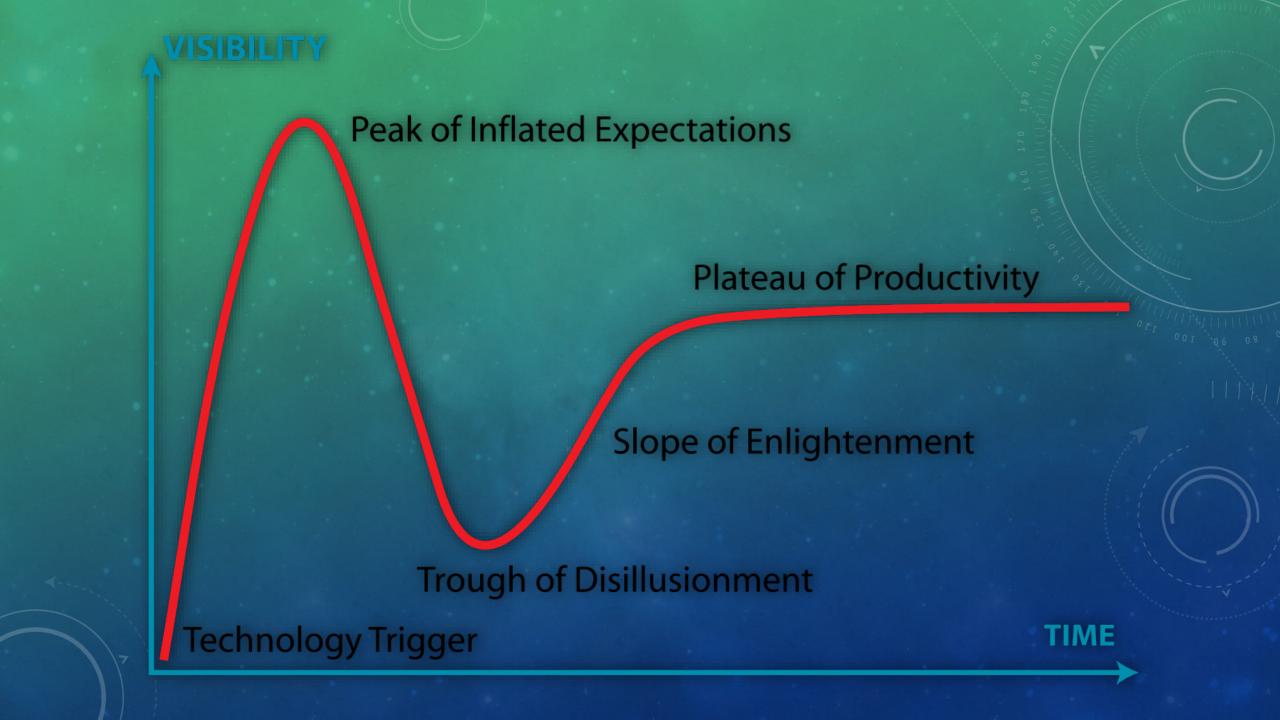
PRACTICAL APPLICATION OF MACHINE LEARNING TO CYBER SECURITY TIM CROTHERS

WHO AM I?

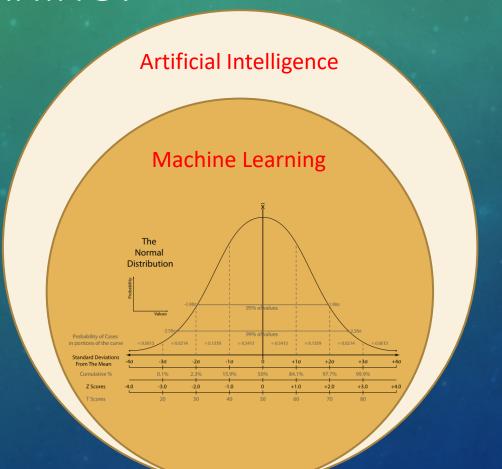
- >30 years in Information Technology and >20 years in Infosec
- Authored/Co-Authored 17 books to date
- Engineer and Maker
- Unabashed Math & Computer Science Geek
- Spent several years "on the ground at some of the largest breaches"

