

DETECTING MALICIOUS CLIENTS IN ISP NETWORKS USING HTTP CONNECTIVITY GRAPH AND FLOW INFORMATION

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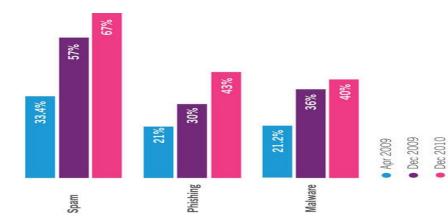
Introduction



- Malware is ...
 - Malicious software
 - Virus, Phishing, Spam, ...

Increasing threats

- 4500 new Web attacks launched per day (Symantec Security Report)
- Continuous and increased attacks on infrastructure
- Threats to business, national security
 - Huge financial stake (Conficker: 10 million machines, loss \$9.1 Billion)
 - Zeus: 3.6 million machines [HTML Injection]
 - Koobface: 2.9 million machines [Social Networking Sites]
 - TidServ: 1.5 million machines [Email spam attachment]
- Attacks are becoming more advanced and sophisticated!





Introduction

- Limitation of existing techniques
 - Signature-based approach
 - Fails to detect zero-day attacks.
 - Fails to detect threats with evolving capabilities such as metamorphic and polymorphic malwares.
 - Anomaly-based approach
 - Producing high false alarm rate.
 - Supervised Learning based approach
 - Poor performance on novel malware

There is no Silver Bullet

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Introduction



- However, the malware cannot hide the communication
 - We know who talks to whom (Connectivity Graph)
 - We can extract some information about what has been communicated

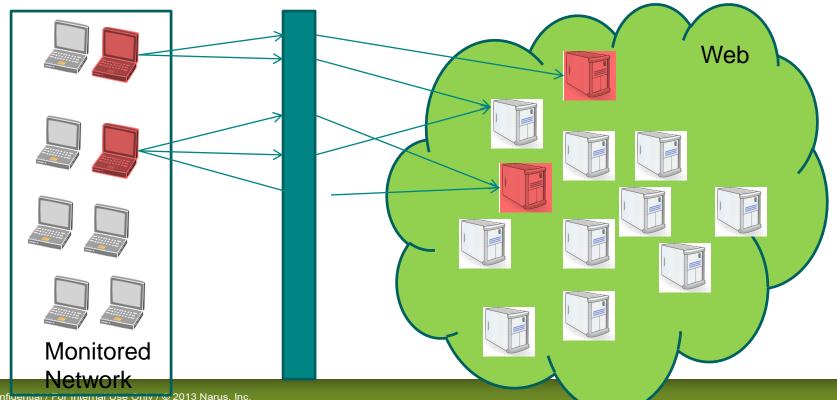
 Goal: Augment current security solutions using connectivity graph and flow information to find hidden malicious nodes

HTTP Connectivity



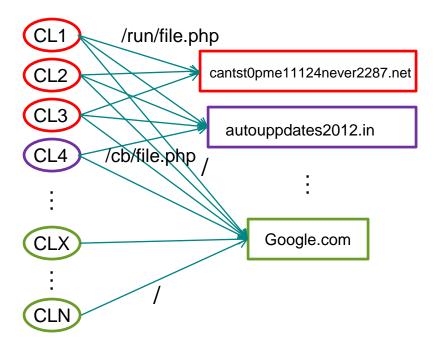
- We focus on HTTP Traffic
 - Most of the malwares are in HTTP







One Example



- CL1|cantst0pme11124never2287.net|/run/file.php
- CL1|google.com|/
- CL1|autouppdates2012.in|/cb/file.php
- CL2|cantst0pme11124never2287.net|/run/file.php
- CL2|google.com|/
- CL2|autouppdates2012.in|/cb/file.php
- CL3|cantst0pme11124never2287.net|/run/file.php
- CL3|google.com|/
- CL3|autouppdates2012.in|/cb/file.php
- CL4|google.com|/
- CL4|autouppdates2012.in|/cb/file.php
- CL5|google.com|/
- CLX|google.com|/
- CLN|google.com|/



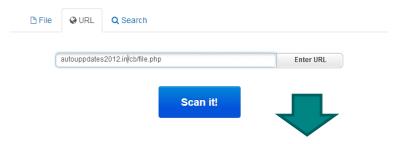
Our Approach

- We propose a two step malicious score propagation approach to identify other malicious nodes in the network
 - Initialize with the malicious nodes having a non-zero score and others having a zero score

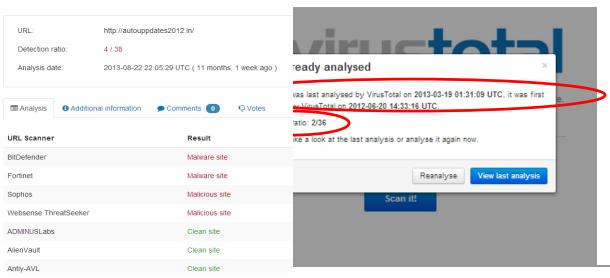


Virustotal

VirusTotal is a free service that **analyzes suspicious files and URLs** and facilitates the quick detection of viruses, worms, trojans, and all kinds of malware.



