Applied Machine Learning Group Coursework: IoT Intrusion Detection Competition using Machine Learning

Student ID 13166549 Siddharth Sengupta - Preprocessing
Student ID 13405463 Alex Bates - Feature Selection
Student ID 12819393 Alex Gorton - Algorithm Comparison
Student ID 13157188 Konstantin Orlovskiy - Algorithm Tuning
Student ID 13159064 Scott Tasker - Model Evaluation
Word count - 4’083 words

Applied Machine Learning:
Birkbeck University: Professor Paul Yoo

Planning - Group section

Project initiation

We formed a group and held our initial meeting on the 10th of November 2019. At this meeting we made a series of decisions for the project:

1. Assignment of sections to group members
2. Workflow methodology
3. Project principles
4. Agreed a work schedule
5. Established communication
6. Programming conventions

1. Collectively this was our first experience using machine learning, so rather than prioritizing experience, we discussed the aspects and requirements of each section. We then individually volunteered for sections based on personal preferences.
2. We identified that each of the data handling steps are sequential, requiring input from the preceding stage. For example, the input of the feature selection step is the pre-processed data. This constraint necessitates a waterfall-like workflow.
3. Due to time constraints and our relative inexperience, we determined that our project should favor speed and simplicity over complexity, for example using available libraries like scikit-learn rather than attempting to build our own tools from scratch.
4. Factoring 10 weeks to complete the project, we agreed to attempt to complete 2 full iterations prior to the Christmas break. The planned schedule is depicted in figure 1.
5. To enable distributed development of the project, we set up a WhatsApp group for communication and created a Github repository to store project files.
6. Further to point 5, we agreed that all programming should be performed in the Python programming language, and each section implemented as a function with documented inputs and outputs to allow easy use by the other group members.

		Sun	Thu	Sun	Thu	Sun	Thu	Sun	Thu	Sun	Thu	Sun	Thu	Sun	Thu	Sun	Thu	Sun	Thu	Sun	Thu	Deadline
PLAN 14/11		10-Nov	14-Nov	17-Nov	21-Nov	24-Nov	28-Nov	1-Dec	5-Dec	8-Dec	12-Dec	15-Dec	19-Dec	22-Dec	26-Dec	29-Dec	2-Jan	5-Jan	9-Jan	12-Jan	16-Jan	19-Jan
Project Planning	(group)																					
Pre-processing	Sid																					
Selecting features	Alex B.																					
Exploring and selecting ML algorithms	Alex G.																					
Refining algorithms	Kostantin																					
Evaluating model and analysing the results	Scott																					
Future work / Discuss results	(group)																					
Report 4,000 words (±10%), ~700 words per section	(group)																		ready			

Figure 1. Planned work schedule.

Project review

We held two review sessions, the first on the 12/12/2019 and a final review session on the 09/01/2020.

In the first session, we reported the conclusions of the first two iterations, and identified critical areas for improvement:

- Trying different scaling methods such as MinMax, StandardScaler
- Exploring dimensionality reduction techniques for feature selection like PCA
- Reviewing the algorithm selection, adding in K-nearest neighbours and Naïve Bayes Classifier
- Expanding the tuning parameters search size.
- Exploring further evaluation parameters such as F1 score, False Alarm rate, Michaels Correlation Coefficient

In the final review session, we discussed the conclusions of the project and assigned responsibilities for the planning section and the future of the report and code clean up.

Summary

- We delivered the project closely to the planned schedule, with several high-performance models developed by the Christmas break, allowing further research than anticipated.
- The WhatsApp group and Github repository were highly effective tools for sharing knowledge.
- By undertaking this project, we have all gained an insight into the application of machine learning algorithms to a real-world application.

Preprocessing – Siddharth Sengupta

Any real-world data, in principle, is generally unclean, incomplete, unscaled, and overall messy. The pre-processing stage is essential to the machine learning pipeline, in order to prepare the data before further analysis and model building.

A pre-processing generally involves some data transformation, filling missing observations with suitable values, scaling various features to a standard scale, among other things.
The following operations were performed on the raw data set during this phase –

1. Metadata transformation – The raw data set provided to us has got column numbers instead of the actual column names. Given the number of features, at later stages, it would be next to impossible to identify the features. To overcome that, we have assigned the actual column names to the features instead of the numbers. The list of attributes is available Aegean data set web page. In the data set provided to us, the frame.time_epoch and frame.time_relative are excluded, so the feature names have been assigned accordingly.

