IoT Intrusion Detection Competition using Machine Learning

Applied Machine Learning – Group Practical Project

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***Abstract*—If not needed, remove it…**

***Index Terms*— AWID, IDS, Machine Learning, Neural Networks**

STRUCTURE

This document has been subdivided into ten parts: an introduction, two group components, five individual components and two appendixes. The individual components have been listed with the responsible and the word count:

I. Introduction - Group;
II. Planning – Group;
III. Pre-processing – Michelangelo Rubino, No. 13140302 – 600 words;
IV. Selecting features – Ian Dickerson, No. 13140302 – 600 words;
V. Exploring and selecting ML algorithms - Timothy Chan, No. 13140302 – 600 words;
VI. Refining algorithms - Cosmin Stanciu, No. 13140302 – 600 words;
VII. Evaluating model and analysing the results - Mike Jun Ming, No. 13140302 – 600 words;
VIII. Future Work – Group;
IX. Appendix A (Figures);
X. Appendix B (Tables).

I. INTRODUCTION

THE Internet of Things (IoT) is growing continuously in the last years for a number of aspects: the fields it is applied to (healthcare, agriculture, cars...), the number of devices, the network traffic. At the same time the cyber-attacks against the 802.11 networks are increasing steeply and becoming more and more aggressive. In the most recent literature on the subject the cyber-attacks have been subdivided into four categories, based on the execution mode [1]: injection, flooding, impersonation, passive attack. Different categorizations are possible based on different criteria. These are the reasons why the Intrusion Detection System (IDS) is one of the critical components of a wireless network: the machine learning techniques, from the more traditional ones [1] to neural networks [2], [3], have been applying to IDS as more static prevention systems (IE. firewalls) have shown unsatisfying rates in detecting false positives and false negatives and in adapting to new threats.

II. PLANNING

This work uses a reduced version of the AWID dataset (maintained by the University of Aegean) and focuses only on the impersonation type of attack. This because the impersonation attacks have been identified as the most dangerous threats to the 802.11 networks [1] (EG. the attacks named as EvilTwin, Honeypot, Hirte). The goal is to build a binary classifier able to identify real intrusions in the network traffic using the machine learning techniques.

It has been decided to use a Gantt chart (Fig 1) to schedule the workload, even though this kind of chart is more suitable to waterfall methodology. The Machine Learning projects instead use an iterative lifecycle: several iterations to find the best setting. The idea in this project is then to test a

certain number of algorithms and parameters for each stage to find the right model. Yet, due to the limited amount of time, around two months, it is not possible to test every machine learning technique. The focus is on those which are more frequently used for binary classifiers. The person accountable for each stage should agree the choices with the person accountable for the following stage, nevertheless the final decision is to be taken by the responsible for that stage.

Generally speaking, there are several challenges in this research area:

- known threats vs new threats (outliers),
- computational issues,
- accuracy vs speed,
- precision vs recall
- ML knowledge vs domain knowledge

To be continued…

III. PRE-PROCESSING

AWID is a public collection of standard data sets often used to evaluate the performances of an IDS, in particular for this project it will be used the reduced version AWID-CLS, comprising a training and a test set where two features have been removed as not useful for predictions. The class is the column 155:

Dataset	Obs.	Features	Classes
AWID-CLS-Train	97,044	152	1
AWID-CLS-Test	40,158	152	1

After loading the data through the pandas library and creating a dataframe, it is possible to see that both the datasets are perfectly balanced, 50% of the observations classified as 1, 50% as 0. This is an important feature as unbalanced datasets may lead to wrong predictions. The dataframe contains no nulls (NaN), then it is not necessary to handle them. The describe() function shows the descriptive statistics and the first thing to notice is that many features have mean and standard deviation equal to zero: this means that the values are always zero and the features are not useful. They can be safely removed (74), ending up with 78 from the original 152. In the following figure three features with no values have been highlighted:

