Applications of Artificial Intelligence in Cyber Security

Elmurad Abbasov
University of Minnesota Morris
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Outline

- **Background information**
  - Cyber Security in the Modern World
  - The Usage of Artificial Intelligence in Cyber Security
  - Intrusion Detection System
  - Machine Learning Overview & Specifics
- Methodology
  - NSL-KDD (Network Security Laboratory - Knowledge Discovery in Databases)
  - Experimental setup
- Results Evaluation
  - Statistical summary
- Conclusion

Cyber Security in the Modern World

- 10.5 billion malware attacks since 2018
- 7.9 billion data breaches around the world in 2019
    - (112 percent more data breaches than in 2018)
    - Data breach - a security violation in which data is manipulated without a permission
- It is predicted that worldwide cyber security spending will reach $133.7 billion by 2022
- The number of cyber attacks is increasing every day

The Usage of Artificial Intelligence in Cyber Security

- Why cyber security is important?
- How AI is used in cyber security?
- Why research “Comparative Analysis of ML Classifiers for Network Intrusion Detection” by Ahmed M. Mahfouz, Deepak Venugopal, and Sajjan G. Shiva is important?

Intrusion Detection System (IDS)

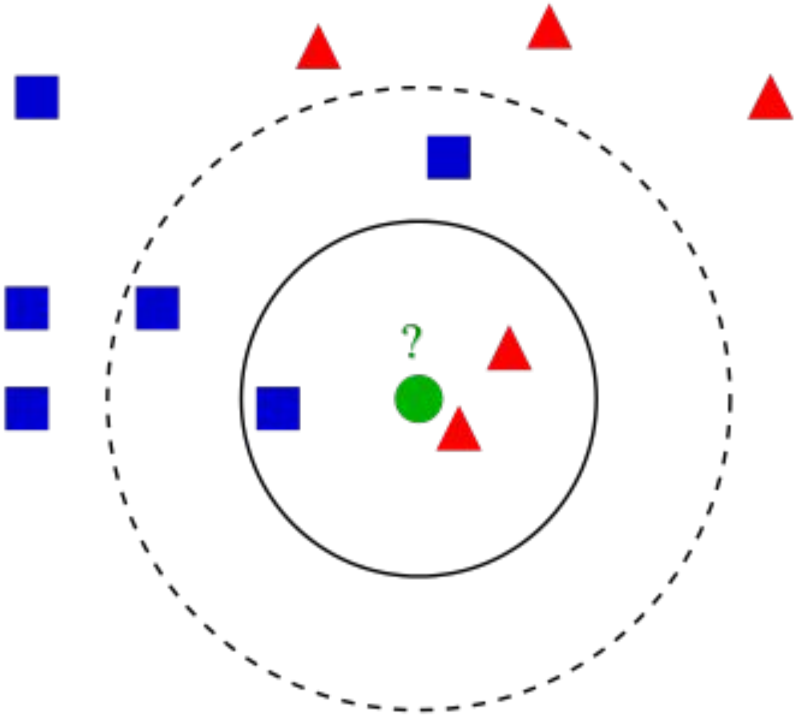
- IDS overview
  - Intrusion is an act of entering a virtual space without a proper permission
  - An IDS is software that is searching for malware in the entire network
- Types of IDS
  - *Signature-based detection*
    - Searches for patterns and compares with predetermined attack types (signatures)
  - *Statistical anomaly-detection*
    - IDS detects a suspicious traffic and compares to an established baseline
    - Usually a dataset of “normal” and “attack” files is used

Machine Learning Overview

- Supervised Learning (already labeled data used for predictions)
  - Labeled - group of samples tagged with a “tag”, “label”, or “class”
  - Prediction - output of an algorithm after it has been trained and applied to new data
  - Paired input records and their desired output
  - The output of a classification problem is a category - “normal” or “attack”
- WEKA: Naive Bayes, Logistic, MultilayerPerception, SMO, IBK and J48
- Original: Naive Bayes, Logistic, ANN, SVM, KNN, DT C 4.5

KNN (*k*-nearest neighbors) [7]

- Uses “majority voting” principle
- An object is classified by the majority vote of its neighbors
- Based on a distance function that measures the difference/similarity between two instances
- If k=1, then the object is assigned to the class of the single nearest neighbor
- The neighbors are taken from a set of objects for which the class is known



https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm

KNN (*k*-nearest neighbors) [7]

- The standard Euclidean distance d(x, y) between two instances x and y is defined in the following figure.
- **Xi** is the feature element of X, **Yi** is the feature element of Y, **n** is the total number of features in the data set.

