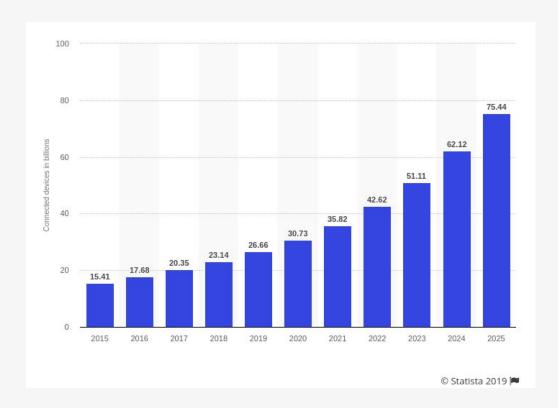


Machine Learning Techinques for Intrusion Detection in Internet Of Things Networks

Why?

Internet of Things (IoT) connected devices installed base worldwide (in billions)



More than 70 000 000 000 IOT devices In 2025

Estimated IOT Market Share 3 trillions \$ In 2026

Definiton

"The Internet of things (IoT) is the extension of Internet connectivity into physical devices and everyday objects."

IOT Application

- Smart Home Devices (fridges, thermostats, lighting)
- Wearebles (smartbands, smartwatches)
- Smart Cars
- Smart grids (Tesla)
- Smart Cities

What if we use Internet of Things in the Industry?

Industry 4.0



Industry 4.0

IoT intelligent systems enables:

- Rapid manufacturing of new products
- Dynamic response to product demands
- Real time optimization of manufacturing
- Predictive maintenance
- Statistical evaluation
- Maximize the reliability

Main Challenges

- Security
- Privacy
- Trust

Security Threats

- Wireless Threats
 - Eavesdropping (overhear information)
 - Data Alteration
 - Identity Theft

Routing Threats

- Spoofing
- Selective Forwarding
- Sinkhole Attacks
- Sybil Attacks
- Wormholes
- Hello flood
- Ackowledgement
- Denial of Service

Main concept

Can we use Machine Learning Techinques for Detect an Intrusion in Industrial Internet Of Things Networks?

How?

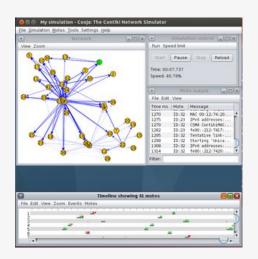
- 1. Use case
- 2. Data collection
- 3. Data Analysis
- 4. Machine Learning
- 5. Results

Use Case and Data creation

Real Use case: IOT-LAB



Simulated Use case: Cooja Simulator



Cooja Simulator

Advantages:

- Memory Allocation
- Full IP Networking
- Power Awareness
- 6lowPan, RPL



Cooja Simulator

Nodes and Router firmware created in the University of Patras and University of Athens

Network Specifications

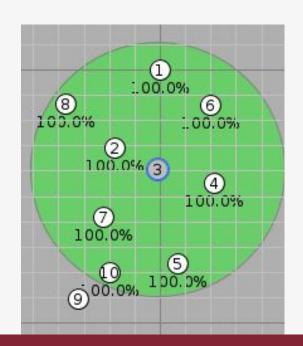
- 9 or 16 nodes
- 6LowPAN-IPV6 (IEEE 802.15.4)
- RPL with DODAG root
- ICMPv6 Control Messages



