Appendices

A Combining continuous outputs

Instead of deciding the class label as output, some learning models may output the probability with which an instance belongs to a class. This probability can be thought of as the degree of support shown by the learning model towards a class.

$$\begin{aligned} s_{c,j}(x_i) &= \text{for the instance } x_i, \\ s_{c,j} &= \text{support received by the } j^{th} \text{ class from the } c^{th} \text{ classifier} \\ w_j &= \text{weight of the } j^{th} \text{ classifier} \\ \text{C} &= \text{total number of classifiers or models} \\ \mu_j(x_i) &= \text{total support for the } j^{th} \text{ class for instance } x_i \end{aligned}$$

Following are commonly used for combining the outputs of base learners.

1. *Sum rule*: According to this rule, the individual supports from all the learning models are added to obtain the final support for a particular class as shown in equation 1. The final output of the ensemble is the class with the highest support.

$$\mu_j(x_i) = \sum_{c=1}^{C} s_{c,j}(x_i) \tag{1}$$

2. *Mean rule*: According to this rule, after adding the individual supports from all the learning models, the total sum is normalized by the total number of learning models ($\frac{1}{C}$) as shown in equation 2.

$$\mu_j(x_i) = \frac{1}{C} \sum_{c=1}^{C} s_{c,j}(x_i) \tag{2}$$

3. *Weighted sum rule*: Each learning model is assigned a weight and the total support is the total sum of the product of the learning model's weights and

their supports as shown in equation 3.

$$\mu_j(x_i) = \sum_{c=1}^{C} w_t s_{c,j}(x_i) \tag{3}$$

4. *Product rule*: According to this rule, for a particular class the supports provided by the learning models are multiplied to obtain the final output.

$$\mu_j(x_i) = \prod_{c=1}^{C} s_{c,j}(x_i) \tag{4}$$

5. *Maximum rule*: According to this rule, for a particular class, the maximum support given by the participating learning models is selected as shown in equation 5.

$$\mu_j(x_i) = \max_{c=1}^{C} s_{c,j}(x_i) \tag{5}$$

6. *Minimum rule*: As the name suggests, for a particular class this rule selects the minimum support given by the participating learning models as shown in equation 6.

$$\mu_j(x_i) = \min_{c=1}^{C} s_{c,j}(x_i) \tag{6}$$

7. *Generalized mean rule*: The rules discussed above are special versions of the generalized mean rule given in equation 7.

$$\mu_{j,\infty}(x_i) = \left[\frac{1}{C} \sum_{c=1}^{C} s_{c,j}(x_i)^{\infty} \right]^{\frac{1}{\infty}} \tag{7}$$

B Hyper-parameter values

B.1 Bagging

Table 1 and Table 2 give the hyper-parameter values for Bagging ensemble method.

Table 1: Hyper-parameter Values for 2-class Security Datasets (Bagging)

		k-Nearest Neighbors	Support Vector Machine	Decision Trees	Logistic Regression
	Android Dataset 1	n_neighbors= 1	C=10, degree=1	criterion='entropy',max_depth=6, min_samples_leaf=2,min_samples_split=2	C=10,penalty="l2"
	Android Dataset 2	n_neighbors= 3	C=1, degree=1	criterion='gini',max_depth=3, min_samples_leaf=1,min_samples_split=2	C=1000,penalty="l2"
Security Datasets	SWaT	n_neighbors= 1	C=10, degree=1	criterion='entropy',max_depth=9, min_samples_leaf=1,min_samples_split=2	C=100,penalty="l2"
	Phishing	n_neighbors= 1	C=10, degree=1	criterion='entropy',max_depth=9, min_samples_leaf=1,min_samples_split=3	C=0.1,penalty="l2"
	Kitsune Network Attack	n_neighbors= 4	C=10, degree=1	criterion='gini',max_depth=8, min_samples_leaf=3,min_samples_split=2	C=0.001,penalty="l2"

Table 2: Hyper-parameter values for ransomware multiclass datasets (Bagging)

