Beyond the blacklists: Detecting malicious URL through machine learning

Hao Dong, Jin Shang, David Yu, Chenghuai Lu

Hillstone Networks

About Us

Hao Dong

- Senior Principle Engineer
  @Hillstonenet.com
- Interested in computer system and network security

Jin Shang, Ph.D.

- Chief Scientist & Fellow
  @Hillstonenet.com
- Marathon Runner In-Training

Hillstone™ NETWORKS

About Us

David Yu

- Distinguished Engineer @Hillstone Networks
- BS and MS in Electrical & Computer Engineering
- Over 20 years experiences in computer networking and security industry

Chenghuai Lu

- Senior Principle Engineer
  @Hillstonenet.com
- Lead efforts in defending against advanced threats in next generation firewall
- Afternoon Tea Party Ping Pong Champion

Hillstone™ NETWORKS

Agenda

- Introduction and Problem Overview
- Malicious HTTP Traffic Detection Methods
- Machine Learning Techniques
- The Results
- Beyond the Malicious URL
- Black Hat Sound Bytes
- Q & A

Introduction

- Hillstone is recommended by NSS lab NGFW test with the best values, but today we talk about the research beyond the NGFW
- Network security defense technology evolution

- Intelligent technologies
  - ❑ Algorithms: Data Analysis, Machine Learning, Anomaly Behavior, …
  - ❑ Modeling: Feature set, customized Model, cloud computing
  - ❑ Product: False Positive & Negative, Forensic, Mitigation

Introduction

- Our thoughts:
  - ❑ iNGFW engines: Intelligent + NGFW
  - ❑ Deploy in perimeters and inside networks
  - ❑ Enhance the defense architecture
    - ➢ Suspicious event detection using AI: DGA, malicious URL, abnormal network behavior
    - ➢ Multi Layer Correlation among iNGFW to improve false positive/negatives

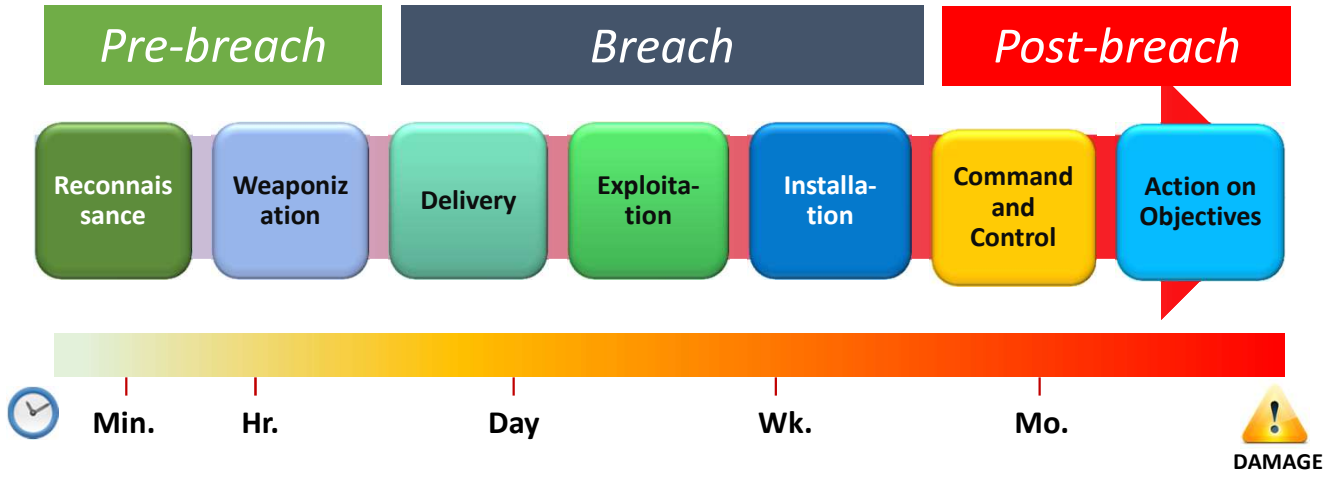
Today, we present one of the best ML work:

malicious URL detection with ML

Overview

WHAT: *Problem to Solve*

- To detect malicious URL connections, esp. in **post-breach** advanced threat protection.



Overview

- **Post-breach detection**
  - ❑Limitation of signature based blacklist
  - ❑To know unknowns from knowns

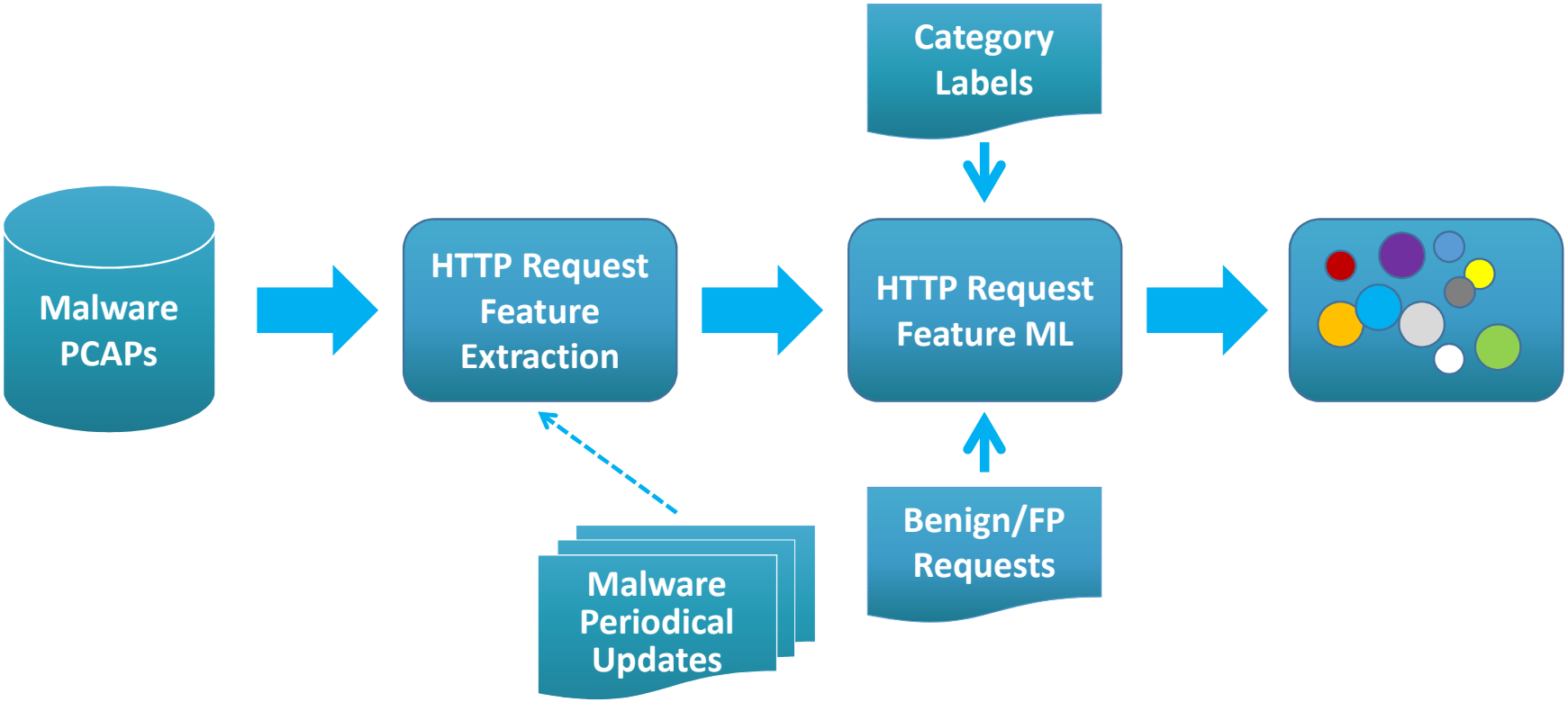
> *“There are known knowns. These are things we know that we know. There are known unknowns. That is to say, there are things that we know we don't know. But there are also unknown unknowns. There are things we don't know we don't know.”*
>
> -- Donald Rumsfeld

Overview

HOW: *Explore machine learning technology*

- Predict malicious connection with knowledge learned from existing ones
- Based on URL lexical features
  - ❑Not by page content
  - ❑Focus on solving URL parameters complex issues
  - ❑Catch commonalities and be generic enough to detect variants

