

An Introduction to Monitoring Encrypted Network Traffic with Joy

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Abstract: TLS encryption has become the standard form of Internet communication. In this session, we will demonstrate our open source project: Joy. It extends flow monitoring technologies by collecting much more detailed information about flows. This information can be used in conjunction with simple rules to detect obsolete cryptography on a network, or can be used by machine learning algorithms to detect malicious, encrypted flows. Both of these use cases will be highlighted.

Technical Level: Introductory
Technology: Open Source, Security
Solutions: Analytics, Threat Defense
Session Type: DevNet
Session Length: 45 min

Obtaining Joy

Wait! These steps have already been completed for you!

```
git clone https://github.com/cisco/joy
./config
make
```

```
cl-berlin@Joy$ sudo apt-get install build-essential python-dev python-numpy
python-setuptools python-scipy

cl-berlin@Joy$ sudo easy_install -U scikit-learn

cl-berlin@Joy$ sudo apt-get install whois
```

Joy Components

```
joy
query.py
model.py
saltUI
```

Walkthrough

Using joy to process pcaps into flow data files

```
cl-berlin@Joy:~/joy$ bin/joy bidir=1 http=1 dns=1 tls=1 dist=1
../benign/capture.pcap > capture.gz
cl-berlin@Joy:~/joy$ zless capture.gz

{"version":"1.2","interface":"none","promisc":0,"output":"none",
"outputdir":"none","info":"none","count":0,"upload":"none","keyfile":"none",
"retain":0,"bidir":1,"num_pkts":0,"type":1,"zeros":0,"dist":1,"cdist":"none",
"entropy":0,"hd":0,"tls":1,"classify":0,"idp":0,"exe":0,"anon":"none",
"useranon":"none","bpf":"none","wht":0,"example":0,"dns":1,"ssh":0,"ip_id":0,
"salt":0,"verbosity":0}
{"sa":"10.0.2.15","da":"151.101.1.69","pr":6,"sp":37558,"dp":80,"ob":461,
"op":25,"ib":28652,"ip":28,"ts":1465338230.479314,"te":1465338261.040187,
"ottl":64,"ittl":64,"otcp_win":14600,"itcp_win":65535,"otcp_syn":40,
"otcp_nop":1,"otcp_mss":1460,"itcp_mss":1460,"otcp_wscale":7,"otcp_sack":1,
"otcp_tstamp":1,"packets":[{"b":461,"dir":>,"ipt":55},
...

```

The first line is metadata that describes the options used to convert the pcap into JSON. The second line is a JSON description of a flow:

```
{
  "sa":"10.0.2.15",      # source address
  "da":"23.56.181.48",  # destination address
  "pr":6,               # protocol (TCP)
  "sp":43286,           # source port
  "dp":80,              # destination port (HTTP)
  "ob":12834,           # number outbound bytes
  "op":93,              # number outbound packets
  "ib":173193,          # number inbound bytes
  "ip":163,             # number inbound packets
  "ts":1465315516.880170, # time start (seconds since epoch)
  "te":1465315547.566770, # time end (seconds since epoch)
  "ottl":64,           # outbound IP TTL
  "ittl":64,           # inbound IP TTL
  "otcp_win":14600,
  "itcp_win":65535,
  "otcp_syn":40,
  "otcp_nop":1,
  "otcp_mss":1460,
  "itcp_mss":1460,
  "otcp_wscale":7,
  "otcp_sack":1,
  "otcp_tstamp":1,
  "packets":[
    {"b":299,"dir":>,"ipt":19},
    {"b":1248,"dir":<,"ipt":86},
    ...
  ]
}
```