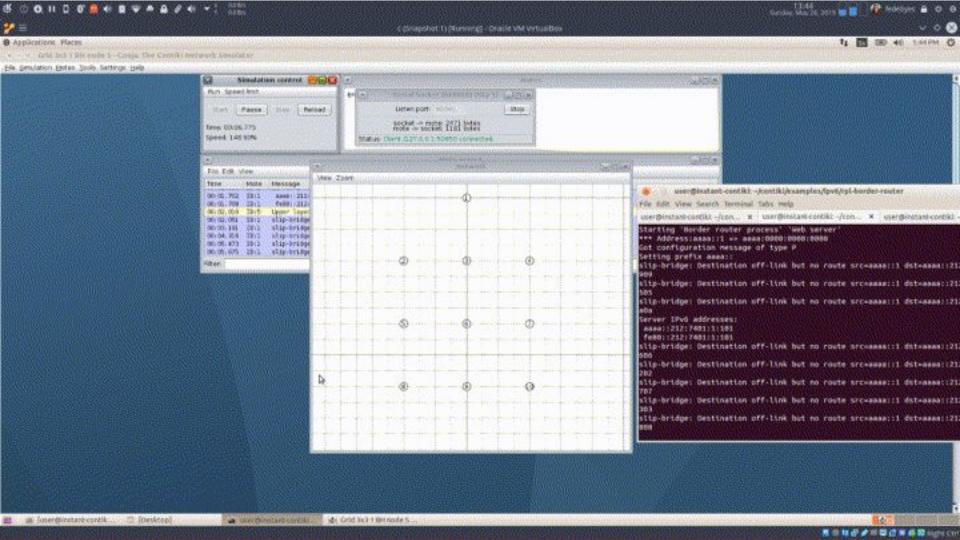
Network Specifications

Random Grid

Square Grid

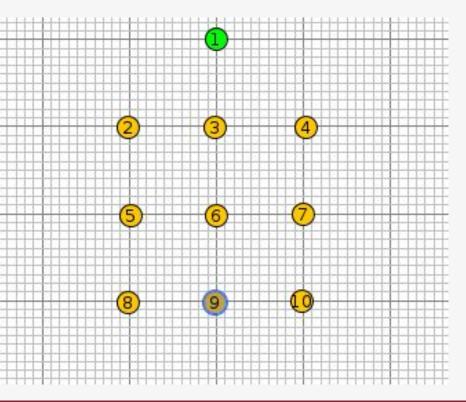


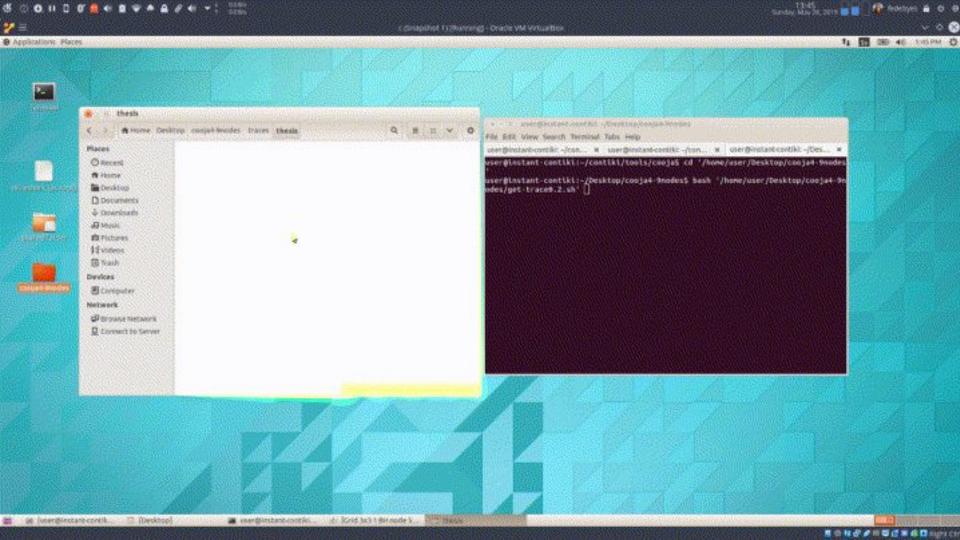




Cooja Simulator

- Router
- Black Hole
- Gray Hole (30, 50, 70)
- White Hole





Data analysis

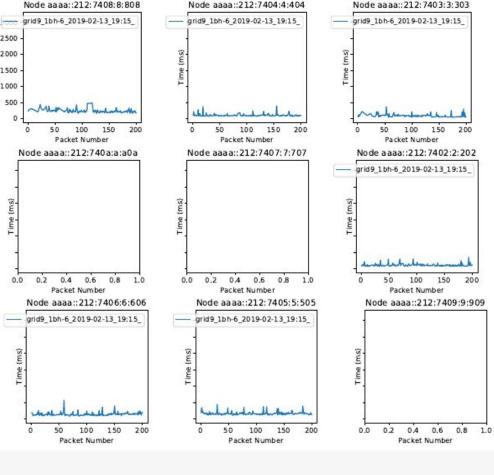
- 1. Find log files
- 2. Load ICMP
- 3. Create statistics

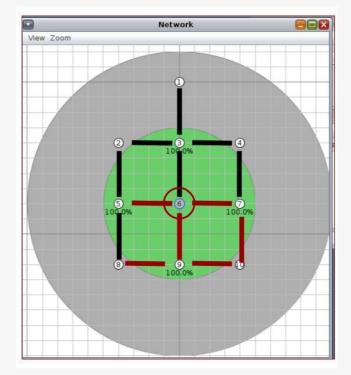
```
def import nodes Cooia 2(directory.tracemask.node defaults):
  # load all files and extract IPs of nodes
  for file in os.listdir(directory):
     if file.startswith(tracemask) and file.index("routes"):
        continue
   except:
      files.append(file)
  nodes = pd.DataFrame(columns=f'node id', 'rank'))
 packets_node = {}
  # Load the ICMP traces
  for file in files:
   packets = pd.read_csv(directory + '/' + file,
                sep=' licmp sea=|ttl=|time='.
               na filter=True.
                header=None,
                skiprows=1.
                skipfooter=4.
                usecols=[3, 5, 7, 9],
                names=f'node id', 'seg', 'hop', 'rtt'].
                engine='python').dropna().drop_duplicates()
   if len(packets) < 1:
     # Nodes affected by a black hole did not receive any packet