OPPORTUNITY

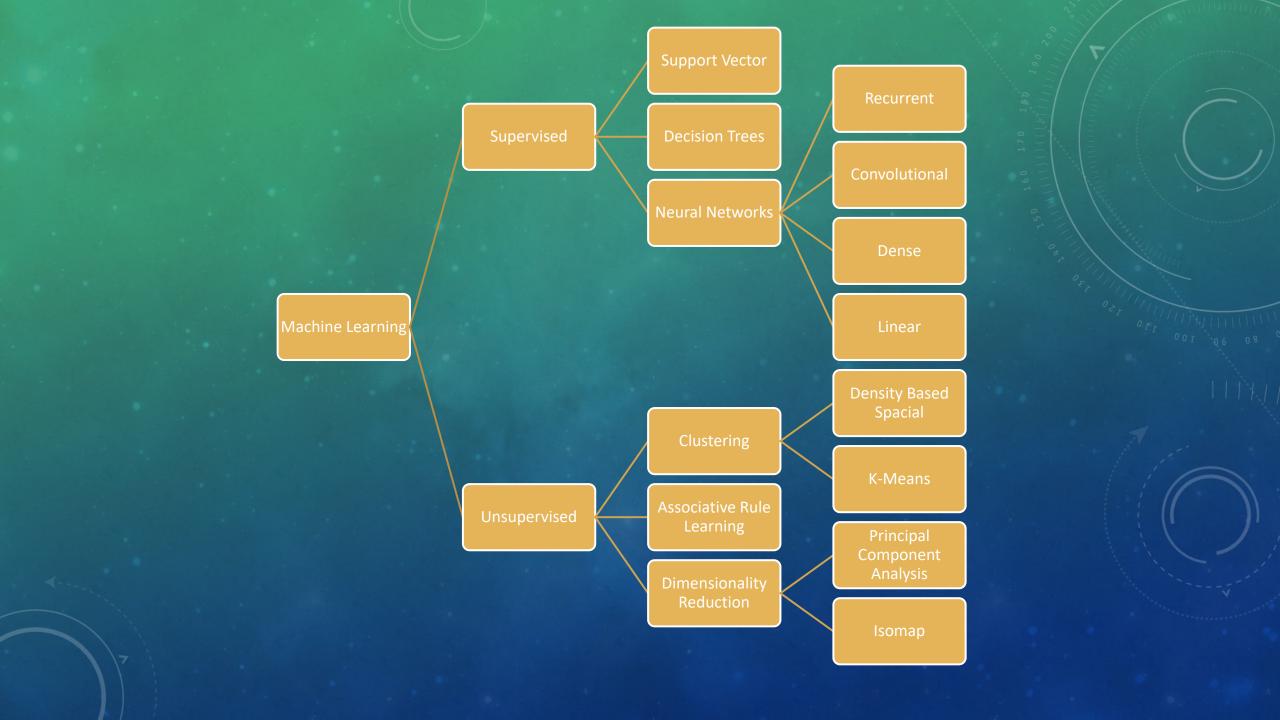
- Breaches continue to grow in number and severity year after year
- Severe shortage in Cyber Security Subject Matter Expertise
- Venture capital funds and research opportunities are readily available



MACHINE LEARNING?



By Heds 1 at English Wikipedia - Transferred from en.wikipedia to Commons by Abdull., Public Domain, https://commons.wikimedia.org/w/index.php?curid=2799839



- Pure anomaly detection
 - Real world networks are messy
 - Real world systems are inconsistently configured
 - Real world vendor applications are usually abnormal
 - Real world hosts are all unique within a few minutes of the end user taking possession

- Trying to be all security things to all security people
 - Determining optimal parameters and features for a tightly scoped use case is pretty easy
 - As the width of the use case increases the difficulty increases exponentially

- Failing to leverage deep cyber security subject matter expertise
 - It's hard to solve a problem you don't understand well
 - Interesting != security problem
 - Security problem != something that will improve security
 - Success in a lab is much easier than success in a real world environment

- Failing to leverage deep ML subject matter expertise
 - Proper parameter and feature selection is critical
 - Proper algorithm selection is really important
 - Proper testing and refinement is critical

HOW DO YOU DO IT?