	1	2	3	5	6
count	97044.0	97044.0	97044.0	97044.000000	97044.000000
mean	0.0	0.0	0.0	0.006252	0.006252
std	0.0	0.0	0.0	0.015541	0.015541
min	0.0	0.0	0.0	0.000003	0.000003
25%	0.0	0.0	0.0	0.001442	0.001442
50%	0.0	0.0	0.0	0.003706	0.003706
75%	0.0	0.0	0.0	0.005916	0.005916
max	0.0	0.0	0.0	0.978440	0.978440

Fig. 1. Features with no values

By combining the pandas dataframe functions loc() and duplicated() it is possible to detect duplicated features, having exactly the same values. These features can be removed as well, leading to a dataframe with only 64 features plus the class. The Tab. 1 lists the remaining features with their original names. Decreasing the number of features is an important stage for a few reasons:

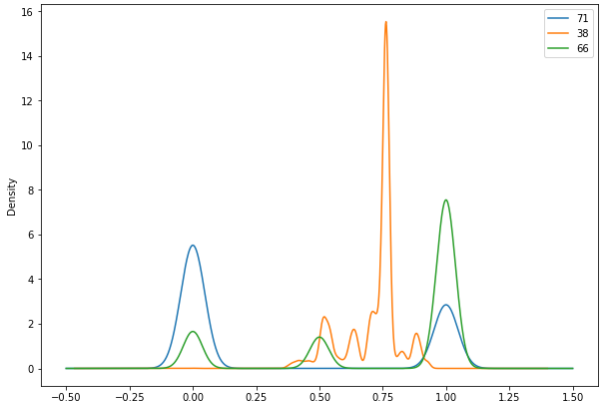
- it reduces the processing time;
- it simplifies the model, avoiding overfitting;
- focusing only on relevant features, it improves the results.

The real selection of features will happen in the next stage, though removing useless features can be done in preprocessing in order to have a clean dataframe. The pandas describe() and nunique() functions show that the features can be categorized into three main classes on the basis of the unique values:

1. floating values between 0 and 1 (ex: 38);
2. only two integer values, 0 or 1 (ex: 71);
3. only a few values, integer or floating ones, between 0 and 1 (ex: 66).

As every features show only values equal or higher than 0 and equal or lower than 1 the data does not need to be rescaled. This term refers to the techniques used in machine learning to give the features the same scale (typically between 0 and 1), which can give the model some improvements [4]. There is often confusion when using the terms scaling, standardizing and normalizing as authors tend to use them interchangeably, then the meanings explained in [5] will be used. Yet, the

three abovementioned classes have different distributions and none has a normal distribution:



The density, the box and whisker plots and the histograms of every features can be seen in the Appendix A (Figg. 2-4). Rather than using the correlation matrix plot or the scatter plot matrix, which are not easy to visualize due to the number of features, it has been computed the correlation between the features and the class 155. Instead of the usual Pearson method, pandas allows you to use non-parametric methods such as the Kendall rank correlation coefficient (commonly known as Kendall's tau coefficient) or the Spearman rank correlation coefficient (Spearman's rho). Differently of the Pearson correlation, these methods do not assume a normal distribution and seem more appropriate to analyze this dataframe for the reasons explained earlier in this section, though not necessarily the features with the highest correlation will be the most useful for the model, as well as the features with the lowest correlation not necessarily will be discarded. In the following stage the features will be selected on the basis of different criteria. The correlation for each feature is listed and sorted in the Tab. 2 and 3. They are quite similar and the output is mainly the same as shown by the two tables below with the five features with the higher positive correlation:

Feature	Kendall corr.
79	0.725743
71	0.708561
50	0.652165
68	0.52784
5	0.517106

Feature	Spearman corr.
79	0.800862
71	0.708561
50	0.652165
5	0.632906
38	0.549358