Overview

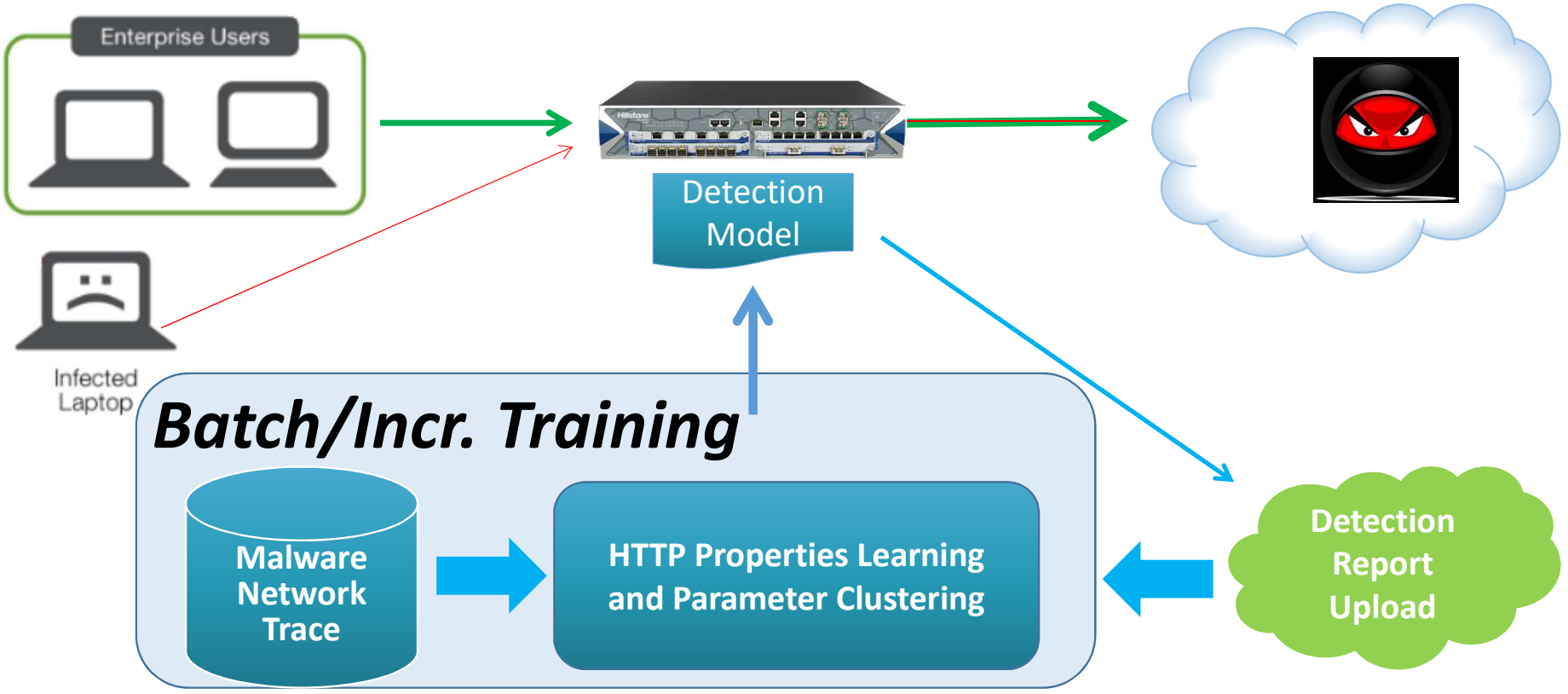

Category Labels
Malware PCAPs
HTTP Request Feature Extraction
HTTP Request Feature ML
Malware Periodical Updates
Benign/FP Requests

Overview

WHERE: *Model build and deployment*

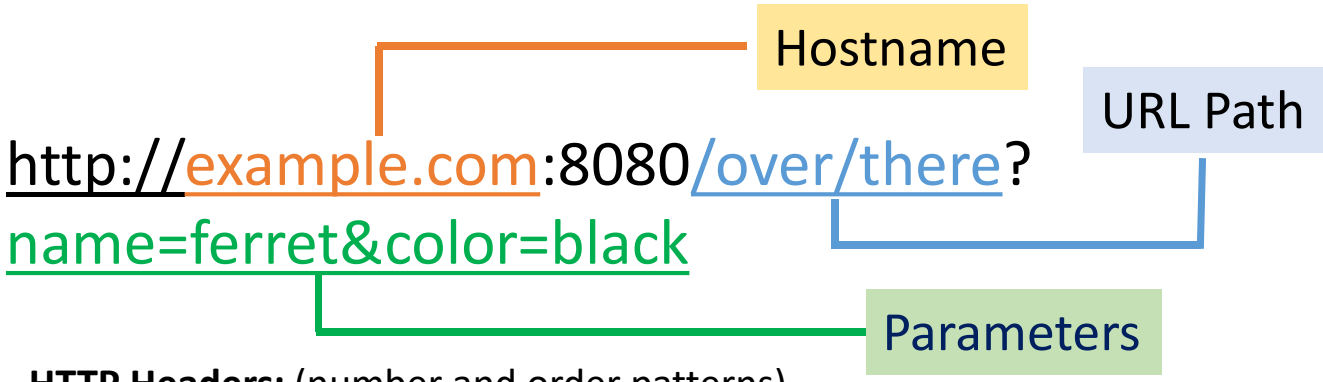
- Network-level detections
- Flexible deployment
  - ❑Network perimeter firewall appliance
  - ❑Server-centric intranet breach detection
- Constantly model update with incoming threat intelligences, user feedbacks and global correlations.

Overview


Enterprise Users
Infected Laptop
Detection Model
Batch/Incr. Training
Malware Network Trace
HTTP Properties Learning and Parameter Clustering
Detection Report Upload

HTTP detection modules

- **User-Agent**
- **Host Domain Name**
- **URL Path**
- **URL Parameters**
- **HTTP headers patterns**



HTTP Headers: (number and order patterns)

Content-Type:
application/x-www-form-urlencoded

Origin:
https://www.youtube.com

Referer:
https://www.youtube.com/embed/LSPJaxHMam4

User-Agent:
Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537..

Put URL Under Microscope

- **Host Domain Name**
  - ❑Known malicious domains
  - ❑DGA (Domain generation algorithms)
- **User-Agent**
  - ❑Known signatures
- **URL Path**
  - ❑http://surusegitimmerkezi.com/administrator/components/com_akeeba/akeeba/engines/proc/mzsystem.php (from ransomware tracker)
- **URL parameters**
  - ❑http://malwaresite.com/contact/info?id=1234&os_type=linux&ver=3.0&state=1
  - ❑Dynamic, extremely large amount of texts hard for efficient signatures

Put URL Under Microscope

HTTP Headers Pattern (browser finger print)

- ❑Mostly useful to reduce false positive
  - ➢ Based on common http header fields
  - ➢ Number of fields and order of fields of common web browsers
- ❑Observations
  - ➢ Malicious connection tend to have less number of header fields
  - ➢ Typical web browser traffic have fixed set of headers and orders
- ❑So we set rules
  - ➢ Threshold number of header fields
  - ➢ Order of header fields match common web browsers