- Problem to solve
- Decide on approach
- Appropriate data
- Determine proper features
- Build your tool
- Test & tune
- Win!

KEYS TO SUCCESS

- Tightly scoped problem statement or use case
- Decide on approach
- Appropriate data
- Determine proper parameters and features
- Test & tune

TIGHTLY SCOPED PROBLEM

- Find the malicious activity in my DNS that my signature based detection isn't finding
- Find malicious PowerShell activity in Windows event logs that isn't being detected otherwise
- Find unknown malicious traffic posing as legitimate applications

DECIDE ON APPROACH

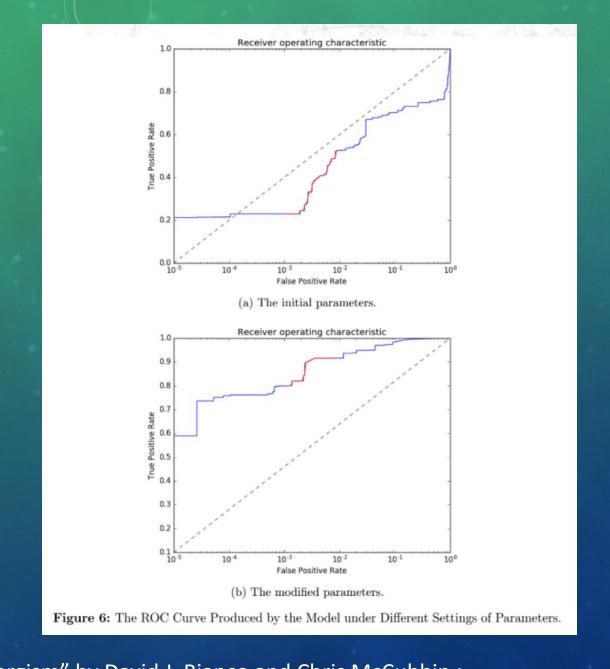
- Supervised
 - Generally best for solving specific problems
 - Needs 'labeled' data
- Unsupervised
 - Essentially anomaly detection
 - Needs large piles of data

APPROPRIATE DATA

- Data appropriate to the problem you selected
- Known good
- Known bad
- Use 80% of each so you can use the other 20% for testing & tuning

DETERMINE PROPER FEATURES

- Features == Specific data points
 - URL in HTTP headers
 - User Agent in HTTP headers
 - Event ID in Windows event logs
 - DNS Query & Response in DNS traffic
- More != better necessarily
- If in doubt you can read in all the possible features and compute the amount of variance in each. High variance features will usually be your best option.



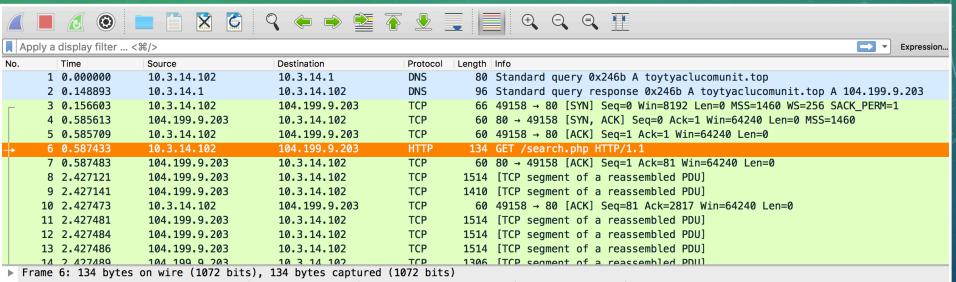
Excerpt from "Practical Cyborgism" by David J. Bianco and Chris McCubbin: https://speakerdeck.com/davidjbianco/practical-cyborgism-getting-started-with-machine-learning-for-incident-detection

BUILD YOUR TOOL

- Python is a great option
 - Pandas, NumPy, and Sci-Kit Learn do almost all of the heavy lifting
- You'll need a way to parse the data so it can be analyzed
- You'll need to select an algorithm
 - When in doubt start with Random Forest
- You'll need a training mode and an analysis mode
- Trainer will need to parse the data, run it through the algorithm and save out the model
- Analyzer will need to load the mode, parse the data to be evaluated, and call out any items flagged by the model

