Detecting of Hidden Anomalies in DNS Communication

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Outline

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Motivation

- Most of the internet communication starts with a DNS query.
- There is a possibility to track communication at a certain level of DNS hierarchy.
- e.g. for intrusion detection, botnet discovery
- We want a tool that is able to:
- detect suspicious behaviour
- scan high volume traffic
- detect low volume anomalies
- works in real-time = low computation cost
- does not need any initial knowledge about the analysed traffic
- Will the tool be able to detect something at a ccTLD?

Original work

K. Fukuda, P. Borgnat, P. Abry, K. Cho Multiresolution Statistical Detection Procedures by G. Dewaele, Extracting Hidden Anomalies using Sketch and Non Gaussian

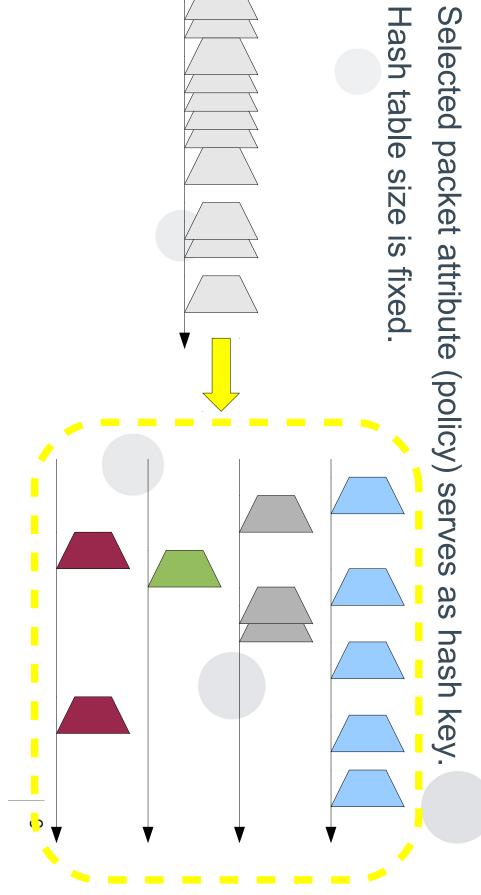
- Blindly analyses large-scale packet trace databases
- Able to detect short-lived anomalies as well as longer ones.
- Detection method is sensitive to statistical characteristics
- Promises a very low computation cost.

Method description

- within which the analysis is performed The algorithm analyses the traffic using a sliding time-window
- The analysis iterates over following steps:
- 1) random projection sketches
- 2) data aggregation
- 3) Gamma distribution estimation
- 4) reference values computation
- 5) distance from reference evaluation
- 6) sketch combination and anomaly identification

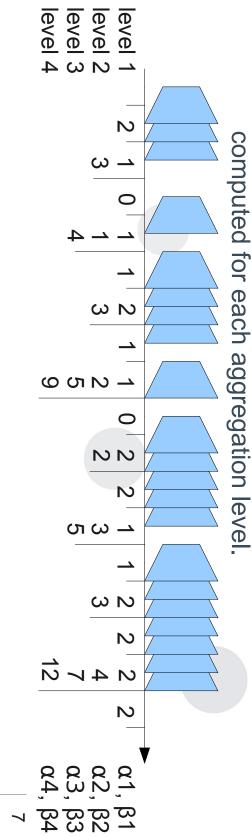
Random projections

- sketches using a hash function A fixed size time-window of captured traffic is split into



