ANALYZING LOGS DATA WITH AI

MCS 2025 Cyber 242

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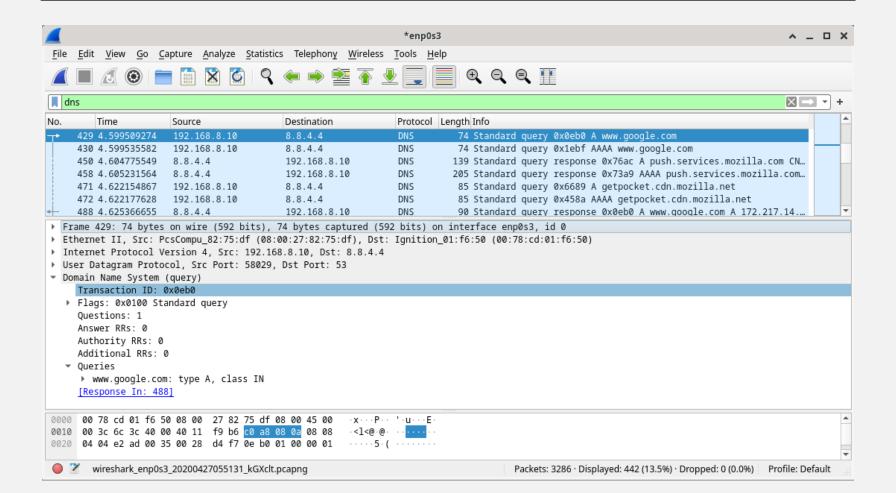


OBJECTIVES

- Understand the nature of log data
- Learn how to transform log data for analysis
- Apply various data analysis techniques to find anomalies in log data
- By "AI" we refer to data analysis tools and algorithms.

UNDERSTANDING LOG DATA

PACKET CAPTURE LOG (WIRESHARK)



DATA AVAILABLE IN PACKET LOGS

- Timestamp
- Source IP
- Destination IP
- Protocol
- Source Port
- Destination Port
- Flags

LIMITATIONS OF LOG DATA

- Snapshot of network activity
- Limited context
- High volume and velocity
- Noise and redundancy
- Data quality issues
- Lack of standardization
- Retention limits
- Privacy and security concerns

THINGS TO BEAR IN MIND

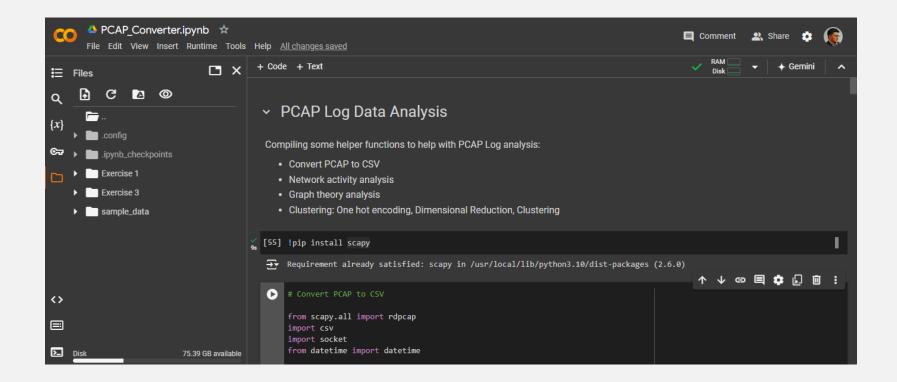
- Data analysis does not replace domain knowledge but complements it
- Data analysis is better at generating questions but it remains the duty of the security analyst to put a case together
- Data analysis is about pattern recognition look for similarities and anomalies as clues to formulating a hypothesis

SETTING UP GOOGLE COLLAB

GITHUB REPOSITORY

- Access/clone/fork from here:
 - https://github.com/docligot.com/pcap_labs

PCAP CONVERTER NOTEBOOK



PCAP CONVERTER NOTEBOOK

- Scripts are provided for the following functions:
 - Convert PCAP to CSV
 - Network Activity Analysis
 - Graph Theory Analysis
 - Clustering Analysis:
 - One-hot-encoding
 - Dimensional Reduction
 - Clustering

PCAP LAB EXERCISES

PCAP LAB EXERCISES

- 3 exercises are provided
- Exercise I will have forensic analysis, alerts, and the PCAP file
- For Exercise I, we will stick purely to data analysis, no need for domain explanations.
- Exercises 2 and 3 will only have the PCAP file. Forensic analysis and alerts will be provided later for discussion.
- For Exercises 2 and 3, class is allowed to speculate on possible explanations for the anomalies.

