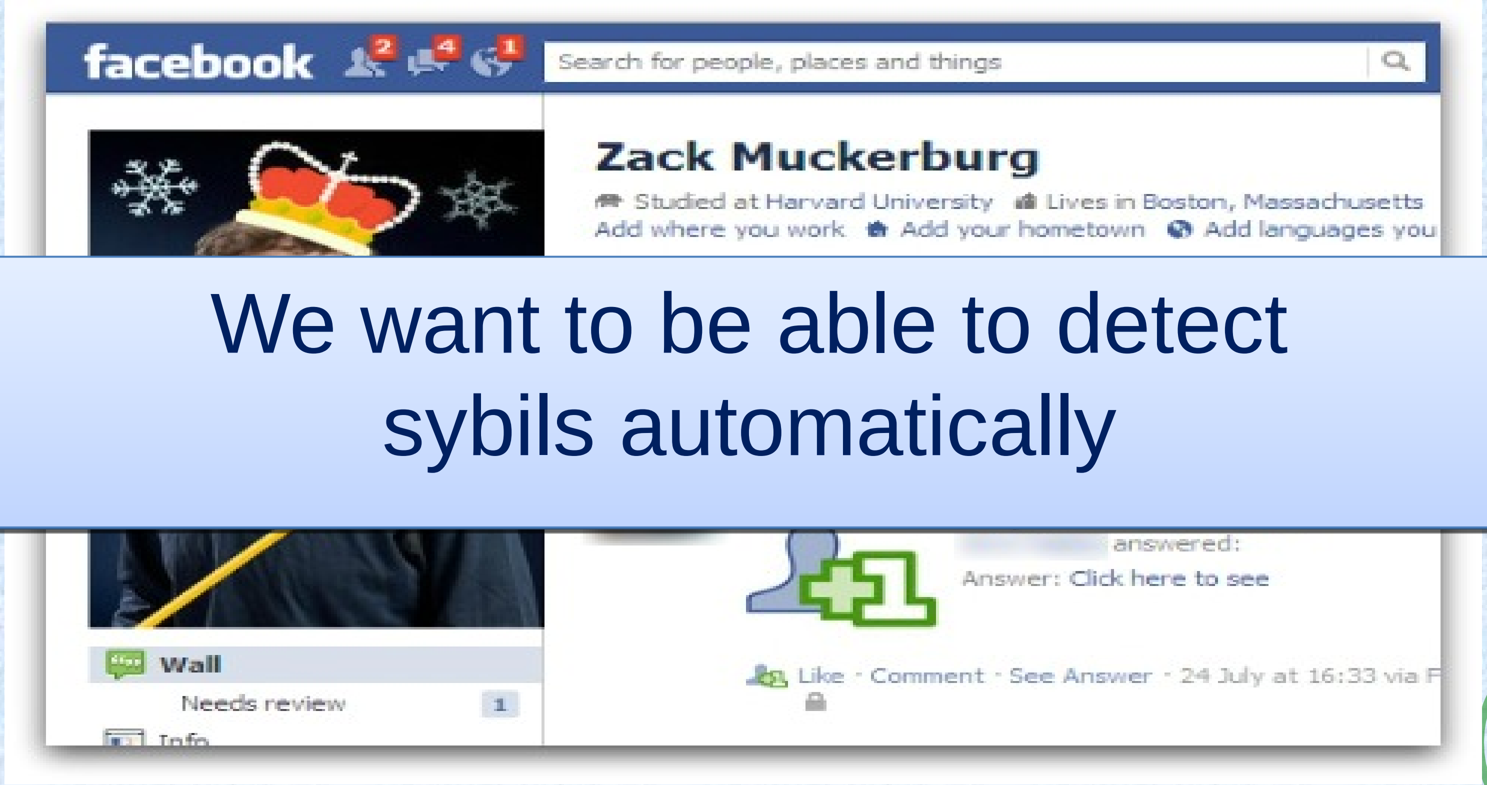
Fake accounts can be used to :

- Send spam
- Do phishing
- Access personal user info
- …



Detecting Sybils is challenging

Detecting sybil accounts is difficult:
These accounts may resemble real users



We want to be able to detect sybils automatically

Existing approaches

There are several approaches to detect sybils

- Content-based approaches
- Behavior-based approaches
- Graph-Structure based approaches

Existing Approaches

- Content-based approaches
  - Collect user’s attributes (genre, age, mobility, power, …)
  - Use machine-learning to classify users

- Behavior-based approaches
  - Collect user’s activity data (like, posts, uploading image, …)
  - Use machine-learning to classify users

