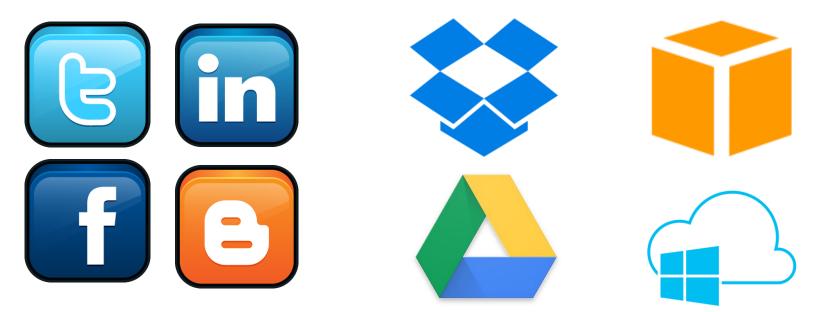
EvilCohort: Detecting Communities of Malicious Accounts on **Online Services**

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Online services are abused by cybercriminals



- Spam
- Crawling sensitive information / documents
- Storing illegal content
- Running DoS attacks / hosting C&C servers

State of the art in malicious account detection

Current techniques leverage domain-specific elements to detect malicious activity on one type of service

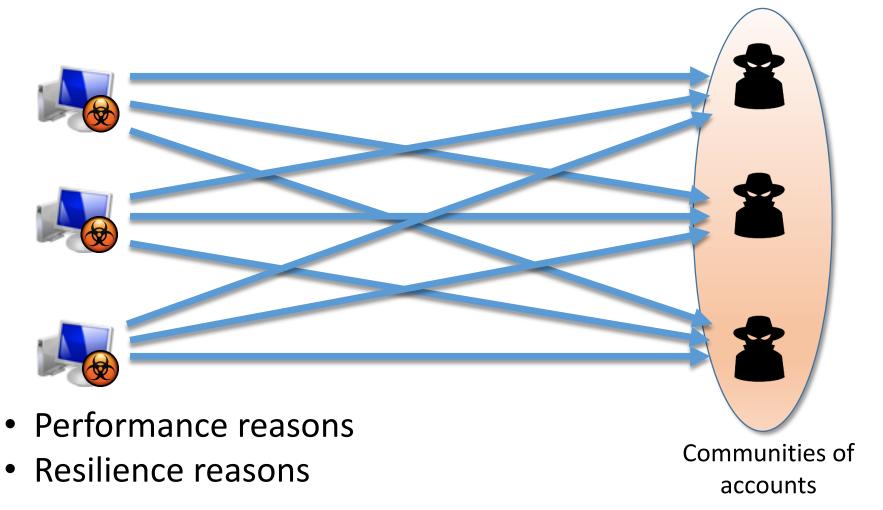
Exam

For

There are elements that are common to malicious activity on all online services!

- Blos
- Youtube [Benevenuto2009]
- Social Networks [Mittal2009], [Grier2010], [Stringhini2010]
- Webmail accounts [Taylor2006], [Stringhini2015]

Botnets accessing online accounts



Advantages of community detection

Service-agnostic

Can be done on any service that uses accounts

Activity-agnostic

We only look at how accounts are accessed

Different types of cybercriminal operations

- Crawl the online service
- Use the service as C&C channel
- Use the service as a "drop" service

Distributed access is prevalent

Web-based email service logs, 1 day period 72M emails sent by 21M distinct accounts

170k vetted spam accounts for ground truth

- 66k accounts accessed by a single IP address
- 104k accounts accessed by multiple IP addresses

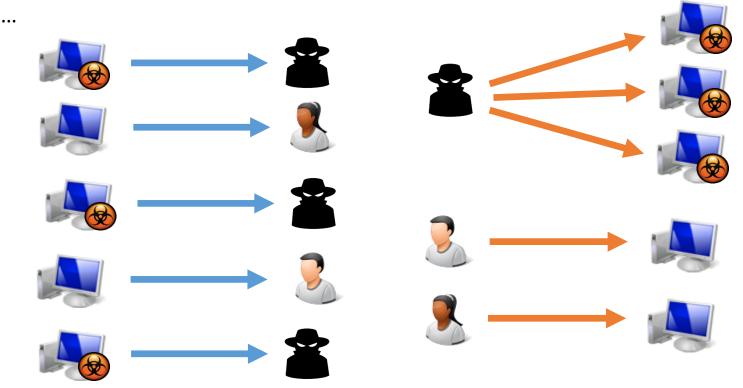
Just looking at accounts that are accessed by many IP addresses does not work (32% FPs for accounts accessed by 10+ IPs)

Our system: EvilCohort

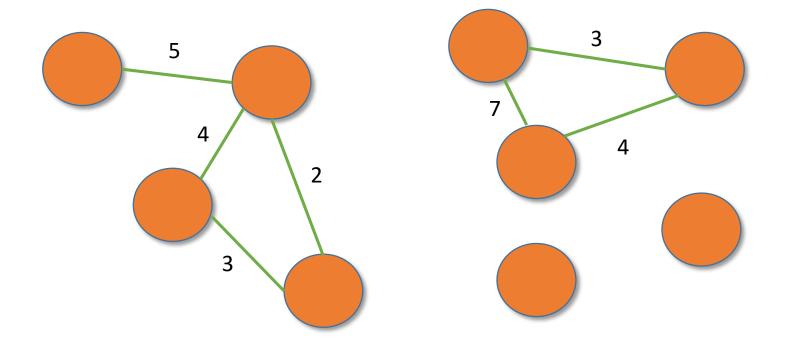
- Phase I: data collection
- Phase II: building the graph representation
- Phase III: finding communities
- Phase IV (optional): characterizing communities