		Classifiers			
		k-Nearest Neighbors	Support Vector Machine	Decision Trees	Logistic Regression
Ransomware Multiclass	Citroni	n_neighbors= 1	C=1, degree=1	criterion='gini', max_depth=3, min_samples_leaf=1, min_samples_split=2	C=1.0, penalty="l2"
	CryptLocker	n_neighbors= 7	C=10, degree=1	criterion='gini', max_depth=7, min_samples_leaf=1, min_samples_split=3	C=10.0, penalty="l2"
	CryptoWall	n_neighbors= 3	C=10, degree=1	criterion='entropy', max_depth=6, min_samples_leaf=1, min_samples_split=2	C=10.0, penalty="l2"
	Kollah	n_neighbors= 2	C=10, degree=1	criterion='gini',max_depth=8, min_samples_leaf=1, min_samples_split=2	C=10.0, penalty="l2"
	Kovter	n_neighbors= 2	C=10, degree=1	criterion='gini',max_depth=5, min_samples_leaf=1, min_samples_split=4	C=1.0, penalty="l2"
	Locker	n_neighbors= 2	C=10, degree=1	criterion='gini',max_depth=5, min_samples_leaf=1, min_samples_split=4	C=1.0, penalty="l2"
	Matsnu	n_neighbors= 4	C=1, degree=1	criterion='entropy',max_depth=7, min_samples_leaf=1, min_samples_split=6	C=1.0, penalty="l2"
	Pgpcoder	n_neighbors= 1	C=0.1, degree=1	criterion='gini',max_depth=3, min_samples_leaf=1, min_samples_split=2	C=0.1, penalty="l2"
	Reveton	n_neighbors= 1	C=10, degree=1	criterion='gini',max_depth=8, min_samples_leaf=1, min_samples_split=7	C=1000.0, penalty="l2"
	TeslaCrypt	n_neighbors= 3	C=1, degree=1	criterion='gini',max_depth=7, min_samples_leaf=3, min_samples_split=2	C=1.0, penalty="l2"
	Trojan-Ransom	n_neighbors= 3	C=10, degree=1	criterion='entropy',max_depth=7, min_samples_leaf=3, min_samples_split=9	C=10.0, penalty="l2"

B.2 Boosting

Table 3, 4, 5, and 6 give the hyper-parameter values for the Boosting ensemble method.

Table 3: Hyper-parameter values for 2-class security datasets (Adaboost, GB and XGB)

		Classifiers		
	Dataset name	AdaBoost	Gradient Boosting	Extreme Gradient Boosting
Security Datasets	Android Dataset 1	learning_rate=0.1, n_estimators=500, algorithm='SAMME.R'	loss= 'exponential', learning_rate=0.1, n_estimators=500,max_features='log2', max_depth=5 ,criterion='mse'	colsample_bytree= 0.5, learning_rate=0.01, max_depth= 10, min_child_weight= 1, n_estimators= 500, subsample= 0.75
	Android Dataset 2	learning_rate=0.1, n_estimators=350, algorithm='SAMME.R'	loss= 'exponential', learning_rate=0.1, n_estimators=300,max_features='log2', max_depth=5 ,criterion='mse'	colsample_bytree= 1, learning_rate=0.1, max_depth= 10, min_child_weight= 1, n_estimators= 100, subsample= 0.5
	SWaT	learning_rate=1.0, n_estimators=500, algorithm='SAMME.R'	criterion='friedman_mse', learning_rate= 1.0, loss='exponential',max_depth= 8, max_features= log2, n_estimators= 500	colsample_bytree= 1, learning_rate=0.01, max_depth= 6, min_child_weight= 1, n_estimators= 300, subsample= 0.5
	Phishing	learning_rate=1.0, n_estimators=200, algorithm='SAMME'	loss= 'exponential', learning_rate=0.1, n_estimators=500, max_features='log2', max_depth=5 ,criterion='friedman_mse'	colsample_bytree= 0.5, learning_rate=0.1, max_depth= 10, min_child_weight= 1, n_estimators= 200, subsample= 1
	Kitsune Network Attack	learning_rate=1, n_estimators=500, algorithm='SAMME.R'	loss= 'exponential', learning_rate=0.1, n_estimators=500,max_features='log2', max_depth=8,criterion='mse'	colsample_bytree= 0.75, learning_rate=0.1, max_depth= 10, min_child_weight= 1, n_estimators= 500, subsample= 1

Table 4: Hyper-parameter values for 2-class security datasets (LGB and HGB)