≥ virustotal

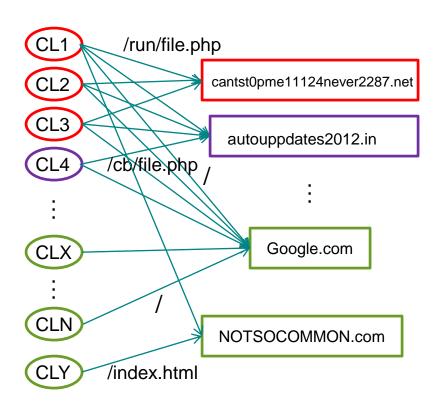


≥ virustotal

URL:	http://autouppdates2012.in/cb/file.php					
Detection ratio:	2/36					
Analysis date:	2013-03-19 01:31:09 UTC (1 year, 4 months ago)					
■ Analysis						
URL Scanner	Result					
Fortnet	Malware site					
Sophos	Malicious site					
ADMINUSLabs	Clean site					
AlienVault	Clean site					
Antiy-AVL	Clean site					
Avira	Clean site					



Example Contd.



- CL1|cantst0pme11124never2287.net|/run/file.php
- CL1|google.com|/
- CL1|autouppdates2012.in|/cb/file.php
- CL2|cantst0pme11124never2287.net|/run/file.php
- CL2|google.com|/
- CL2|autouppdates2012.in|/cb/file.php
- CL3|cantst0pme11124never2287.net|/run/file.php
- CL3|google.com|/
- CL3|autouppdates2012.in|/cb/file.php
- CL4|google.com|/
- CL4|autouppdates2012.in|/cb/file.php
- CL5|google.com|/
- CLX|google.com|/
- CLN|google.com|/
- CL1|NOTSOCOMMON.com|index.html
- CLY|NOTSOCOMMON.com|index.html

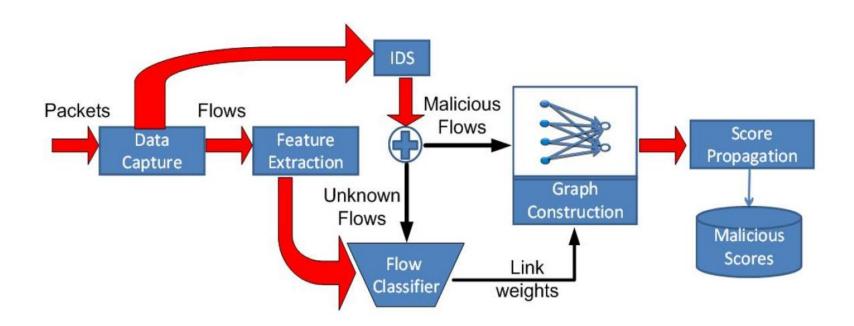


Our Approach

- We weigh the edges of the graph using malicious flow similarity
 - If the flow through the edge has any similarity with the malicious flows in the data
 - Used a SVM based classifier with 270 flow-based features
- Then use the same two step malicious score propagation approach to identify other malicious nodes in the network

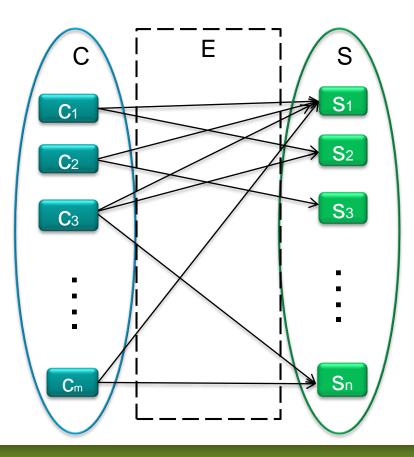


System Architecture





HTTP Graph Construction



- HTTP bipartite graph
 - G = ((C,S),E) denote a directed graph constructed from the HTTP connections
 - C, set of client IP addresses
 - S, set of server IP addresses
 - E, set of directed links