IV. Selecting Features

Ian here…

V. Exploring and Selecting ML Algorithms

Tim here…

VI. Refining Algorithms

Cosmin here…

VII. Evaluating Model and Analysing the Results

Mike here…

VIII. Future Work

IX. Appendix A (Figures)

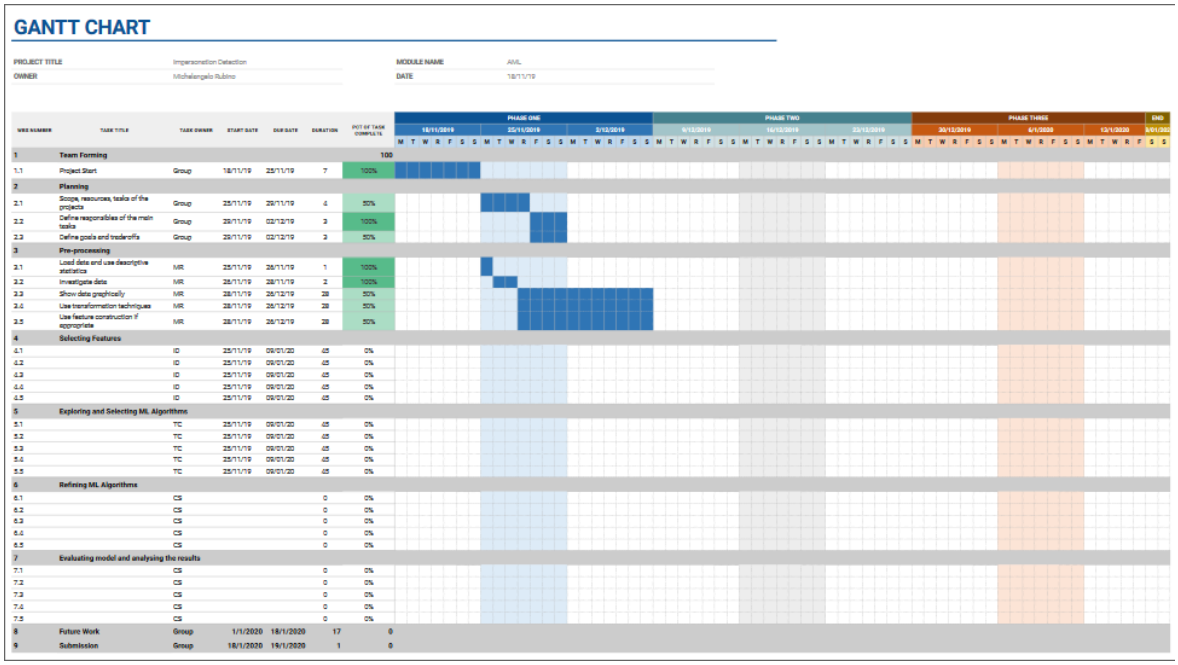


Fig. 1. GANTT chart

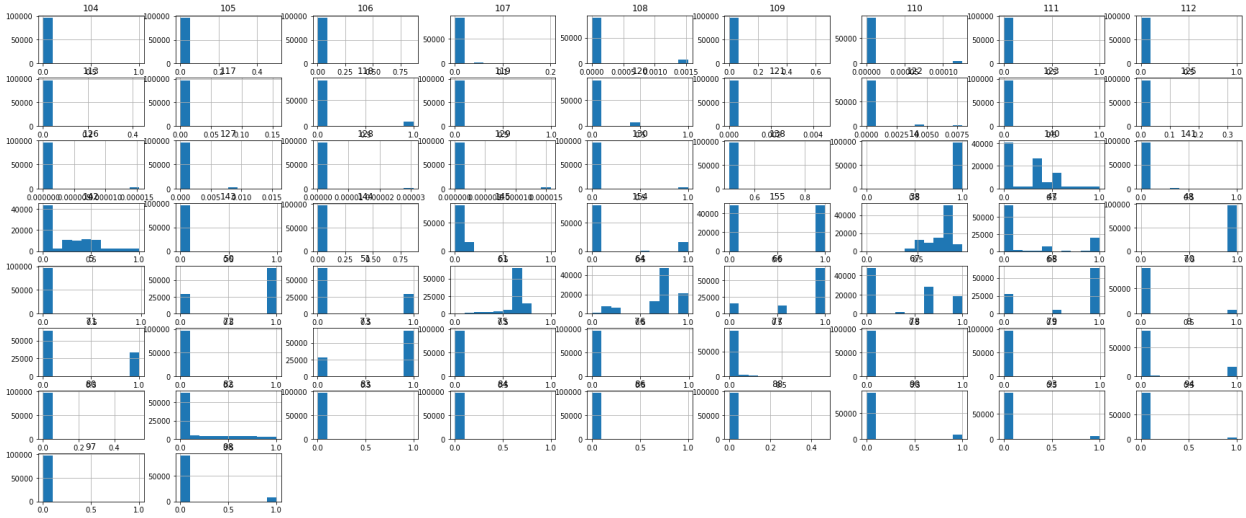


Fig. 2. Histograms for the df65

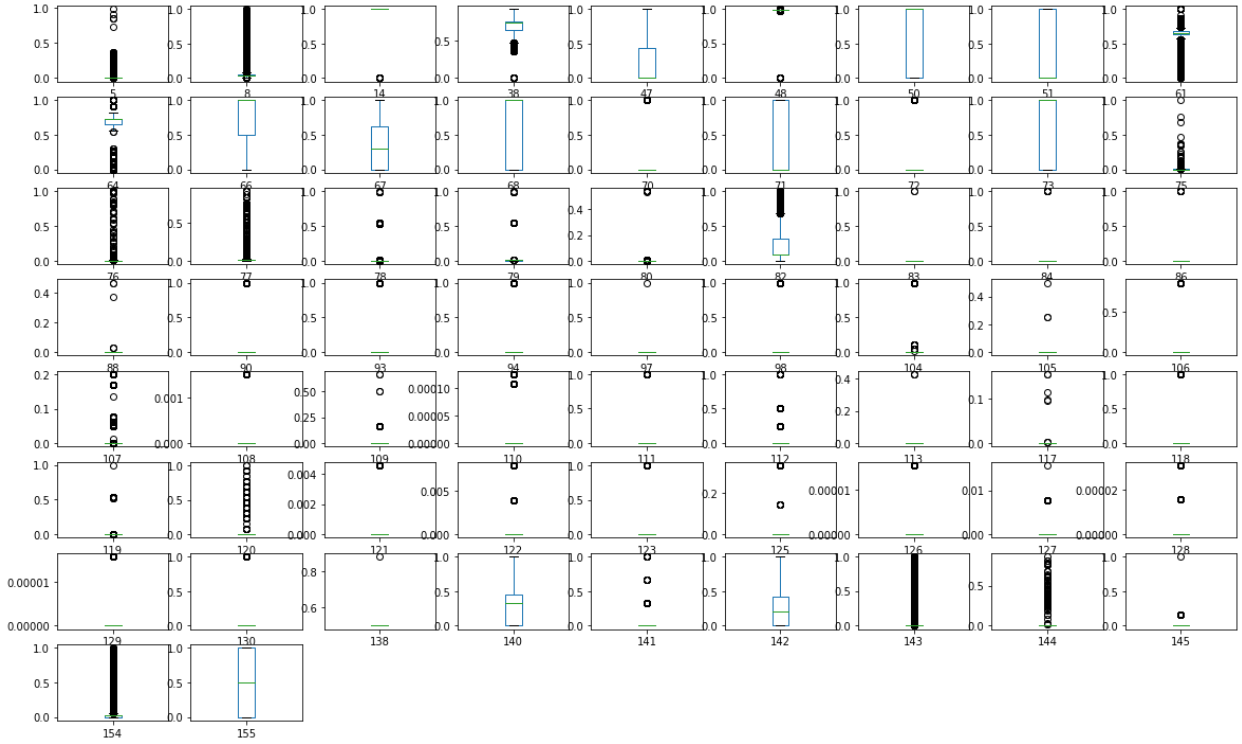


Fig. 3. Box and Whisker plot for the df65

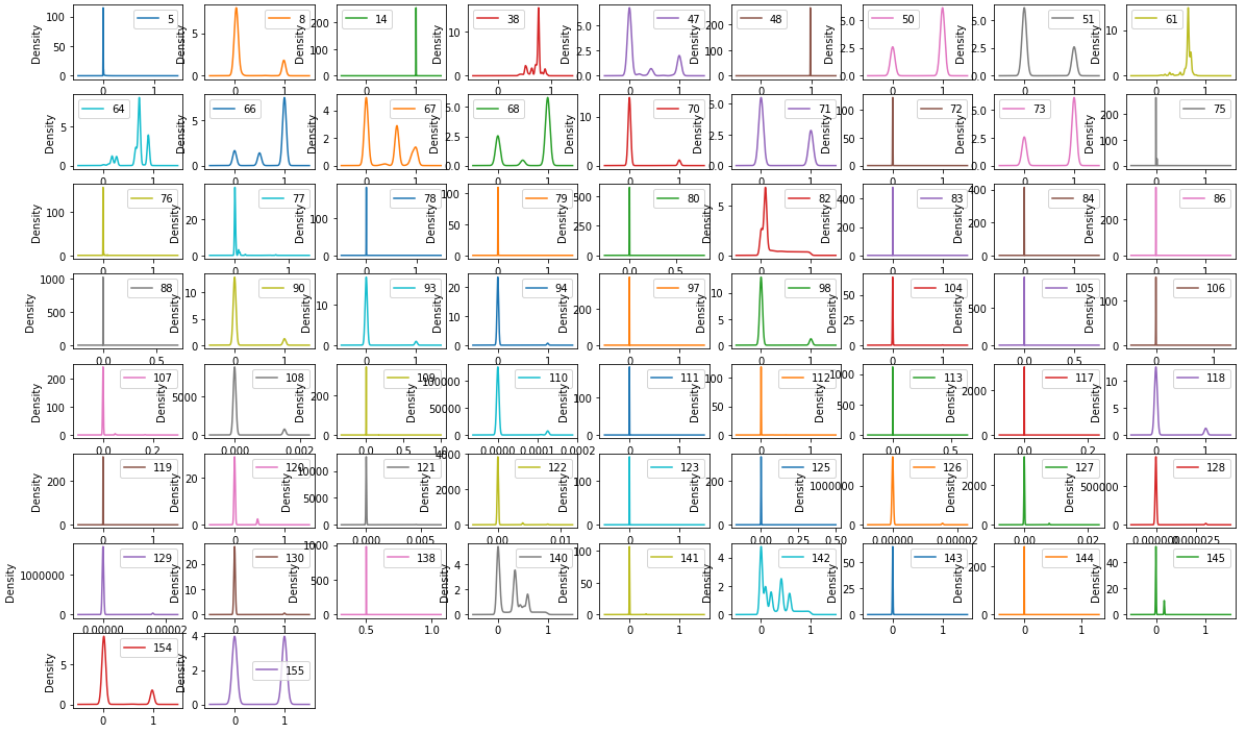


Fig. 4. Density plot for the df65

X. Appendix B (Tables)

TABLE 1
Features names of df65

5	frame.time_delta
8	frame.len
14	radiotap.length
38	radiotap.mactime
47	radiotap.datarate
48	radiotap.channel.freq
50	radiotap.channel.type.cck
51	radiotap.channel.type.ofdm
61	radiotap.dbm_antsignal
64	wlan.fc.type_subtype
66	wlan.fc.type
67	wlan.fc.subtype
68	wlan.fc.ds
70	wlan.fc.retry
71	wlan.fc.pwrmgt
72	wlan.fc.moredata
73	wlan.fc.protected
75	wlan.duration
76	wlan.ra