		Classifiers	
	Dataset name	Light Gradient Boosting	Hist Gradient Boosting
Security Datasets	Android Dataset 1	boosting_type= 'dart', num_leaves= 10, learning_rate= 0.5, min_child_weight= 1, min_child_samples=100, colsample_bytree= 0.66,reg_alpha= 0.5, reg_lambda= 1, subsample= 0.5	learning_rate=0.1, max_iter=150, max_leaf_nodes=30, min_samples_leaf=20
	Android Dataset 2	boosting_type= 'gbdt',colsample_bytree= 1,learning_rate= 0.5, min_child_samples= 50,min_child_weight=1,num_leaves=10, reg_alpha=0.5,reg_lambda= 1.4,subsample= 0.5	learning_rate=0.1, max_iter=100, max_leaf_nodes=40, min_samples_leaf=5
	SWaT	boosting_type= 'dart', colsample_bytree= 0.66, learning_rate=1, min_child_samples= 50, min_child_weight=1, num_leaves=20, reg_alpha=0.5, reg_lambda= 1.2, subsample= 0.5	learning_rate=0.01, max_iter=100, max_leaf_nodes=30, min_samples_leaf=3
	Phishing	boosting_type= 'dart', num_leaves= 20, learning_rate= 1, min_child_weight= 1, min_child_samples=20, colsample_bytree= 1, reg_alpha= 0.5, reg_lambda= 1.2, subsample= 0.5	learning_rate=0.1, max_iter=200, max_leaf_nodes=40, min_samples_leaf=10
	Kitsune Network Attack	boosting_type= 'dart', num_leaves= 20, learning_rate= 0.5, min_child_weight= 1e-05, min_child_samples=20, colsample_bytree= 1, reg_alpha= 0.5, reg_lambda= 1.2, subsample= 0.5	learning_rate=0.1, max_iter=200, max_leaf_nodes=40, min_samples_leaf=10

Table 5: Hyper-parameter values for Ransomware multiclass dataset (Adaboost, GB and XGB)

	Class	Adaboost	Gradient Boosting	Extreme Gradient Boosting
Ransomware Multiclass	Citroni	learning_rate=1.0, n_estimators=100, algorithm='SAMME'	loss= 'exponential', learning_rate=1.0, n_estimators=100, max_depth=8, criterion='friedman_mse'	colsample_bytree= 1, learning_rate=0.1, max_depth= 2, min_child_weight= 1, n_estimators= 100, subsample= 1
	CryptLocker	learning_rate=1.0, n_estimators=200, algorithm='SAMME.R'	loss= 'exponential', learning_rate=1.0, n_estimators=500, max_depth=5 , criterion='friedman_mse'	colsample_bytree= 0.5, learning_rate=0.01, max_depth= 2, min_child_weight= 1, n_estimators= 100, subsample= 0.5
	CryptoWall	learning_rate=0.1, n_estimators=200, algorithm='SAMME.R'	loss= 'deviance', learning_rate=0.1, n_estimators=100, max_depth=3, criterion='friedman_mse'	colsample_bytree= 0.5, learning_rate=0.01, max_depth= 2, min_child_weight= 1, n_estimators= 100, subsample= 0.5
	Kollah	learning_rate=0.1, n_estimators=50, algorithm='SAMME.R'	loss= 'exponential', learning_rate=0.1, n_estimators=200, max_depth=3, criterion='friedman_mse'	colsample_bytree= 0.5, learning_rate=0.3, max_depth= 6, min_child_weight= 1, n_estimators= 100, subsample= 1
	Kovter	learning_rate=1.0, n_estimators=500, algorithm='SAMME'	loss= 'exponential', learning_rate=0.01, n_estimators=500,max_depth=3, criterion='friedman_mse'	colsample_bytree= 0.75, learning_rate=0.1, max_depth= 2, min_child_weight= 1, n_estimators= 100, subsample= 1
	Locker	learning_rate=1.0, n_estimators=500, algorithm='SAMME'	loss= 'exponential', learning_rate=0.01, n_estimators=500, max_depth=3, criterion='friedman_mse'	colsample_bytree= 0.75, learning_rate=0.1, max_depth= 2, min_child_weight= 1, n_estimators= 100, subsample= 1
	Matsnu	learning_rate=1.0, n_estimators=200, algorithm='SAMME'	loss= 'exponential', learning_rate=1.0, n_estimators=100, max_depth=8, criterion='friedman_mse'	colsample_bytree= 0.75, learning_rate=0.1, max_depth= 10, min_child_weight= 1, n_estimators= 300, subsample= 1
	Pgpcoder	learning_rate=1.0, n_estimators=50, algorithm='SAMME'	loss= 'deviance', learning_rate=0.01, n_estimators=200, max_depth=3, criterion='friedman_mse'	colsample_bytree= 0.5, learning_rate=0.01, max_depth= 2, min_child_weight= 1, n_estimators= 300, subsample= 0.5
	Reveton	learning_rate=0.1, n_estimators=500, algorithm='SAMME.R'	loss= 'exponential', learning_rate=0.1, n_estimators=500, max_depth=8, criterion='friedman_mse'	colsample_bytree= 1, learning_rate=0.3, max_depth= 6, min_child_weight= 1, n_estimators= 100, subsample= 1
	TeslaCrypt	learning_rate=0.1, n_estimators=100, algorithm='SAMME.R'	loss= 'deviance', learning_rate=0.1, n_estimators=200, max_depth=8, criterion='friedman_mse'	colsample_bytree= 0.5, learning_rate=0.01, max_depth= 10, min_child_weight= 1, n_estimators= 200, subsample= 1
	Trojan-Ransom	learning_rate=0.1, n_estimators=350, algorithm='SAMME.R'	loss= 'exponential', learning_rate=1.0, n_estimators=300, max_depth=3, criterion='mse'	colsample_bytree= 1, learning_rate=0.01, max_depth= 10, min_child_weight= 1, n_estimators= 500, subsample= 0.75