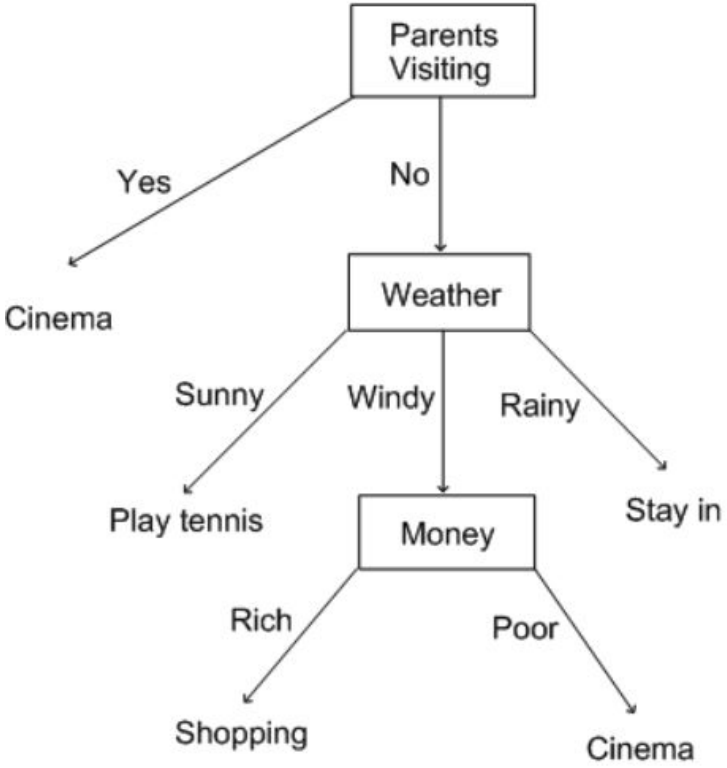
$$d(x,y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2}$$

KNN (*k*-nearest neighbors) [7]