      node_id = file[-24:-4]
      if(node id=="aa::212:7411:11:1111"); node id="aaaa::212:7411:11:1111"
      packets = pd.DataFrame(columns=['node_id', 'seq', 'hop', 'rtt'],
                  data=[[node_id, 1, node_defaults[node_id], 1]])
      nodes.loc[len(nodes)] = [file[-24:-4], node_defaults[node_id]]
      packets_node[file[-24:-4]] = packets
      packets['node id'] = packets.apply(lambda row: row['node id'][:-1], axis=1)
      packets = packets.sort_values(by=['node_id', 'seq'], ascending=True, na_position='first')
      packets = packets[packets['rtt'] > 1]
      packets["hop"]= 64-packets['hop']
      packets_node[packets['node_id'][0]] = packets
  nodes=nodes.sort_values(by=['rank', 'node_id'])
  #tranformation in node
 nodeList=∏
  for n in packets node.kevs():
   #print((packets node(n1),head())
   pkts=packets_node[n].drop(["node_id","hop"],axis=1)
   hop=int(packets_node[n]("hop")[0])
   ip=packets_node[n]["node_id"][0]
   n=node(ip,hop,pkts)
   nodeList.append(n)
```

Data analysis

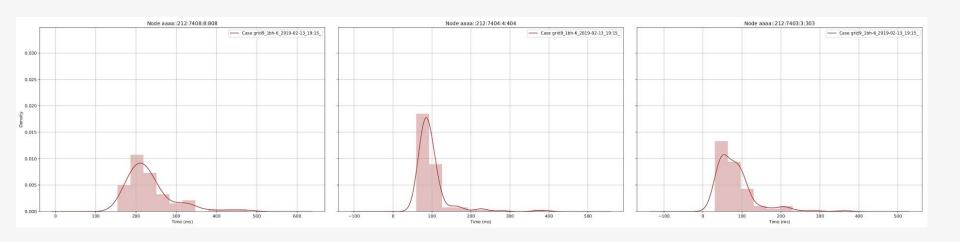
- Packet loss percentage
- Number of packets
- Standard deviation (rtt)
- Mean (rtt)
- Variance (rtt)
- Node hop
- Minimum (rtt)
- Maximum (rtt)
- Number of outliers
- Amplitude of the window