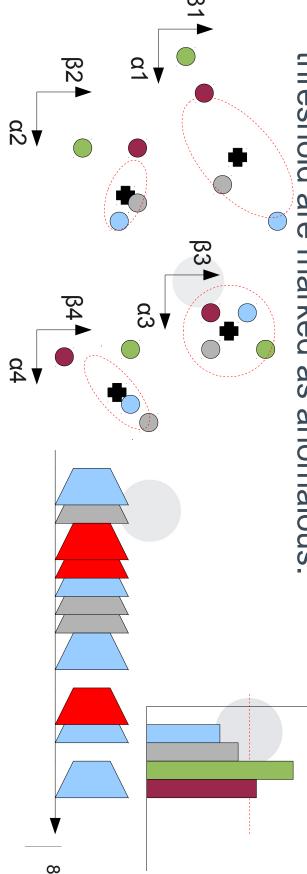
Aggregation, gamma distribution parameters

- aggregation levels to form a series of packet counts which arrived during an aggregation period. The sketches are aggregated jointly over a collection of
- Aggregation levels transform the time-scale granularity.
- Data from the aggregated time series are modelled using Gamma distribution.
- Shape (α) and scale (β) Gamma distribution parameters are



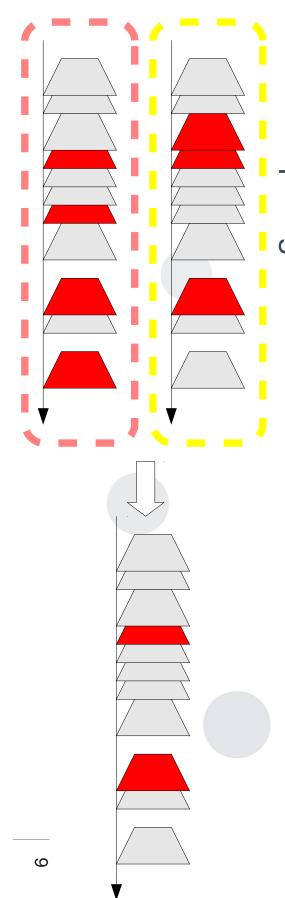
of anomalous sketches Reference values, identification

- For each aggregation level across all sketches standard sample mean and variance of the computed Gamma parameters are computed.
- 'centre of gravity' is computed. For each sketch the average Mahalanobis distance to the
- Sketches with their average distance exceeding a given threshold are marked as anomalous



Anomaly identification

- All packet attributes (hash keys) contained in an anomalous sketch are considered suspicious
- Using a different hash function provides a different mapping into sketches resulting in various anomalous sketches
- A list of attributes corresponding to detected anomalies is and computing the intersection of anomalous sketches. obtained by combining the results for several hash functions



Modification for DNS

- The method was designed to analyse the whole TCP/IP
- Works with TCP/IP connection identifiers (src/dst port/address).
- We extended it to meet DNS traffic specifics.
- Policies:
- IP address policy
- Based on original paper, uses the TCP/IP connection identifiers
- Supports IPv4 and IPv6.
- Helps finding suspicious traffic sources.
- Query name policy
- First domain name of the query is extracted and used as hash key.
- Helps finding suspicious traffic from legitimate sources

The tool

- git://git.nic.cz/dns-anomaly/ Standalone application is freely available at
- Command line parameters:
- window size + detection interval
- count of aggregation levels
- Aggregation steps are power of 2 in seconds (i.e. 1,2,4,8,...).
- analyse shape, scale or both
- detection threshold
- policy
- hash function count
- sketch count (hash table size)

Experiments

authoritative DNS servers Tested on DITL 2011 data collected in April 2011 on .cz

0.8	distance threshold
8	aggregation levels
32	hash table size
25	hash function count
10 minutes	detection interval
10 minutes	time-window size
value	parameter

