Detecting Credential Spearphishing Attacks in Enterprise Settings

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Spear Phishing

Targeted email that tricks victim into giving attacker privileged capabilities

Anthem Breach: Phishing Attack Cited

Phishing Campaigns Now Targeting Anthem Members

Russia-linked phishing the DNC breach also hit

Homeland Security Chief Cites Phishing As Top Hacking Threat

White House Hackers Used Spear-Phishing To Crack Unclassified Network

Hackers breached an unclassified computer network used by the White House, but did not appear to have stolen any data, a White House official said Monday.
Our Focus: Enterprise Credential Spearphishing

“Credentials are king”
- Rob Joyce, Director of NSA’s Tailored Access Operations

• Wealth of access & lower barrier than 0-day malicious attachments

• What about 2FA?
  • Cost, usability, incomplete deployment, often still phish-able

• Detection today: user reporting, phish-able 2FA, post-mortem forensics
Our Work

*Practical* detection system for an enterprise’s security team

1. Extremely low FP burden (Goal: < *minutes per day*)

2. Raises bar & detects many attacks, but *not* silver bullet
Our Work

Worked with the Lawrence Berkeley National Laboratory (LBL)
  • US DoE National Lab w/ 5,000 employees

Anonymized datasets:
  • SMTP header information (From and RCPT-TO headers)
  • URLs in emails
  • Network traffic logs
  • LDAP logs
Key Challenges

1. **Small set of labeled attack data**
   - < 10 known successful credential spearphishing attacks

2. **Base rate**
   - 372 million emails over 4 years (Mar 2013 – Jan 2017)
   - Even detector w/ 99.9% accuracy = 372,000 alerts
Structure-Driven Features
Spearphishing Attack Taxonomy

• Successful spearphishing attacks have two necessary stages:

1. The Lure
   • Successful attacks *lure/convince* victim to perform an action

2. The Exploit
   • Successful attacks execute some *exploit* on behalf of the attacker
   • Malware, revealing credentials, wiring money to “corporate partner”
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----BEGIN PGP SIGNED MESSAGE----
Hash: SHA1

_AirBears UID 1051850 will be blocked, per the SNS notice associated with tracking number [SNS #902375].

To avoid being blocked from the Airbears network, you must go to the link below and login with your Calnet id and password:

http://auth.berkeley.edu/cas/login/?service=https%3A%2F%2Fsecurity.berkeley.edu%2Flogin%2Fcasm

The blocking will be suspended if valid Calnet id and password have been provided no later than 23:59 on Mar 24.

System and Network Security

----BEGIN PGP SIGNATURE----
Version: GnuPG v2.0.22 (FreeBSD)

iD8JJIi1id+8923IjsdwWTf6yM0oJEjOljwenfiOlEIFFXOwefhliuuNSACeLXkaEJUyJEoe992webRAURx4xbx=6Nch
----END PGP SIGNATURE----
Modern Credential Spearphishing: The Lure

From: “Berkeley IT Staff” <security@berkeley.net>

Lure

1. Attacker sends catchy email under trusted/authoritative identity
Modern Credential Spearphishing: The Exploit

Exploit
1. Victim **clicks on embedded link**
2. Victim arrives at phishing website & submits credentials

Actual Destination for linked text: auth.berkeley.netne.net
Lure Features: Suspicious Sender Present

• Common lure: impersonate a trusted or authoritative entity

• Four “impersonation” classes - each has own set of lure features
  1. Name spoofing attacker
  2. Address spoofing attacker
  3. Previously unseen attacker
  4. Lateral attacker

• This talk: lateral attackers
Lure Features (Cont.): Suspicious Sender Present

• Lateral spearphishing lure: attacker compromises trusted entity’s account

• Feature intuition: email = suspicious if employee sent it during a suspicious login session

• **Lure** features for lateral spearphishing:
  • was email sent in a session where sender logged in w/ new IP address?
  • # prior logins by the sender from the geolocated city of login IP addr
  • # of other employees who’ve also logged in from city of login IP addr
Exploit Features: Suspicious Action Occurred

• **Winnow** pool of candidate alerts to:
  
  Emails where recipient clicked on embedded URL (a *click-in-email* action)

• **Exploit** features: URL’s **Fully-qualified domain** (hostname) is suspicious
  
  • # of prior visits to FQDN across all enterprise’s network traffic
  
  • # of days between 1st employee’s visit to FQDN & current email’s arrival
How do we leverage our features?

• Combine lure + exploit features to get FVs for emails

• How do we use these features for detecting attacks?

Approach 1: Manual rules
• Problems: soundly choosing thresholds & generalizability

Approach 2: Supervised ML
• Problems: tiny # of labeled attacks and base rate
Limitations of Standard Techniques

Approach 3: Unsupervised learning/anomaly detection

- Clustering/Distance Based: kNN
- Density-based: KDE, GMM
- Many others...

Three common problems:
1. Require hyperparameter tuning
Classical Anomaly Detection: Limitations

Three thematic problems:

1. Parametric and/or hyperparameter tuning

2. Direction-agnostic (standard dev of +3 just as anomalous as -3)

Feature:
# prior logins by current employee from city of new IP addr
Classical Anomaly Detection: Limitations

Three thematic problems:

1. Parametric and/or hyperparameter tuning
2. Direction-agnostic
3. Alert if anomalous in only one dimension
Classical Anomaly Detection: Limitations

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• **DAS**: *simple*, new method that overcomes these 3 problems
DAS: Directed Anomaly Scoring

1. Security analysts w/ limited time: specify $B = \text{alert budget}$

2. For set of events, assign each event a “suspiciousness” score

3. Rank events by their “suspiciousness”

4. Output the $B$ most suspicious events for security team
DAS: Directed Anomaly Scoring

- Score(Event X) = # of other events that are as *benign* as X in *every* dimension
- i.e., Large score = many other events are more benign than X
DAS: Directed Anomaly Scoring

- Score(Event X) = # of other events that are as **benign** as X in **every** dimension
DAS: Directed Anomaly Scoring

• Score(Event X) = # of other events that are as **benign** as X in **every** dimension
Detection Results

• Real-time detector on 370 million emails over ~4 years

• Ran detector w/ total budget of 10 alerts/day
  • Practical for LBL’s security team (~240 alerts/day typical)

• Detected 17 / 19 spearphishing attacks (89% TP)
  • 2 / 17 detected attacks were previously undiscovered

• Best classical anomaly detection: 4/19 attacks for same budget
  • Need budget >= 91 alerts/day to detect same # of attacks as DAS
Results: Cost of False Positives

- **10 alarms / day**: How much time does this cost the security team?

- LBL’s security staff manually investigated all our alerts
  - 24 alerts / minute (avg rate for one analyst)
  - **< 15 minutes** for 1 analyst to investigate alerts from an entire month

- Subject + URL + “From:” = quick semantic filter
  - “Never Lose Your Keys, Wallet, or Purse Again!”
  - “Invitation to Speak at Summit for Energy...”
Conclusion

• Real-time system for detecting credential spearphishing attacks
  • TP = 89%: detects known + previously undiscovered attacks
  • FP = 0.004%: 10 alerts / day (alerts processed in < minutes per day)

Key ideas
1. Leverage lure + exploit structure of spearphishing to design features
2. DAS: unsupervised, non-parametric technique for anomaly detection
   1. Generalizes beyond spearphishing
   2. “Needle-in-haystack” problems w/ curated & directional features

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