DATA ANALYSIS OF PCAP

TIME SERIES – EYEBALLING

Count of Packet_Number	er Column Labels 🖅			
Row Labels	172.17.0.17	172.17.0.99	79.124.78.197	Grand Total
⊕:00	4	43	4	51
⊕:01	2	17	6	2 5
⊕:02	10	34	4	48
⊕:03	4	6	1	11
⊕:04	2	31	5	38
⊕:05	2	23	7	32
⊕:06	2	10		12
± :07	1	29	9	39
⊕:08	1	12	5	18
± :09	1	5	2	8
±:10	3	9	4	16
⊕:11	1	7	6	14

IP TO PORT - EYEBALLING

Count of Packet_Number	Column Labels 🔻
Row Labels	53 67 68 80 88 123 135 137 138 139 389 443
23.45.119.143	14
23.45.119.144	199
23.45.119.147	13
40.119.249.228	22
40.126.28.12	20
40.126.28.22	11
46.254.34.201	504
52.109.0.142	13
52.109.0.91	16
52.113.194.132	73
79.124.78.197	261
(blank)	
Grand Total	87 2 2 290 45 8 30 18 18 55 177 1536

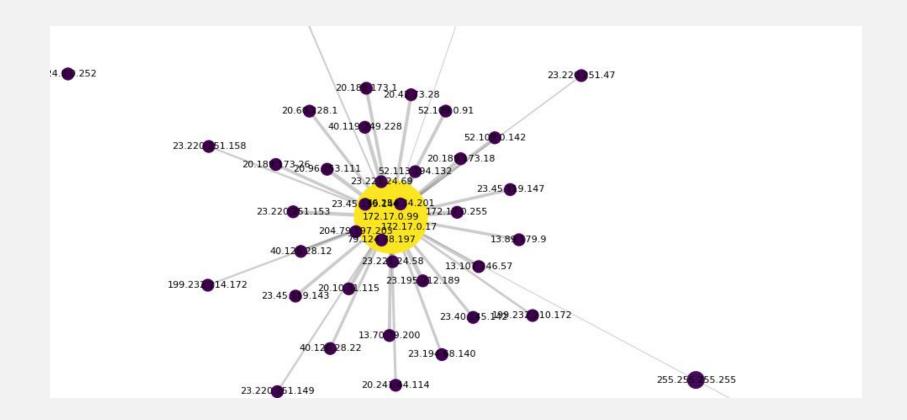
IP TO IP - EYEBALLING

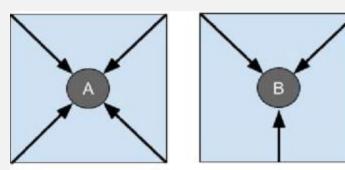
Count of Packet_Number	Column Labels			
Row Labels	172.17.0.99	255.255.255.255	(blank)	Grand Total
23.45.119.147	13			13
40.119.249.228	22			22
40.126.28.12	20			20
40.126.28.22	11			11
46.254.34.201	504			504
52.109.0.142	13			13
52.109.0.91	16			16
52.113.194.132	73			73
79.124.78.197	261			261
(blank)			294	294
Grand Total	1826	2	294	2122

NETWORK ACTIVITY STATISTICS

```
=== Network Traffic Analysis Report ===
Basic Statistics:
total packets: 5091
unique_ips: 42
unique connections: 77
avg_packet_size: 423.1392537002293
duration_seconds: 3576.159984
Top Talkers:
Top Source IPs:
172.17.0.99: 2358 packets
172.17.0.17: 611 packets
46.254.34.201: 504 packets
79.124.78.197: 261 packets
23.45.119.144: 199 packets
23.221.24.69: 147 packets
204.79.197.203: 144 packets
23.221.24.58: 91 packets
52.113.194.132: 73 packets
23.195.212.189: 37 packets
```

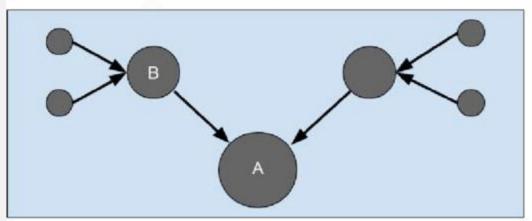
NETWORK VISUALIZATION





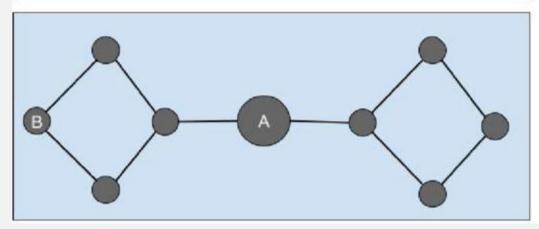
In-degree Centrality

User A has a higher in-degree centrality than user B because user A has more followers than user B.



