New Approaches to Characterizing Scam-Hosting Connectivity

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Motivation

- 1. On-line scams (pharmacy sales, phishing sites) continually evolve
- Most recently, using multiple levels/ types of indirection (HTTP, DNS)
- Existing passive traffic analysis techniques rely on IP addresses, communication structure, redirection patterns, etc – can be evaded
- 4. Traffic characteristics should be agnostic to evasion

Experiment

- Web-crawl: Alexa Top 10K and 35K known-scam URLs from spam sink
- Record transport layer information of each HTTP GET (including redirections):
- Find statistical discriminators between scam and non-scam hosts

Facts

- 1. Prior work finds significant redirection and traffic proxying by botnets
- 2. Scam content hosted by bot CDNs and by countries with poor connectivity

Hypothesis

Transport-layer traffic analysis of intermediate and landing pages reveal poor connectivity?

How connected are scam servers?

Redirection Summary

- Scam URLs = 23,762, 1.45 per
- Non-Scam URLs = 3,075, 1.8 per
- Does redirection information still aid in discrimination?



- 1. We're agnostic to IP, DNS names, registrars, etc.
- 2. Collect Transport-layer traffic features that reveal:
 - Asymmetric bandwidth
 - Busy bots and/or poorly connected hosts
- 3. More detailed than NetFlow-style statistics:
- Retransmits (in/out)
- RSTs/FINs (in/out)
- Congestion Window (min, zero)
- 3WHS and per-segment RTT variance
- Packet inter-arrival jitter



Transport-Layer Features

- Very different distributions (scam/ non-scam) depending on redirection stage (initial, intermediate, terminal)
- Confirms previous observations that bots perform redirection



Minimum Congestion Window over Flow Lifetime

Classification

•Using data with 50% "good", 50% "scam":

Method	Acc	Sens	Spec	PPV	NPV
Bayes	0.760	0.715	0.808	0.795	0.731
SVM	0.874	0.816	0.935	0.929	0.830
Decision Tree	0.937	0.943	0.931	0.934	0.940

* Supported by: Cisco Systems Unive