Table 6: Hyper-parameter values for Ransomware multiclass dataset (LGB and HGB)

		Classifiers	
	Class	Light Gradient Boosting	HistGradient Boosting
Ransomware Multiclass	Citroni	boosting_type= 'gbdt', colsample_bytree= 1, learning_rate= 0.1, min_child_samples= 20, min_child_weight=1e-05, num_leaves=5, reg_alpha=0.5, reg_lambda= 1.4, subsample= 0.5	learning_rate=0.1, max_iter=150, max_leaf_nodes=10, min_samples_leaf=10
	CryptLocker	boosting_type= 'dart',colsample_bytree= 0.5, learning_rate= 1, min_child_samples= 20, min_child_weight=1, num_leaves=10, reg_alpha=1.2, reg_lambda= 1.4	learning_rate=1,max_iter=100, max_leaf_nodes=10,min_samples_leaf=3
	CryptoWall	boosting_type= 'gbdt', colsample_bytree= 1, learning_rate= 1.0, min_child_samples= 20, min_child_weight=1e-05, num_leaves=5, reg_alpha=0.5 , reg_lambda= 1.2, subsample= 0.5	learning_rate=1, max_iter=100, max_leaf_nodes=30, min_samples_leaf=5
	Kollah	boosting_type= 'dart', colsample_bytree= 0.5, learning_rate= 1, min_child_samples= 20, min_child_weight=1e-05, num_leaves=10, reg_alpha=0.5, reg_lambda= 1, subsample= 0.5	learning_rate=1, max_iter=100, max_leaf_nodes=10, min_samples_leaf=3
	Kovter	boosting_type= 'dart',colsample_bytree= 0.5, learning_rate= 0.1,min_child_samples= 20, min_child_weight=1e-05,num_leaves=5, reg_alpha=0.5,reg_lambda= 1,subsample= 0.5	learning_rate=0.01, max_iter=200, max_leaf_nodes=10, min_samples_leaf=3,
	Locker	boosting_type= 'dart',colsample_bytree= 0.5, learning_rate= 0.1,min_child_samples= 20, min_child_weight=1e-05,num_leaves=5, reg_alpha=0.5,reg_lambda= 1,subsample= 0.5	learning_rate=0.01, max_iter=200, max_leaf_nodes=10, min_samples_leaf=3
	Matsnu	boosting_type= 'gbdt',colsample_bytree= 1, learning_rate= 1.0,min_child_samples= 50, min_child_weight=1,num_leaves=5, reg_alpha=0.5,reg_lambda= 1.2,subsample= 0.5	learning_rate=0.1, max_iter=100, max_leaf_nodes=10, min_samples_leaf=3
	Pgpcoder	boosting_type= 'gbdt', colsample_bytree= 0.5, learning_rate= 1.0,min_child_samples= 20, min_child_weight=1e-05,num_leaves=5, reg_alpha=0.5,reg_lambda= 1.2,subsample= 0.5	learning_rate=0.01, max_iter=100, max_leaf_nodes=10, min_samples_leaf=3
	Reveton	boosting_type= 'gbdt',colsample_bytree= 0.5, learning_rate= 0.1,min_child_samples= 20, min_child_weight=1e-05,num_leaves=10, reg_alpha=0.5,reg_lambda= 1,subsample= 0.5	learning_rate=0.1, max_iter=100, max_leaf_nodes=30, min_samples_leaf=10
	TeslaCrypt	boosting_type= 'gbdt',colsample_bytree= 0.66, learning_rate= 1.0,min_child_samples= 20, min_child_weight=1e-05,num_leaves=10, reg_alpha=1,reg_lambda=1.4,subsample= 0.5	learning_rate=0.1, max_iter=100, max_leaf_nodes=10, min_samples_leaf=5
	Trojan-Ransom	boosting_type= 'gbdt',colsample_bytree= 0.5, learning_rate= 0.5,min_child_samples= 50, min_child_weight=1e-05,num_leaves=5, reg_alpha=1.2,reg_lambda= 1,subsample= 0.5	learning_rate=0.1, max_iter=100, max_leaf_nodes=30, min_samples_leaf=20