Eigenvector Centrality

While users A and B both have the same in-degree centrality (two followers), user A has a higher Eigenvector centrality because the weight of the two followers is higher.



Betweenness Centrality

User A has a higher betweenness centrality than user B. A message sent from user A will reach many more users in a shorter path compared to user B.

Source: https://www.researchgate.net/figure/Pictorial-description-of-In-degree-Eigenvector-centrality-and-betweenness-centrality_fig1_313416055

NETWORK GRAPH ANALYSIS

```
=== Network Graph Analysis Report ===
Basic Graph Metrics:
nodes: 42
edges: 41
density: 0.047619047619047616
avg clustering: 0.0
avg shortest path: 2.085946573751452
diameter: 4
avg_degree: 1.9523809523809523
Protocol Distribution:
UDP: 575 packets (11.99%)
TCP: 4222 packets (88.01%)
Most Important Nodes:
                degree centrality betweenness centrality eigenvector centrality total packets importance score
172.17.0.99
                         0.95122
                                                0.996341
                                                                        0.706847
                                                                                         4793.0
                                                                                                      1198.913602
172.17.0.17
                         0.04878
                                                0.095122
                                                                        0.116203
                                                                                         1310.0
                                                                                                       327.565026
46.254.34.201
                         0.02439
                                                0.000000
                                                                        0.113148
                                                                                          782.0
                                                                                                       195.534384
79.124.78.197
                         0.02439
                                                0.000000
                                                                        0.113148
                                                                                          591.0
                                                                                                       147.784384
```