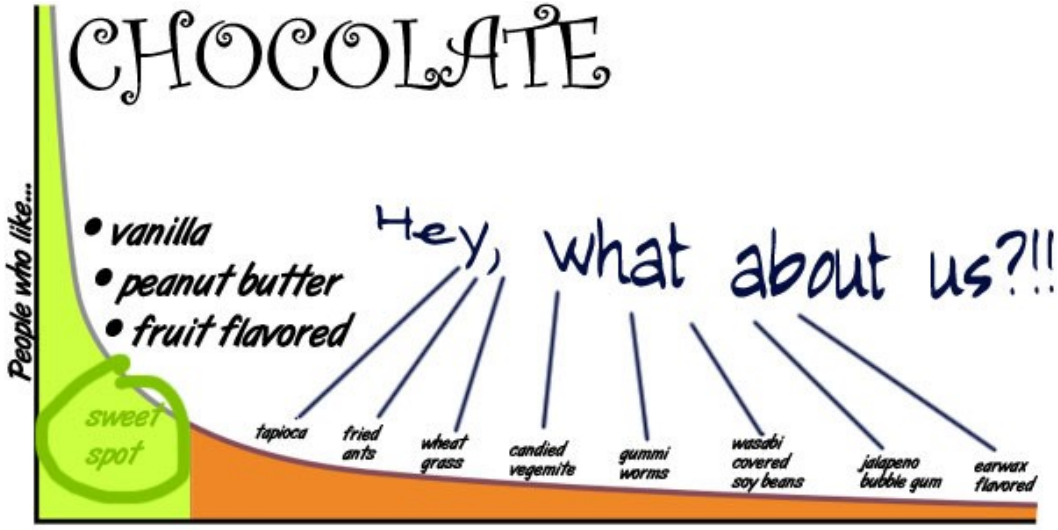
ACCEPT	text/html,application/xhtml+xml,application/xml;q=0.9,image/webp,*/*;q=0.8
ACCEPT_ENCODING	gzip, deflate, sdch, br
ACCEPT_LANGUAGE	en-US,en;q=0.8
CONNECTION	keep-alive
DNT	1
HOST	www.whatismybrowser.com
REFERER	https://www.google.com/
USER_AGENT	Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537…
COOKIE	…

URL Parameter Features

- Challenges:
  - ❑Dynamic, huge amount of text strings and keep increasing
- We treat parameters as collection of key/value pairs
  - ❑param_name=param_value is a feature
  - ❑Unlimited amount of strings, means high number of feature dimensions
- The way to reduce dimensions:
  - ❑Sorting method vs. hashing

URL Parameter Features

- Sorting method
  - ❑Parameters sorted by hit numbers (total hits, malware hits, etc.)
  - ❑Select top N as feature set

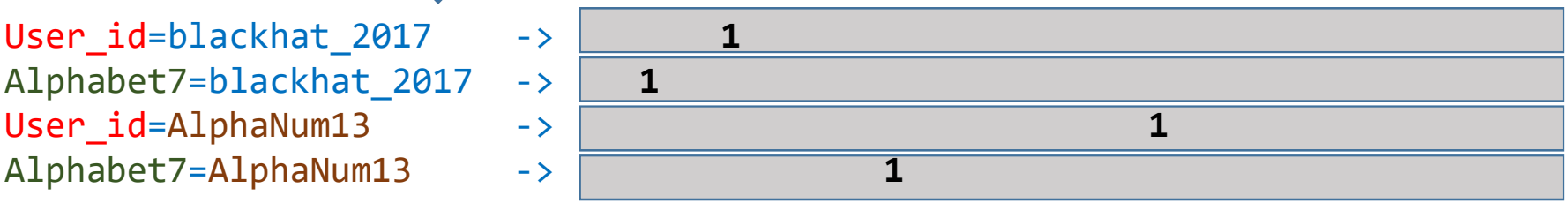


URL Parameter Features

- Hashing method
  - ❑Fixed size of feature space
  - ❑Transform a parameter to multiple features to emphasize field weight
  - ❑Expand features using combinations of field value, type and length
    - ➢ Numeric - 123456
    - ➢ Alphabets - abcdefg
    - ➢ NumAlpha - abc123
    - ➢ Base64 - d2VsY29tZSBibGFja2hhdCBhdHRlbmRlZXMh
    - ➢ Etc.

Transforming parameters

User_id=blackhat_2017

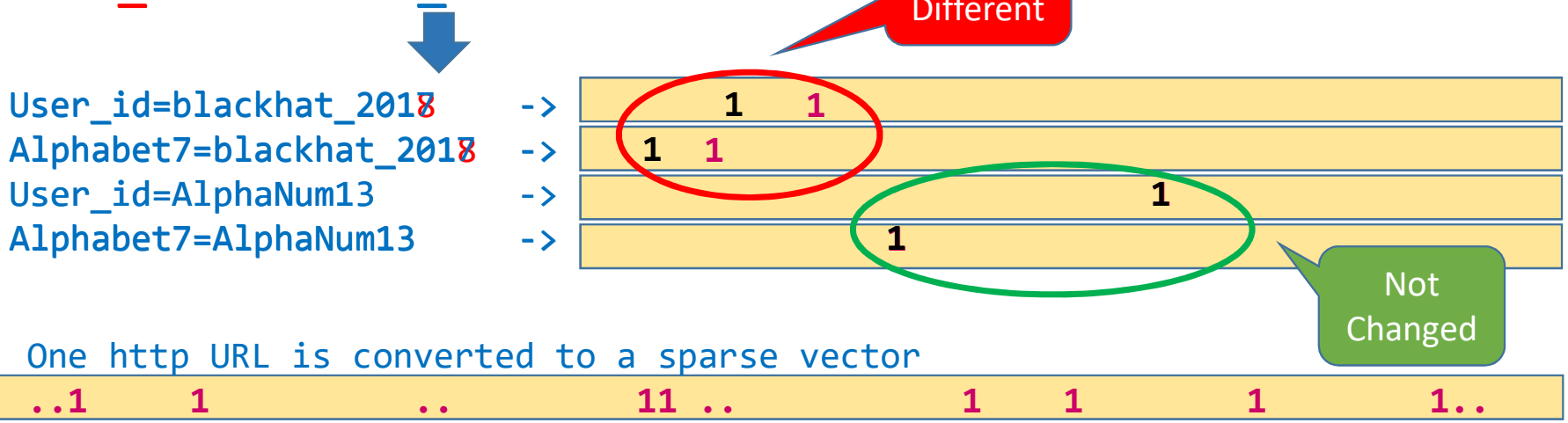


One http URL is converted to a sparse vector

Feature Space

Transforming parameters

User_id=blackhat_2018



One http URL is converted to a sparse vector

..1 1 .. 11 .. 1 1 1 1..

Feature Space

Machine Learning

- HTTP URL collections
  - ❑From malware network trace PCAPs
  - ❑From clean legitimate traffic collections
- Choose learning method
  - ❑Supervised vs. Unsupervised
  - ❑Pros and Cons

Supervised Machine Learning

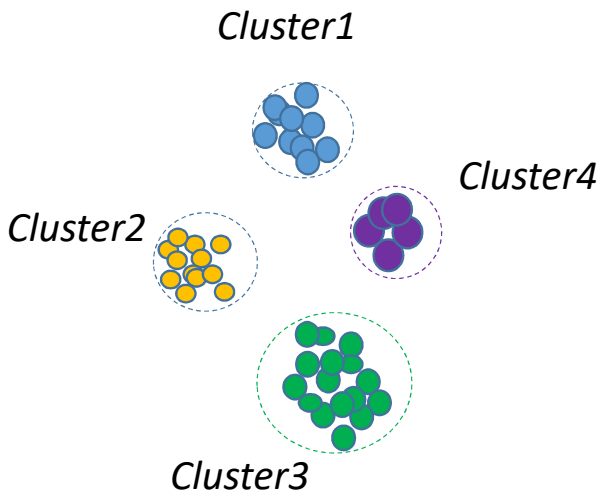
Supervised learning is the machine learning task of inferring a function from *labeled training data*.[1] The training data consist of a set of *training examples*. In supervised learning, each example is a *pair* consisting of an input object (typically a vector) and a desired output value (also called the *supervisory signal*). A supervised learning algorithm analyzes the training data and produces an inferred function, which can be used for mapping new examples. An optimal scenario will allow for the algorithm to correctly determine the class labels for unseen instances. This requires the learning algorithm to generalize from the training data to unseen situations in a "reasonable" way (see inductive bias).

Un-supervised Clustering

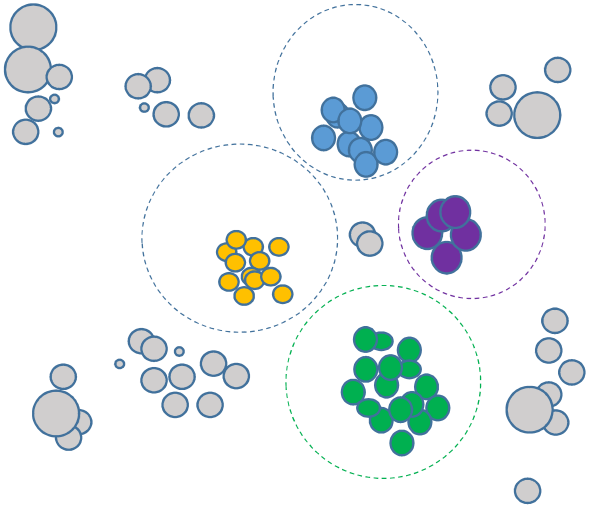
Cluster analysis or **clustering** is the task of grouping a set of objects in such a way that objects in the same group (called a **cluster**) are more similar (in some sense or another) to each other than to those in other groups (clusters). It is a main task of exploratory data mining, and a common technique for statistical data analysis, used in many fields, including machine learning, pattern recognition, image analysis, information retrieval, bioinformatics, data compression, and computer graphics.

