ML based network traffic analysis on UNSW-NB15 public dataset

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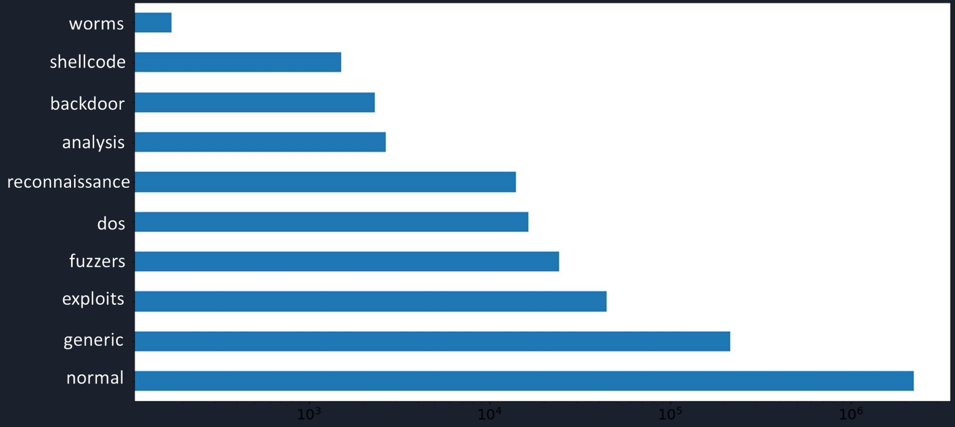
Overview

- Introduction to NB15
- Preprocessing
- Multi class classification
- Binary classification
- Conclusion

UNSW-NB15: An unbalanced dataset

The UNSW-NB 15 dataset contains an hybrid of realistic normal traffic activities and synthetic attack behaviors simulated in a laboratory environment with three interconnected virtual machines.

It contains 9 different attack categories:
Analysis, Backdoor, Dos, Exploits, Fuzzers, Generic, Reconnaissance, Shellcode, Worms



Distribution of network traffic:

normal	**2218761**
generic	**215481**
exploits	**44525**
fuzzers	**24246**
dos	**16353**
reconnaissance	**13987**
analysis	**2677**
backdoor	**2329**
sheelcode	**1511**
worms	**174**

UNSW-NB15: A packet-based analysis

It contains a total of 49 features divided in **flow-based** and **packet-based** features.

Flow-based: Source IP, Source Port, Destination IP, Destination Port of the three virtual machines in the laboratory environment

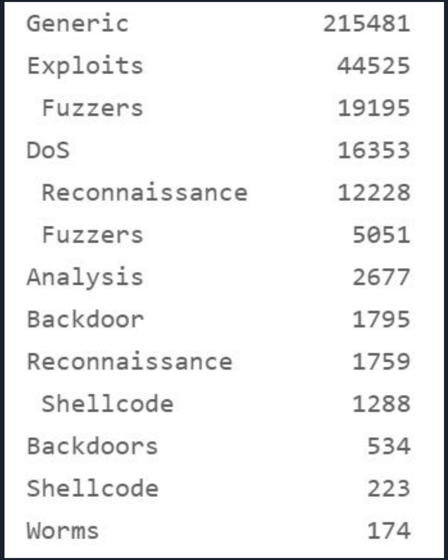
Packet-based: Divided in four sub-features

1. *Basic features* (i.e bytes, type of the service, bps…)
2. *Content features* (i.e body length in case of HTTP, TCP window of Source and Destination…)
3. *Time features* (i.e jitter, time between SYN/SYN-ACK, time between SYN-ACK/ACK…)
4. *Additional features* (i.e if the FTP session is accessed with a password…)