Using query.py to process JSON flow data files

We can get output that looks like Netflow:

```
cl-berlin@Joy:~/joy$ ./query.py capture.gz --summary | less
```

source address	destination address	prot	sport	dport	obytes	opkts	ibytes	ipkts	date	time	seconds
10.0.2.15	151.101.1.69	6	37558	80	461	25	28652	28	2016-06-07	22:23:50	30.561
10.0.2.15	151.101.1.69	6	37568	80	488	7	396	6	2016-06-07	22:23:50	30.234
10.0.2.15	72.21.91.121	6	41646	443	1279	20	10080	19	2016-06-07	22:23:50	30.599
10.0.2.15	72.21.91.121	6	41645	443	1279	19	9876	18	2016-06-07	22:23:50	30.599
10.0.2.15	72.21.91.121	6	41647	443	1279	20	9460	19	2016-06-07	22:23:50	30.554
10.0.2.15	72.21.91.121	6	41643	443	1730	21	10590	21	2016-06-07	22:23:50	30.662
10.0.2.15	72.21.91.121	6	41648	443	828	16	8073	15	2016-06-07	22:23:50	30.594
10.0.2.15	72.21.91.121	6	41644	443	1730	22	11259	22	2016-06-07	22:23:50	30.694
10.0.2.15	172.217.1.4	6	60364	443	449	10	3915	12	2016-06-07	22:23:39	61.03
10.0.2.15	66.150.118.20	6	58790	80	539	8	357	7	2016-06-07	22:23:51	40.371
10.0.2.15	172.232.36.95	6	43882	443	1041	14	4704	13	2016-06-07	22:23:51	40.495
10.0.2.15	23.23.170.52	6	56237	443	1026	14	4295	14	2016-06-07	22:23:51	40.219
...											

But we can also get a lot more information:

```
cl-berlin@Joy:~/joy$ ./query.py capture.gz | less
```

```
{
  "itcp_mss": 1460,
  "ip": -9,
  "i_probable_os": "FreeBSD / OS X",
  "ib": 311,
  "pr": 6,
  "otcp_syn": 40,
  "otcp_win": 14600,
  "ts": 1465339229.163859,
  "ottl": 64,
  "te": 1465339288.182719,
  "otcp_nop": 1,
  "itcp_win": 65535,
  "otcp_mss": 1460,
  "otcp_sack": 1,
  "da": "172.217.1.196",
  ...
}
```

The --select option will select certain fields to be printed:

```
cl-berlin@Joy:~/joy/saltUI$ ./query.py capture.gz --select "sa, da, dp"
```

The --where option will filter the flows to meet certain criteria.

```
cl-berlin@Joy:~/joy/saltUI$ ./query.py capture.gz --select "sa, da, dp"
--where "pr=17"
```

High entropy flows can be identified by using the Byte Distribution:

```
cl-berlin@Joy:~/joy$ ./query.py capture.gz --select "sa, da, dp, bd"
--where "entropy(bd)>7.99"
{
  "name": [
    {
      "sa": "10.0.2.15", "da": "172.217.1.4", "dp": 443,
      "bd": [186, 70, 64, 97, 82, 69, 68, 61, 67, 63, 63, 63, 64, 60, 64,
63, 63, 64, 63, 66, 61, 61, 65, 78, 62, 61, 63, 60, 60, 64, 63, 58, 66, 63,
62, 62, 63, 66, 62, 67, 64, 62, 63, 64, 61, 63, 69, 63, 68, 65, 64, 61, 62,
65, 62, 66, 63, 63, 63, 60, 67, 60, 60, 63, 63, 58, 62, 61, 61, 62, 63,
62, 60, 62, 62, 63, 60, 62, 65, 64, 64, 60, 57, 60, 63, 68, 61, 60, 61, 61,
63, 57, 59, 65, 64, 65, 62, 60, 61, 63, 60, 64, 61, 63, 66, 62, 60, 57, 62,
62, 62, 67, 65, 63, 63, 59, 66, 61, 62, 63, 63, 62, 64, 62, 64, 63, 65, 63,
64, 62, 61, 62, 59, 61, 65, 65, 60, 64, 63, 62, 60, 68, 63, 64, 61, 57, 63,
62, 58, 64, 64, 60, 61, 61, 62, 57, 64, 60, 64, 63, 61, 61, 60, 61, 59, 61,
61, 59, 63, 62, 58, 57, 62, 60, 64, 60, 59, 63, 63, 60, 62, 60, 61, 62, 62,
61, 60, 63, 64, 63, 63, 67, 63, 60, 60, 60, 62, 64, 63, 63, 62, 63, 61, 63,
63, 62, 63, 63, 63, 64, 62, 62, 59, 61, 64, 64, 63, 63, 61, 76, 62, 64, 60,
62, 63, 62, 64, 61, 63, 59, 65, 60, 62, 60, 61, 58, 61, 63, 62, 61, 64, 62,
64, 61, 63, 61, 61, 60, 62, 64, 64, 65, 62, 63, 63, 62] }
    ]
  }
}
```