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Glossary

Crawl The act of searching and indexing of Web content by a software program.. 4

DDoS A form of an attack where an army of bots simultaneously send HTTP traffic to an application to disrupt its services. 7

Dynamic Analysis Analysis done by executing the software.. 5

IP Address A unique address with which every device connected to the Internet is identified.. 4

Static Analysis Analysis done by examining the source code and not by way of execution.. 4

Vulnerabilities Weaknesses or flaws existing in the system.. 2

Web Application Software which runs on an application server and are accessed with the help of browsers,. 1

Worms Malicious software which tries to self-replicate and spread to other devices. . 7

List of Publications

Journal Publications

1. Upasana Sarmah, Dhruba Kr Bhattacharyya, Jugal K. Kalita, “A survey of Detection Methods for XSS Attacks”, Journal of Network and Computer Applications, 118, 113-143, 2018. (Scopus Indexed)

2. Upasana Sarmah, Parthajit Borah, Dhruba Kr Bhattacharyya, “Supervised Ensemble Learning Approaches and Methods: An experimental Investigation”, Springer Nature Computer Science, 5(7), 924, 2024. (Scopus Indexed)

3. Parthajit Borah, Upasana Sarmah, Dhruba Kr Bhattacharyya, Jugal K. Kalita, “Unmasking the common traits: an ensemble approach for effective malware detection", International Journal of Information Security, 1-11, 2024. (Scopus Indexed)

4. Upasana Sarmah, Dhruba Kr Bhattacharyya, Jugal K. Kalita, “MICC-UD: A Mutual Information and Correlation based Feature Selection Algorithm”. (Under Review)

5. Upasana Sarmah, Dhruba K. Bhattacharyya, “INFS-MICC: An Incremental Feature Selection Algorithm based on Mutual Information and Correlation”. (Under Review)

Conference Publications

1. Upasana Sarmah, Dhruba Kr Bhattacharyya, Jugal K. Kalita,“XSSD: A Cross-site Scripting Attack Dataset and its Evaluation”, 3rd ISEA Conference on Security and Privacy (ISEA-ISAP), 21-30, 2020.

Book Chapter Publications

1. Upasana Sarmah, Dhruba Kr. Bhattacharyya, "Cost-Effective Detection of Cyber Physical System Attacks", Advances in Machine Learning for Big Data Analysis, Springer Nature Singapore, 33-69.
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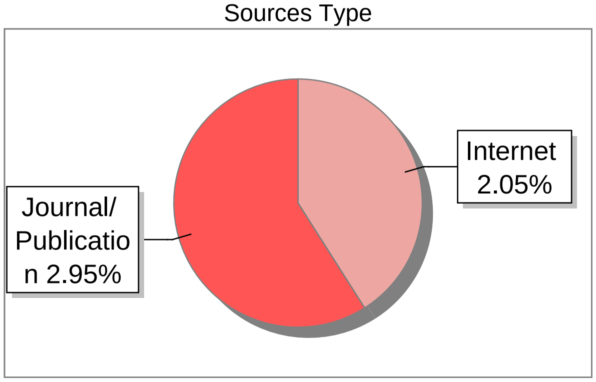

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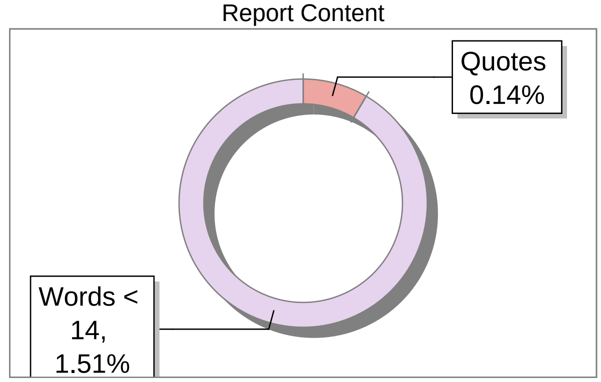

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1	A survey of detection methods for XSS attacks, by Sarmah, Upasana Bh-2018	3	Publication
2	A survey of detection methods for XSS attacks, by Sarmah, Upasana Bh-2018	3	Publication

3	A survey of detection methods for XSS attacks, by Sarmah, Upasana Bh- 2018	1	Publication
4	A survey of detection methods for XSS attacks, by Sarmah, Upasana Bh- 2018	1	Publication
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