77	wlan.da
78	wlan.ta
79	wlan.sa
80	wlan.bssid
82	wlan.seq
83	wlan.bar.type
84	wlan.ba.control.ackpolicy
86	wlan.ba.control.cbitmap
88	wlan.ba.bm
90	wlan_mgt.fixed.capabilities.ess
93	wlan_mgt.fixed.capabilities.privacy
94	wlan_mgt.fixed.capabilities.preamble
97	wlan_mgt.fixed.capabilities.spec_man
98	wlan_mgt.fixed.capabilities.short_slot_time
104	wlan_mgt.fixed.listen_ival
105	wlan_mgt.fixed.current_ap
106	wlan_mgt.fixed.status_code
107	wlan_mgt.fixed.timestamp
108	wlan_mgt.fixed.beacon
109	wlan_mgt.fixed.aid
110	wlan_mgt.fixed.reason_code
111	wlan_mgt.fixed.auth.alg
112	wlan_mgt.fixed.auth_seq
113	wlan_mgt.fixed.category_code
117	wlan_mgt.fixed.sequence
118	wlan_mgt.tagged.all
119	wlan_mgt.ssid
120	wlan_mgt.ds.current_channel
121	wlan_mgt.tim.dtim_count
122	wlan_mgt.tim.dtim_period
123	wlan_mgt.tim.bmapctl.multicast
125	wlan_mgt.country_info.environment
126	wlan_mgt.rsn.version
127	wlan_mgt.rsn.gcs.type
128	wlan_mgt.rsn.pcs.count
129	wlan_mgt.rsn.akms.count