2. Data cleaning – Next we checked the data for missing values. For each feature, we checked if there are any missing observations, and filled them with the median of that feature. The reason for choosing the median, instead of mean is that, in case the overall mean of a feature is very large, it might introduce unnecessary bias in the data, while a median would just assign the most common observation, which should be fair enough.

3. Data transformation – One of the crucial steps in this phase is to ensure that all features are numeric, since ML models generally work with numbers, and Python, unlike R, cannot implicitly handle the categorical features. To do that, first we identified the categorical features, and then used LabelEncoder to assign numbers to the observations. Then, using OneHotEncoder, we transformed those observations into dummy variables. This gives a binary variable for each of the categories.

4. Standardization – The last step we performed on this phase is to standardize the data. The features in any data set are likely to have very different variance with respect to each other, and feeding them to an ML model without scaling them might unfairly tip it in favour of few specific features with greater variance.

   StandardScaler and MinMaxScaler are two of the most popular scalers available. However, both these scalers are sensitive to outliers. In this data set, we did not handle the outliers explicitly because we do not possess enough domain knowledge to determine whether a particular outlier is a human error, or a genuinely useful observation. Also, since these are all signal data, and we trying to detect unusual activities through this model, some of the outliers might contain the most useful observation. Therefore, we did not touch the outliers. However, while scaling, we need to keep the outliers in mind as well. For that purpose, we used a different scaler called the RobustScaler. Unlike StandardScaler, which removes the mean and scales to unit variance, RobustScaler removes the median and scales according to the quantile range. Therefore, it is more robust to outliers than any of the other scalers.

A couple of things to keep in mind here,

- The data set provided to us is quite clean, as we couldn't find any missing values in any of the features. However, in our code, we still handled the missing observation condition as a contingency.

- There were no categorical variables either. There were binary features, but those are most likely signal values. Again, we handled the conversion of categorical to dummy variables, just in case.

Feature Selection – Alex Bates

There are various techniques used for selecting features for machine learning models. 'Filter' methods select features based on their intrinsic properties. 'Wrapper' methods measure the worth of a feature using a classifier performance. Embedded methods are like wrapper methods but where the feature selection is embedded with the learning algorithm. Sometimes, just domain knowledge can be used to pick relevant features [1].

The AWID dataset contains 152 features to consider. Initially, features with zero variance were removed, as they can have no predictive power on the target. This left 78 features for consideration.

Due to the way the pipeline was organised, with different individuals working remotely on different stages, embedded feature selection methods were deemed to be too difficult to implement. Instead, various wrapper methods were investigated to consolidate the features to a reasonable number for the algorithmic stage from the 78 candidates.

One common technique from the academic literature is the use of an auto-encoder to reduce dimensionality in the dataset and generate new features [1]. This technique was not considered initially due to its complexity and the time constraints on the project, but could be investigated in future. Simpler methods, with greater interpretability, were first considered instead.

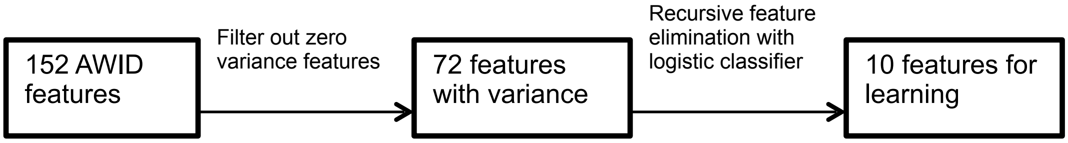
One key question is to decide how many features to select to train the model. Aminanto et. al [2] found, when training an artificial neural network on the AWID dataset, that there was little improvement in the F1 score from increasing the number of features beyond 10. In light of this, 10 features were selected in the first iteration.

On this first iteration, recursive feature elimination ('RFE') with a logistic regression classifier was used as the primary feature selection method. This gave a satisfactory result on several algorithms. The same method with just 5 features gave worse performance, suggesting that the model is not over-fitting due to the number of features. Using a different classifier with RFE resulted in broadly similar features being selected.

The first alternative to RFE considered was to use a randomised decision tree classifier and pick the top 10 features by feature importance. This approach yielded a very different set of features to RFE with only two common features between the approaches. Furthermore, the top two features by feature importance in the decision tree approach were not selected by any of the RFE algorithms tested. The decision tree approach yielded good results when used with a KNN algorithm in the learning phase. However, this set of features did not generally do as well in the learning phase as the features selected through RFE.