Phase I: data collection

Timestamp_1, IP_address_1, Account_1 Timestamp_2, IP_address_2, Account_2 Timestamp_3, IP_address_3, Account_3 Timestamp_4, IP_address_4, Account_1



Phase II: building graph representation



- Vertices are online accounts
- Edges' weight is number of shared IP addresses

Phase III: finding communities

We apply the ``Louvain'' method for clustering:

- Iterative method
- Based on modularity optimization

We can prune edges with low weight to improve precision (threshold *s*)

Phase IV (optional): characterizing communities

- User agent correlation
- Event-based time series
- IP address and account usage

These filters can be used to further prune false positives

Selection of s

Ground truth: 103k spam accounts accessed by 2+ IPs False positive if \leq 10% of the accounts sent spam



Grown knowledge: 88884200000(110(110(12829%))

Results in the wild

Webmail activity dataset: email events 5 month period, 1.2B emails

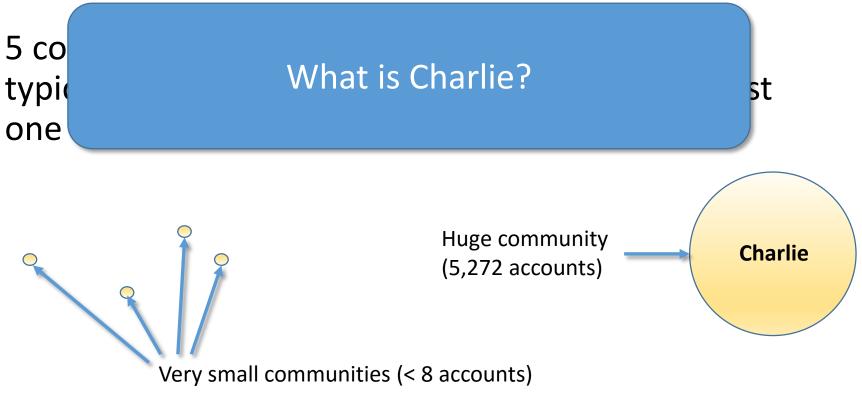
1.2M malicious accounts, 500k unknown, 23k FP (1.9%)

Online social network dataset: login events 8 day period, 14M events, 4 social networks

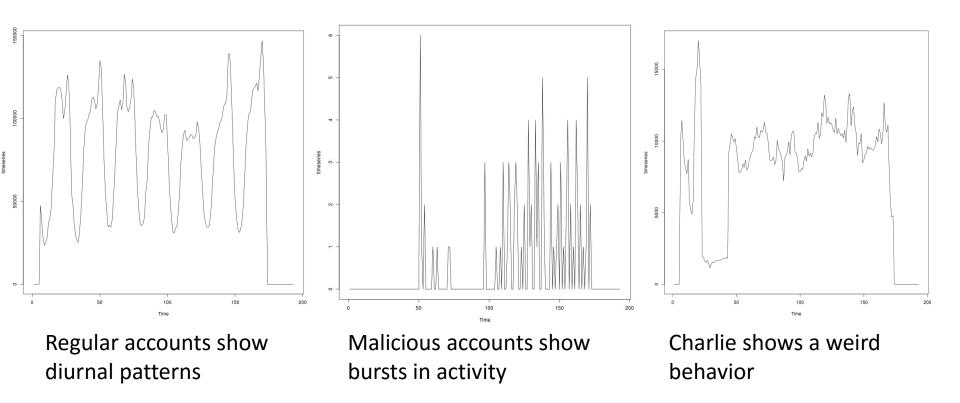
111k malicious accounts

Analysis of the results

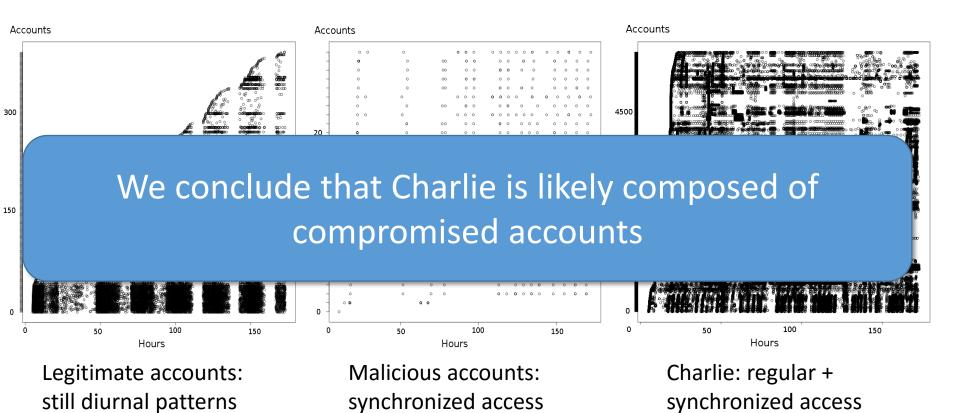
111k accounts formed 83 communities



Event-based time series



Account usage over time



EvilCohort: discussion

Service and activity independent

Accounts do not need to perform malicious activity to be detected

Our system detects botnet-like activity, legitimate accounts are unlikely to form communities

Limitations

- Only works on accounts accessed by multiple IP addresses
- Does not distinguish between fake and compromised accounts

Conclusions

I presented EvilCohort, a system that detects malicious accounts on online services by identifying communities of accounts that are accessed by a common set of IP addresses

We ran EvilCohort on two real-world datasets, and detected more than one million malicious accounts

Questions?

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