130	wlan_mgt.rsn.akms.type
138	wlan_mgt.tcprep.trsmt_pow
140	wlan.wep.iv
141	wlan.wep.key
142	wlan.wep.icv
143	wlan.tkip.extiv
144	wlan.ccmp.extiv
145	wlan.qos.tid
154	data.len
155	class

TABLE 2
Features sorted by Kendall correlation

79	0.725743
71	0.708561
50	0.652165
68	0.52784
5	0.517106
73	0.477183
80	0.452988
38	0.44858
66	0.420697
78	0.269324
140	0.24599
142	0.230346
14	0.014712
154	0.006752
111	0.005809
48	0.003032
97	-0.00321
138	-0.00321
83	-0.00454
105	-0.00556
113	-0.00556
84	-0.00786
88	-0.00786
108	-0.00877
86	-0.00908
117	-0.00908
119	-0.01171
120	-0.01314
64	-0.01967
123	-0.02487
144	-0.02872
106	-0.02873
72	-0.02955
98	-0.02997
90	-0.03385
125	-0.03921
118	-0.04226
93	-0.05423
109	-0.0579
104	-0.05973
112	-0.06228
121	-0.06841
143	-0.10554
141	-0.10583
61	-0.10681
8	-0.11996

128	-0.14825
127	-0.14836
126	-0.14836
129	-0.14836
130	-0.14836
94	-0.1682
122	-0.19312
107	-0.20429
82	-0.23428
110	-0.25602
70	-0.28538
77	-0.28997
145	-0.45347