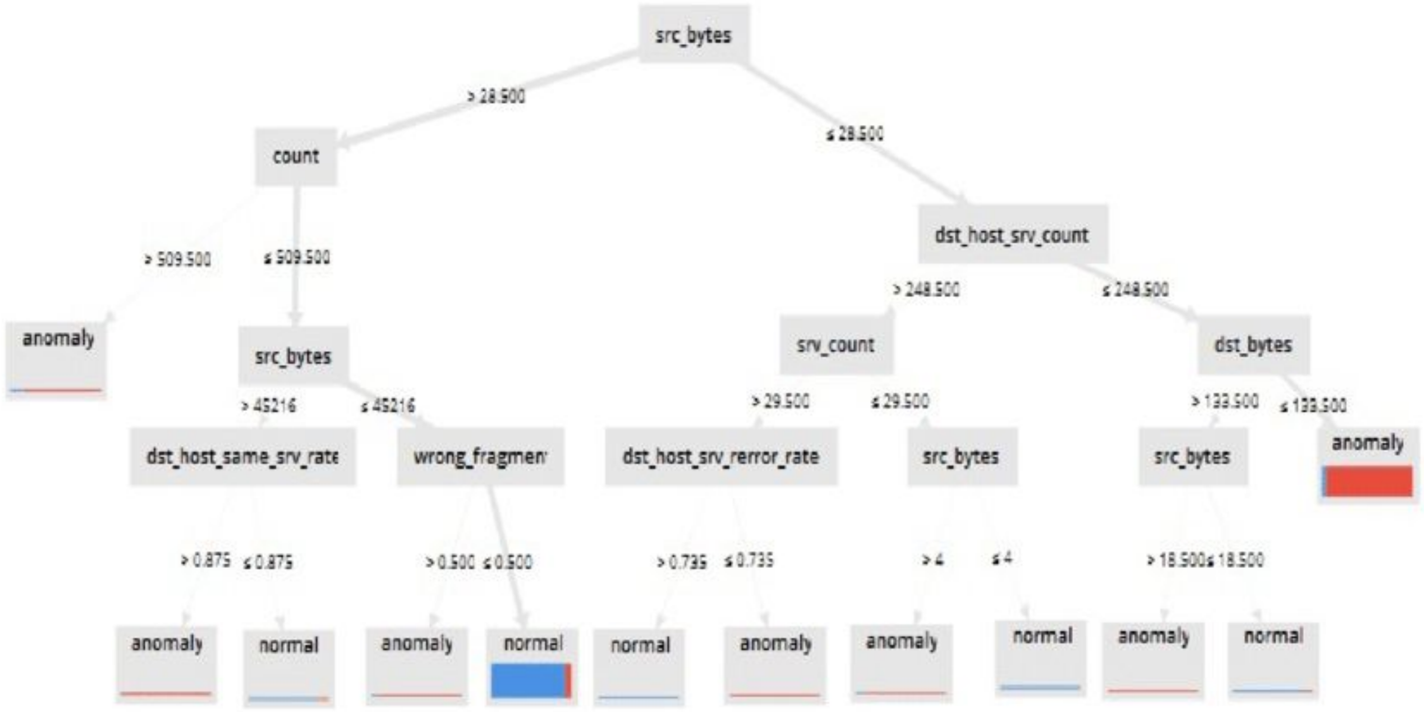
- Load the data to the model
- Choose k value as the number of neighbors
- Calculate distance between the sample and its neighbors
- Store the distance and sort in ascending order
- List out the first k entries
- Assign a class based on the majority present in the neighbor points

Decision Tree C 4.5 [9]

- Splits data recursively into subsets so that each subset contains more or less homogeneous states of target variable
- When the recursive process is completed, a DT is formed which can be converted in simple If - Then rules
- Uses **Information Gain (IG)** and **Entropy**
- **IG** - a measure of how much information a feature provides about a class and helps to determine order of features in the nodes
- **Entropy** - measures uncertainty in observations (probability of an event happening) and determines how a DT chooses to split data
- IG is inversely proportional to entropy



Decision Tree C 4.5 NSL-KDD Example [8]



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NSL-KDD: Overview

- Currently a benchmark in the research of IDS
- Contains malware connections (attacks) and safe connections (normal)
- 42 features per records
  - 41 features are about traffic input (data packets traveling across the internet)
  - The other feature is a label of either a safe connection or a threat connection
- Includes both training and testing sets

NSL-KDD: Features [6]

- For ML model to successfully process the data, it has to be in numerical values.
- Not all features all numerical (protocol_type, service, etc.), but all must be converted to numerical values.
- **Logged_in** = If logged in then logged_in = 1, else 0
- **Root_shell** = If root shell is obtained then root_shell = 1, else 0
- **Is_guest_login** = If login as guest then is_guest_login = 1, else 0
- **Count No.** = number of connections to the same host in last 2 seconds

#	Feature	#	Feature
1	duration	22	is_guest_login
2	protocol_type	23	Count
3	service	24	srv_count
4	flag	25	serror_rate
5	src_bytes	26	srv_serror_rate
6	dst_bytes	27	rerror_rate
7	land	28	srv_rerror_rate
8	wrong_fragment	29	same_srv_rate
9	urgent	30	diff_srv_rate
10	hot	31	srv_diff_host_rate
11	num_failed_logins	32	dst_host_count
12	logged_in	33	dst_host_srv_count
13	num_compromised	34	dst_host_same_srv_rate
14	root_shell	35	dst_host_diff_srv_rate

NSL-KDD: Example Data [6]

```
0,tcp,http,SF,181,5450,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,8,8,0.00,0.00,0.00,0.00,1.
00,0.00,0.00,9,9,1.00,0.00,0.11,0.00,0.00,0.00,0.00,0.00,normal.
0,tcp,http,SF,239,486,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,8,8,0.00,0.00,0.00,0.00,1.0
0,0.00,0.00,19,19,1.00,0.00,0.05,0.00,0.00,0.00,0.00,0.00,normal.
```

Figure 2. Original samples from NSL-KDD dataset.

```
0,3,19,10,181,5450,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,8,8,0,0,0,0,1,0,0,9,9,1,0,0.1
1,0,0,0,0,22
0,3,19,10,239,486,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,8,8,0,0,0,0,1,0,0,19,19,1,0,0.
05.0.0.0.0.22
```

Figure 3. Results after data transformation.