Considered features: 49-4-2 (start timestamp, final timestamp) = **43**

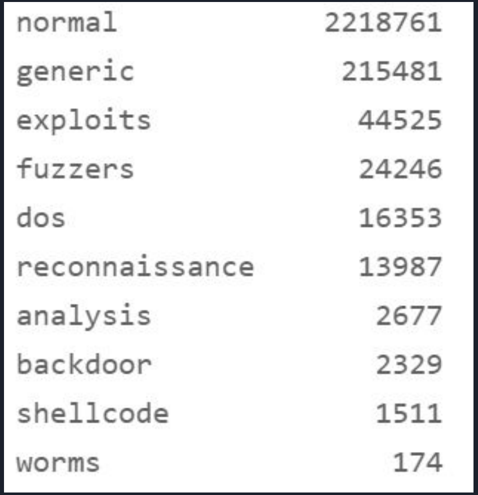
UNSW-NB15: Preprocessing [1/3]

Two errors in *attack_cat* feature: “normal” category is missing and values are incorrect



```
Generic                215481
Exploits                44525
 Fuzzers                19195
DoS                     16353
 Reconnaissance         12228
 Fuzzers                 5051
Analysis                 2677
Backdoor                 1795
Reconnaissance           1759
 Shellcode               1288
Backdoors                 534
Shellcode                 223
Worms                     174
```

Adjust values, fix missing ‘normal’ traffic



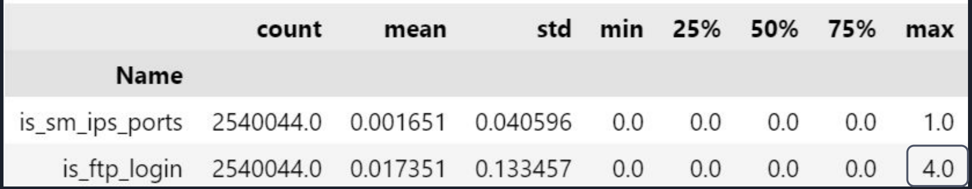
```
normal            2218761
generic            215481
exploits            44525
fuzzers             24246
dos                 16353
reconnaissance      13987
analysis             2677
backdoor             2329
shellcode            1511
worms                 174
```

UNSW-NB15: Preprocessing [2/3]

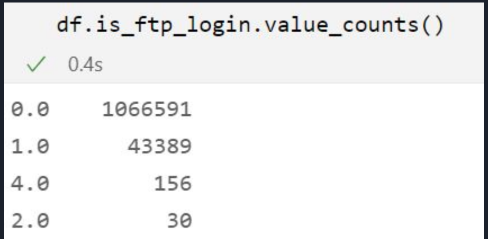
The attributes *ct_flw_http_mthd and is_ftp_login* and *ct_ftp_cmd* contains null values:

1. *No. of flows that has methods such as Get and Post in HTTP service (ct_flw_http_mthd, numerical variable)*
2. *If the FTP session is accessed by user and password then 1 else 0 (is_ftp_login, binary variable)*
3. *No. of flows that has a command in FTP session (ct_ftp_cmd , numerical variable)*

Moreover,



Name	count	mean	std	min	25%	50%	75%	max
is_sm_ips_ports	2540044.0	0.001651	0.040596	0.0	0.0	0.0	0.0	1.0
is_ftp_login	2540044.0	0.017351	0.133457	0.0	0.0	0.0	0.0	4.0



```
df.is_ftp_login.value_counts()
✓ 0.4s
0.0    1066591
1.0      43389
4.0        156
2.0         30
```

Solution adopted for null values:

→ **0** where the service is not HTTP (for *ct_flw_http_mthd*) or FTP (for *is_ftp_login*)
→ **The attribute mean** for all sample belonging to the same class where service is HTTP/FTP

Solution adopted for binary out of range:

→ Substituting with **the most probable value** (that is 0)

UNSW-NB15: Preprocessing [3/3]

Three types of attributes:

1. **Numerical attributes**
    - Z-score normalization has been applied
    - sklearn.preprocessing.StandardScaler
2. **Categorical attributes** (*proto, state, service*):
    - converted into binary: from **43 up to 202 features** after conversion
    - sklearn.preprocessing.OneHotEncoder
3. **Binary attributes**

UNSW-NB15: Classification

Starting from the entire dataset, a **Stratified K-Fold cross validation** is applied

- it provides train/test indices to split data in train/test sets
- K=5
- stratified folds: the folds are made by preserving the percentage of samples for each class.