Two-phase Alternating Score propagation

Objective Function

$$Q(\mathbf{y}) = \frac{1}{2} \sum_{ij} W_{ij} \left[\frac{y_i}{\sqrt{D_{ii}}} - \frac{y_j}{\sqrt{D_{jj}}} \right]^2 + \frac{\mu}{2} \sum_i (y_i - y_i^{(0)})^2$$

Where **W** is a adjacency matrix, and **D** is a diagonal matrix whose diagonal elements are given by $D_{ii} = \sum_{j} W_{ij}$

Our objective can be reduced to:

$$x_{i} = (1 - \beta_{s})x_{i}^{0} + \beta_{s} \sum_{k \in C} w_{ki}^{cs} y_{k}$$
 (1)
$$y_{k} = (1 - \beta_{c})y_{k}^{0} + \beta_{c} \sum_{j \in S} w_{jk}^{sc} x_{j}$$
 (2)

 Iteratively updating the malicious score based on its initial value and weighted average of scores for its neighbors until convergence



Two-phase Alternating Score propagation

 Link-only: the weight of a link depends on the existence of a flow between the node pair

$$w_{ij}^{(l)} = \begin{cases} 1, & \text{if } (v_i, v_j) \in \mathcal{E} \text{ (or } \pi_{ij} \neq \emptyset); \\ 0, & \text{otherwise.} \end{cases}$$

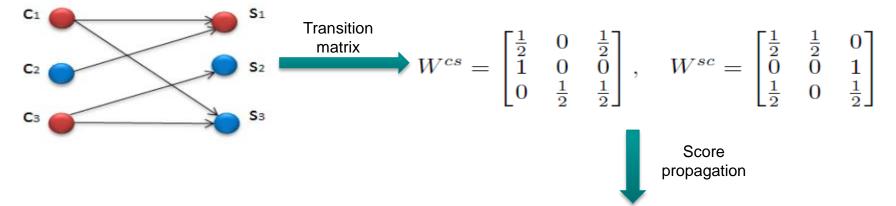
Normalizing the link weight by its out-degree:

$$\hat{\mathbf{W}}_{ij} = \frac{w_{ij}}{\sum_{j} w_{ij}}$$



Two-phase Alternating Score propagation

Example



node	initial score	iteration 1	iteration 2	iteration 3
c_1	1	0.7556	0.7230	0.7220
c_2	0	0.2444	0.2981	0.3222
c_3	1	0.8725	0.8485	0.8253
s_1	1	0.575	0.6165	0.6529
s_2	0	0.425	0.4346	0.4258
s_3	0	0.85	0.8195	0.7908

HTTP Flow Features



SessionID|SourceIP|DestIP|1314281856|example.com|mozilla/2.0||||0|1|1|0|63973|80|477|1628|189|1460|7|4| 1|/blog/images/3521.jpg||GET|tq=RA1DQxZBDVIUFQN0AQUDAh|57|200 OK|image/jpeg|190984||

- Hostname
 - Length of the second domain
 - Randomness of the second domain
 - Is it a IP address?
 - Reliability score from .com, .info, etc.
 Etc.
- User agent
- URI
 - Keywords separated by delimiters
 - Length of the URI
 - # of fields
- Referrer
- Method (GET, POST)

- Additional parameters
 - -Length of the first key, value (categorical)
 - (For each key-value pair) characters, numbers or mix
- Server status
- Content type
- Error on request
- Number of requests
- Number of URLs requested in a session
- Number of pages requested in a session
- Bytes Sent
- Bytes Received
- Data sent, Data received, Pkts sent, Pkt rcvd
- Response time
- Bytes transferred
- Content length



Flow Classification

Classifying from malicious and unknown flows

$$\min_{\omega,b} \quad \frac{1}{2}\omega^T \omega + C^l \sum_{i=1}^{k-1} \xi_{i^l} + C^u \sum_{j=k}^{m} \xi_{j^u}$$
subject to
$$y_{i^l}(\omega^T \phi(x_{i^l}) + b) \ge 1 - \xi_{i^l}$$

$$y_{j^u}(\omega^T \phi(x_{j^u}) + b) \ge 1 - \xi_{j^u}$$

$$\xi_{i^l} \ge 0, i = 1, 2, \cdots, k - 1$$

$$\xi_{j^u} \ge 0, j = k, k + 1, \cdots, m$$

Cost for misclassifying malicious flows

Cost for misclassifying unknown flows

in which, assigning $C^l > C^u$ could guide the classifier towards classifying more accurately flows that belong to malicious class.



