

IoT Intrusion Detection By kNN:

Multi-Objective Optimization

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# IoT Cyber Security

- [People's Republic of China-Linked Actors Compromise Routers and IoT Devices for Botnet Operations](#)
- Intrusion Detection
  - AI Use Case
    - Attack Accuracy
      - Type
    - False alarm
    - Detection rate

# Multi-Objective Optimization

- kNN
  - Change k
  - Optimize accuracy and F1-score

## Swarm-Based Algorithm

- Particle Swarm Optimization (PSO)
- Whale Optimization Algorithm (WOA)

<b>Runtime type</b>	Python 3
<b>Hardware accelerator</b>	CPU
<b>Initial k Nearest Neighbor</b>	5
<b>Population</b>	30
<b>Epoch</b>	3
<b>Filter Out</b>	Analysis, Backdoor, Shellcode, Worms
<b>Optimize For</b>	k, f1

# Libraries

## MEALPY

- Open Source Python Library

## Scikit-Learn

- kNN model
- Metrics
  - Classification, Confusion

## Pandas

- Load Data

# Data

## UNSW-NB15

- Intelligent Security Group at UNSW Canberra
- 100GB network capture data
- Initial Training Subset
  - Exclude Analysis, Backdoor, Shellcode, Worms
  - 10,000 of each Attack, 56,000 Normal
- Final Training Subset
  - Exclude Analysis, Backdoor, Shellcode, Worms
  - 2,000 of each Attack, 10,000 Normal
- 49 Features
  - Standard Scaling

Attack Categories	Training Dataset Total Count	Testing Dataset Total Count
Analysis	2000	37000
Backdoor	1746	18871
DoS	12264	11132
Exploits	33393	6062
Fuzzers	18184	4089
Generic	40000	3496
Normal	56000	677
Reconnaissance	10491	583
Shellcode	1133	378
Worms	130	44
<b>Grand Total</b>	<b>175341</b>	<b>82332</b>

# Baseline kNN Model Attack Cat Classification

	Precision	Recall	F1-score	Support
<b>DoS</b>	0.19	0.47	0.27	4089
<b>Exploits</b>	0.62	0.48	0.54	11132
<b>Fuzzers</b>	0.17	0.66	0.27	6062
<b>Generic</b>	0.99	0.52	0.68	18871
<b>Normal</b>	0.88	0.48	0.62	37000
<b>Reconnaissance</b>	0.24	0.52	0.33	3496
<b>Accuracy</b>			0.51	80650
<b>Macro avg</b>	0.51	0.52	0.45	80650
<b>Weighted avg</b>	0.71	0.51	0.57	80650

# Baseline kNN Model Attack Cat Confusion

	<b>DoS</b>	<b>Exploits</b>	<b>Fuzzers</b>	<b>Generic</b>	<b>Normal</b>	<b>Reconnaissance</b>
<b>DoS</b>	1933	634	813	5	440	264
<b>Exploits</b>	2625	5361	1685	10	630	821
<b>Fuzzers</b>	981	78	4030	8	402	563
<b>Generic</b>	2426	297	5699	9768	386	295
<b>Normal</b>	1989	1975	11167	89	17870	3910
<b>Reconnaissance</b>	222	249	594	0	606	1825

# Baseline kNN Model Attack Label

	Precision	Recall	F1-score	Support
Normal	0.88	0.48	0.62	37000
Attack	0.68	0.95	0.79	43650
Accuracy			0.77	82332
Macro avg	0.76	0.76	0.76	82332
Weighted avg	0.77	0.77	0.77	82332

	Normal	Attack
Normal	27291	9709
Attack	9448	35884



# Optimization Results (Attack Category)

## PSO

- k, 23.18

## WOA

- k, 22.52

Both F1 and accuracy improved slightly

	Baseline F1-score	PSO F1-score
DoS	0.27	0.32
Exploits	0.54	0.55
Fuzzers	0.27	0.28
Generic	0.68	0.71
Normal	0.62	0.64
Reconnaissance	0.33	0.40
Accuracy	0.51	0.53
Macro avg	0.45	0.48
Weighted avg	0.57	0.59

# Optimization Results (Attack Label)

- F1 score improved
- Accuracy worsened

	Baseline F1-score	PSO F1-score
Normal	0.62	0.65
Attack	0.79	0.82
Accuracy	0.77	0.76
Macro avg	0.76	0.73
Weighted avg	0.77	0.74

# Conclusion

## Multi-Objective Optimization

- Marginally improved F1 scores and accuracy for Attack Category
- Marginally improved F1 scores for Attack Label

## Future Possible Work

- Improve objective function
  - Fitness Score, Search Space
- Try three objectives
- Move to a more complicated machine learning model
- Increase Epoch

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