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APPLIED MACHINE LEARNING FOR DATA EXFIL AND OTHER FUN TOPICS

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CYLANCE

GOALS OF THIS TALK:
APPLIED MACHINE LEARNING

- Identify suitable problems for ML approaches
- Demonstrate by example how to apply ML
- Help jumpstart additional research in the Security + ML space

WHO WE ARE/CYLANCE

- Endpoint security company built around the capabilities of artificial intelligence
- Protecting millions of enterprise endpoints
- Founded in 2012, $177 mm raised
- Booth #1124

Matt Wolff
Chief Data Scientist

Brian Wallace
Senior Security Researcher

Xuan Zhao
Data Scientist

TALK OVERVIEW

- Machine Learning Introduction
- NMAP Clustering
  - Feature Spaces
  - Distances
  - Clustering
- Botnet Panel Identification
  - Classification
  - Feature Reduction
- Obfuscating Data with Markov Chains

MACHINE LEARNING OVERVIEW

- Machine learning techniques are data driven
- Available data should be able to solve the problem in a meaningful way
- Approaches exist for dealing with raw data, as well as labeled or annotated data

MACHINE LEARNING OVERVIEW

- Given some data, different types of machine learning can be applied
- Clustering is useful for finding similarity across dataset to uncover trends or other insight
- With labeled data, classification can be useful to build predictive models

MACHINE LEARNING OVERVIEW

- Often, raw data has to be transformed in some way to be used by machine learning algorithms
- Typical process is to extract features from data, and turn those features into vectors
- Vectors are then fed into ML algorithms for training or other purposes

MACHINE LEARNING OVERVIEW

- Recommended resources
  - Scikit-learn.org
  - Python
- Source code for all tools in this talk available on the Cylance public git repo
  - https://github.com/CylanceSPEAR
- Should be able to pull talk source and start modifying as needed to suit data driven problems in your own organization or research group.

TOOL – NMAP CLUSTERING

- NMAP is a popular port scanning tool
- Produces large amount of data per IP address
- Scans over large number of IPs can be difficult to make sense of
- NMAP Clustering is a tool which clusters (groups) IPs based on their open ports, services, etc