The final method considered was Principal Component Analysis. This method has the advantage of specifically capturing the variance in the *entire* dataset. However, by reducing dimensionality and combining features, some interpretability is lost. In our initial analysis (on the dataset using the Robust Scaler approach) the first 5 principal components explained over 98% of the variance in the dataset. On this basis, the top 5 components were selected for the learning phase but the results were not very encouraging and the method was discarded.

The best model evaluated in the project used RFE with 10 features. The final feature selection process can be summarised in the following flow chart:



The 10 features selected in this method were:

- radiotap.datarate
- wlan.fc.retry
- wlan.fc.pwrmgt

- wlan.fc.protected
- wlan_mgt.fixed.capabilities.preamble
- wlan_mgt.fixed.capabilities.short_slot_time
- wlan_mgt.fixed.timestamp
- wlan_mgt.fixed.auth_seq
- wlan_mgt.rsn.akms.type
- wlan.wep.key

The feature selection methods adopted have the advantage of simplicity and speed of computation (in both the feature selection and learning phase). A possible next step would be to increase the number of features and complexity of method and assess the impact this has during learning.

Please see the relevant appendix for relevant snippets of python code and a brief explanation of the different feature selection algorithms discussed above.

Algorithm Comparison - Alex Gorton

After selecting features, we moved into testing which algorithms might work better.

We reviewed a couple pieces of previous literature. In Kolias, they used the Weka framework to run a series of supervised classifiers over the dataset, J48 was top performer, but had a lot longer build time compared to Random Forest and OneR. In Aminatou, they use an ANN, C4.5, and an SVM, the SVM was the best performer, but takes alot longer to build. In Parker they chose a Radial Basis Function Classifier (RBFC) for the DEMISe Model and C4.5 for feature extraction/Logistic Regression for classification for DETEReD.

We decided to narrow it down to Supervised Learning as since the AWID dataset is all labelled and balanced, it seemed to be a better use case for supervised learning algorithms. We further narrowed it down to classification algorithms as we wanted the accuracy of it predicting a certain class.

I read through SciKit-Learn's documentation and used their stratified dummy classifier to create a baseline to test the classifiers against. The stratified dummy classifier works by creating a random prediction by respecting the class distribution [1]. This allows us to see how much better the model is against just a random guess.

At first, we started with Logistic Regression, Decision Tree, Naïve Bayes, and SVM. these were the ones that had been tried in the earlier papers, so they sounded like a good base. Logistic Regression is actually a linear model for classification, instead of regression as it sounds. Decision Tree's create predictive models by breaking down a dataset and using the data features as nodes to build the resulting tree with, this makes them good for categorisation tasks like the AWID data set. Naïve Bayes is a supervised classifier that works by applying Bayes theorem while assuming conditional independence among the predictors. Support vector Machines are supervised learning algorithm that can be used for classification. They work by "*If n is the number of input features, the SVM plots each feature value as a coordinate point in n-dimensional space. Subsequently, a classification process is executed by finding the hyperplane that distinguishes two classes*."[2]

As we iterated, we added others to see how they would do and if there was an improvement with different feature sets/ pre-processing. Random forest we added as it is an ensemble classifier that improves on a basic Decision Tree, they work by running several decision trees at the same time during training and the output the average of the prediction, this also allows them to correct some of the error of overfitting present in regular Decision Tree's. K Nearest Neighbour we added as they have a good reputation for classification issues, and it seemed worth it to test it out initially in SciKit-Learn.

Given the problem was classifying impersonation attacks in a balanced dataset we decided to go with these six algorithms and choose the best ones from among them. As we only had less than two months part-time, a deep learning model was considered to probably enough time that we would neglect the other models, so it was left for future improvements if possible.

We ran through the following algorithms with Kfold cross-validation to see which would have the best accuracy above the SciKit-Learn's dummy classifier. We chose normal K-fold as the dataset was already balanced so stratified was not needed. As you can see from the below table, Decision Tree, Random Forest, and KNN had the highest accuracy above the baseline. I was expecting Random forest to be better rather than the same, but that will come out with tuning of hyperparameters and model evaluation.