- Graph-based approaches
  - Leverage the relationship between nodes

Existing Approaches

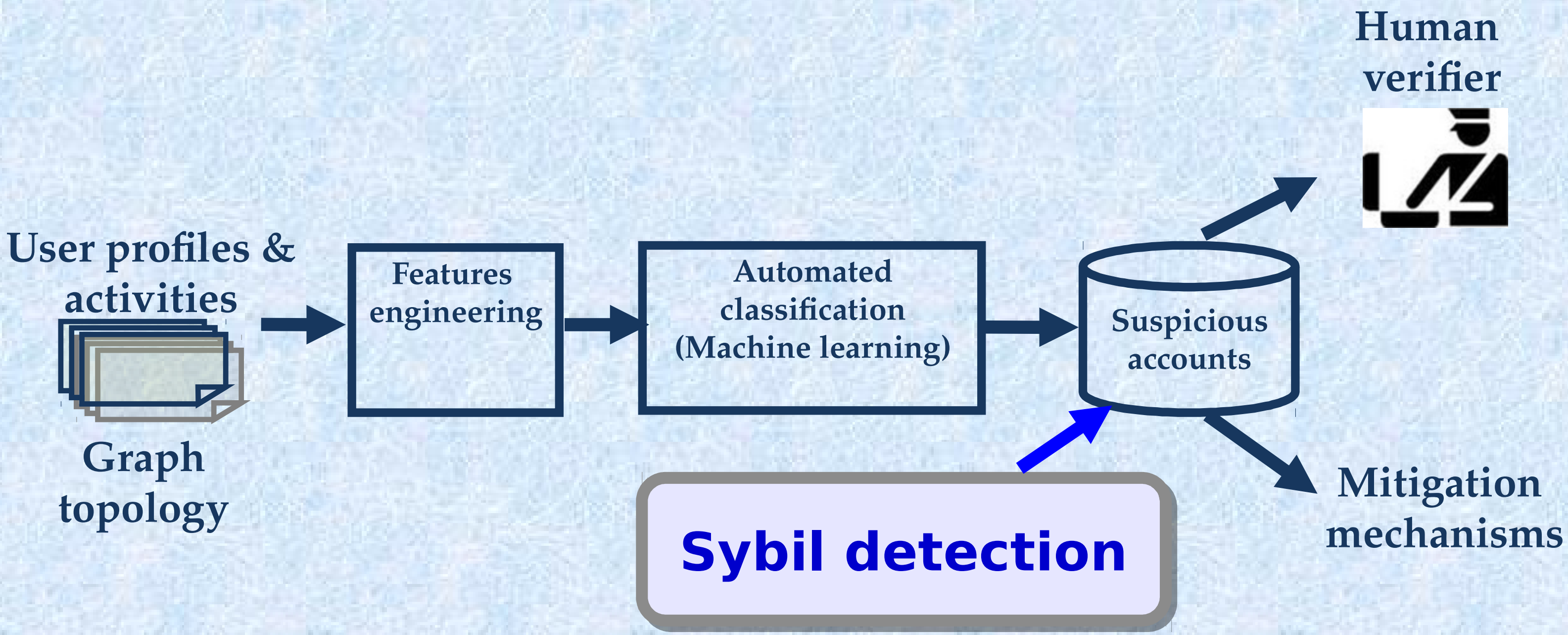
- Content-based approaches
- **Problems** :
  - High false positive and negative rates
  - Some profiles are too easy to mimick
  - Information can be found online

Existing Approaches

- Content-based approaches
- The Fix : Hybrid approaches
  - Add features from activity data (Behavior-based approach)
  - Add features from the social graph (Graph-based appraoche)
  - Use machine-learning to classify accounts.

Existing Approaches

- Hybrid approach : The workflow



Existing Approaches

- **What is wrong?**
  - Users do not always provide all the info requested in the profile
  - Collecting user activities data raises the concern about user privacy

- **New Direction** :
  - Design features ONLY from network topology
  - Use machine-learning to classify accounts.