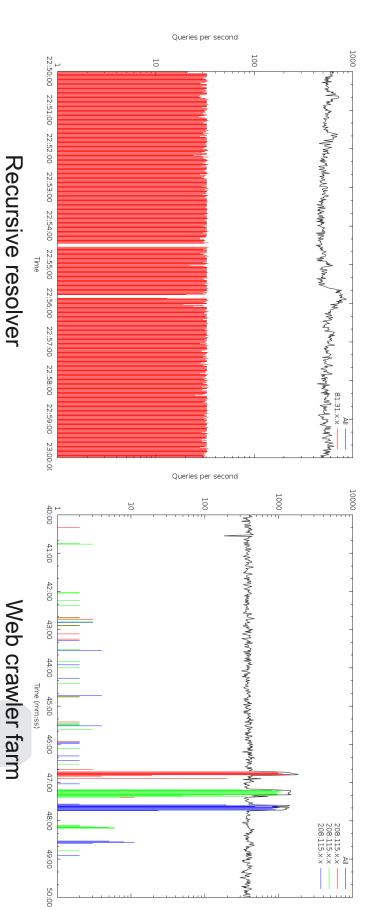
of traffic (126MB) in 1.8 second on a E5400@2.70GH. Using these settings the analyser is able to process 10 minutes

Results

Types of traffic labelled as anomalies:

- Traffic form legitimate sources (exhibiting specific patterns)
- large recursive resolvers, web crawlers
- Domain enumeration
- Blind or dictionary based (gTLD domain, prefix and postfix alteration for given words – e.g. bank or various trademarks)
- With the knowledge of the content (little or no NXDOMAIN replies)
- Suspicious
- Traffic generated by broken resolvers or testing scripts.
- e.g. bursts of queries for the same name from single host
- Repeated queries due to short TTL

Generic traffic



srcIP policy
Originates at webhosting/ISP. The pattern is very

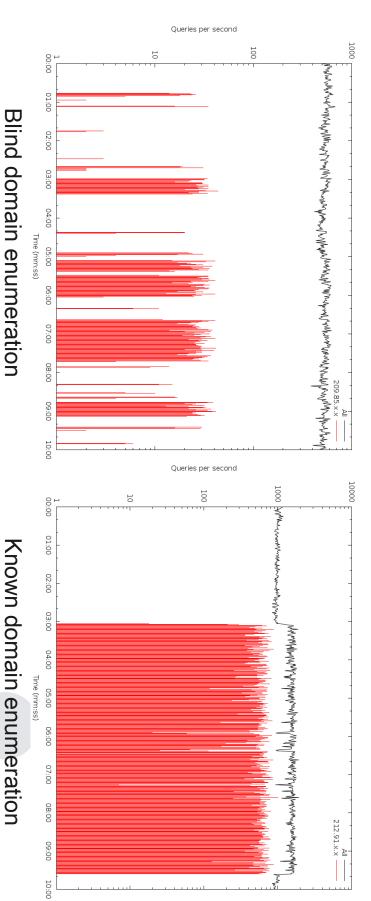
srcIP policy
Possibly web crawlers. They generate lots of

queries whenever they encounter sites with

many references.

regular with a period of approximately 12 seconds

Domain enumeration



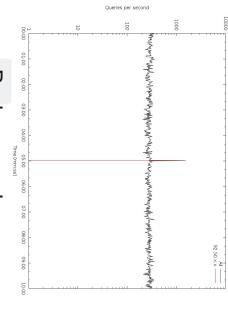
srcIP policy The source must have a very good knowledge about the content of the domain. Very few NXDOMAIN replies are generated.

When analysing the DNS queries a pattern emerged – prefixes and postfixes variation using

well-known trademarks.

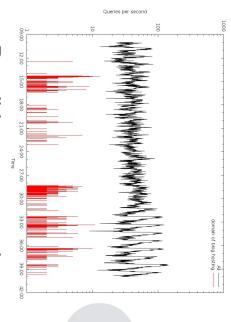
srcIP policy

Other suspicious



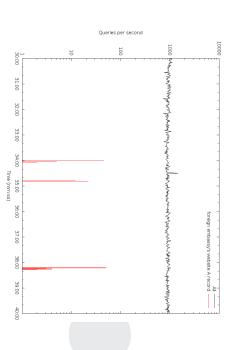
Broken resolver

srcIP policy
Hundreds of queries for a single record are generated in less than two seconds.



