Detecting Spammers with SNARE: Spatio-temporal Network-level Automatic Reputation Engine

Shuang Hao, Nadeem Ahmed Syed, Nick Feamster, Alexander G. Gray, Sven Krasser
Spam: More than Just a Nuisance

Spam: unsolicited bulk emails

Ham: legitimate emails from desired contacts

• 95% of all email traffic is spam
  (Sources: Microsoft security report, MAAWG and Spamhaus)
  – In 2009, the estimation of lost productivity costs is $130 billion worldwide
    (Source: Ferris Research)

• Spam is the carrier of other attacks
  – Phishing
  – Virus, Trojan horses, ...

by S. Hao, N. A. Syed, N. Feamster, A. Gray, S. Krasser
Current Anti-spam Methods

• Content-based filtering: What is in the mail?
  – More spam format rather than text (PDF spam ~12%)
  – Customized emails are easy to generate
  – High cost to filter maintainers

• IP blacklist: Who is the sender? (e.g., DNSBL)
  – ~10% of spam senders are from previously unseen IP addresses (due to dynamic addressing, new infection)
  – ~20% of spam received at a spam trap is not listed in any blacklists
SNARE: Our Idea

- Spatio-temporal Network-level Automatic Reputation Engine
  - Network-Based Filtering: How the email is sent?
    - Fact: > 75% spam can be attributed to botnets
    - Intuition: Sending patterns should look different than legitimate mail
      - Example features: geographic distance, neighborhood density in IP space, hosting ISP (AS number) etc.
      - Automatically determine an email sender’s reputation
        - 70% detection rate for a 0.2% false positive rate
Why Network-Level Features?

• Lightweight
  – Do not require content parsing
    • Even getting one single packet
    • Need little collaboration across a large number of domains
  – Can be applied at high-speed networks
  – Can be done anywhere in the middle of the network
    • Before reaching the mail servers

• More Robust
  – More difficult to change than content
  – More stable than IP assignment
Talk Outline

- Motivation
- **Data From McAfee**
- Network-level Features
- Building a Classifier
- Evaluation
- Future Work
- Conclusion
Data Source

- McAfee’s TrustedSource email sender reputation system
  - Time period: 14 days
    October 22 – November 4, 2007
  - Message volume:
    Each day, 25 million email messages from 1.3 million IPs
  - Reported appliances
    2,500 distinct appliances (≈ recipient domains)
  - Reputation score: certain ham, likely ham, certain spam, likely spam, uncertain
Finding the Right Features

• Question: Can sender reputation be established from just a single packet, plus auxiliary information?
  – Low overhead
  – Fast classification
  – In-network
  – Perhaps more evasion resistant

• Key challenge
  – What features satisfy these properties and can distinguish spammers from legitimate senders?
Network-level Features

- Feature categories
  - Single-packet features
  - Single-header and single-message features
  - Aggregate features

- A combination of features to build a classifier
  - No single feature needs to be perfectly discriminative between spam and ham

- Measurement study
  - McAfee’s data, October 22-28, 2007 (7 days)
### Summary of SNARE Features

<table>
<thead>
<tr>
<th>Category</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Single-packet</strong></td>
<td>geodesic distance between the sender and the recipient</td>
</tr>
<tr>
<td></td>
<td>average distance to the 20 nearest IP neighbors of the sender</td>
</tr>
<tr>
<td></td>
<td>probability ratio of spam to ham when getting the message</td>
</tr>
<tr>
<td></td>
<td>status of email-service ports on the sender</td>
</tr>
<tr>
<td></td>
<td>AS number of the sender’s IP</td>
</tr>
<tr>
<td><strong>Single-header/message</strong></td>
<td>number of recipient</td>
</tr>
<tr>
<td></td>
<td>length of message body</td>
</tr>
<tr>
<td><strong>Aggregate features</strong></td>
<td>average of message length in previous 24 hours</td>
</tr>
<tr>
<td></td>
<td>standard deviation of message length in previous 24 hours</td>
</tr>
<tr>
<td></td>
<td>average recipient number in previous 24 hours</td>
</tr>
<tr>
<td></td>
<td>standard deviation of recipient number in previous 24 hours</td>
</tr>
<tr>
<td></td>
<td>average geodesic distance in previous 24 hours</td>
</tr>
<tr>
<td></td>
<td>standard deviation of geodesic distance in previous 24 hours</td>
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**Total of 13 features in use**
What Is In a Packet?