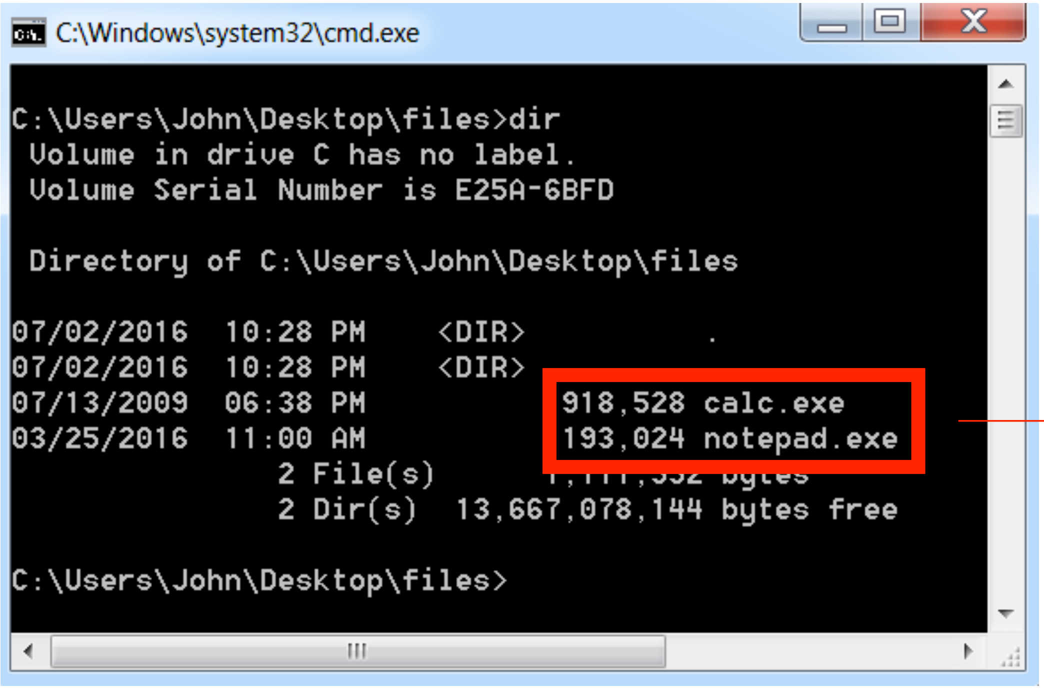
FEATURES

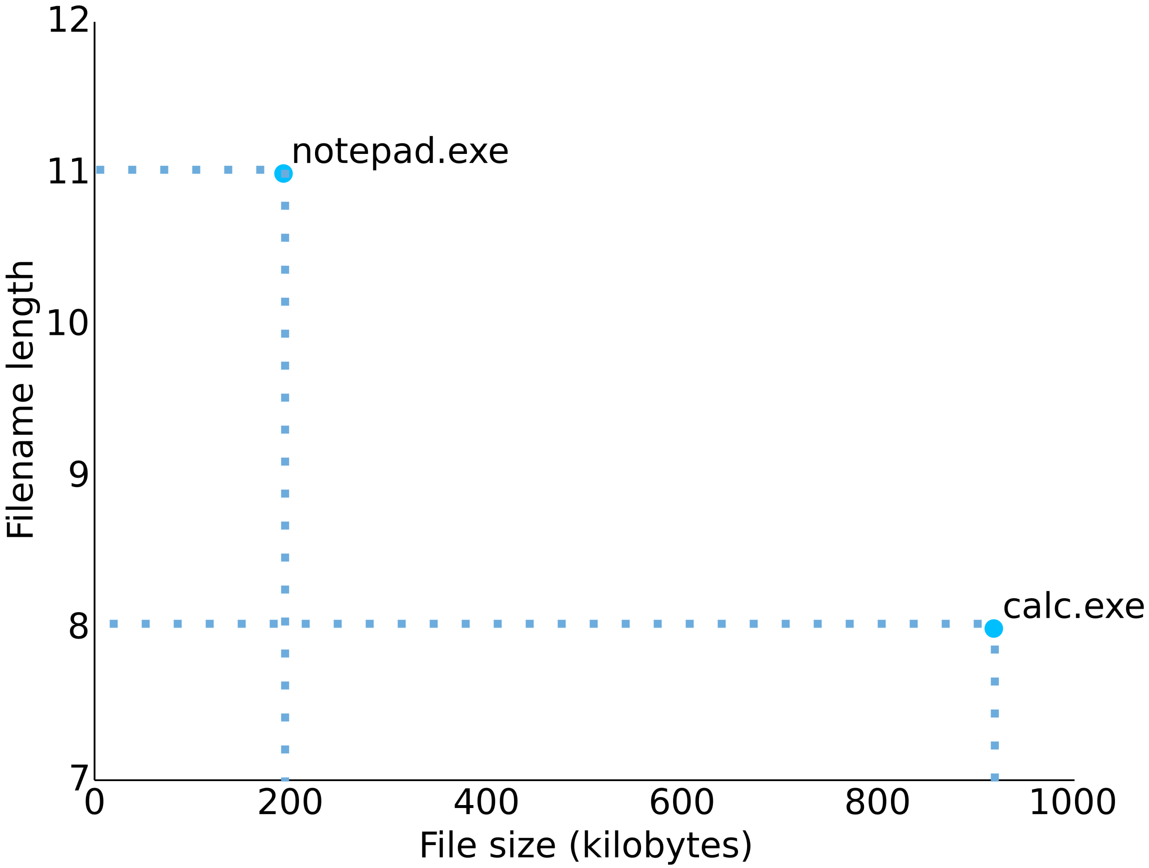
- Features are informative, discriminative information that can describe a sample/observation/phenomenon/etc.
- Feature extraction is pivotal to the machine learning pipeline
- Our features are based on NMAP output
- Each port is a feature, each service on each port is a feature, each version of each service on each port is a feature, etc
- Script output included in features (including website titles, public keys, etc)

VECTORS

- Numerical representation of a sample (IP in NMAP case)
- Array of values which represent all features from one sample
- Vectors can be thought of as points in high dimensional space
- Each feature is a dimension, the value of the feature in the vector is the position in that dimension
- If we have only two features, it is really easy to visualize

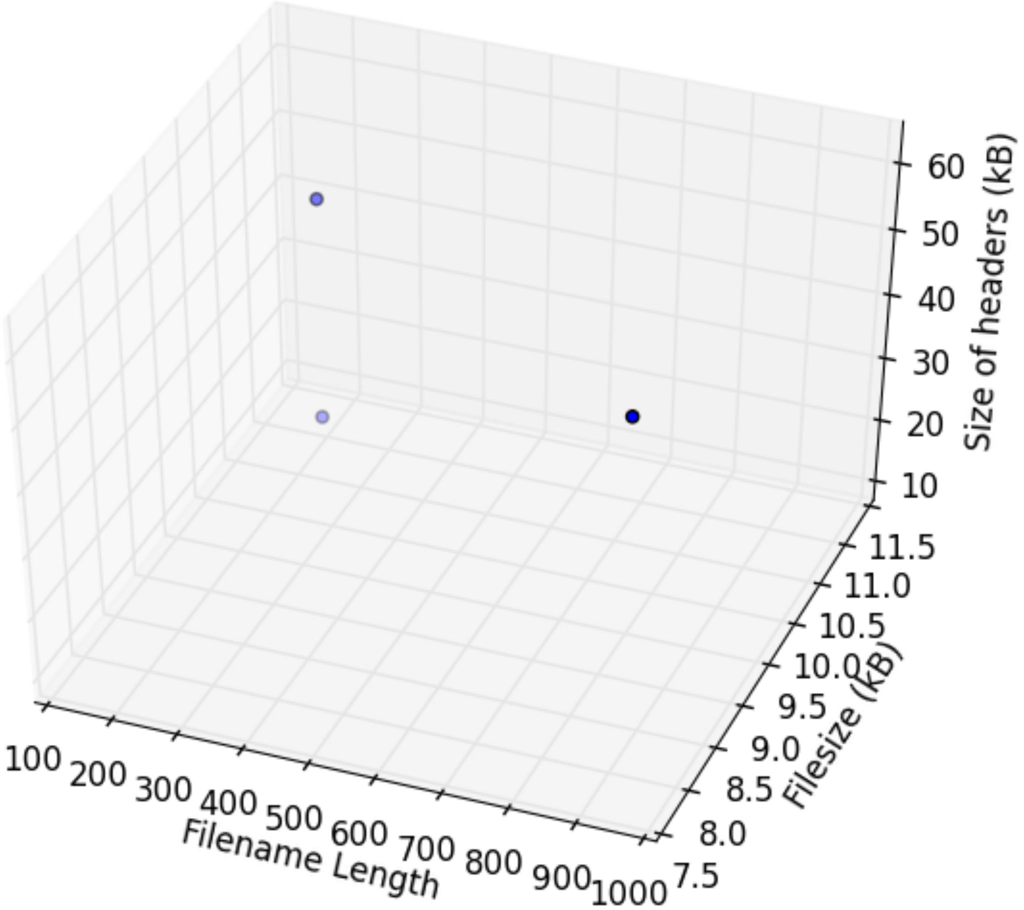
VECTORS – 2D


C:\Windows\system32\cmd.exe
C:\Users\John\Desktop\files>dir
Volume in drive C has no label.
Volume Serial Number is E25A-6BFD
Directory of C:\Users\John\Desktop\files
07/02/2016 10:28 PM <DIR> .
07/02/2016 10:28 PM <DIR>
07/13/2009 06:38 PM 918,528 calc.exe
03/25/2016 11:00 AM 193,024 notepad.exe
2 File(s)
2 Dir(s) 13,667,078,144 bytes free
C:\Users\John\Desktop\files>