ML Methods Comparison

Unsupervised Clustering



Supervised Machine Learning

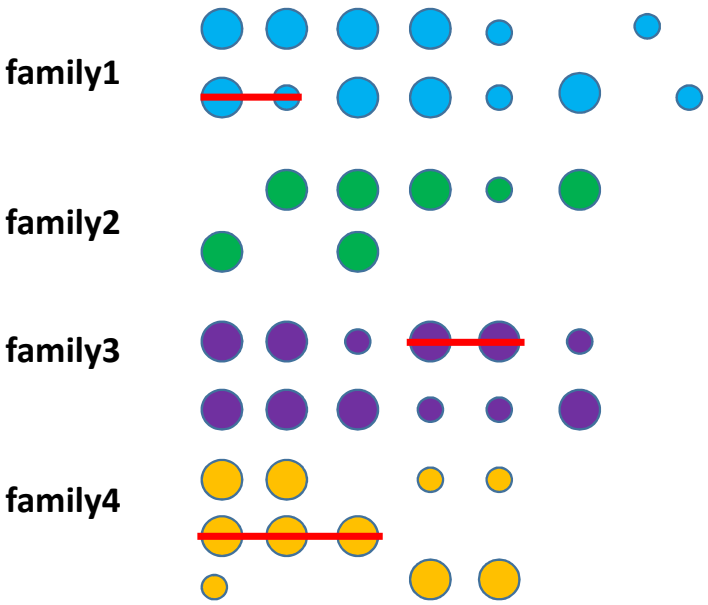


Benign

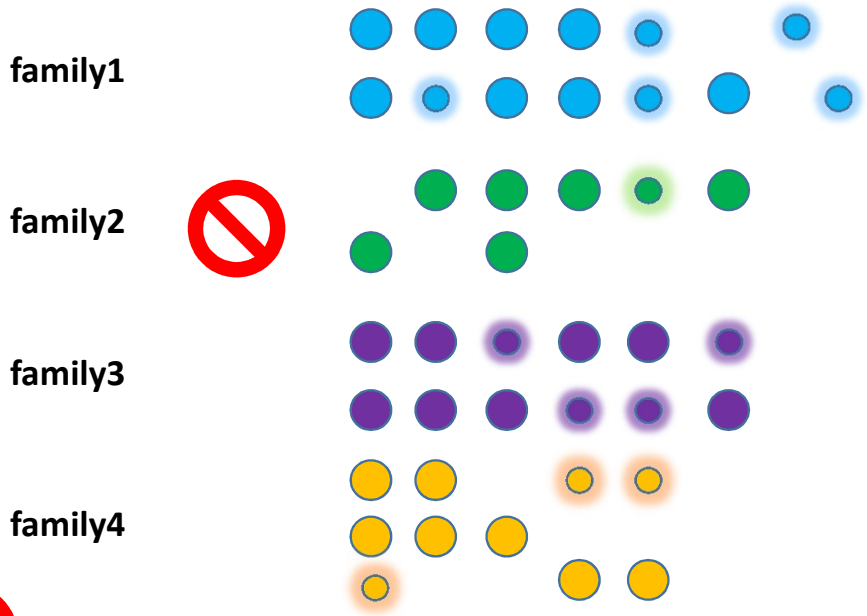
Malicious

ML Methods Comparison

Adjust models with false positive feedbacks



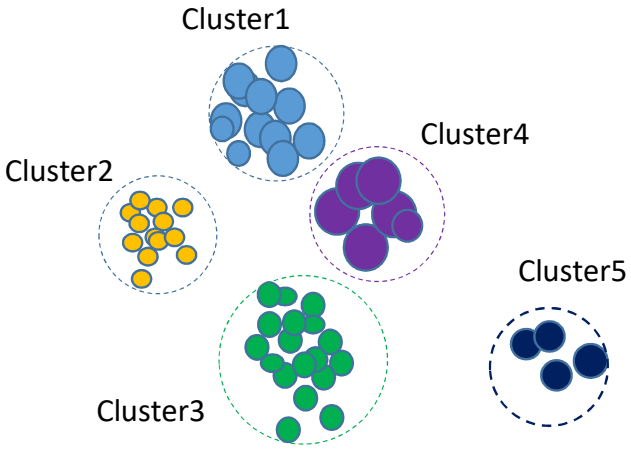
Hard to change models. Need take feedback and re-learn. Or use whitelist



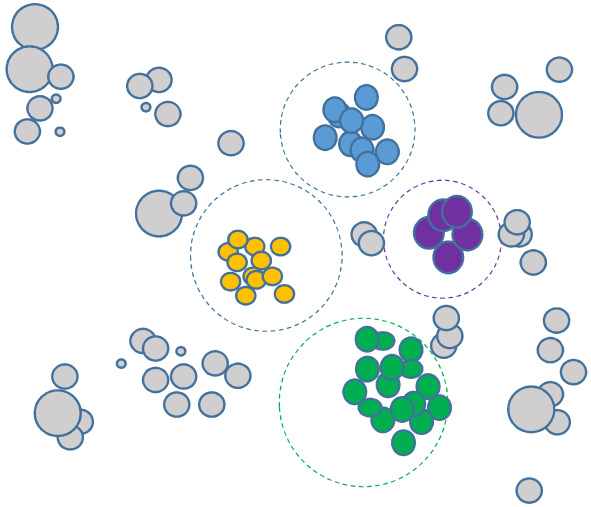
Whitelist to bypass

ML Methods Comparison

Easy for incremental update (add and remove)



