


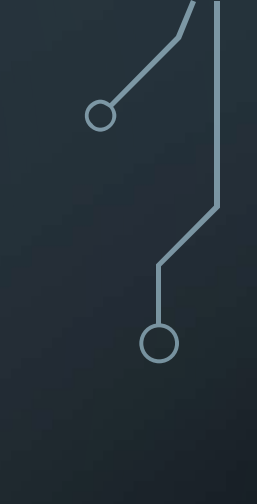
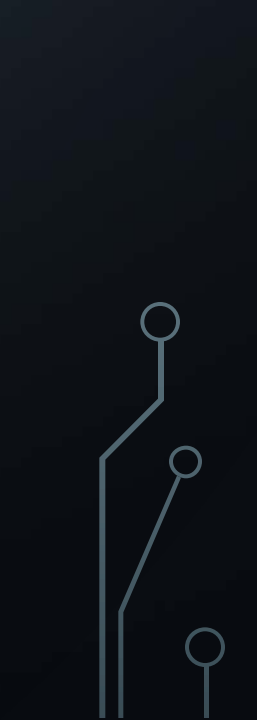
A decorative graphic on the left side of the slide, consisting of a network of thin, light blue lines and small circles, resembling a circuit board or a neural network diagram. The lines are vertical and horizontal, with some diagonal connections, and the circles are small and white, scattered along the lines.

# THE REAL WORLD APPLICATION OF ML TO CYBER SECURITY

TIM CROTHERS






# BACKGROUND

- >30 years in Information Technology and >20 years in Infosec
  - Authored/Co-Authored 16 books to date
  - Engineer and Maker
  - Unabashed Math & Computer Science Geek
  - Spent several years “on the ground at some of the largest breaches”
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# 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
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The image features a dark blue background with white circuit-like lines in the corners. These lines consist of straight segments and small circles, resembling a stylized electronic circuit or data flow diagram. They are positioned in the top-left, top-right, bottom-left, and bottom-right corners, framing the central text.

92%

# COMMON FAILURE #1

- 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

## COMMON FAILURE #2

- 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

## COMMON FAILURE #3

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

## COMMON FAILURE #4

- 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



# SUCCESS IS POSSIBLE!

Clearcut – <https://github.com/DavidJBianco/Clearcut>

- Finds interesting security entries in HTTP Proxy Logs

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


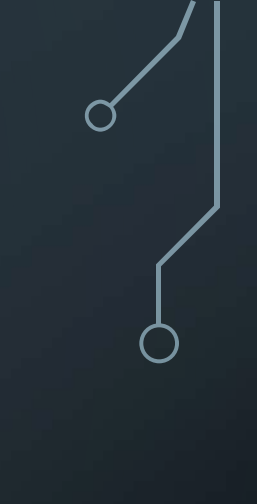
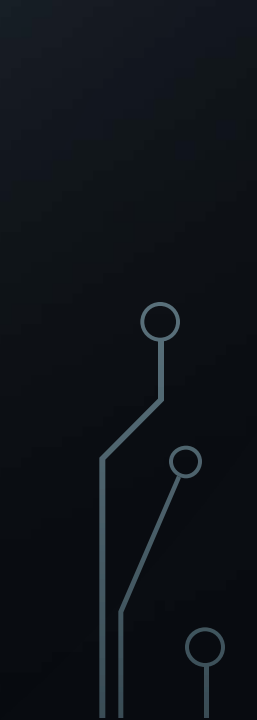
- Is a document macro malicious?