Possible spam attack

qname policy
Multiple hosts are querying same MX record.



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qname policy

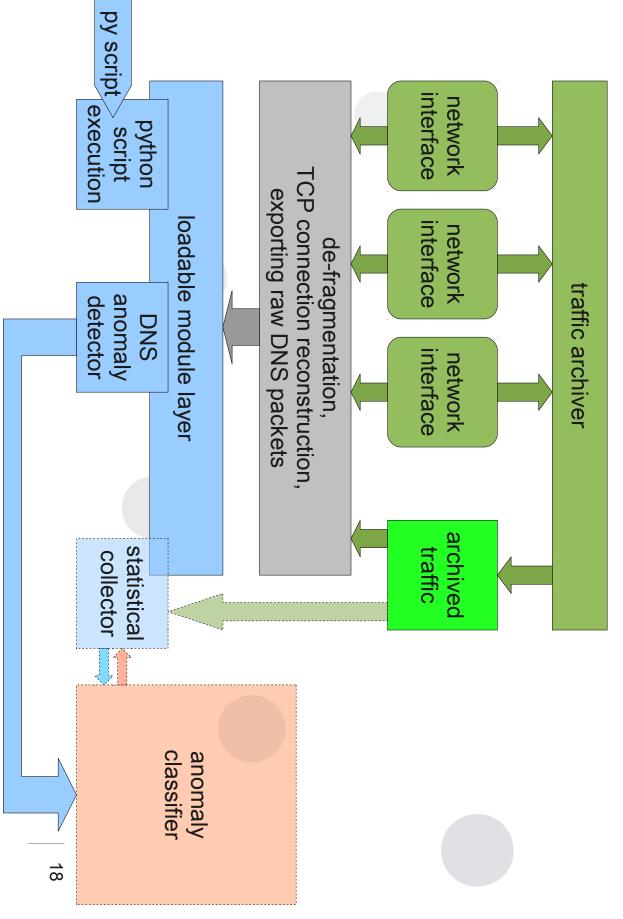
Multiple hosts evenly distributed around the world are generating bursts of queries for the same record.

The pattern is visible throughout the entire tested period - always as characteristic spikes.

Anomaly detection conclusion

- The tool is able to pinpoint low- and high-volume anomalies.
- Two policies implemented with different effect:
- IP policy serves best for domain enumeration detection.
- Query name policy divulges domain-related events
- e.g. presence of short TTL domains (fast flux)
- The classification of the anomalies is currently left to be done manually.
- Future work: automate this process.

A system under development



DNS anomaly classifier

- used to classify output from the DNS anomaly detector
- random forest classifier is being used because
- highly accurate classifier
- efficient run on large data sets
- gives an estimate of what variables are important in the classification
- soft decisions
- classifiers can be saved for future use
- Classifiers are sensitive to the source of classified data. Different sources need to have separate classifiers

Input variables – statistical data

- 62 variables serve for classification of anomalous data
- relative and absolute measures regarding the volume of
- query types, return codes, ttl
- penetration of various selected identifiers
- BGP prefixes, ASN, IP addresses, country of origin, query names
- also takes into account
- query time, total traffic volume, server response time

accuracy Classifier performance and

- samples (six days of anomalous traffic). The training set contains approximately 1 million classified
- Training a classifier containing 200 trees each containing 15 nodes lasts about 2 hours
- Classifying of such a large data set using the trained forest lasts about 10 minutes
- Classifying out-of-bag data yields 80% accuracy.
- The accuracy was determined by comparing classifier results with hand classified data.

Work in progress

- statistical collector module
- replacement for DSC?
- performance improvements in the random forest classifier
- increasing accuracy, increasing speed, reducing memory consumption
- communication protocol
- change collector settings, module reloading, attaching/detaching network devices

The End

Thank you for your attention.

Questions?