CMSC 449/691 Malware Analysis

Lecture <flexible> Malware Data Science Revised April 7, 2025

Malware Data Science

- Hundreds of thousands of unique, new malware samples daily
- Impossible for human analysts to investigate every file
- Need to rely on automation and data science!
 - Can we automate common analysis tasks?
 - □ Can we enhance threat hunting, malware classification, etc.?

Public Malware Datasets

- EMBER2018 Dataset PE metadata extracted from ~500,000 malicious files and ~500,000 benign files
 <u>https://github.com/elastic/ember</u>
- SOREL-20M Dataset PE Metadata from ~10M benign files and ~10M disarmed malware samples from 11 categories
 <u>https://github.com/sophos/SOREL-20M</u>
- MOTIF Dataset 3,095 malicious PE files from 454 malware family families with ground truth labels
 <u>https://github.com/boozallen/MOTIF/</u>

Automating Malware Analysis

Malware Analysis Pipeline

- Most large malware analysis shops have a pipeline which automatically processes malware

 Newly-ingested files
 Re-processing older files
- Basic static analysis
- Basic dynamic analysis
- Malware signatures (YARA, Snort, AV)

Automating Basic Static Analysis

- Extract file metadata
 - Python libraries such as pefile, lief for extracting PE metadata
- Compute similarity-preserving hashes
 SSDEEP
 TLSH
 - LZJD / BWMD
- Compute metadata hashes
 - pehash
 - imphash

Side Note: Automating Disassembly

- Can automate many advanced static analysis tasks
 Too slow to apply to every malware sample though
- Capstone library for Python is an excellent linear disassembler
 - Pefile can also do some of this
- Most modern disassemblers/decompilers (including IDA Pro, Ghidra, Binary Ninja) support plugins
 Can use these for automating many advanced static analysis tasks

Automating Basic Dynamic Analysis

- Automated sandboxes such as Cuckoo and DRAKVUF can be self-hosted and used for identifying malware behavior
- Generate report about the malware's actions:
 - Process tree
 - Created files
 - Network traffic
 - Configuration changes

Malware Signatures

- Many malware analysis shops have a collection of in-house antivirus products
- May also maintain other large collections of signatures:
 YARA rules based on file contents
 Snort rules based on network traffic
- The yara-python library lets YARA be used programmatically

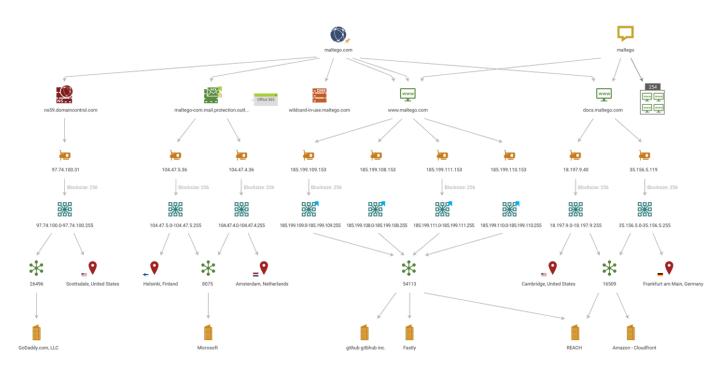
Malware Data Science Problems

Threat Hunting

- Goal is to identify malware of interest, usually related to a set of known IOCs
 - □ Often investigating a malware family, campaign, or threat group
- File similarity metrics, metadata hashing
- Identifying files which contact the same IPs / domain names
- Lots of nearest-neighbor lookup research in this area!

Threat Hunting with Maltego

- Threat hunting tool which can be used to pivot from known IOCs to related ones
- Generates a graph showing how IOCs are related



Malware Featurization

- A feature vector is the standard input for most machine learning algorithms (nearest-neighbor lookup, clustering, classification, outlier detection etc.)
- Essentially a list of numbers which somehow describe the attributes of a data point
 - $\Box < 10, -2, 3, 7, 0 >$
- Each number in the feature vector describes a specific attribute of the data point

Malware Featurization

- How do we best represent malware as a feature vector?
- **EMBER vector** Based on metadata from PE files
 - Features include byte frequency, metadata from PE headers, strings, imports, resources, etc.
 - Vector contains 2,351 features
- BWMD vector Based on the Burrows-Wheeler Transform
 Converts any sequence of bytes into a fixed-length vector
 Vector contains 65,536 features

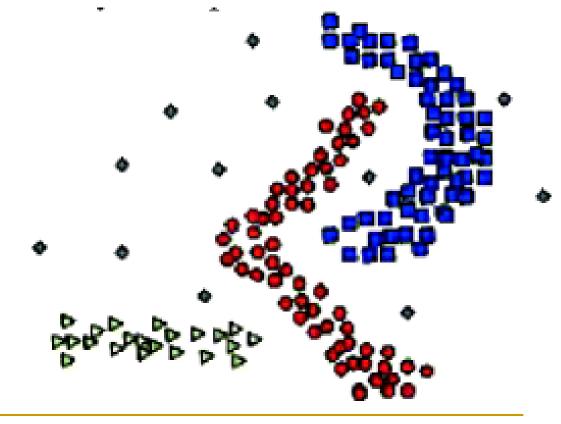
Malware Clustering

- Clustering: Identify groups of similar malware samples
- Usually need to convert malware into feature vectors first!
 Or have a method for computing similarity between two files
- Many different clustering algorithms, depending on your situation and goals
 - Density-based and hierarchical clustering algorithms work best
 - But may run slowly on large datasets