TEST & TUNE

- Use the trainer to build the model off of the 80% known good and known bad data
- Run the resulting model against your 20% known good and known bad to see if the model predicts them properly
- Try changing your feature selection
- Try substituting different algorithms
- If you're models are still performing badly then you most likely have problems in your data



- ▶ Ethernet II, Src: HewlettP_1c:47:ae (00:08:02:1c:47:ae), Dst: Netgear_b6:93:f1 (20:e5:2a:b6:93:f1)
- ▶ Internet Protocol Version 4, Src: 10.3.14.102, Dst: 104.199.9.203
- ▶ Transmission Control Protocol, Src Port: 49158, Dst Port: 80, Seq: 1, Ack: 1, Len: 80
- ▼ Hypertext Transfer Protocol
- ► GET /search.php HTTP/1.1\r\n

Host: toytyaclucomunit.top\r\n
Connection: Keep-Alive\r\n

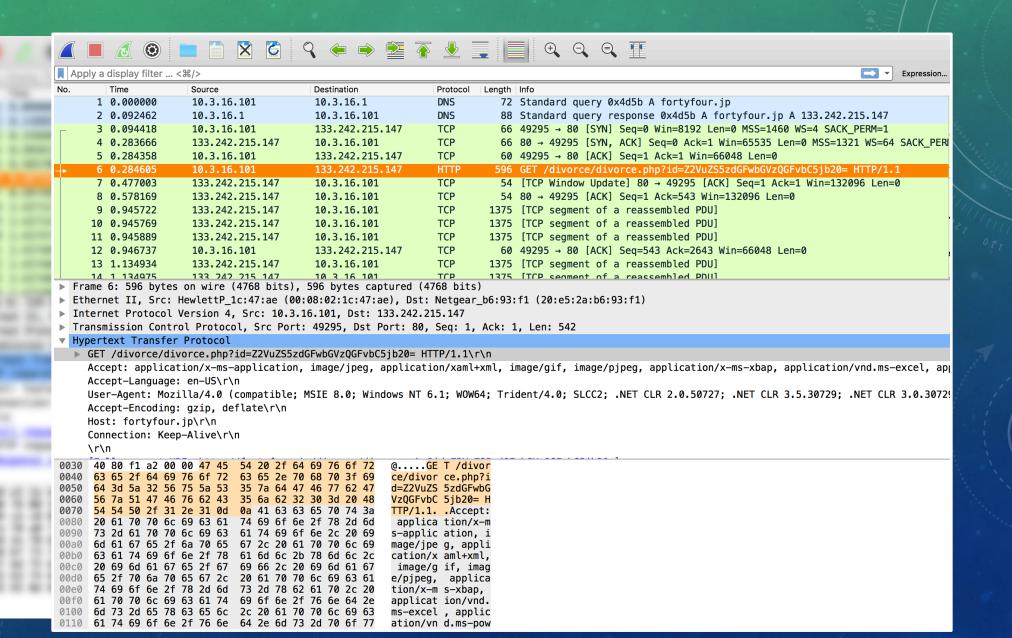
\r\n

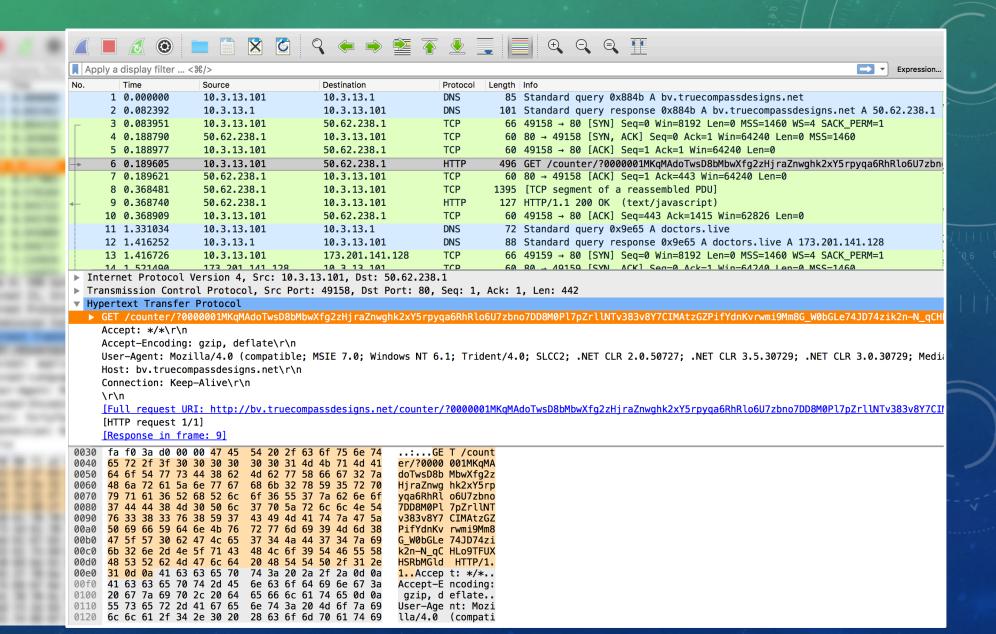
[Full request URI: http://toytyaclucomunit.top/search.php]