Add new data and labels, and re-learn the whole model



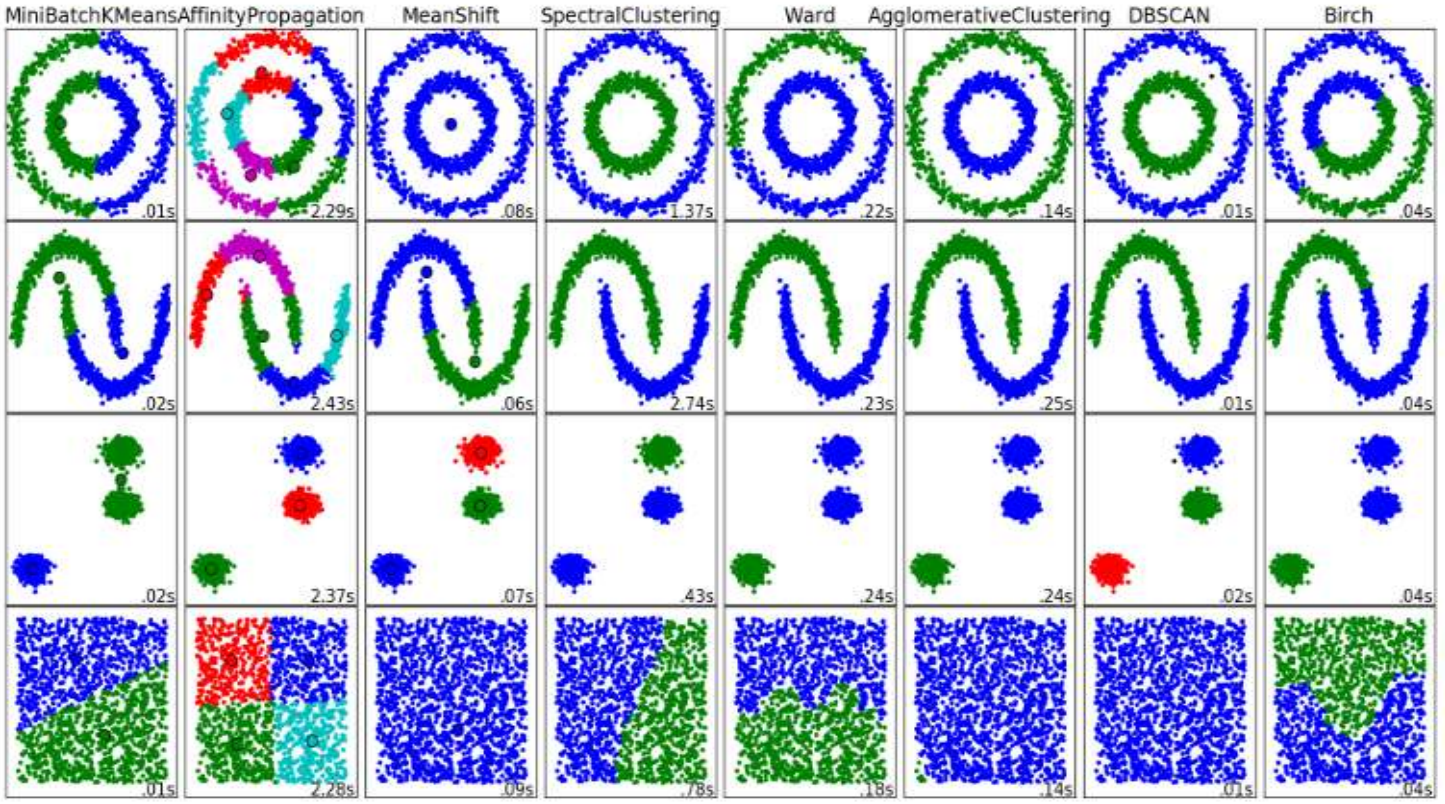
ML Methods Comparison

- **Supervised ML**
  - ❑Logistic Regression. Small model size, good for binary classification, e.g. black and white
  - ❑Random Forrest. Big model size, good result for multi-family classification
  - ❑Ground truth labeling of malware family is important. Model can be biased
- **Unsupervised ML**
  - ❑Need only malware (black) samples. Good to find common similarities
  - ❑Sample noises (mislabeling) can be mitigated
  - ❑Benign (white) samples are not needed in learning, but for clusters cleanup (pruning)
  - ❑True positive is easy to explain
- We chose semi-supervised clustering method for our work
  - ❑Clustering of labeled data

A comparison of the clustering algorithms

Method name	Parameters	Scalability	Usecase	Geometry (metric used)
K-Means	number of clusters	Very large n_samples, medium n_clusters withMiniBatch code	General-purpose, even cluster size, flat geometry, not too many clusters	Distances between points
Affinity propagation	damping, sample preference	Not scalable with n_samples	Many clusters, uneven cluster size, non-flat geometry	Graph distance (e.g. nearest-neighbor graph)
Mean-shift	bandwidth	Not scalable with n_samples	Many clusters, uneven cluster size, non-flat geometry	Distances between points
Spectral clustering	number of clusters	Medium n_samples, small n_clusters	Few clusters, even cluster size, non-flat geometry	Graph distance (e.g. nearest-neighbor graph)
Ward hierarchical clustering	number of clusters	Large n_samples and n_clusters	Many clusters, possibly connectivity constraints	Distances between points
Agglomerative clustering	number of clusters, linkage type, distance	Large n_samples and n_clusters	Many clusters, possibly connectivity constraints, non Euclidean distances	Any pairwise distance
DBSCAN	neighborhood size	Very large n_samples, medium n_clusters	Non-flat geometry, uneven cluster sizes	Distances between nearest points
Gaussian mixtures	many	Not scalable	Flat geometry, good for density estimation	Mahalanobis distances to centers
Birch	branching factor, threshold, optional global clusterer.	Large n_clustersand n_samples	Large dataset, outlier removal, data reduction.	Euclidean distance between points

A comparison of the clustering algorithms

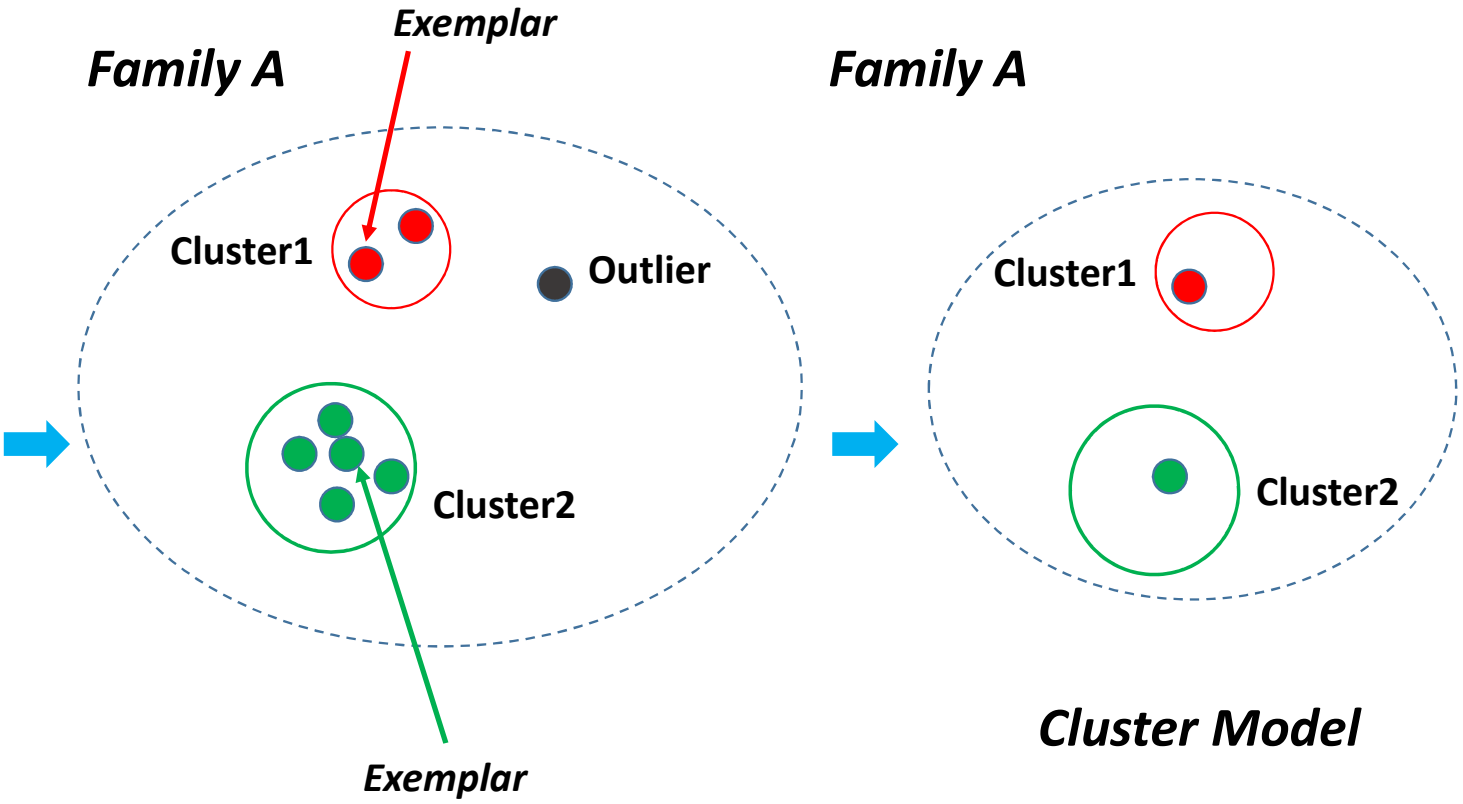


Clustering Method

- Coarse-grained grouping by malware families
- Fine-grained clustering within families based on URL parameters
  - ❑Feature vectors
- Clustering algorithm
  - ❑Similarity, Distance (or cost) function $D_{i,j} = f(V_i, V_j)$
  - ❑Algorithm: K-mean, DBScan
  - ❑Minimal number of URLs in a cluster and distance threshold
  - ❑Auto removal of noises
  - ❑Cluster centroid representation (picking an exemplar)

●	1 11 1 111 1…
●	11 1 1 1 1…
●	11 11 1 1 …
●	1111 1 1…
●	1 1 1 11 1…
●	1 1 1 111 …
●	1111 11 …
●	1 1 1 11 1…