0.000000

0.113148

376.0

94.034384

0.02439

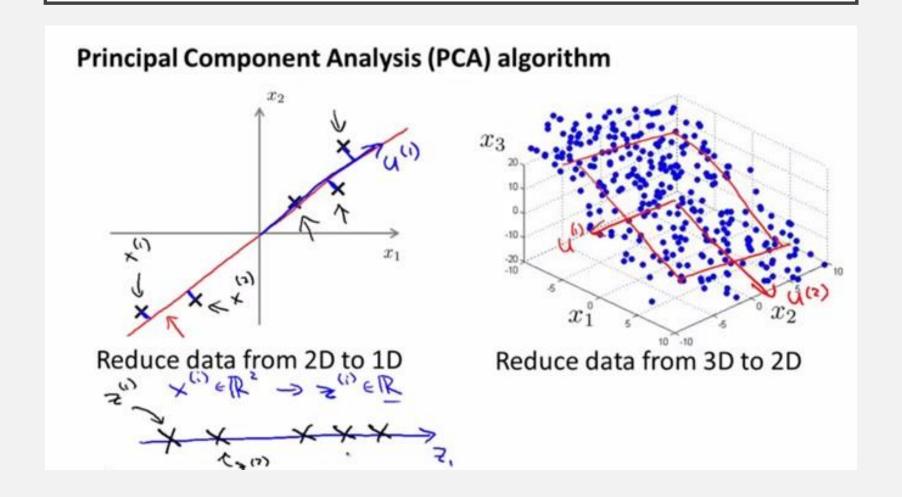
23.45.119.144

ONE HOT ENCODING

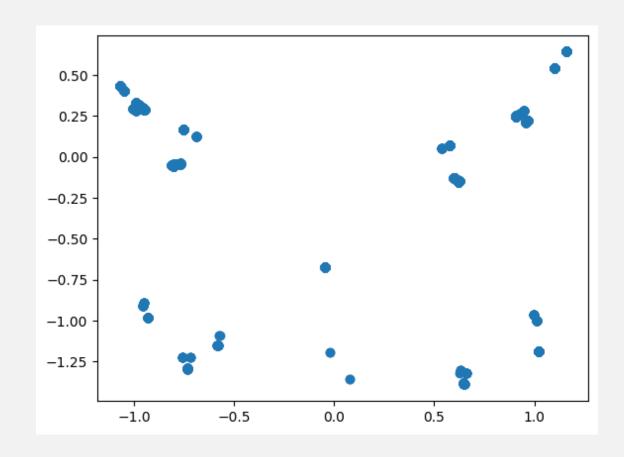
Source P OO	go Sarte P 13	Jan 246.57 3	A.A.Ma	501 to 19 17	LIDIT SOUTH P. IT	1.1710.98 South 19.19	13 3796 Sante P 36	3.232.20.372 Source 19.29	3.23.2.24.172 Source 19.20	90 31.125 Source 19 3
1	0	0	0	0	0	0	0	0	0	C
0	0	0	0	1	0	0	0	0	0	C
1	0	0	0	0	0	0	0	0	0	C
0	0	0	0	1	0	0	0	0	0	C
0	0	0	0	0	0	0	0	0	0	C
0	0	0	0	0	0	0	0	0	0	C
0	0	0	0	0	1	0	0	0	0	C
0	0	0	0	0	1	0	0	0	0	C
0	0	0	0	1	0	0	0	0	0	C
0	0	0	0	0	1	0	0	0	0	C
0	0	0	0	0	1	0	0	0	0	C
0	0	0	0	0	1	0	0	0	0	C

Source: https://medium.com/analytics-vidhya/principal-component-analysis-pca-8a0fcba2e30c

DIMENSIONAL REDUCTION



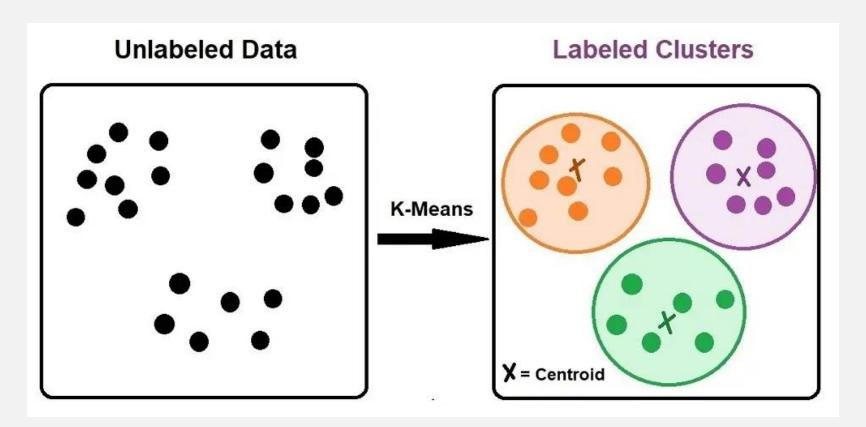
DIMENSIONAL REDUCTION



DIMENSIONAL REDUCTION

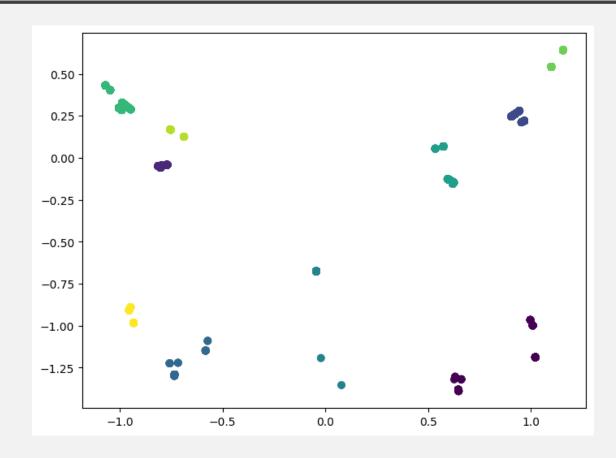
Destinatio	Destinatio	Destination	x_pos	y_pos							
0	0	0	0	0	0	0	0	0	0	-0.02114	-1.19303
0	0	0	0	0	0	0	0	0	0	0.078709	-1.35421
0	0	0	0	0	0	0	0	0	0	-0.02114	-1.19303
0	0	0	0	0	0	0	0	0	0	0.078709	-1.35421
0	0	0	0	0	0	0	0	0	0	-0.04392	-0.6761
0	0	0	0	0	0	0	0	0	0	-0.04392	-0.6761
0	0	0	0	0	0	0	0	0	0	-0.73347	-1.29116
0	0	0	0	0	0	0	0	0	0	-0.57256	-1.09145
0	0	0	0	0	0	0	0	0	0	0.647581	-1.38131
0	0	0	0	0	0	0	0	0	0	-0.57256	-1.09145
0	0	0	0	0	0	0	0	0	0	-0.57211	-1.08896
0	0	0	0	0	0	0	0	0	0	-0.73366	-1.29214
0	0	0	0	0	0	0	0	0	0	-0.73366	-1.29214
0	0	0	0	0	0	0	0	0	0	0.647753	-1.38236
0	0	0	0	0	0	0	0	0	0	0.647753	-1.38236