Outline

1) Overview
2) Attack model
3) The Insights
4) Feature Engineering
   - Existing features
   - Proposed features
5) Feature selection
6) Dataset
7) Classification
8) Results
9) Conclusion

Our Work

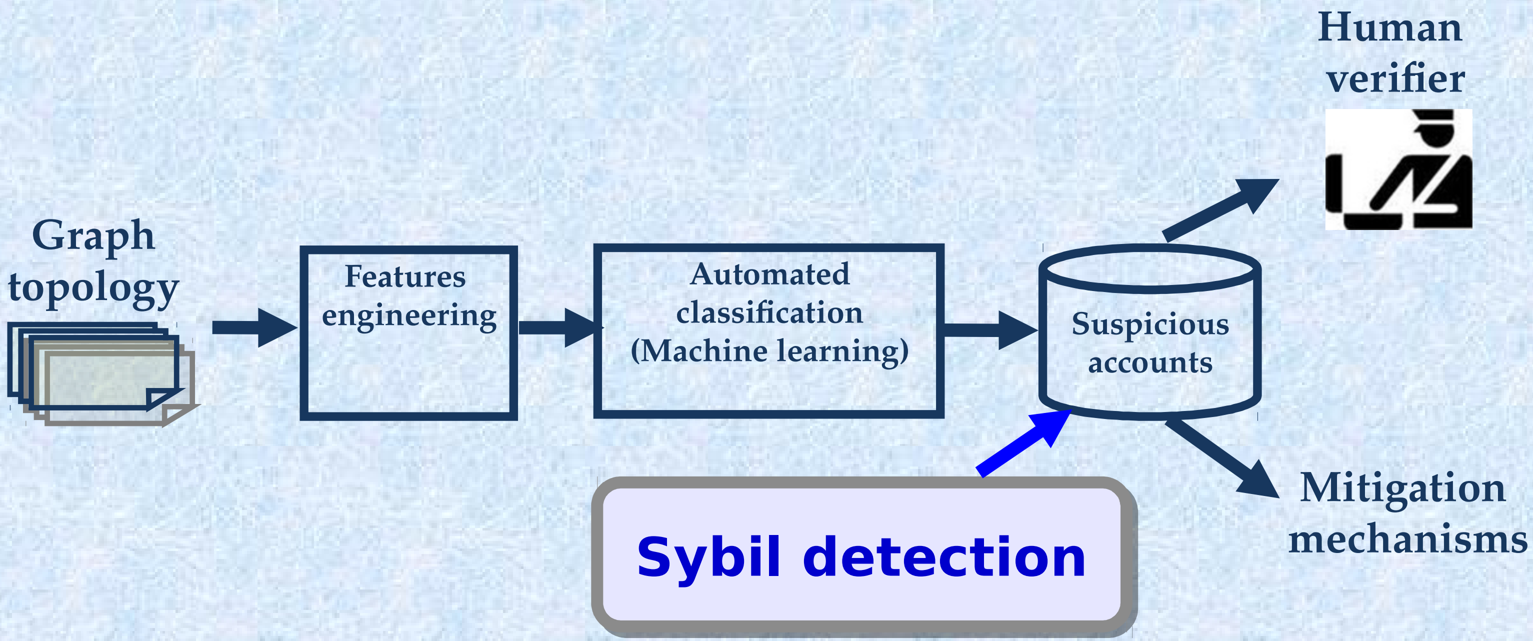
- Avoid using features from user profiles, and user activity data
- Design features only from the topology of the social network
- Uses Machine-learning to detect Sybils
- Have evaluated results on many different types of synthetic datasets
  - Varies in size, and graph properties
- Have evaluated results on a real world OSN data (Twitter)

Our Work: Overview

- Convert the social network into an undirected graph
- Use graph theory to engineer features
- Select relevant features through features selection
- Build classification models
- Evaluate the results

Our Work: Overview

- Our approach : The workflow



Our Work: Attack Model

- No assumption about attacker capabilities
- Attacker can create unlimited number of sybils
- Sybils may be connected to each other
- Attacker can befriend an unlimited number of benign nodes
- Attacker does not have control on the number of friend requests accepted

Our Work: The insight

- Features are engineered to capture the following patterns:
  - Sybils that form a dense friendship subgraph
  - Sybils that form a sparse friendship subgraph
  - Sybils tend to have friendship relationship with popular users

Our Work: The Features

- Features are designed using graph theory (centrality metrics)
- Existing features are :
  1. Average degree
  2. Average nearest neighbor degree
  3. Core number
  4. Average core number
  5. Clustering coefficient
  6. Average clustering coefficient
  7. Edge volume
  8. Weighted vertex volume

Our Work: The Features

- Features are designed using graph theory (centrality metrics)

- Proposed features are :
  1. Degree-intensity centrality
  2. Degree-coherence centrality
  3. Core-intensity centrality
  4. Core-coherence centrality
  5. Weighted degree-core centrality
  6. Weighted degree-clustering centrality