75	-0.62075
47	-0.6505
51	-0.65183
76	-0.74737
67	-0.7832

TABLE 3
Features sorted by Spearman correlation

79	0.800862
71	0.708561
50	0.652165
5	0.632906
38	0.549358
68	0.539139
73	0.477183
80	0.463607
66	0.43509
140	0.285182
78	0.280235
142	0.267047
14	0.014712
154	0.007297
111	0.005809
48	0.003033
97	-0.00321
138	-0.00321
83	-0.00454
105	-0.00556
113	-0.00556
84	-0.00786
88	-0.00786
108	-0.00877
86	-0.00908
117	-0.00908
119	-0.01185
120	-0.01315
64	-0.02145
123	-0.02487
144	-0.02872
106	-0.02873
72	-0.02955
98	-0.02997
90	-0.03385
125	-0.03921
118	-0.04226

93	-0.05423
109	-0.0579
104	-0.05973
112	-0.06232
121	-0.06841
143	-0.10584
141	-0.10584
61	-0.12261
8	-0.13387
128	-0.14836
126	-0.14836
127	-0.14836
129	-0.14836
130	-0.14836
94	-0.1682
122	-0.19381
107	-0.20639
110	-0.25671
82	-0.27956
70	-0.28538
77	-0.31502
145	-0.45347
75	-0.64472
51	-0.65183
47	-0.6791
76	-0.80979
67	-0.83998

XI. REFERENCES

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