abel = typ=	type_col =	type_cor =	pa≡	node	= coun =	std =	mean =	var =	hop =	0
grid_1bh-9_2019-02-20_00 BH	normal	normal	2	aaaa::212:7403:3:303	98	76.05565228	120.8887755	5784.462244	1	
grid_1gh30-9_2019-02-20_BH	normal	normal	3	aaaa::212:7402:2:202	97	102.0977565	152.8463918	10423.95189	2	
grid_1bh-9_2019-02-20_00 BH	normal	normal	4	aaaa::212:7405:5:505	96	109.6936084	186.6666667	12032.68772	2	- 0
grid_1bh-9_2019-02-20_00 BH	normal	normal	4	aaaa::212:740e:e:e0e	96	104.7791155	383.3229167	10978.66305	5	- 4
grid_1bh-9_2019-02-20_00 BH	normal	normal	4	aaaa::212:7407:7:707	96	119.1651879	182.0729167	14200.342	2	
grid_1gh50-9_2019-02-19_ BH	normal	normal	5	aaaa::212:740b:b:b0b	95	404.6223683	373.6842105	163719.2609	3	
grid_1gh50-9_2019-02-19_ BH	normal	normal	5	aaaa::212:7404:4:404	95	81.87068502	98.68631579	6702.809066	1	
grid_1gh70-7_2019-02-19_ BH	normal	normal	5	aaaa::212:740e:e:e0e	95	142.484334	399.6421053	20301.78544	5	
grid_1bh-9_2019-02-20_00 BH	normal	normal	6	aaaa::212:740a:a:a0a	94	84.21884656	278.1170213	7092.814116	4	
grid_1gh30-9_2019-02-20_ BH	normal	normal	6	aaaa::212:7403:3:303	94	30.98190749	75.20319149	959.8785919	1	
grid_1bh-7_2019-02-19_22 norma	normal	normal	7	aaaa::212:740e:e:e0e	93	253.9215146	561.4086022	64476.13558	5	
grid_1gh30-9_2019-02-20_ BH	normal	normal	7	aaaa::212:7404:4:404	93	83.04367269	93.59247312	6896.251573	1	
grid_1gh30-9_2019-02-20_ BH	normal	normal	8	aaaa::212:740f:f:f0f	92	151.9781285	323.0108696	23097.35153	4	
grid_1gh50-9_2019-02-19_ BH	normal	normal	8	aaaa::212:740e:e:e0e	92	216.0088642	418.1956522	46659.82943	5	
grid_normal_2019-02-26_1 norma	normal	normal	8	aaaa::212:7403:3:303	92	124.7764051	143.0804348	15569.15126	1	
grid_1bh-9_2019-02-20_00 BH	normal	normal	9	aaaa::212:7406:6:606	91	146.1388429	325.1648352	21356.56142	3	
grid_1gh50-9_2019-02-19_ BH	normal	normal	9	aaaa::212:7407:7:707	91	248.2625506	304.9230769	61634.29402	2	
grid_1bh-7_2019-02-19_22 BH	normal	normal	10	aaaa::212:740a:a:a0a	90	166.3555452	405.9666667	27674.16742	4	
grid_1bh-9_2019-02-20_00 BH	normal	normal	11	aaaa::212:740f:f:f0f	89	170.8553386	388.4606742	29191.54673	4	
grid_1gh70-7_2019-02-19_ BH	normal	normal	11	aaaa::212:7407:7:707	89	128.0426315	245.247191	16394.91547	2	
grid_normal_2019-02-26_1 norma	normal	normal	11	aaaa::212:7406:6:606	89	348.924725	621.3033708	121748.4637	3	
grid_normal_2019-02-26_1 norma	normal	normal	11	aaaa::212:7402:2:202	89	260.1215954	310.7752809	67663.24438	2	
grid_1bh-7_2019-02-19_22 norma	normal	normal	12	aaaa::212:7402:2:202	88	160.0573535	187.4215909	25618.35643	2	
grid_1bh-9_2019-02-20_00 BH	normal	normal	12	aaaa::212:7402:2:202	88	93.42733082	171.7727273	8728.666144	2	
grid_1gh30-9_2019-02-20_ BH	normal	normal	12	aaaa::212:7406:6:606	88	82.53669508	224.625	6812.306034	3	
grid_1bh-9_2019-02-20_00 BH	normal	normal	13	aaaa::212:740c:c:c0c	87	155.8397229	325.6551724	24286.01925	3	
grid_normal_2019-02-26_1 norma	normal	normal	13	aaaa::212:7406:6:606	87	317.5891025	596.1034483	100862.838	3	
grid_normal_2019-02-26_1 norma	normal	normal	13	aaaa::212:7403:3:303	87	119.0138971	183.8793103	14164.30771	1	
prid_normal_2019-02-26_1 norma	normal	normal	13	aaaa::212:740e:e:e0e	87	197.3916663	625.1724138	38963.46993	5	
grid_normal_2019-02-26_1 norma	normal	normal	13	aaaa::212:740a:a:a0a	87	278.40635	509.2988506	77510.0957	4	
grid_1bh-9_2019-02-20_00 BH	normal	normal	15	aaaa::212:7404:4:404	85	46.26066597	104.9352941	2140.049216	1	
arid 1ah70_7 2010_02_10 RH	normal	normal	15	22221217-7405-5-505	95	170 1/120567	2/6 //20/112	28050 2612	2	