Different types of experiment: classification with a

- unbalanced training set
- a 60/40 rebalanced training set with undersampling of the majority class
- a 50/50 rebalanced training set with a combination of undersampling and SMOTE of the minority class

UNSW-NB15: Classification

Classification algorithm

- ✔ **Naive Bayes**
- ✔ **Decision Tree**
  - ○ experimented with GINI index and min_samples_leaf=[3,5,7]
- ✔ **Random Forest**
  - ○ experimented with GINI index and n_estimators=[10,20]

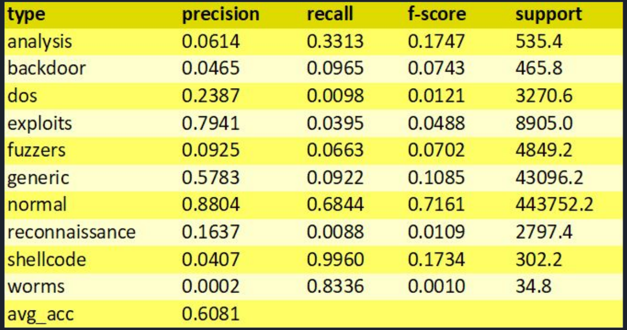
Additional

- ✓ **Random Forest with PCA (n_components=0.99)**
  - ○ experimented with GINI index and n_estimators=20

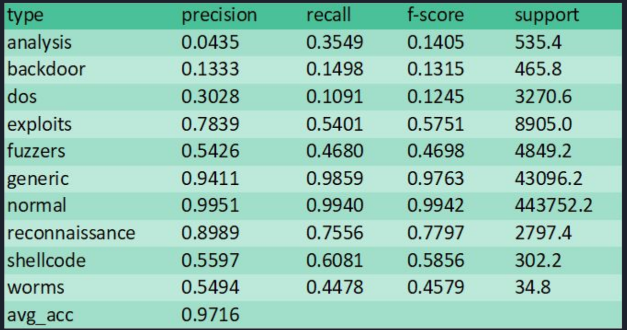
UNSW-NB15: Multi-class classification

From left to right results for:

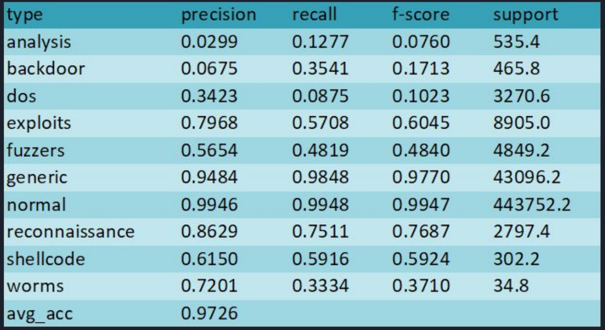
Naive Bayes, **Decision Tree**, **Random Forest**



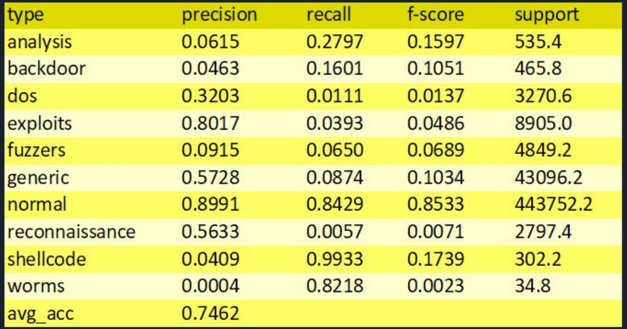
type	precision	recall	f-score	support
analysis	0.0614	0.3313	0.1747	535.4
backdoor	0.0465	0.0965	0.0743	465.8
dos	0.2387	0.0098	0.0121	3270.6
exploits	0.7941	0.0395	0.0488	8905.0
fuzzers	0.0925	0.0663	0.0702	4849.2
generic	0.5783	0.0922	0.1085	43096.2
normal	0.8804	0.6844	0.7161	443752.2
reconnaissance	0.1637	0.0088	0.0109	2797.4
shellcode	0.0407	0.9960	0.1734	302.2
worms	0.0002	0.8336	0.0010	34.8
avg_acc	0.6081			