NSL-KDD: Attack Classes

- Denial of Service (DoS)
  - Overloads a server with abnormal traffic that shuts down the connection to and from the target system
- Probe
  - Extracting specific personal information from the target system
- Remote to Local (R2L)
  - Gains local access to a remote machine
- User to Root (U2R)
  - Gains root access to the interested system or a network

NSL-KDD: Attack Classes Summary in Table 2 [5]

Table 2. No of samples for normal and attack classes.

Class	Training Set	Occurrences Percentage	Testing Set	Occurrences Percentage
Normal	67343	53.46 %	9711	43.08 %
DoS	45927	36.46 %	7460	33.08 %
Probe	11656	9.25 %	2421	10.74 %
R2L	995	0.79 %	2885	12.22 %
U2R	52	0.04 %	67	0.89 %
Total	125973	100.0 %	22544	100.0 %

NSL-KDD: Imbalance Issue

- An imbalance in the dataset creates biased results toward the samples from the majority classes
- The classification accuracy is higher for the majority classes than for minority classes
- The researchers offer a method to deal with the imbalance

Experimental Setup: Overview

- First phase:
  - Compare classifiers with default settings and original data set
- Second phase:
  - NSL-KDD was modified to reduce its dimension
- Third phase:
  - NSL-KDD was modified to solve imbalance issue

Experimental Setup: First Phase

- First phase:
  - Compare classifiers with default settings
  - Default data set without modifications
  - Cross-Validation of 10-folds [3]
    - Used for evaluating and comparing ML models
    - Works by separating the dataset into K equally sized folds
    - K-1 folds used to train the model, the last fold is left for model testing
    - Process reiterated until every fold gets the chance to act as the test dataset
    - The capability of the model is estimated by averaging the performance measures across all folds

Experimental Setup: Second Phase

- Second phase:
  - NSL-KDD was modified to reduce its dimension (transformation of data from a high-dimensional space into a low-dimensional space to keep only meaningful properties) [1]
    - Feature selection process (selecting a subset of the original features so that the feature space is optimally reduced to the evaluation criteria) done with InfoGainAttributeEval algorithm
      - Evaluates the worth of a feature by measuring the IG with respect to the class
      - The algorithm measured how each feature contributes in decreasing the overall entropy
    - Selected 14 out of 41 features
  - Hyperparameter optimization (the process of choosing a set of optimal hyperparameters) is done by CVParameterSelection
    - Hyperparameter - a parameter whose value is used to control the learning process [2]
    - Performs parameter selection by cross-validation

Experimental Setup: Phase Three

- Third phase:
    - NSL-KDD was modified to solve imbalance issue
        - Under-sampling the dominant classes [4]
            - WEKA’s Resample filter that takes a random subsample
            - Uses either sampling with replacement or without replacement
        - Over-sampling the minority classes [4]
            - WEKA’s (Synthetic Minority Over-sampling Technique) SMOTE filter that generates synthetic instances
            - As a result increases the minority group

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Results Evaluation: Overview & Parameters

- Parameters such as **TP**, **TN**, **FP**, **FN** are commonly used in Machine Learning in evaluating results.
- **True Positive (TP)** - an outcome where the model correctly predicts the positive class (malware was identified as a threat)
- **True Negative (TN)** - an outcome where the model correctly predicts the negative class (a clean file was identified as a non-threat)
- **False Positive (FP)** - an outcome where the model incorrectly predicts the positive class (a clean file was identified as a threat)
- **False Negative (FN)** - an outcome where the model incorrectly predicts the negative class (a malware was identified as a non-threat)