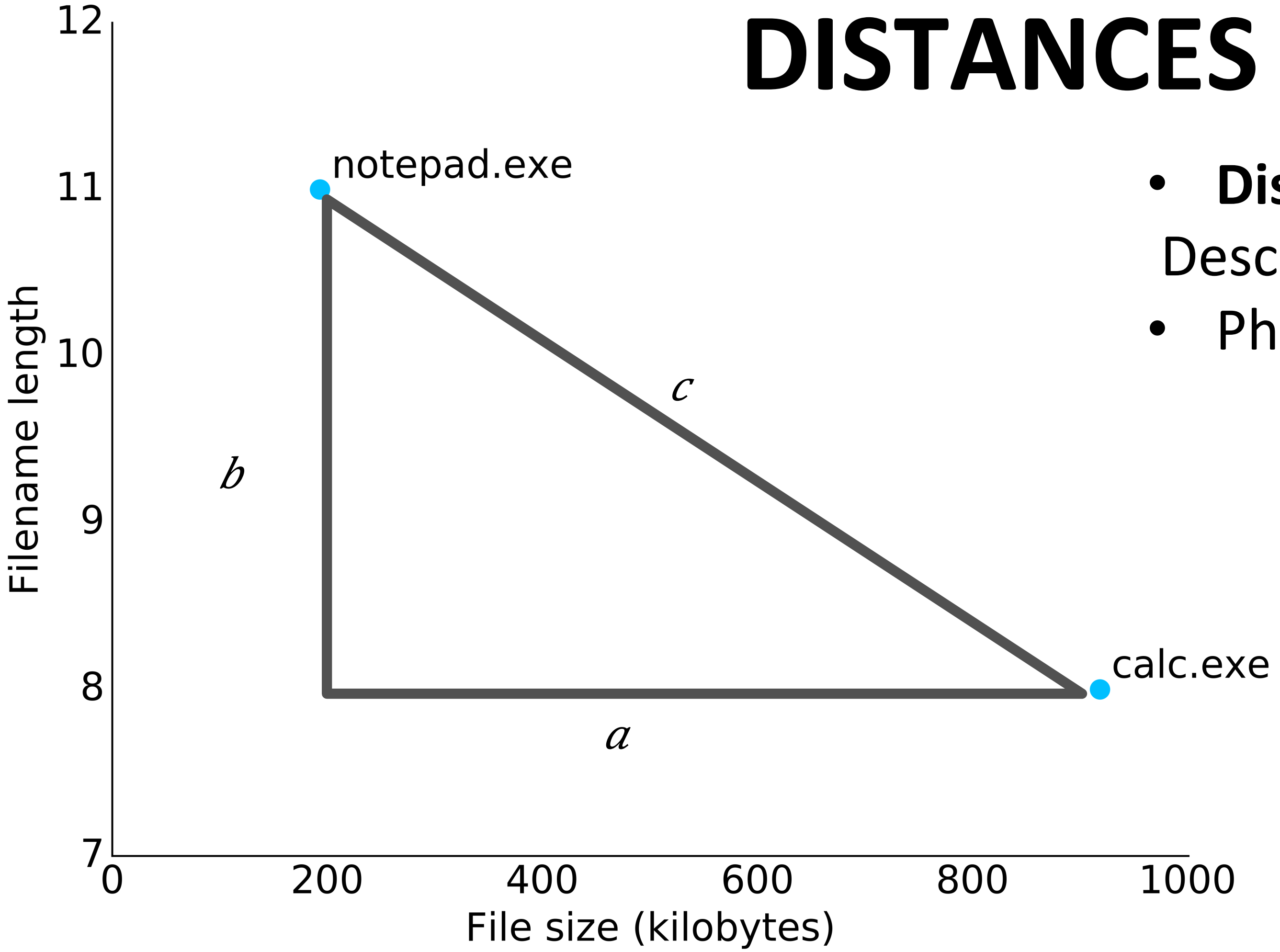

notepad.exe
calc.exe
Filename length
12
11
10
9
8
7
0
200
400
600
800
1000
File size (kilobytes)

VECTORS – 3D

File	Filename Length	Filesize (kB)	Size of headers (kB)
calc.exe	8	918.528	63
notepad.exe	11	193.024	45
malware.exe	11	193.024	10



DISTANCES



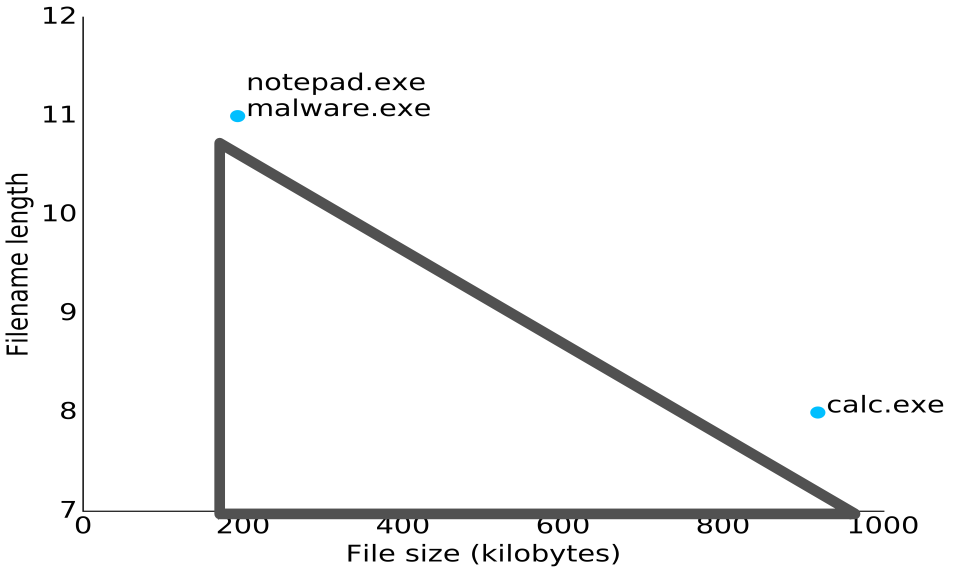
- **Distance:**
  Describe the discrepancy between two points
- Physical distance between two points:

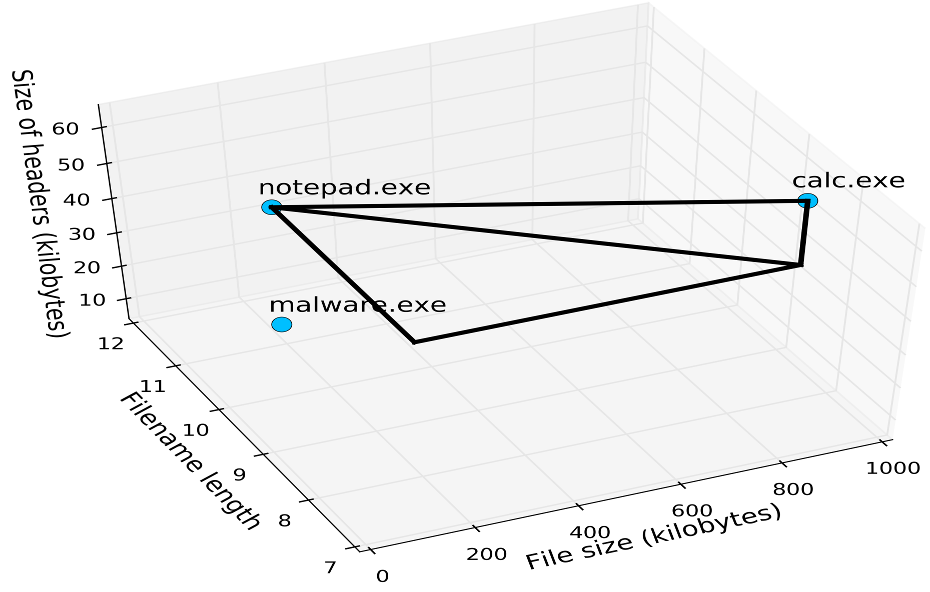
Pythagorean's theorem:

$$a^2 + b^2 = c^2$$

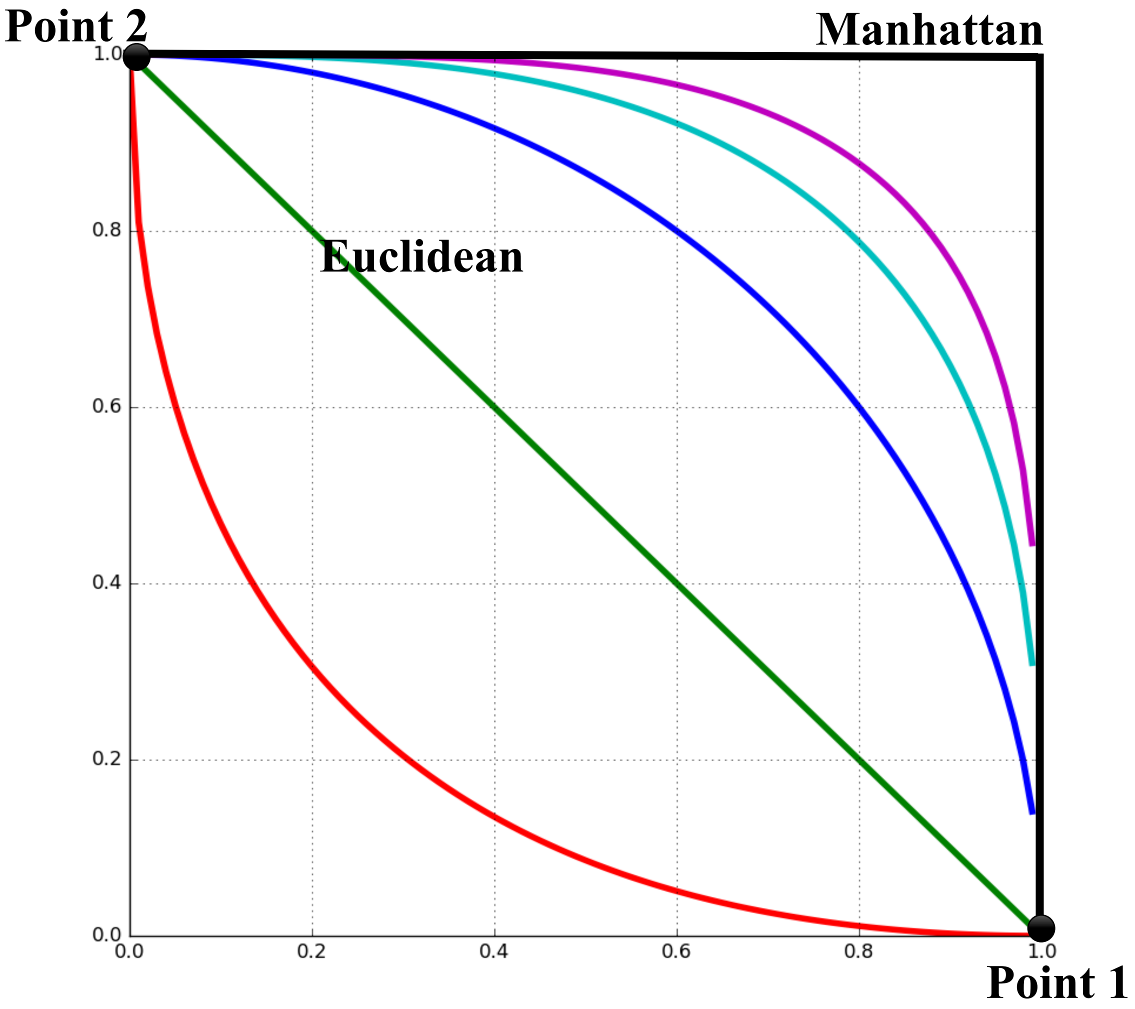
File	Filename Length	Filesize (kB)	Size of headers (kb)
calc.exe	8	918.528	63
notepad.exe	11	193.024	45
malware.exe	11	193.024	10