- Packet format (incoming SMTP example)

  - **IP Header**
    - Source IP, Destination IP
  - **TCP Header**
    - Destination port: 25
  - **SMTP**
    - Text Command
      - Empty for the first packet

- Help of auxiliary knowledge:
  - Timestamp: the time at which the email was received
  - Routing information
  - Sending history from neighbor IPs of the email sender
Sender-receiver Geodesic Distance

• Intuition:
  – Social structure limits the region of contacts
  – The geographic distance travelled by spam from bots is close to random
Distribution of Geodesic Distance

- Find the physical latitude and longitude of IPs based on the MaxMind’s GeoIP database
- Calculate the distance along the surface of the earth

90% of legitimate messages travel 2,500 miles or less

Observation: Spam travels further
Sender IP Neighborhood Density

**Features**
- Single-packet Based (2)

**Intuition:**
- The infected IP addresses in a botnet are close to one another in numerical space
- Often even within the same subnet

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Distribution of Distance in IP Space

- IPs as one-dimensional space (0 to $2^{32}-1$ for IPv4)
- Measure of email sender density: the average distance to its $k$ nearest neighbors (in the past history)

For spammers, $k$ nearest senders are much closer in IP space

• Observation: Spammers are surrounded by other spammers
Local Time of Day At Sender

- Intuition:
  - Diurnal sending pattern of different senders
  - Legitimate email sending patterns may more closely track workday cycles
Differences in Diurnal Sending Patterns

- Local time at the sender’s physical location
- Relative percentages of messages at different time of the day (hourly)

Observation: Spammers send messages according to machine power cycles
Status of Service Ports

- Ports supported by email service provider

<table>
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<th>Port</th>
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<td>SMTP</td>
<td>25</td>
</tr>
<tr>
<td>SSL SMTP</td>
<td>465</td>
</tr>
<tr>
<td>HTTP</td>
<td>80</td>
</tr>
<tr>
<td>HTTPS</td>
<td>443</td>
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</table>

- Intuition:
  - Legitimate email is sent from other domains’ MSA (Mail Submission Agent)
  - Bots send spam directly to victim domains
Distribution of number of Open Ports

- Actively probe back senders’ IP to check out what service ports open
- Sampled IPs for test, October 2008 and January 2009

90% of spamming IPs have none of the standard mail service ports open

Observation: Legitimate mail tends to originate from machines with open ports

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AS of sender’s IP

- Intuition: Some ISPs may host more spammers than others

- Observation: A significant portion of spammers come from a relatively small collection of ASes*
  - More than 10% of unique spamming IPs originate from only 3 ASes
  - The top 20 ASes host ~42% of spamming IPs

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**Total 13 features in use**

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SNARE: Building A Classifier

- RuleFit (ensemble learning)
  - \( F(x) = a_0 + \sum_{m=1}^{M} a_m f_m(x) \)
  - \( F(x) \) is the prediction result (label score)
  - \( f_m(x) \) are base learners (usually simple rules)
  - \( a_m \) are linear coefficients

- Example

<table>
<thead>
<tr>
<th>Rule</th>
<th>( F(x) )</th>
<th>( a_m )</th>
<th>( f_m(x) )</th>
</tr>
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<tbody>
<tr>
<td>Rule 1</td>
<td>0.080</td>
<td>0.080</td>
<td>Geodesic distance &gt; 63 AND AS in (1901, 1453, …)</td>
</tr>
<tr>
<td>Rule 2</td>
<td>+</td>
<td>0.257</td>
<td>Port status: no SMTP service listening</td>
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Feature instance of a message
Geodesic distance = 92, AS=1901, port SMTP is open
Talk Outline

• Motivation
• Data From McAfee
• Network-level Features
• Building a Classifier
• Evaluation
  – Setup
  – Accuracy
  – Detecting “Fresh” Spammers
  – In Paper: Retraining, Whitelisting, Feature Correlation
• Future Work
• Conclusion
Evaluation Setup

• Data
  – 14-day data, October 22 to November 4, 2007
  – 1 million messages sampled each day (only consider certain spam and certain ham)

• Training
  – Train SNARE classifier with equal amount of spam and ham (30,000 in each categories per day)

• Temporal Cross-validation
  – Temporal window shifting

Trial 1  Trial 2

Data subset
**Receiver Operator Characteristic (ROC)**

- False positive rate = Misclassified ham/Actual ham
- Detection rate = Detected spam/Actual spam
  (True positive rate)

FP under detection rate 70%

<table>
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<td><strong>Single Packet</strong></td>
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<tr>
<td><strong>24+ Hour History</strong></td>
<td>0.20%</td>
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**As a first of line of defense, SNARE is effective**

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Detection of “Fresh” Spammers

- “Fresh” senders
  - IP addresses not appearing in the previous training windows
- Accuracy
  - Fixing the detection rate as 70%, the false positive is 5.2%

SNARE is capable of automatically classifying ‘fresh’ spammers (compared with DNSBL)
Future Work

• Combine SNARE with other anti-spam techniques to get better performance
  – Can SNARE capture spam undetected by other methods (e.g., content-based filter)?

• Make SNARE more evasion-resistant
  – Can SNARE still work well under the intentional evasion of spammers?
Conclusion

- Network-level features are effective to distinguish spammers from legitimate senders
  - Lightweight: Sometimes even by the observation from one single packet
  - More Robust: Spammers might be hard to change all the patterns, particularly without somewhat reducing the effectiveness of the spamming botnets

- SNARE is designed to automatically detect spammers
  - A good first line of defense