Results Evaluation: ML Efficiency Metric

- **Accuracy** - the number of correct predictions divided by the total number of predictions

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Test Set Results [5]

Phase 1

Classifier	Accuracy
NB	76.12 %
Logistic	75.60 %
MLP	77.60 %
SMO	75.39 %
IBK	79.35 %
J48	81.69 %

Phase 2

Classifier	Accuracy
NB	78.15 %
Logistic	81.51 %
MLP	78.15 %
SMO	79.83 %
IBK	84.35 %
J48	82.67 %

Comparison of Classifiers in Table 8 [5]

Table 8. Classifiers accuracy detection for different classes of attacks.

Classifier	Class	Phase I	Phase II	Phase III
IBK	Normal	79.3 %	86.8 %	99.4 %
	DoS	80.5 %	90.7 %	99.5 %
	Probe	71.8 %	76.2 %	99.0 %
	R2L	00.0 %	00.0 %	53.2 %
	U2R	00.0 %	00.0 %	41.5 %
J48	Normal	81.6 %	84.8 %	99.5 %
	DoS	80.1 %	89.2 %	99.2 %
	Probe	67.9 %	63.2 %	91.6 %
	R2L	18.9 %	18.2 %	55.1 %
	U2R	00.0 %	00.0 %	39.3 %

Conclusion

- Six different classifiers were evaluated on their performance to detect cyber attacks on the NSL-KDD data set
- KNN (IBK) and DT C 4.5 (J48) showed good performance comparing to other algorithms
- Imbalance mitigation method improved limitations in detecting R2L and U2R attacks

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Questions?

References

[1] Wikipedia contributors. (2021, August 26). Dimensionality reduction. In Wikipedia, The Free Encyclopedia. Retrieved 10:54, November 13, 2021, from https://en.wikipedia.org/w/index.php?title=Dimensionality_reduction&oldid=1040808431

[2] Wikipedia contributors. (2021, August 8). Hyperparameter optimization. In Wikipedia, The Free Encyclopedia. Retrieved 11:06, November 13, 2021, from https://en.wikipedia.org/w/index.php?title=Hyperparameter_optimization&oldid=1037728107

[3] Wikipedia contributors. (2021, October 28). Cross-validation (statistics). In Wikipedia, The Free Encyclopedia. Retrieved 11:15, November 13, 2021, from https://en.wikipedia.org/w/index.php?title=Cross-validation_(statistics)&oldid=1052330597

[4] Wikipedia contributors. (2021, October 26). Oversampling and undersampling in data analysis. In Wikipedia, The Free Encyclopedia. Retrieved 11:21, November 13, 2021, from https://en.wikipedia.org/w/index.php?title=Oversampling_and_undersampling_in_data_analysis&oldid=1051894978

[5] Mahfouz, Ahmed & Venugopal, Deepak & Shiva, Sajjan. (2019). Comparative Analysis of ML Classifiers for Network Intrusion Detection.

[6] Harb, Hany & Zaghrot, Afaf & Gomaa, Mohamed & S. Desuky, Abeer. (2011). Selecting Optimal Subset of Features for Intrusion Detection Systems. Advances in Computational Sciences and Technology. 4. 179-192.

[7] Wikipedia contributors. (2021, October 24). K-nearest neighbors algorithm. In Wikipedia, The Free Encyclopedia. Retrieved 12:19, November 13, 2021, from https://en.wikipedia.org/w/index.php?title=K-nearest_neighbors_algorithm&oldid=1051590352

[8 Hassannataj Joloudari, Javad & Haderbadi, Mojtaba & Mashmool, Amir & Ghasemigol, Mohammad & Band, Shahab & Mosavi, Amir. (2020). Early Detection of The Advanced Persistent Threats Attacks Using Performance Analysis of Deep Learning. 10.20944/preprints202007.0745.v1.]

[9] Saha, S. (2018, November 16). What is the C4.5 algorithm and how does it work? Medium. Retrieved November 13, 2021, from https://towardsdatascience.com/what-is-the-c4-5-algorithm-and-how-does-it-work-2b971a9e7db0.