[HTTP request 1/1]

[Response in frame: 233]

02 1c 47 ae 08 00 45 00 20 e5 2a b6 93 f1 00 08 .*.... ..G...E. 0010 00 78 00 5d 40 00 80 06 6f 28 0a 03 0e 66 68 c7 .x.]@... o(...fh. 0020 09 cb c0 06 00 50 cd ac ca 69 f8 fd 05 42 50 18P.. .i...BP. 0030 fa f0 a0 f2 00 00 47 45 54 20 2f 73 65 61 72 63GE T /searc h.php HT TP/1.1.. 0040 68 2e 70 68 70 20 48 54 54 50 2f 31 2e 31 0d 0a 0050 48 6f 73 74 3a 20 74 6f 79 74 79 61 63 6c 75 63 Host: to vtvacluc omunit.t op..Conn 0060 6f 6d 75 6e 69 74 2e 74 6f 70 0d 0a 43 6f 6e 6e 0070 65 63 74 69 6f 6e 3a 20 4b 65 65 70 2d 41 6c 69 ection: Keep-Ali 0080 76 65 0d 0a 0d 0a ve....





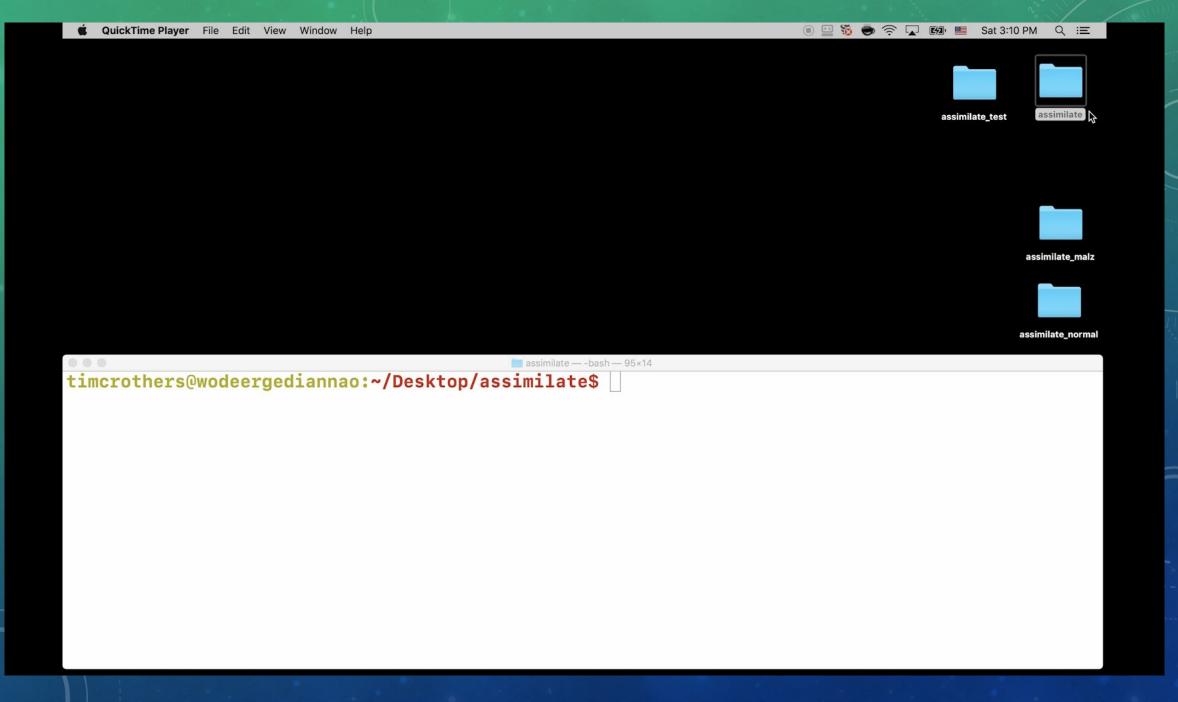
CYBER HUNTING CHALLENGES

- Too few experienced practitioners
- Takes too long to develop experienced practitioners
- Too much data to look through
- Hunts are periodic

ASSIMILATE BUILD STEP-BY-STEP

- Gathered the real world network data (one week > 10TB)
- Used Bro (Zeek) to convert the packet captures into metadata (HTTP)
- Compiled over a years worth of packet captures from malware and converted with Bro similarly