2D





3D



DISTANCES

Multiple Distance Metrics –

As long as an operation satisfy certain mathematical criteria, it can be used as a distance metric

- Euclidean Distance: $\sqrt{(a^2 + b^2)}$
- Manhatttan Distance: $|a| + |b|$
- Other Distances
  - L_p Norms: $(a^p + b^p)^{1/p}$
  - cosine Distance: $\frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}$

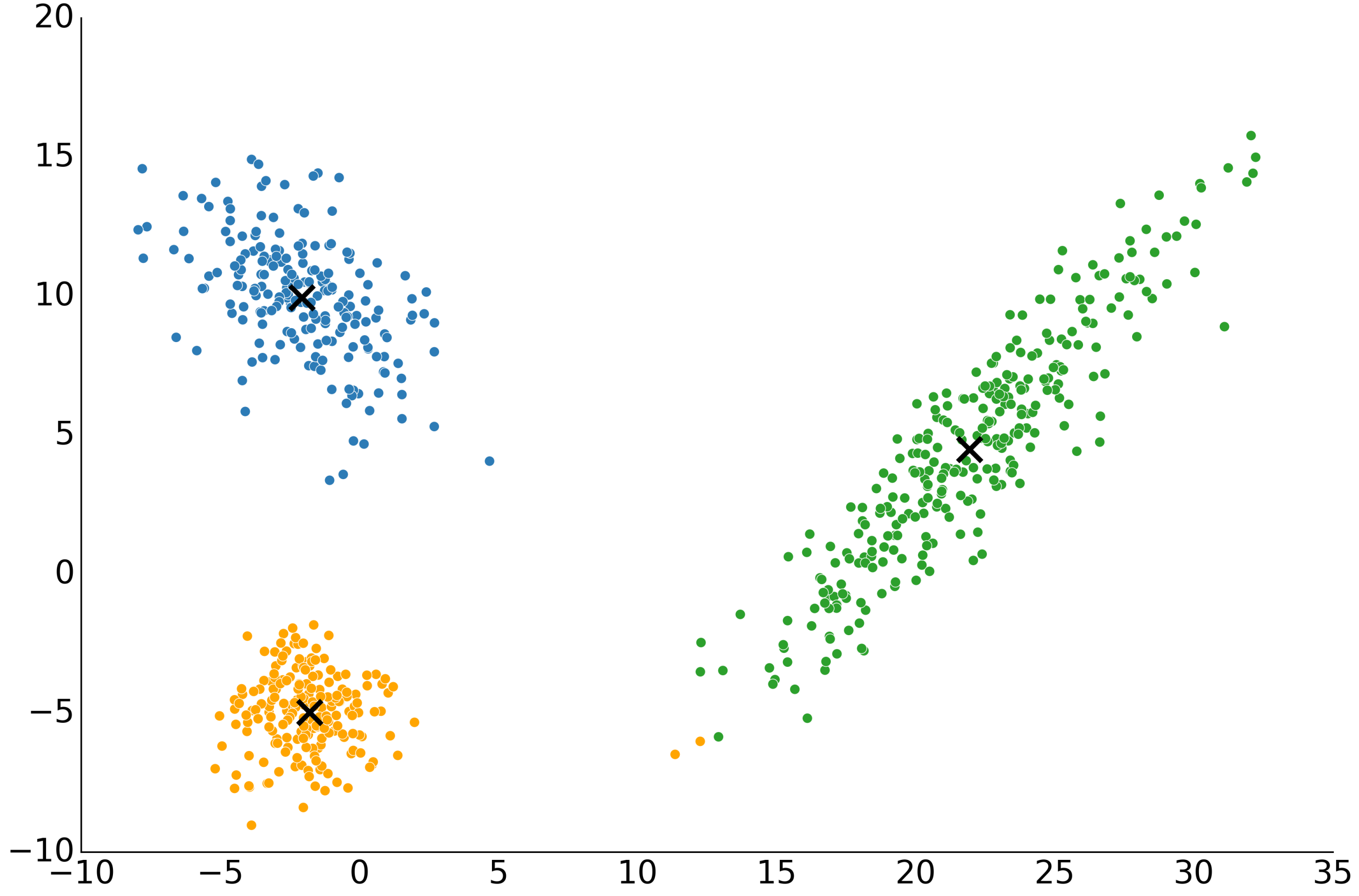
CLUSTERING

- With a way to measure distance, we can group items by how close they are, aka clustering
- Clusters are distinct groups of samples (IP) which have been grouped together
- Clustering is generally unsupervised learning
- Different algorithms with different configurations group these samples in different ways

k-Means

- Clustering algorithm
- User supplies *k* (destinated number of clusters)
- All samples are assigned to random clusters
- Center of each cluster is computed by taking mean (average) of all samples in cluster
- Samples are then assigned to the cluster whose center they are closest to
- Centers are recomputed, algorithm loops until no samples change clusters