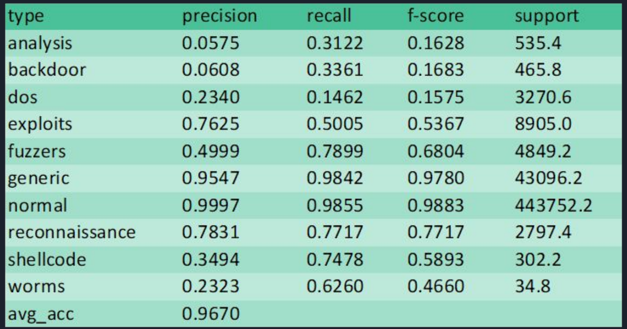
type	precision	recall	f-score	support
analysis	0.0435	0.3549	0.1405	535.4
backdoor	0.1333	0.1498	0.1315	465.8
dos	0.3028	0.1091	0.1245	3270.6
exploits	0.7839	0.5401	0.5751	8905.0
fuzzers	0.5426	0.4680	0.4698	4849.2
generic	0.9411	0.9859	0.9763	43096.2
normal	0.9951	0.9940	0.9942	443752.2
reconnaissance	0.8989	0.7556	0.7797	2797.4
shellcode	0.5597	0.6081	0.5856	302.2
worms	0.5494	0.4478	0.4579	34.8
avg_acc	0.9716			



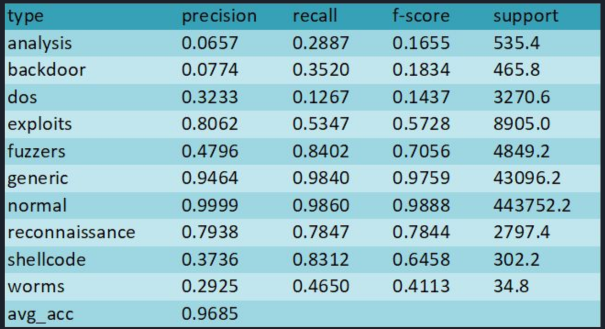
type	precision	recall	f-score	support
analysis	0.0299	0.1277	0.0760	535.4
backdoor	0.0675	0.3541	0.1713	465.8
dos	0.3423	0.0875	0.1023	3270.6
exploits	0.7968	0.5708	0.6045	8905.0
fuzzers	0.5654	0.4819	0.4840	4849.2
generic	0.9484	0.9848	0.9770	43096.2
normal	0.9946	0.9948	0.9947	443752.2
reconnaissance	0.8629	0.7511	0.7687	2797.4
shellcode	0.6150	0.5916	0.5924	302.2
worms	0.7201	0.3334	0.3710	34.8
avg_acc	0.9726			



type	precision	recall	f-score	support
analysis	0.0615	0.2797	0.1597	535.4
backdoor	0.0463	0.1601	0.1051	465.8
dos	0.3203	0.0111	0.0137	3270.6
exploits	0.8017	0.0393	0.0486	8905.0
fuzzers	0.0915	0.0650	0.0689	4849.2
generic	0.5728	0.0874	0.1034	43096.2
normal	0.8991	0.8429	0.8533	443752.2
reconnaissance	0.5633	0.0057	0.0071	2797.4
shellcode	0.0409	0.9933	0.1739	302.2
worms	0.0004	0.8218	0.0023	34.8
avg_acc	0.7462			