- Cleaned the Malicious Bro metadata of the non-malware activity
- Used the malicious data to clean the real world network data
- Tested for algorithm, parameters and features
- Coded trainer & model application, tested, iterated





SO WHAT DID YOU JUST SEE?

- Python script using a trained Naïve Bayes algorithm based model against 37,440 HTTP headers
- Found 46 things that looked suspicious
- 0.12% suspicious

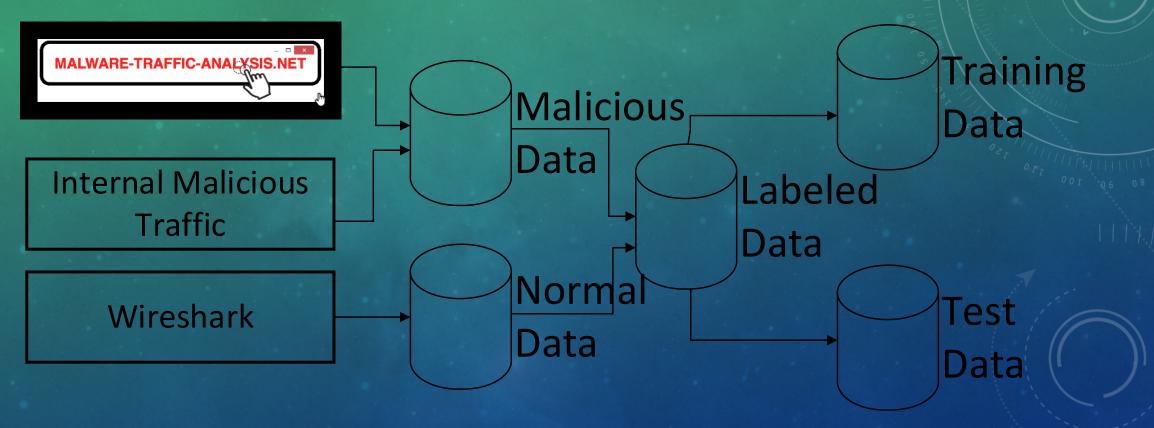
WHAT'S NEEDED TO DO THIS?

- Python
- Sci-kit Learn & Pandas (python modules)
- Packet captures of non-malicious activity
- Packet captures of malicious activity
- Bro
- Bro HTTP_Header script
- Assimilate python scripts
 Customized code at: https://github.com/Soinull/assimilate

STEP BY STEP

- 1. Collect and process training data
- 2. Train model
- 3. Assess actual data files
- 4. Validate suspicious entries
- 5. Retrain as needed to improve accuracy
- 6. **T**

TRAINING DATA



PROCESSING PACKET CAPTURES

- Install customized HTTP_Headers Bro module
- Process all packet captures with "Bro –r"