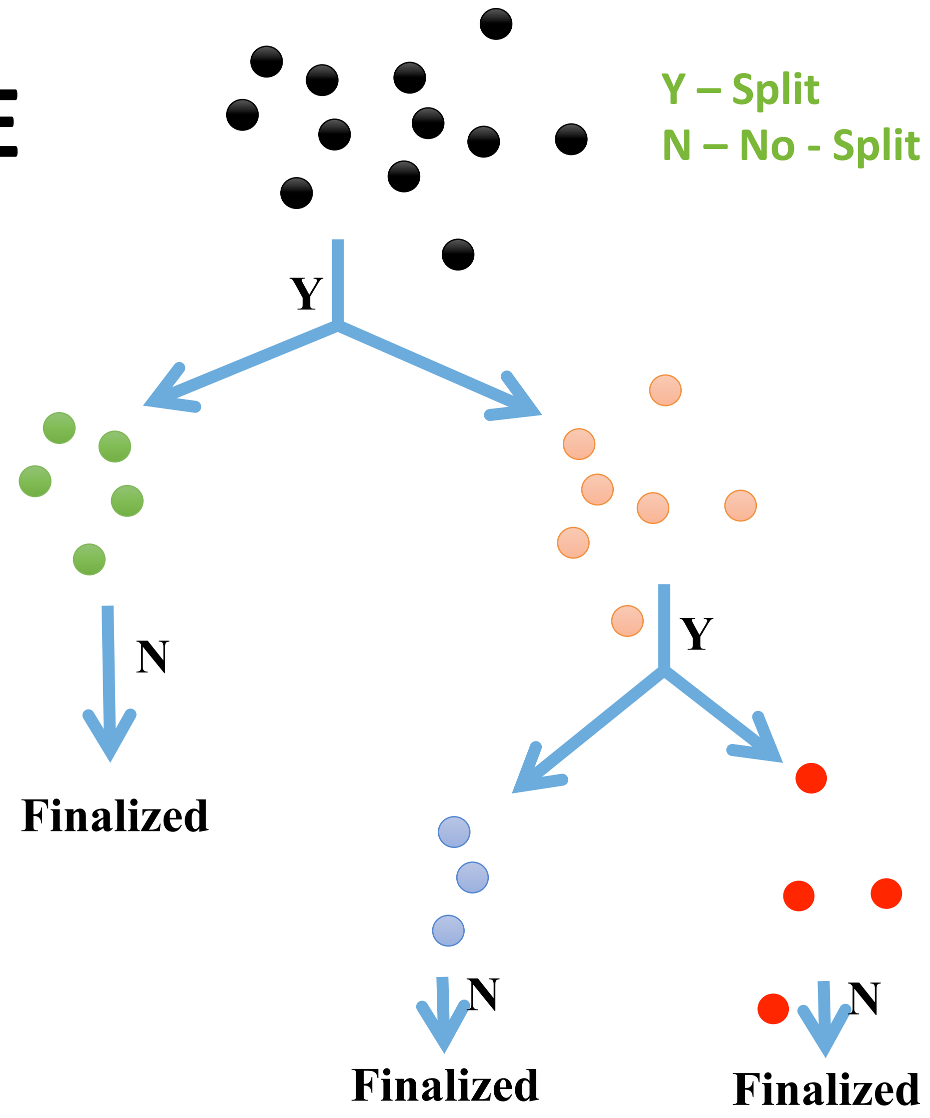
k-Means



NMAP CLUSTERING – MANUAL/AUTOMATIC

- Manual allows you to supply your own clustering parameters
- Automatic tries many different methods with theoretically-found optimal parameters and picks what it determines to be the best
- Demo with manual strategy
- Demo with automatic strategy

NMAP CLUSTERING - INTERACTIVE



- Incorporate the User's decision into the clustering process.
- The Clustering result will be customized according to customer's preference in this way
- Process (will show with a demo):
    1. User decide whether the cluster needs to be split or not:
    2. If yes, then split using divisive clustering
    3. If no, finalize this cluster
    4. Recursively split until users are satisfied with all the clusters

TOOL – ID PANEL

- Botnet panels (command and control websites) can be difficult to identify
  - Need previous knowledge of the botnet panels
  - Often modified to avoid detection or vanity
  - Many are based off others, so distinguishing can be difficult
- We can train a model to identify if we are looking at a bot panel and which one it is, with a small number of requests
- Minimizing the number of requests to classify improves stealth and rate of classification

CLASSIFICATION

- This is a classification problem
- Classification answers "Is it what we are looking for?"
- Classification is generally supervised learning
- Supervised learning requires training samples to have labels
- Classification methods range from simple to highly complex