Feature Matrix

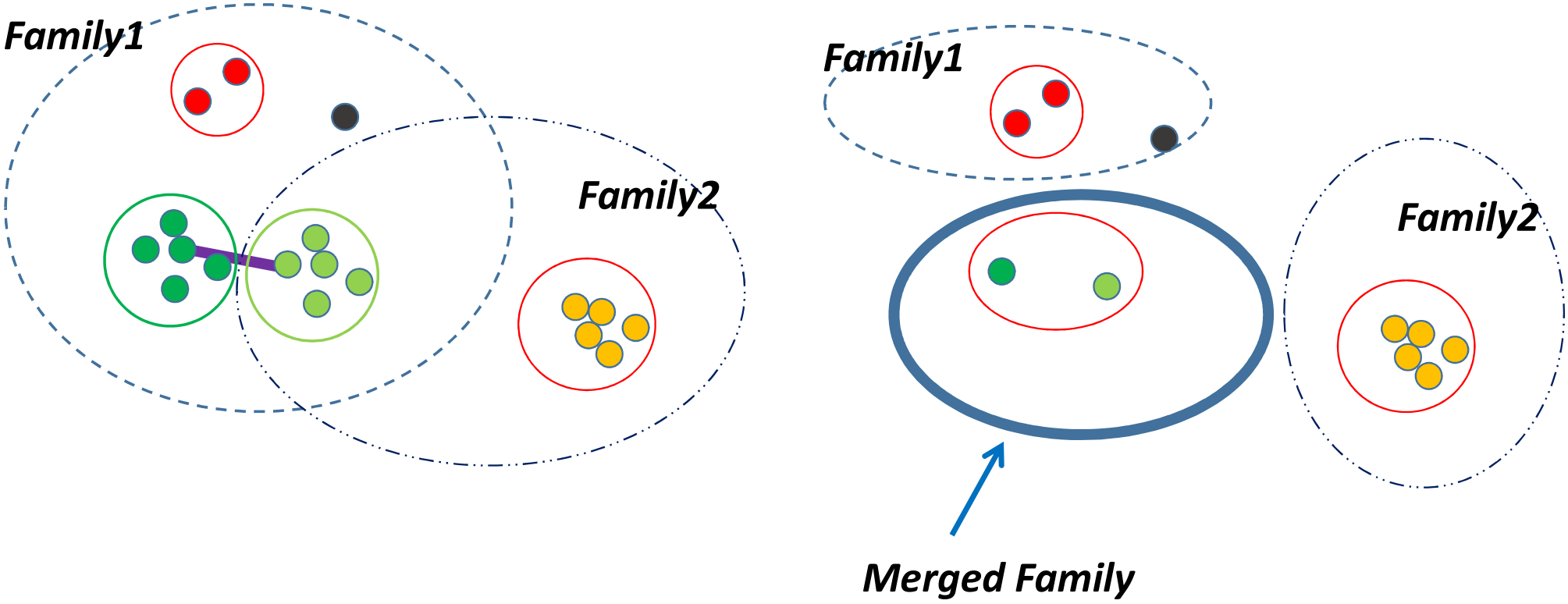


● *Sample feature vector*

Clustering Method

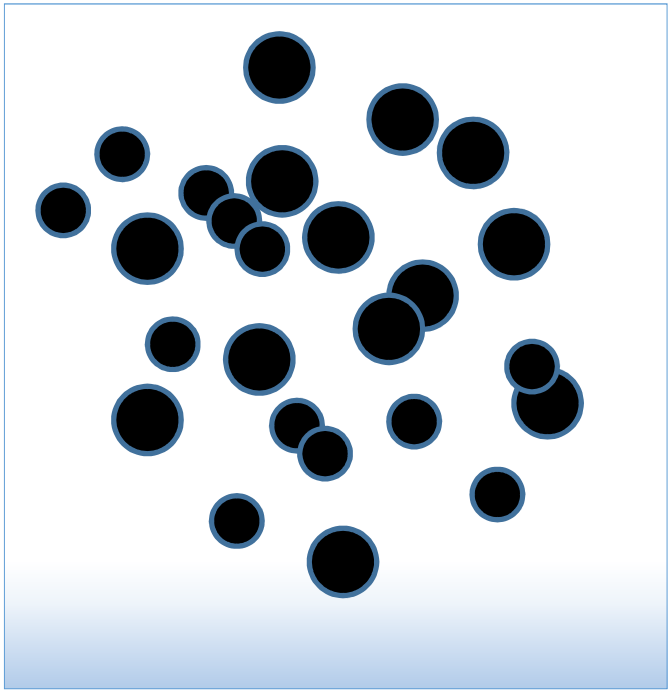
- Cross-family clusters merge
  - ❑The intuition: code re-use in malware
  - ❑For collection of cluster exemplars, do a second-round clustering.
  - ❑For example, f1c1, f1c2, f2c1, f3c1, f4c1, f4c2, are six clusters from families f1, f2, f3, f4.
  - ❑Cluster centroids can be further merged to (f1c1, f2c1, f4c2), (f1c2), (f3c1, f4c1) three clusters
  - ❑Reduce redundancy

Cross-Family Cluster Merging

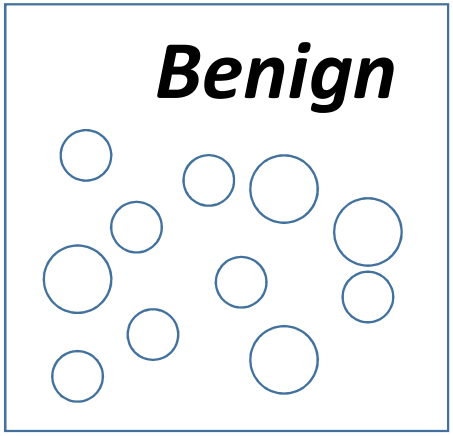


Clustering Method

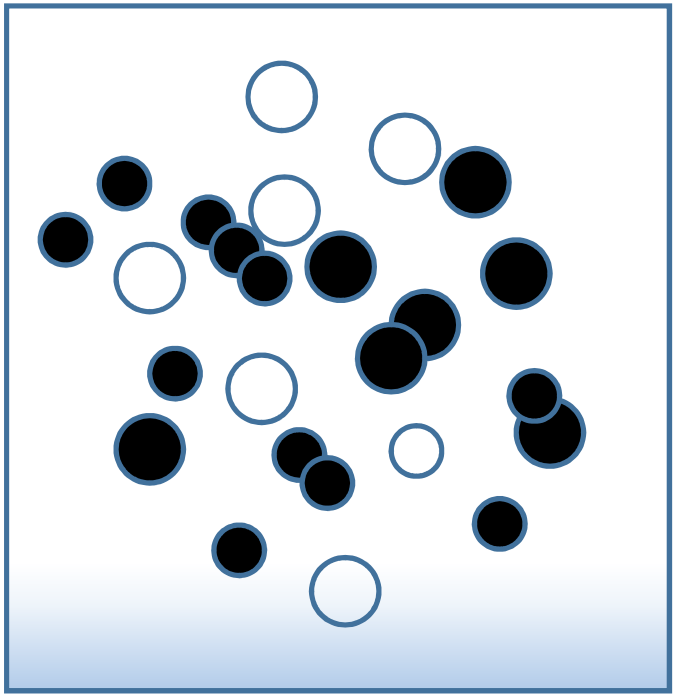
- Cluster Cleanup (pruning)
  - ❑Malware network trace may contain benign legitimate URL connections
  - ❑Clusters are pruned with benign URL parameters
  - ❑Reduce false positives



Clusters



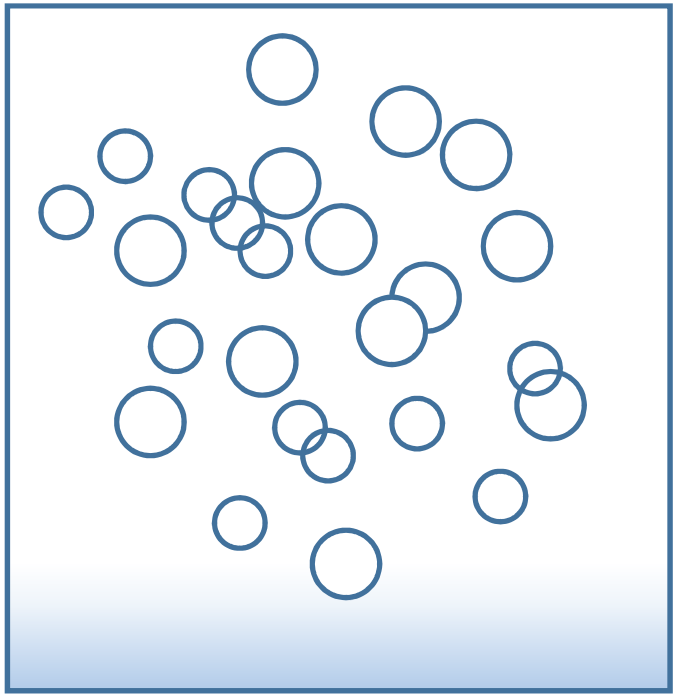
Again, the same distance function matching method