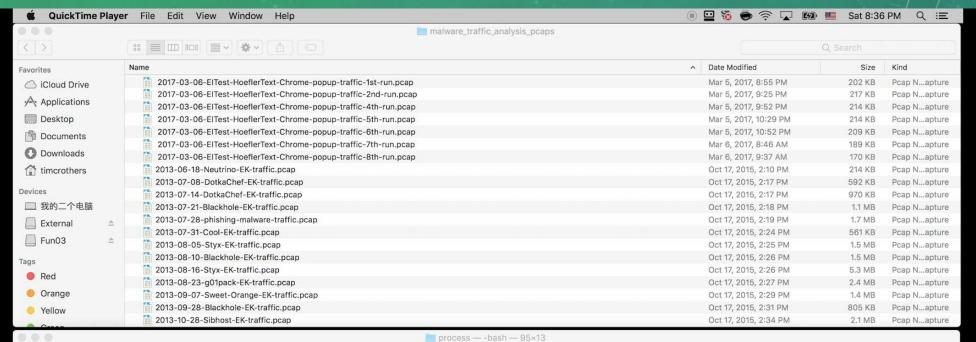
CUSTOMIZED BRO HTTP_HEADERS

```
event http_all_headers(c: connection, is_orig: bool, hlist: mime_header_list)
    local my_log: Info;
    local origin: string;
    local identifier: string;
    # local event_json_string: string;
    local event_kv_string: string;
   # Is the header from a client request or server response
   if ( is_orig )
       origin = "client";
    else
        origin = "server";
   # If we don't have a header_info_vector than punt
    if ( ! c?$http || ! c$http?$header_info_vector )
        return;
    print c$http$header_info_vector;
```

PROCESS SHELL SCRIPT

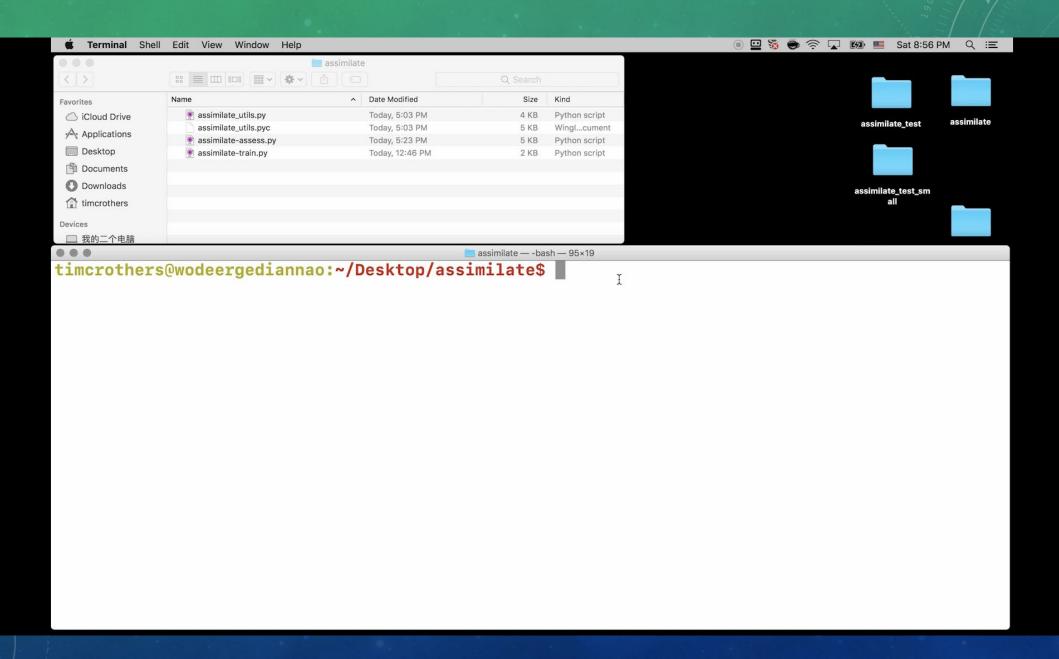
```
# Example script to iterate over pcap files to get corresponding
http.log and httpheader.log files
for file in ../*.pcap
do
   name=${file##*/}
   echo $name
   base=${name%.pcap}
   echo $base
   cp ../"$file" .
   bro -r "$file" custom/BrowserFingerprinting/http-headers.bro
   mv http.log ../"$base"_http.log
   mv httpheaders.log ../"$base"_httpheaders.log
   rm -f *.log *.pcap
done
```