Looking at TLS:

```
cl-berlin@Joy:~/joy$ ./query.py capture.gz --where "dp=443" | less
"tls": {
  "tls_irandom":
"57574d7d1e6a95a0304ccc2d71bb14765c2bd8a3cd966039bae034329471e462",
  "tls_iv": 5,
  "tls_ov": 5,
  "SNI": [
    "www.google.com"
  ],
  "srlt": [
    {
      "b": 512,
      "tp": "22:1",
      "ipt": 0,
      "dir": ">"
    },
    {
      "tls_ext": [
        {
          "data": "00",
          "length": 1,
          "type": "ff01"
        },
        {
          "tls_orandom":
"4e6fbeb21d3549c945fd52f17dc4190f195561117b970866dfd8651225691e59",
          "cs": [
            "c02b",
            "c02f",
            "c00a",

```

Looking at TLS security levels:

```
cl-berlin@Joy:~/joy$ ./query.py capture.gz --where "dp=443" --select "sa,
da, seclevel(tls)"

{
  "name": [
    {"sa": "10.0.2.15" , "da": "72.21.91.121" , "seclevel(tls)": "recommended"
    },
    ...
  ]
}
```

Identify malware flows based on SPLT and BD

The built-in classifier can detect malware based on its Sequence of Packet Lengths and Times (SPLT) behavior and it's Byte Distribution:

```
cl-berlin@Joy:~/joy$ bin/joy bidir=1 dist=1 classify=1
../benign/capture.pcap > capture.gz
cl-berlin@Joy:~/joy$ ./query.py capture.gz --select "da, dp, p_malware"
--where "p_malware > 0.01"

{
  "name": [
    {"da": "151.101.1.69", "dp": 80, "p_malware": 0.084},
    {"da": "172.217.1.195", "dp": 443, "p_malware": 0.021}
  ]
}
```

Example showing a similar run on a malicious PCAP:

```
cl-berlin@Joy:~/joy$ bin/joy bidir=1 dist=1 classify=1
../malware/133d773a8ca64c24bd81b594cf5240dd.pcap > malware.gz
cl-berlin@Joy:~/joy$ ./query.py malware.gz --select "da, dp, p_malware"
--where "p_malware > 0.99"

{
  "name": [
    { "da": 86.59.21.38, "dp": 443 , "p_malware": 0.997 } ,
    { "da": 108.61.179.216, "dp": 443 , "p_malware": 0.995 } ,
    { "da": 5.9.123.81, "dp": 9001 , "p_malware": 0.999 } ,
    { "da": 109.238.6.25, "dp": 443 , "p_malware": 0.992 } ,
    { "da": 176.31.159.231, "dp": 443 , "p_malware": 0.998 } ,
    ...
  ]
}
```