Our Work: Features Selection

- The feature selection model is : The Recursive Feature Elimination (RFE)
- Selected features are :
  1. Core number
  2. Average degree centrality
  3. Average clustering centrality
  4. Degree-coherence centrality
  5. Core-coherence centrality
  6. Edge volume centrality
  7. Weighted degree-core centrality
  8. Weighted degree-degree centrality

Our Work: Dataset

Facebook dataset

- Benign region : Facebook dataset
- Sybil region : network synthetically generated

Region	Nodes	Edges
Benign	4,039	88,234
Sybils	4,000	88,000
Attack edges	None	60,000
Total	8,039	236,234

Our Work: Dataset

Twitter dataset

- Real world dataset

Region	Nodes	Edges
Benign	372,251	906,102
Sybils	97,253	1,147,939
Attack edges	None	99,385
Total	469,504	2,153,426

Our Work: Classification

- **Classifiers:**
  - Adaboost (100 Estimators)
  - K-Nearest Neighbor (KNN)
  - Random Forest (100 trees)
- **Evaluation metrics:**
  - Precision
  - Recall
  - F-measure
  - Area Under the Curve (AUC)

Our Work: Results

- Classification on Facebook dataset

Classifier	Precision	Recall	F-measure	AUC
Adaboost	1.00	1.00	1.00	1.00
KNN	1.00	1.00	1.00	1.00
Random Forest	1.00	1.00	1.00	1.00

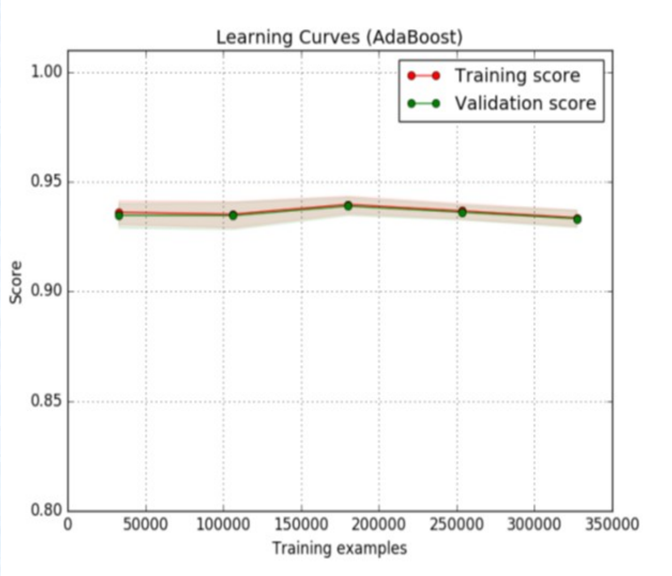
Our Work: Results

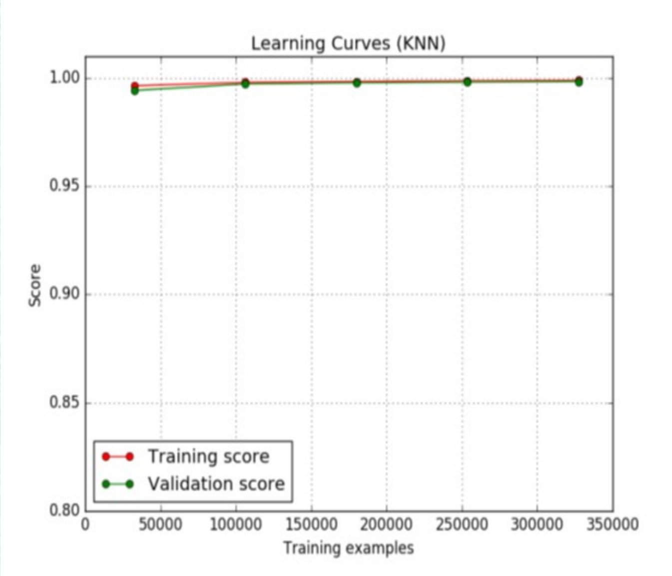
- Classification on Twitter dataset

Classifier	Precision	Recall	F-measure	AUC
Adaboost	0.95	0.94	0.94	0.94
KNN	0.99	0.99	0.99	0.99
Random Forest	0.99	0.99	0.99	0.99

Our Work: Results

- Our method is very accurate
- We want to check for over-fitting
- We plot the learning curve to check for over-fitting
- There is not over-fitting





Conclusion

- We proposed a practical Sybil detection mechanism
- We classify users according to the topology of the graph
- We classify sybils with high accuracy (AUC=0.99)
- Topological features are hard to evade
- Future works: Use a dynamic graph

THANK YOU