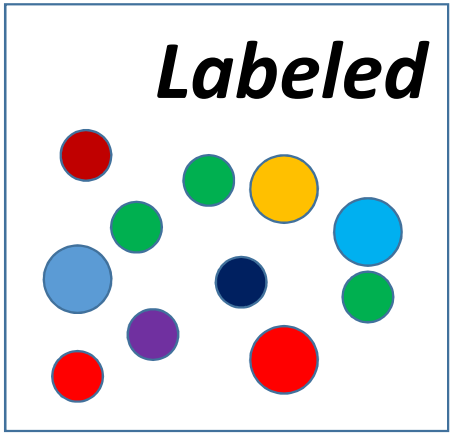
White Pruned

Clustering Method

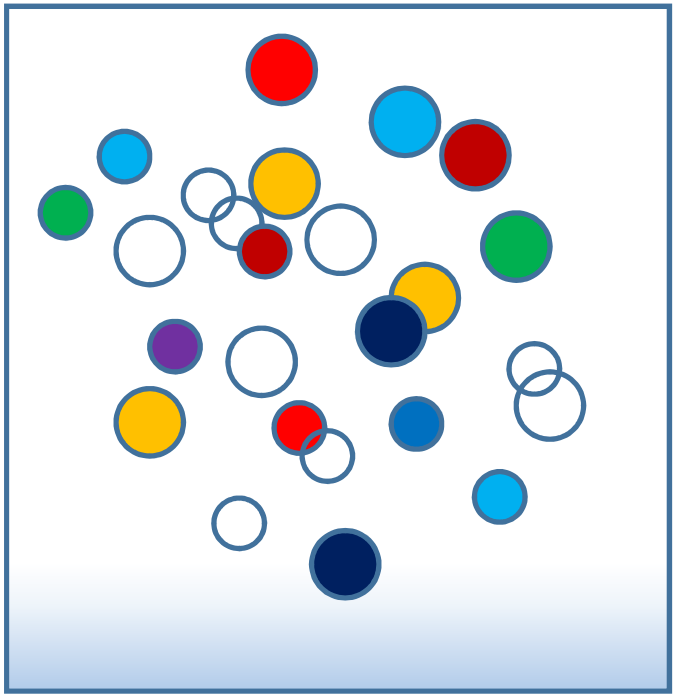
- Cluster Categorization
  - ❑Known URL categories
  - ❑Apply to clusters and mark similar URLs with the same category type
  - ❑C&C, remote access, advertisement, etc.



Cluster Centroids



Again, the same distance function matching method



Labeled Cluster Centroids

Our Work – Data Source

- Malware Samples:
  - ❑Third party vendor, Hillstone Network security lab
  - ❑Network trace captured in PCAP when run in sandboxes
- Number of samples:
  - ❑300,000 initial samples, and 10k updates/week
  - ❑~4500 malware families (variants are merged)
- Malware samples and their PCAPs are labeled by malware families
  - ❑Family variants are grouped under malware family labels.
  - ❑Collect HTTP traces from PCAPs. HTTPs inherit malware family labels.

Our Work – Data Source

- Clustering based on URL parameters
  - ❑HTTP GET
- HTTP POST method
  - ❑Some suspicious content is stored in http post body
  - ❑Private format/encoding
  - ❑Some are simple key: value pairs
  - ❑Analyze POST body content for certain patterns. And treat them the same as parameters

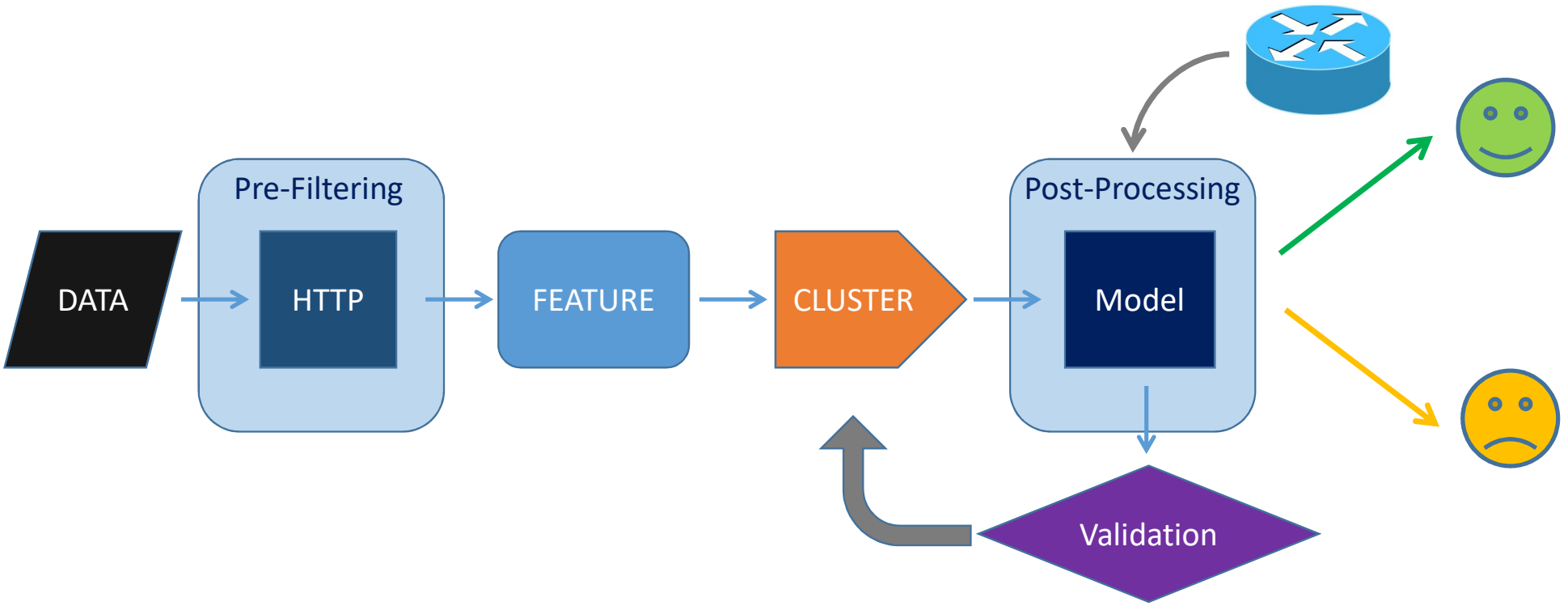
Our Work – Data Source

- HTTP POST Examples
  - ❑http://imp.myappz02.com/impression.do

    event=loader_start&implementation_id=min.0.0.30&user_id=ef2443da-1705-4437-8280-878105582da1&adprovider=treasure&source=RedUKBeaconRON&page=Workstation
  - ❑http://stan.mxp30.com/__dmp__/

    data={"msg":";PAYLOAD NOT FOUND","url":"PAYLOAD NOT FOUND","WaitCreateFile":"","MethodTrace":"returnNewPayload","Language":"Chinese","jscript":"","jscript":"Notfind","lno":"","version":"1.7.7","ieversion":"6.0.2900.5512","trace":"U3RhcnRTZXRVbmhhbmRsZWRFeGNlcHRpb25GaWx0ZXJnZXQgcGF5bG9hZFBBWUxPQUQgTk9UIEZPVU5E","osname":"Microsoft Windows XP Professional 5.1.2600 x86","av":"","method":"PAYLOAD NOT FOUND"}