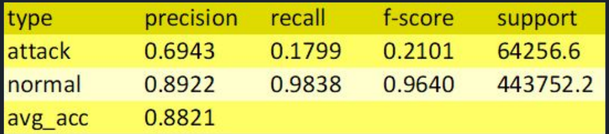
type	precision	recall	f-score	support
analysis	0.0575	0.3122	0.1628	535.4
backdoor	0.0608	0.3361	0.1683	465.8
dos	0.2340	0.1462	0.1575	3270.6
exploits	0.7625	0.5005	0.5367	8905.0
fuzzers	0.4999	0.7899	0.6804	4849.2
generic	0.9547	0.9842	0.9780	43096.2
normal	0.9997	0.9855	0.9883	443752.2
reconnaissance	0.7831	0.7717	0.7717	2797.4
shellcode	0.3494	0.7478	0.5893	302.2
worms	0.2323	0.6260	0.4660	34.8
avg_acc	0.9670			



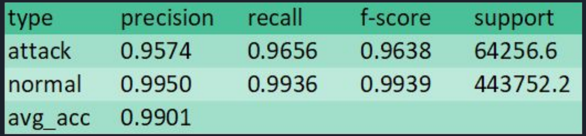
type	precision	recall	f-score	support
analysis	0.0657	0.2887	0.1655	535.4
backdoor	0.0774	0.3520	0.1834	465.8
dos	0.3233	0.1267	0.1437	3270.6
exploits	0.8062	0.5347	0.5728	8905.0
fuzzers	0.4796	0.8402	0.7056	4849.2
generic	0.9464	0.9840	0.9759	43096.2
normal	0.9999	0.9860	0.9888	443752.2
reconnaissance	0.7938	0.7847	0.7844	2797.4
shellcode	0.3736	0.8312	0.6458	302.2
worms	0.2925	0.4650	0.4113	34.8
avg_acc	0.9685			

UNSW-NB15: Binary classification

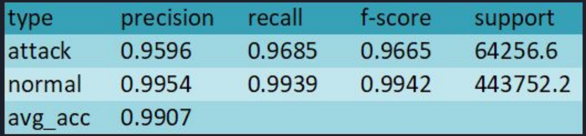
From left to right results for:
Naive Bayes, **Decision Tree**, **Random Forest**



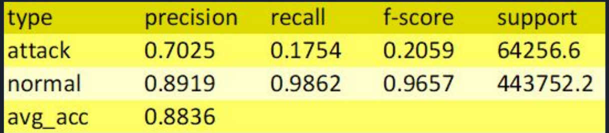
type	precision	recall	f-score	support
attack	0.6943	0.1799	0.2101	64256.6
normal	0.8922	0.9838	0.9640	443752.2
avg_acc	0.8821			



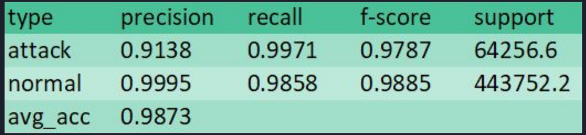
type	precision	recall	f-score	support
attack	0.9574	0.9656	0.9638	64256.6
normal	0.9950	0.9936	0.9939	443752.2
avg_acc	0.9901			



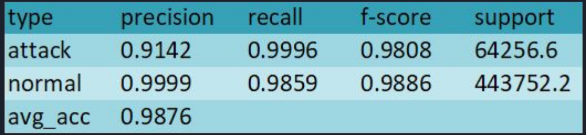
type	precision	recall	f-score	support
attack	0.9596	0.9685	0.9665	64256.6
normal	0.9954	0.9939	0.9942	443752.2
avg_acc	0.9907			



type	precision	recall	f-score	support
attack	0.7025	0.1754	0.2059	64256.6
normal	0.8919	0.9862	0.9657	443752.2
avg_acc	0.8836			