Flow-based Graph Construction

Combining Flow information and Link structure:

– The weight of a link is determined from its malicious score:

$$w_{ij}^{(f)} = \begin{cases} 1, & \text{if } \exists f_{ijk} \in \pi_{ij} : \mathcal{I}(f_{ijk}) = 1; \\ \max_{\sigma_k \in \Sigma_{ij}} \{\sigma_k\}, & \text{otherwise.} \end{cases}$$

- Link is associated with set of flows $\pi_{ij} = \{f_{ij1}, f_{ij2}, \cdots, f_{ij|\pi_{ij}|}\}$ $\Sigma_{ij} = \{\sigma_1, \sigma_2, \cdots, \sigma_{|\pi_{ij}|}\}$ corresponding outputs of flow classifier
- If the malicious score for the link from IDS is 1, we set the weight of the edge as 1
- Otherwise, we set it to the maximum value of the flow classification



Experimental Settings

Data Sets

Four 1-hour data sets, which we name D1~D4,
 more detailed information in following table.

Datasets D1 \sim D4

Data set	Time of day	Number of	Number of	Number of malicious	Number of malicious
		HTTP flows	labeled flows	clients/ Total number	servers/ Total number
				of clients	of servers
D1	4 pm	1926620	1088	26/5856	25/25627
D2	6 pm	973271	1649	30/6533	25/26346
D3	7 pm	1033292	1736	26/7360	22/26216
D4	9 pm	1078765	65	21/7936	23/27518

Used a commercial IDS to identify flag malicious flows



Experimental Evaluation

- Validation
 - To validate a predicted client, which receives a high propagation score, we check if this client connects to any malicious web server
 - To validate the web server
 - Google SafeBrowsing, Malware Blacklists
 - WOT (Web of Trust) score



Experimental Evaluation

- Metric
 - The precision of top n ranking clients is used to indicate the final performance.

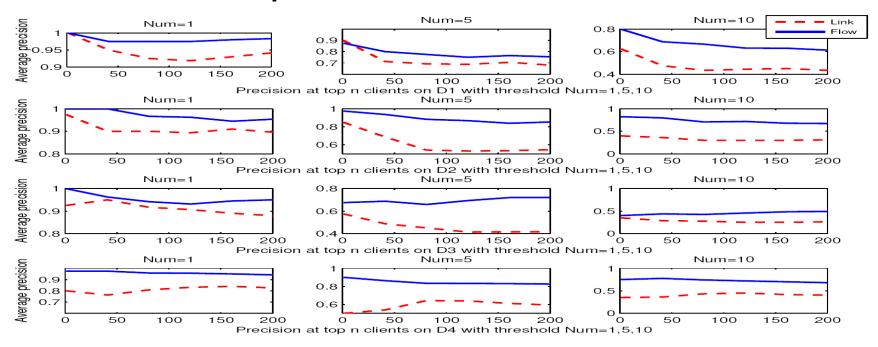
$$P@n = \frac{num(TM)}{n}$$

 Num(TM) is the number of true malicious clients show up in top n clients. We report the precision from p@1 to p@1000.



Results

Results Comparison for All Clients

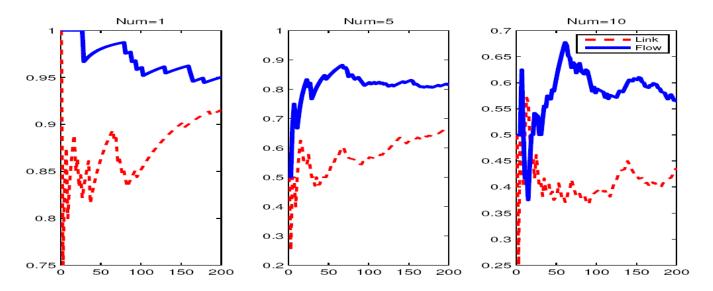


Precision at top n clients on D1 ~ D4 with threshold Num = 1,5,10



Results

 Results of Clients that are indirectly Connect to Malicious nodes



Precision at top n highest ranked clients that are indirectly connected to malicious hosts



Conclusion

- Proposed a method that combine the links and flow-level information in the HTTP communication graph for malicious clients detection
- Proposed an efficient two-phase score propagation algorithm to identify malicious clients
- Experimental results on large ISP data verified that our proposed method could detect clients that infected with known/new malwares



Future Work

- Extent the framework beyond HTTP traffic
 - Flow features will change
- To be added



Thank You

Future Work

- Validate with diverse data sets
- Propagating malicious score for server by treating each URL as a node instead of server IP.
- Consider the hidden connections in URL-URL connectivity graph.