Making a classifier

We can use `model.py` to learn a logistic regression classifiers from two data directories, one containing malicious output and one containing benign output. The arguments to `model.py` are:

```
-p POS_DIR, --pos_dir POS_DIR      Directory of Positive Examples (JSON Format)
-n NEG_DIR, --neg_dir NEG_DIR      Directory of Negative Examples (JSON Format)
-m, --meta                          Parse Metadata Information
-l, --lengths                       Parse Packet Size Information
-t, --times                         Parse Inter-packet Time Information
-d, --dist                          Parse Byte Distribution Information
-o OUTPUT, --output OUTPUT         Output file for parameters
```

Joy uses two classifiers, one with only metadata and packet lengths/times, and one that also contains the byte distribution. To generate the parameter file that does use the byte distribution, we run:

```
cl-berlin@Joy:~/joy$ bin/joy bidir=1 dist=1 ../malware/*.pcap >
../malware_train/malware.gz
cl-berlin@Joy:~/joy$ bin/joy bidir=1 dist=1 ../benign/*.pcap >
../benign_train/benign.gz
cl-berlin@Joy:~/joy$ python saltUI/model.py -m -l -t -p ../malware_train/
-n ../benign_train/ -o params.txt
```

```
Num Positive:      470
Num Negative:      276
```

```
Features Used:
  Metadata          (7)
  Packet Lengths    (100)
  Packet Times      (100)
Total Features: 207
```

```
non-zero parameters: 22
```

Then we generate the parameters that use the byte distribution:

```
cl-berlin@Joy:~/joy$ python saltUI/model.py -m -l -t -d -p
../malware_train/ -n ../benign_train/ -o params_bd.txt
```

```
Num Positive:      470
Num Negative:      276
```

```
Features Used:
  Metadata          (7)
  Packet Lengths    (100)
  Packet Times      (100)
  Byte Distribution  (256)
Total Features: 463
```

```
non-zero parameters: 22
```

We can now visualize these classifiers by copying the params.txt and params_bd.txt files to the saltUI directory. Edit the saltUI/laui.cfg file by replacing line 16:

```
classifier Malware logreg logreg_parameters.txt logreg_parameters_bd.txt
```

with:

```
classifier Malware logreg params.txt params bd.txt
```

Move into the saltUI directory. Start the UI with:

```
cl-berlin@Joy:~/joy/saltUI$ python server.py
```

Point your browser to <http://localhost:8080/home> and click on Local Analytics -> Upload JSON File. You will then see the following page:

LAUI 0.2a Home Contact Admin Local Analytics ▾

Select a JSON file:

Browse ...

Start upload

Click the “Browse...” button to choose the joy/malware.gz JSON file that we made earlier by processing pcaps (sitting under the root directory of joy). Finally, click the “Start upload” button. Using the new classifiers that we created, the results will be displayed:

LAUI 0.2a Home Contact Admin Local Analytics ▾

Number of flows classified: 589

P(Malware)	P(TLS)	P(CKL)	Source Address	Dest.Address	Source Port	Dest. Port	Inbound Packets	Outbound Packets
1.0	1.0	-1.0	172.16.45.20	104.237.132.39	1034	443	15	11
1.0	1.0	-1.0	172.16.45.20	104.237.132.39	1035	443	15	11
1.0	1.0	-1.0	172.16.45.20	104.237.132.39	1036	443	15	11
1.0	1.0	-1.0	172.16.45.20	104.237.132.39	1037	443	15	11
1.0	1.0	-1.0	172.16.45.20	104.237.132.39	1038	443	15	11
1.0	1.0	-1.0	172.16.45.20	104.237.132.39	1039	443	15	11
1.0	1.0	-1.0	172.16.45.20	104.237.132.39	1040	443	15	11
1.0	1.0	-1.0	172.16.45.20	104.237.132.39	1041	443	15	11
1.0	1.0	-1.0	172.16.45.20	104.237.132.39	1042	443	15	11
1.0	1.0	-1.0	172.16.45.20	104.237.132.39	1044	443	15	11
1.0	1.0	-1.0	172.16.45.20	104.237.132.39	1045	443	15	11