CLUSTERING



Source: https://www.ejable.com/tech-corner/ai-machine-learning-and-deep-learning/k-means-clustering/

CLUSTERING



CLUSTERING

Count of Packet_Number	Column Labels 🔻										
Row Labels ▼	0	1	2	3	4	5	6	7	8	9 (Grand Total
40.119.249.228			22								22
40.126.28.12			20								20
40.126.28.22			11								11
46.254.34.201								504			504
52.109.0.142			13								13
52.109.0.91			16								16
52.113.194.132			73								73
79.124.78.197						261					261
(blank)					294						294
Grand Total	320 5	99	814	138	298	797	1144	504	364	113	5091

RECAPAND Q&A

OBJECTIVES

- Understand the nature of log data
- Learn how to transform log data for analysis
- Apply various analysis techniques to find anomalies in log data
 - Time Series
 - Matching
 - Network Activity
 - Graph Network Analysis
 - Clustering

FOR NEXT SESSION

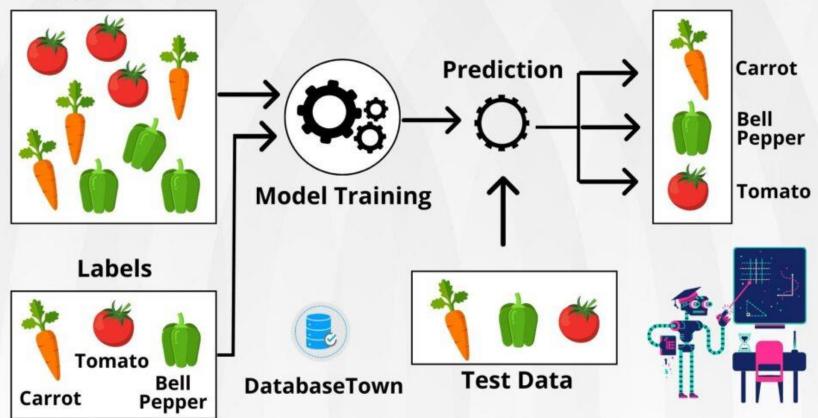
- Perform similar analysis for Exercise 2 and 3
- Identify any suspicious anomalies
- Add some insight, based on possible scenarios
- Send your assignments to: docligot@cirrolytix.com

SUPERVISED LEARNING

SUPERVISED LEARNING

Supervised machine learning is a branch of artificial intelligence that focuses on training models to make predictions or decisions based on labeled training data.

Labeled Data



PREDICTED PROBABILITIES (SCORING)

0	1	2	3	4	5	6	predicted cluster
0.995197	0.000184	0.002055	0.001561	0.000374	0.000442	0.000187	0
0.993225	0.000203	0.003103	0.002276	0.000446	0.000539	0.000208	0
0.002374	0.000163	0.99554	0.001095	0.000307	0.000357	0.000165	2
0.002077	0.9848	0.002156	0.001384	0.00505	0.001709	0.002824	1
0.000679	0.006335	0.00064	0.001137	0.001627	0.000636	0.988946	6
0.995197	0.000184	0.002055	0.001561	0.000374	0.000442	0.000187	0
0.002374	0.000163	0.99554	0.001095	0.000307	0.000357	0.000165	2
0.995197	0.000184	0.002055	0.001561	0.000374	0.000442	0.000187	0
0.995197	0.000184	0.002055	0.001561	0.000374	0.000442	0.000187	0
0.002374	0.000163	0.99554	0.001095	0.000307	0.000357	0.000165	2
0.004628	0.000568	0.002491	0.982691	0.003388	0.005641	0.000594	3
0.000515	0.002049	0.000491	0.000753	0.000958	0.000487	0.994748	6

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