ID PANEL FEATURES

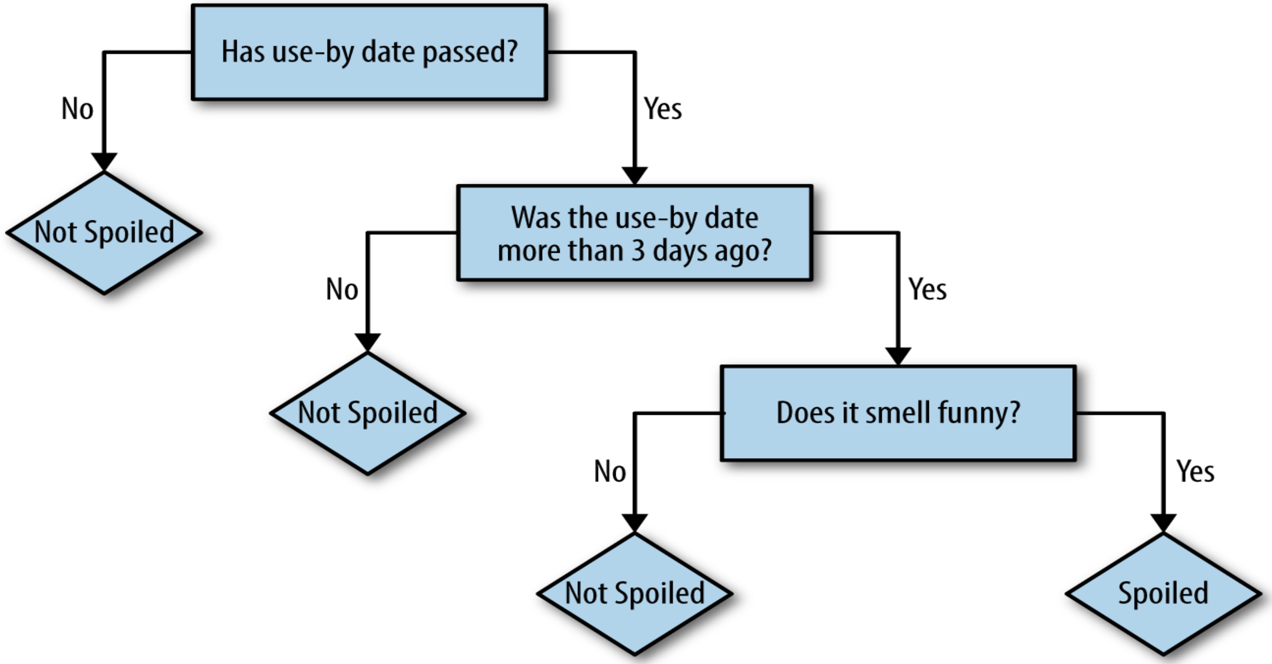
- Botnet panels are similar to normal websites
- Contain various file types, often edited
- HTTP response codes + content comparison
- Encoding content as features difficult
- ssDeep provides a continuous value by comparing content

COLLECTING DATA

- Collection of known botnet panels
- Request all known paths for all known botnet panel types
- Store HTTP status code and ssDeep of content
- Collection of sites that are not botnet panels needed as well

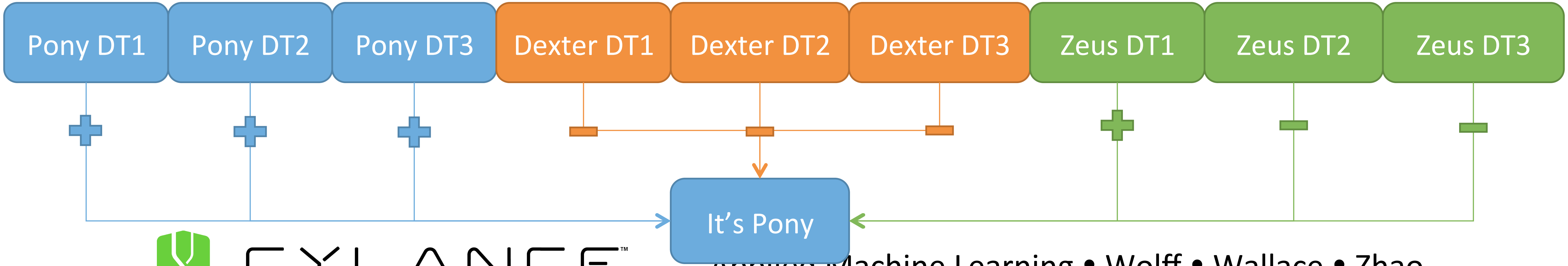
DECISION TREES

- Decision trees are simple classifiers
- Splits the dataset one feature at a time until decision is confident
- Results in a tree of queries where the results produce a decision
- Simple to train



ENSEMBLE OF DECISION TREES

- A single decision tree may be over focused on training data
- Can alleviate this problem by building multiple Decision Trees for each label
- Combining the results allows each Decision Tree to vote
- Partial answers may still be of interest to the user
- Ensembles can obtain better predictive performance



ID PANEL DEMO – COMMAND LINE

- Quick way to check if a website directory contains a botnet panel
- Easy to batch searching of multiple websites/directories
- Easy to grep results

ID PANEL DEMO – CHROME EXTENSION

- Every website directory visited is tested
- Results are stored in browser
- ssDeep ported from C to Javascript
- https://github.com/kripken/emscripten
- Extension available in Chrome extension store (free, of course)

TOOL – MARKOV OBFUSCATE

- Data exfiltration from a network often requires avoiding an outbound firewall
- Deep packet inspection looks to block anything undesirable
- Easy to encrypt data, but its also easy to drop information that can’t be read
- We can make our data look like something else entirely

MARKOV CHAIN

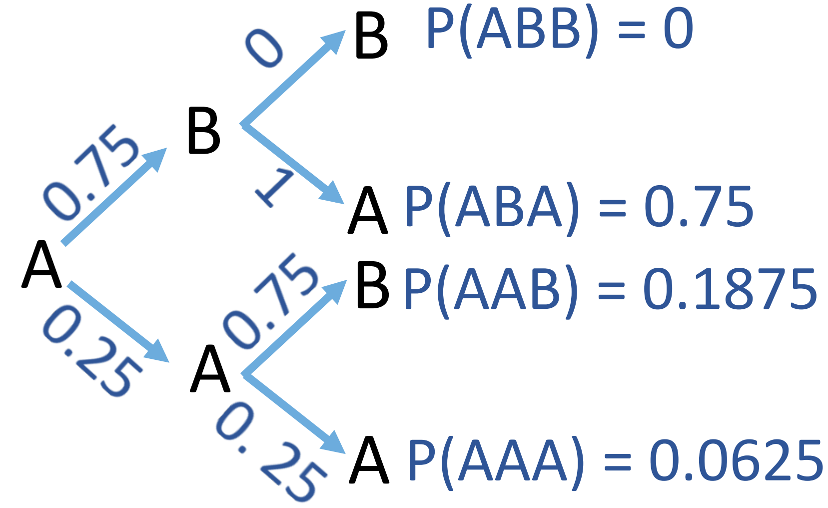
- Simple machine learning method for characterizing sequence data
- Learns the transition pattern from a state to another based on how likely a state comes after another state in the training data
- We can create sequences with transition patterns that are learned from the data it was trained on