Data analysis



Machine Learning Techniques

Supervised Learning

- Random Forest
- KNN
- SVM

Unsupervised Learning

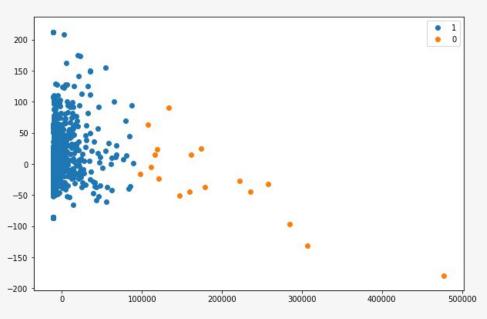
K-Means

K-Means

```
randomly chose k examples as initial centroids while true:
    create k clusters by assigning each
    example to closest centroid
    compute k new centroids by averaging
    examples in each cluster
    if centroids don't change:
```

break

Results Unsupervised Learning

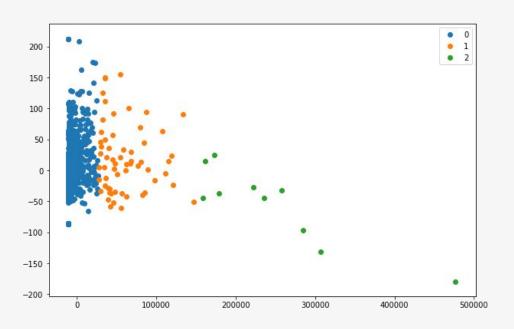


2 Cluster division by Kmeans

Blue: Normal Behaviour

Orange: Affected by a Malicious Node

Results Unsupervised Learning



3 Cluster division by Kmeans

Blue: Normal Behaving Node Orange: Affected from Gray Hole Green: Affected from Black Hole

Accuracy Supervised Learning

Machine Learning Tecnique	Mean Accuracy				
Random Forest	99%				
SVM	87%				
KNN	84.2%				

Conclusion

Can we use Machine Learning Techinques for Detect an Intrusion in Industrial Internet Of Things Networks?

Yes!

Future Work

- Try in a real world Industry 4.0
- Different types of attacks

Thanks

Questions



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Master Research Thesis in Engineering in Computer Science

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Machine Learning Techinques for Intrusion Detection in Internet Of Things Networks