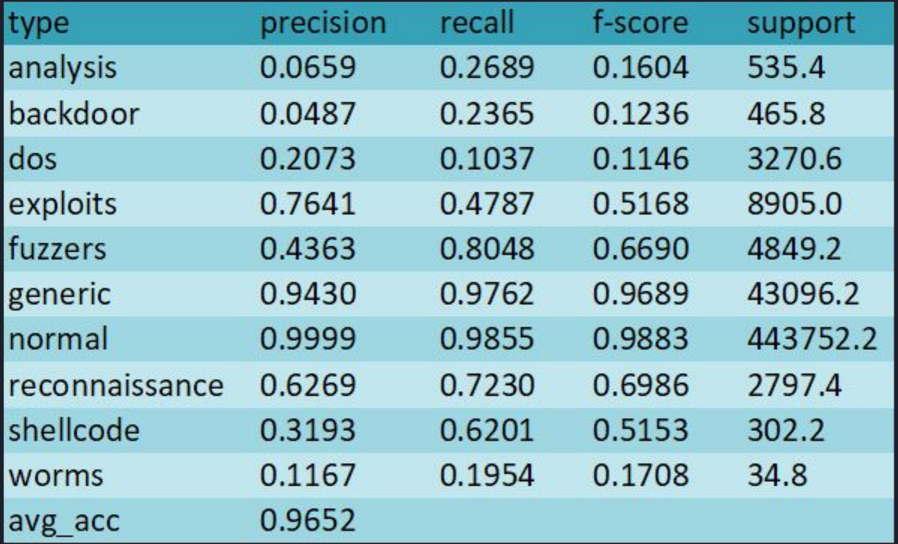


type	precision	recall	f-score	support
attack	0.9138	0.9971	0.9787	64256.6
normal	0.9995	0.9858	0.9885	443752.2
avg_acc	0.9873			

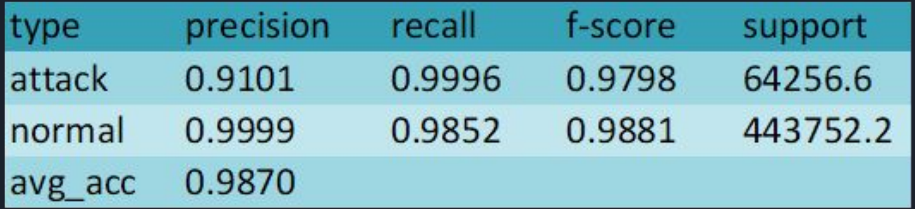


type	precision	recall	f-score	support
attack	0.9142	0.9996	0.9808	64256.6
normal	0.9999	0.9859	0.9886	443752.2
avg_acc	0.9876			

UNSW-NB15: PCA and Random Forest in multi-class classification



type	precision	recall	f-score	support
analysis	0.0659	0.2689	0.1604	535.4
backdoor	0.0487	0.2365	0.1236	465.8
dos	0.2073	0.1037	0.1146	3270.6
exploits	0.7641	0.4787	0.5168	8905.0
fuzzers	0.4363	0.8048	0.6690	4849.2
generic	0.9430	0.9762	0.9689	43096.2
normal	0.9999	0.9855	0.9883	443752.2
reconnaissance	0.6269	0.7230	0.6986	2797.4
shellcode	0.3193	0.6201	0.5153	302.2
worms	0.1167	0.1954	0.1708	34.8
avg_acc	0.9652			



type	precision	recall	f-score	support
attack	0.9101	0.9996	0.9798	64256.6
normal	0.9999	0.9852	0.9881	443752.2
avg_acc	0.9870			

UNSW-NB15: Conclusion

Possible future analysis:

- Approach an analysis on attributes by studying correlation among them (for ex. Pearson coefficient)
- Try an NLS-KDD approach by leave out from training set some attack categories and evaluate performance

THANK YOU FOR YOUR ATTENTION