Our Work – Process Flow



Experimental Results

- ~9000 clusters. Each cluster is represented as a sparse vector
- 84% detection rate on ~950K malicious URLs
  - ❑Some malicious URLs are indistinguishable from benign URLs
- Malware family coverage
  - ❑More than 3000 families of malware PCAPs
  - ❑About half have data for clustering
  - ❑Cluster model covers more than 95% of the 1500 families
- New malware variant detected
  - ❑Malware variant detected in deployment before our partner reported data to us

Example of Detection Result

RiskWare[Downloader]/Win32.Donex

Detection Time: 2016/07/13 11:42:34

Domain: api.down.72zx.com

URI:

/xml/18?winver=6.2&sdsoft=4&webid=18&softid=29621&ver=1.3.1.14&usesnum=1&mac=vYXbi0zPoms%253D&filename=office2015%25BC%25A4%25BB%25EE%25B9%25A4%25BE%25DF(KMSpico)+_18@29621.exe&errcode=0&userev=0&rnd=4124

Known URL:

http://api.down.72zx.com/xml/34?winver=5.1&sdsoft=8&webid=34&softid=0&ver=1.3.1.14&usesnum=1&mac=zPKt%252BjWzpGo%253D&filename=C6F5BAD88E23D89DE798C4D6FFCFA789.BC492044&errcode=0&userev=0&rnd=9324

Beyond the Malicious URL: Limitations

- Sample
  - ❑Sandbox execution and evasive technologies
  - ❑Label accuracy
  - ❑Lack large collection of clean benign traffics
- Malware
  - ❑Non-HTTP
  - ❑Non-URL Para. (JSON/Restful API, Post)
  - ❑Encryption

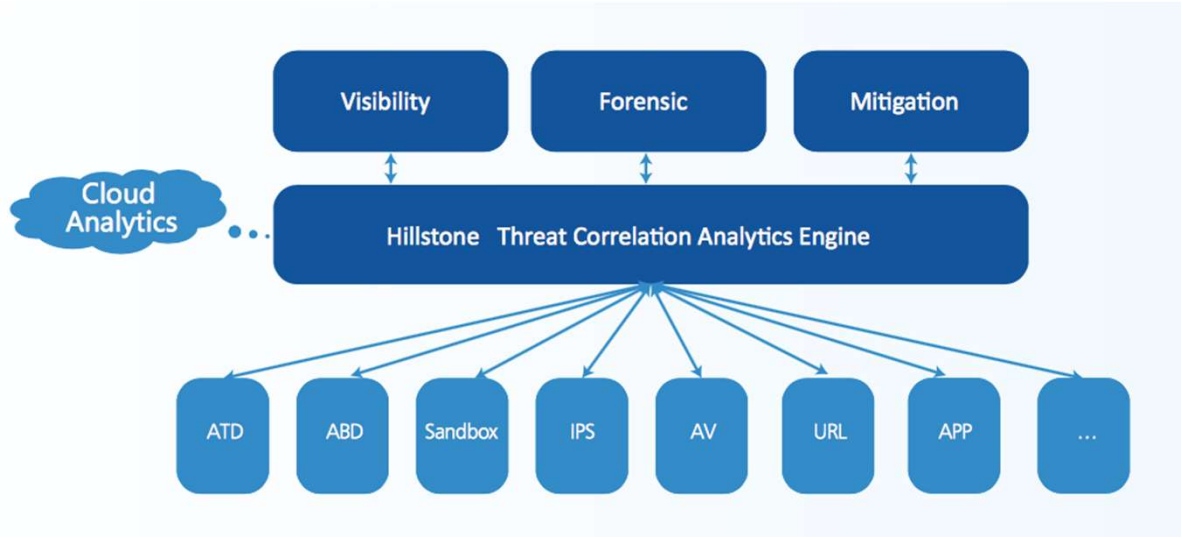
False Positive/Negative

Intelligent correlation

- The suspicious threat (malicious URL) accuracy
  - ❑ In a single HTTP packet, suspicious detection models include HTTP Method, Headers, User-Agent, Path, and host domain name
  - ❑ Do the correlation
  - ❑Spatial correlation: Within the network, check the number of the same incidents in a period of time
    - ➢ E.g. more than 20 hosts made the same connection in one hour

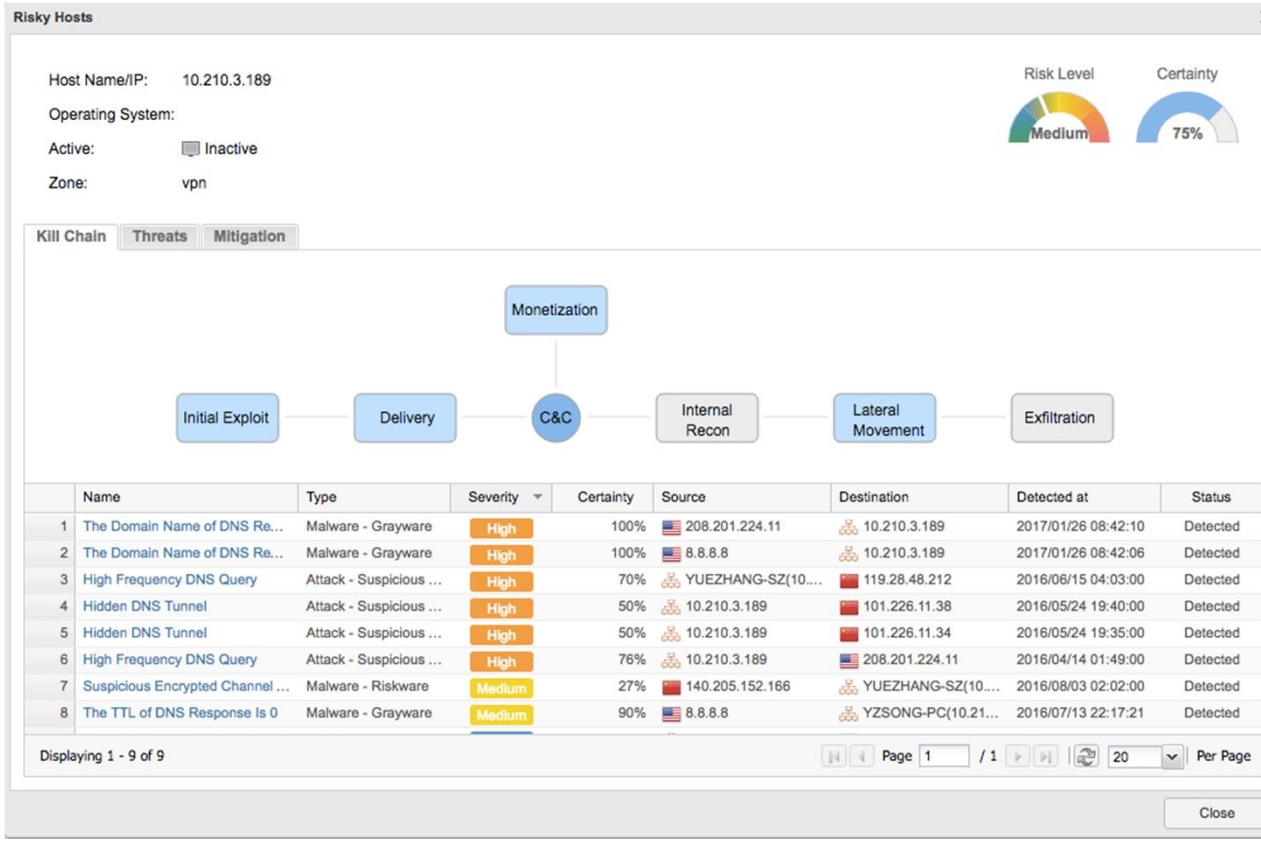
The better security arch.

- Multiple defender architecture
  - ❑NGFW, WAF and other traditional defenders
  - ❑Intelligent: ML and Data Analysis for DGA, Malicious URL and abnormal network behavior



The better security arch.

- Multiple intelligent correlation: correlation and scoring of
  - ❑ a cyber kill stage
  - ❑ among the cyber kill stages for a Host
  - ❑ among Hosts and global scope
  - ❑ updatable correlation models



Black Hat Sound Bytes

- Analysis of HTTP traffic has benefit in detecting compromised hosts.
- A novel way to extract URL parameter feature dimensions, and an unique method to transform infinite dimensions into limited feature space.
- Semi-supervised clustering method with filtering, post-processing and correlation demonstrates strength in precision, model size, variance coverage.

Thank you!