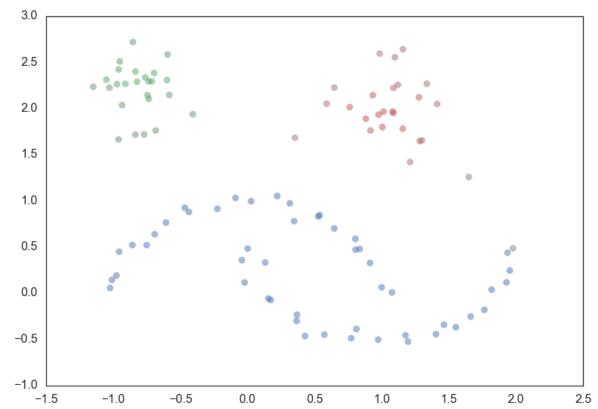
Density-Based Clustering

- Assume that malware data tends to form lots of small, dense clusters (each cluster being a malware family)
- Dense groups and their neigbors become a cluster

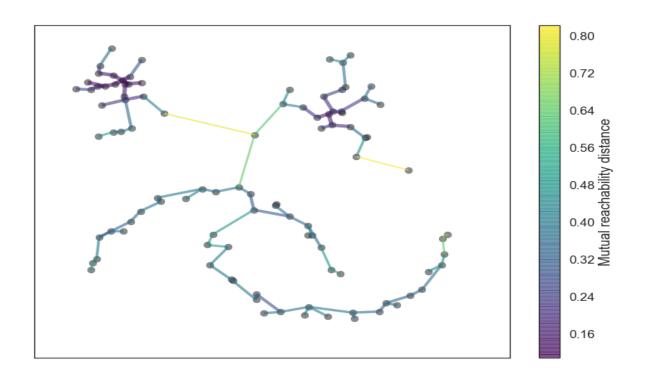
 Algorithms such as DBSCAN and OPTICS often work well!



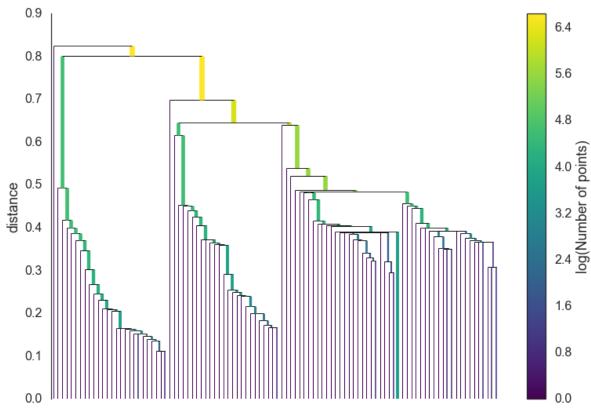
- Idea is to form a "hierarchy" of data points, iteratively grouping the nest most similar points
- Algorithms such as Hierarchical Agglomerative Clustering (HAC) and HDBSCAN are good!



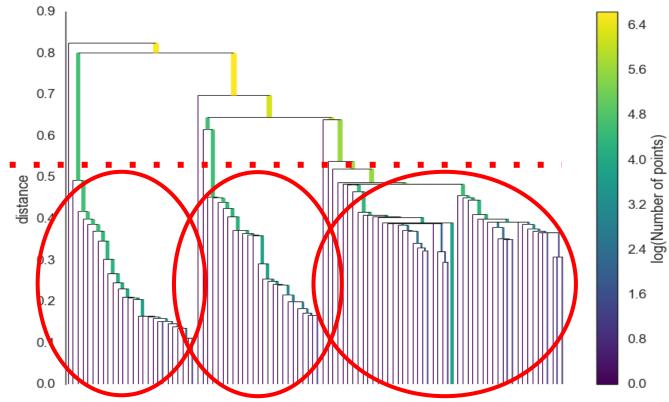
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- Hierarchical Clustering can be used to produce a dendrogram



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- Algorithms such as Hierarchical Clustering can be agglomerative (bottom-up) or divisive (top-down)

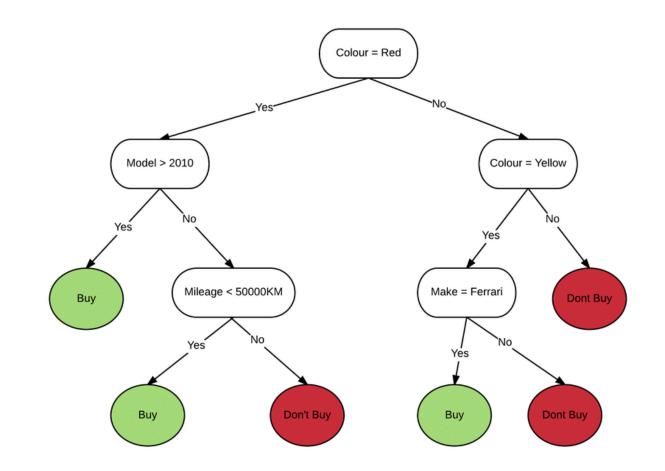


Malware Classification

- **Classification:** Task of assigning a data point to a class
- Malware Detection: Classify file as benign/malicious
- Category Classification: Classify file by behavior category (e.g. ransomware, keylogger, etc.)
- Family classification: Classify file by malware family

Decision Tree Classifiers

- Decision Tree simple classification algorithm that maps combinations of features to a class outcome
- In the figure, the result for red cars newer than 2010 is the "buy" class



Decision Tree-Based Ensemble Classifiers

- Ensemble: Powerful machine learning technique where a collection of classifiers (often decision trees) vote on a class
- Algorithms like Random Forests, XGBoost, and LightGBM are extremely accurate for malware detection

 Usually trained on EMBER feature vectors

Deep Learning-Based Malware Classifiers

- Lots of research using neural networks and deep learning for malware classification
- MalConv and MalConv2 are leading models

 Treat malware as a large sequence of bytes
 Apply 1-D convolution to extract spatial relationships from data
 Features are learned through convolution!