Assimilate – <https://github.com/Soinull/assimilate>

- Finds interesting security HTTP/HTTPS headers



# KEYS TO SUCCESS


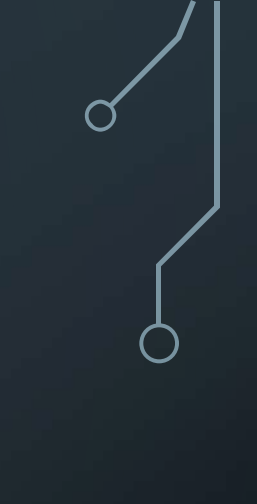
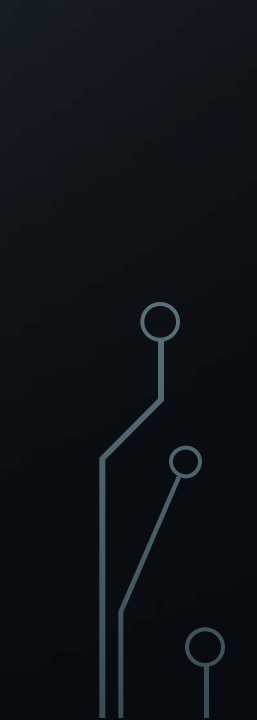
- Tightly scoped problem statement or use case
  - Decide on approach
  - Appropriate data
  - Determine proper parameters and features
  - Test & tune
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# TIGHTLY SCOPED PROBLEM

- 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

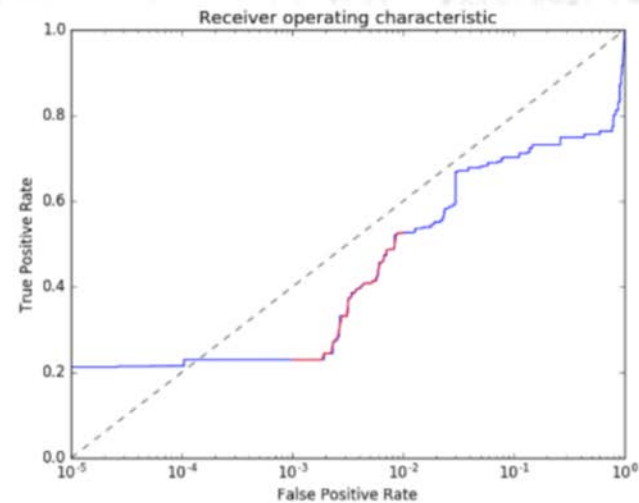
- Supervised
    - Generally best for solving specific problems
    - Needs 'labeled' data
  - Unsupervised
    - Essentially anomaly detection
    - Needs large piles of real world data
    - Inherent assumption attacks are rare
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# APPROPRIATE DATA

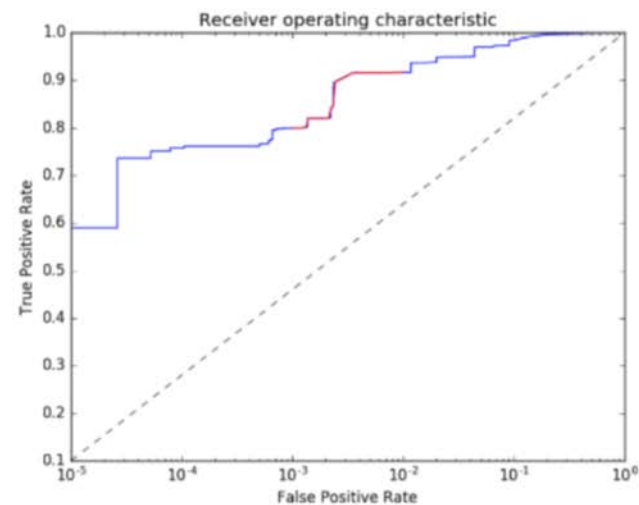
- Hardest part of doing in the real world
- Data appropriate to the problem you selected
- Known good & known bad
  - Bad Samples: <https://www.malware-traffic-analysis.net/>
- Use 80% of each so you can use the other 20% for testing & tuning

# DETERMINE PROPER FEATURES

- Blend of ML and Cyber Security Expertise really critical
  - Start with Cyber Security
  - Validate using standard Data Science techniques



(a) The initial parameters.



(b) The modified parameters.

**Figure 6:** The ROC Curve Produced by the Model under Different Settings of Parameters.

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>

# ASSIMILATE BUILD STEP-BY-STEP

- Gathered the real world network data (one week > 10TB)
- Used Bro 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





# PACKET CAPTURES (PCAP) PROCESSING

```
# 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
```

# TEST & TUNE

- Standard ML best practices apply
- If the accuracy is too low:
  - Is your sample data solid?
  - Is your parameter & feature selection strong?
  - Try swapping different algorithms

# 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!

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 @soinull

 linkedin.com/in/tim-crothers-5458738/

 [https://github.com/soinull/ML\\_for\\_Cyber](https://github.com/soinull/ML_for_Cyber)