PROCESSING PCAPS



timcrothers@wodeergediannao:~/Desktop/malware_traffic_analysis_pcaps/process\$

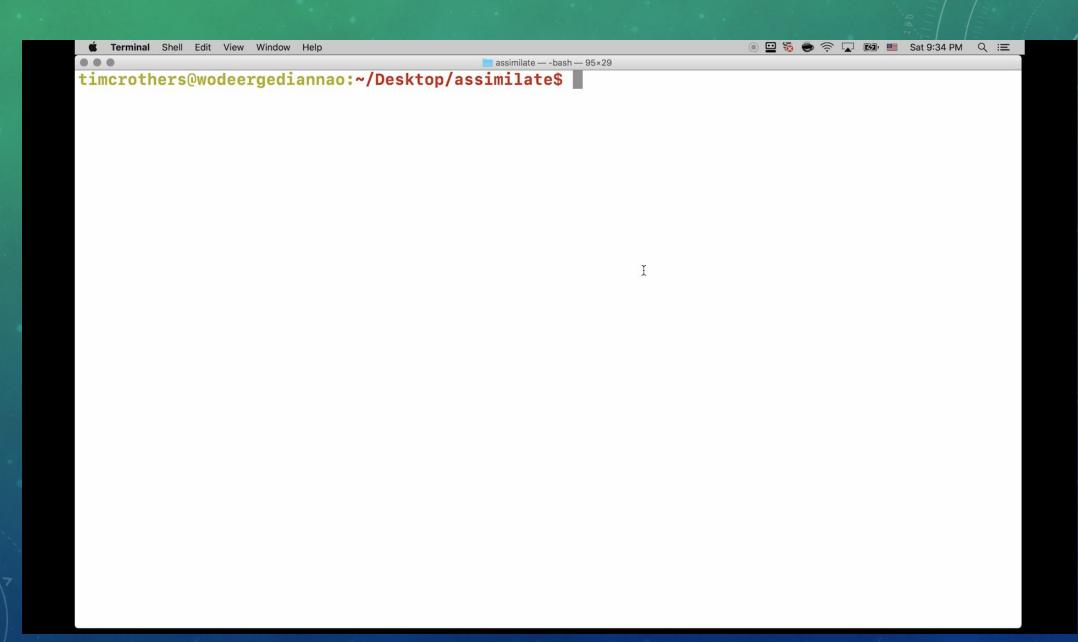
ASSIMILATE-TRAIN.PY



BUILDING ML MODELS FOR HUNTING

- More data == More accuracy
- More data == Slower speed
- Bro Header Normalization == Lower Accuracy
- Tighter Scoping == More Accuracy

ASSIMILATE-ASSESS.PY



DIFFICULT?

```
data = DataFrame({'header': [], 'class': []})
blr = BroLogReader()
print('Reading normal data...')
data = data.append(blr.dataFrameFromDirectory(opts.normaldata, 'good'))
print('Reading malicious data...')
data = data.append(blr.dataFrameFromDirectory(opts.maliciousdata, 'bad'))
print('Vectorizing data...')
vectorizer = CountVectorizer()
counts = vectorizer.fit_transform(data['header'].values)
classifier = MultinomialNB()
targets = data['class'].values
classifier.fit(counts, targets)
print('Writing out models...')
joblib.dump(vectorizer, opts.vectorizerfile)
joblib.dump(classifier,opts.bayesianfile)
```

EXAMPLES

Clearcut - https://github.com/DavidJBianco/Clearcut

Assimilate - https://github.com/Soinull/assimilate

Malicious Macro Bot – https://github.com/egaus/MaliciousMacroBot

RECOMMENDED RESOURCES

Real world bad traffic - https://www.malware-traffic-analysis.net/

Basics - https://speakerdeck.com/davidjbianco/introduction-to-data-analysis-with-security-onion-and-other-open-source-tools

Mid-level - https://speakerdeck.com/davidjbianco/practical-cyborgism-getting-started-with-machine-learning-for-incident-detection

THANK YOU!

- badsecurity@gmail.com
- https://github.com/soinull/PracticalApplicationofML
- in linkedin.com/in/timcrothers/