Training Data

AAB
BAB
ABA

Transition Matrix

	A	B
A	1 (25%)	3 (75%)
B	2 (100%)	0 (0%)

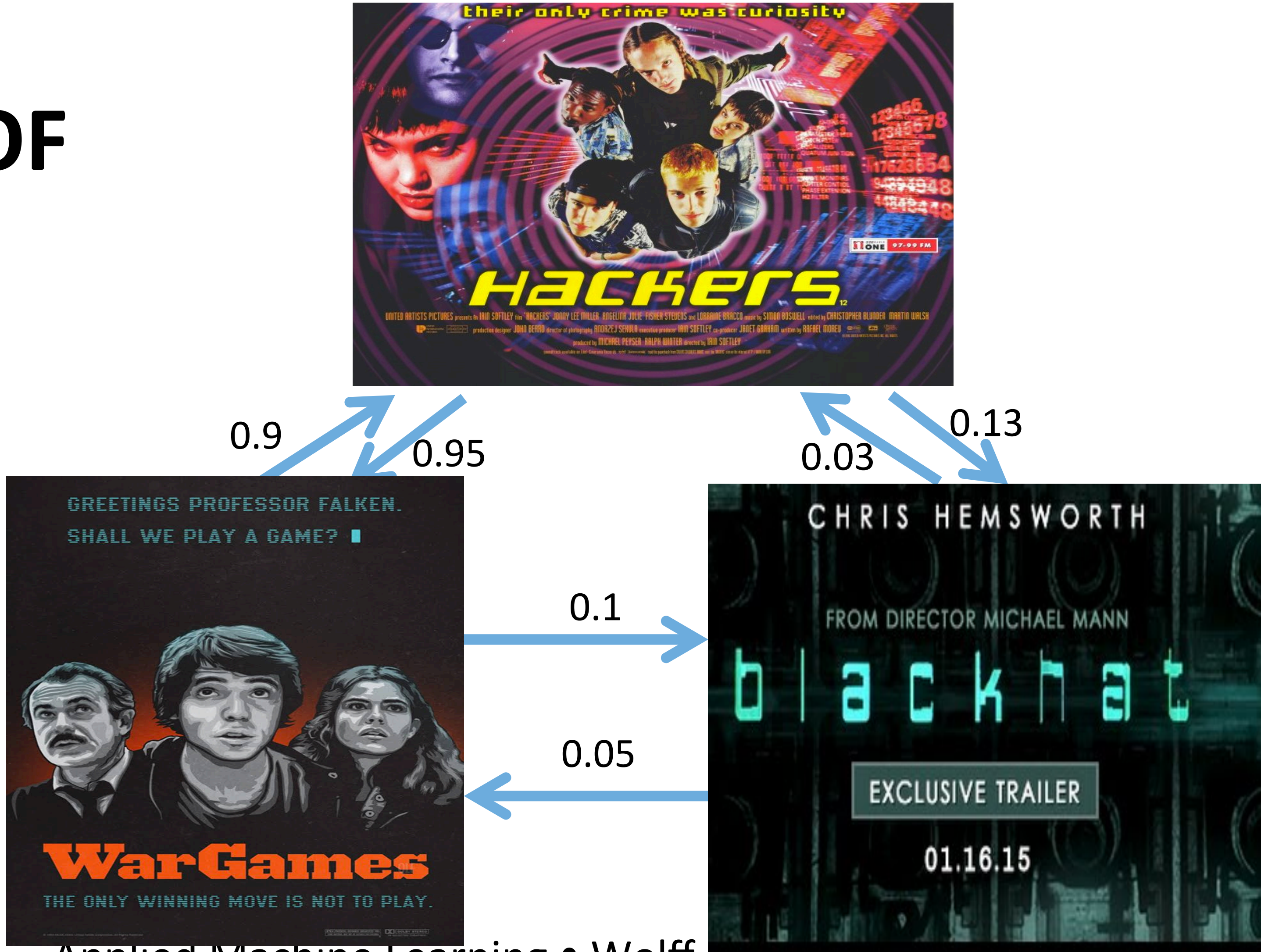


POPULAR USE CASES OF MARKOV CHAINS

Weather Prediction

	Sunny	Rainy
Sunny	0.9999	0.0001
Rainy	0.9	0.1

Recommendation



ENCODING DATA WITH A MARKOV CHAIN

- Given a transition matrix, we can sort items by how likely they are to follow our current item
- If we choose the 5^{th} most likely item, we can identify it's the 5^{th} most likely with a model trained on the same data
- This encodes the number 5 in the transition from our first item to our second item

MARKOV OBFUSCATE - ENCODING

- Train our model with a book
- Observing transitions from word to word
- Generate data based on transition probabilities
- Demo

MARKOV OBFUSCATE - WRAPPING

- Simple to transfer our data through a pipeline that looks like normal HTTP traffic
- Looks like a user posting to their blog
- Demo

MARKOV OBFUSCATE – HAVING FUN

- Train our models on Taylor Swift lyrics
- Train a Markov Model based on Taylor Swift songs
- Play the generate lyrics through festival with tones/beats learned from songs
- First live “Tylance Swift” concert, demo

WRAPPING UP

- Any problem where there is a significant amount of data generated could benefit from a machine learning approach
- Lots of great online resource to help anyone get started
- Having labeled or annotated data makes more ML approached viable compared to unlabeled data

QUESTIONS?

- Email: machinelearning@cylance.com
- Stop by booth #1124
- Career opportunities: https://www.cylance.com/cylance-careers