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Classifier	K-fold Accuracy	Percentage above Baseline
Dummy Classifier	0.9582149933672758	n/a
Logistic Regression	0.9887371837807203	%3.086987210972905
K Nearest neighbour	0.9998660415271265	%4.1656628418178725
Decision Tree	0.9998969550208667	%4.168625721309562
Naive Bayesian	0.9744757586686589	%1.6686680152617404
Support Vector Machine_ classification	0.9921170590962956	%3.4171437148657287
Random Forest	0.9998969550208667	%4.168625721309562

Model Tuning - Konstantin Orlovskiy

Background / Intro

While the machine learning models are trained on the data there is a set of parameters that can be set manually and does not depend on the data. This set is called hyperparameters and they impact the prediction performance [1]. Python library Scikit-learn which will be used for improving the models, has the default settings for each pod the machine learning algorythms. These default settings are continuously being updated by the community with new version releases. Each of the algorythms has a specific set of hyperparameters which can be found in the documentation. The range of possible values for each hyperparameter varies and is determined by the library authors.

This is not a trivial task to tune the model hyperparameters to improve the performance. The appropriate combination of settings can be either set based on the recommendations from literature or empirically. In this project the approach is used. Following the recommendations given in documentation [2], [3], [4], [5], [6], [7], for each of the hyperparameters the initial array of values was chosen to look for the best performing combination. Iteratively the arrays were changed according to the performance aiming to find nearest values which can improve the accuracy.

Approach

Considering the number of possible combinations of outputs from preprocessing, feature and algorithm selection stages the following approach was chosen for refining the algorithms:

- Build a skeleton for tuning all algorithms on one combination of preprocessed data and selected features.
- Use this skeleton to refine algorithms for all other combinations of preprocessed data and features.

The intrusion detection is the classification problem therefore the classificatory models are used for predictions. For each algorithm the approach was the following:

- Default model: test model with default hyperparameters. The result accuracy and confusion matrix is used as a benchmark to evaluate the improvement after refining hyperparameters.
- Hyperparameter selection depending on the type of the algorythm based on the documentation.
- Search for best estimator (a combination of hyperparameters) using randomized search cross-validation (RandimizedSearchCV) from sklearn library on the train set. The cross-validation approach leads to detecting the generalized model hyperparameters. RandimizedSearchCV was chosen instead of GridSearchCV because it is less computationally extensive and proved to provide relatively the same result [8]. Bayesian optimisation was not used due to the lack of time and resource considering the range of models to be tuned. For reproducibility of results set random_state = 2019.
- Test refined model on the test set.
- Iteratively analyze the selected set of the hyperparameters and refine the arrays with the nearest values for each selected hyperparameter to achieve better accuracy with the next iteration. For models that are not improving run more extensive search of hyperparameters to achieve even slight improvement in accuracy.

Since different algorithms have different computational cost, initially LR/DT/RF have been run with default n_iter=10 which means the RandimizedSearchCV is trying 10 combinations of hyperparameters randomly, while for KNN/NBC/SVC are computationally expensive and n_iter=3 was chosen but when there was significant improvement from default model, the value of n_iter was increased. In some cases n_iter value was chosen to try all possible combinations which is technically grid search. This approach was used for only those models where there was a potential for improvement.

Results

Results of refining each model were added to summary table which contains model accuracy, confusion matrix as well as calculated based on the confusion matrix attributes like specificity, sensitivity, precision, etc. which are required to evaluate the model performance and compare to others and choose the best model at next stage.

The best performing algorithm appeared to be Random Forest with RFE log 10 feature selection from Robust Scaler preprocessed dataset. Hyperparameters tuned are below. The tradeoff of improvement of accuracy is the computational cost/speed of the algorithm.

- ’n_estimators’ determines the number of trees in the forest, the higher it is the better the data is learnt;
- 'max_depth': shows the depth of each tree, the higher it is the more information is considered;
- ‘min_samples_leaf’: limits the minimum number of samples needed to be in the leaf node, the higher the parameter is, the more under fitted is the model;
- 'max_features': determines the number of features to consider when splitting the node which improves the model accuracy.

The refined best model specifications and performance:

- accuracy: 0.9761442302903531
- parameters: {'bootstrap': True, 'class_weight': None, 'criterion': 'gini', 'max_depth': 50, 'max_features': 'log2', 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0, 'min_impurity_split': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 10, 'n_jobs': None, 'oob_score': False, 'random_state': None, 'verbose': 0, 'warm_start': False}
- Confusion matrix: [[19124 955]
  [3 20076]]

Model tuning report:

	precision	recall	f1-score	support
0.0	1.00	0.95	0.98	20079
1.0	0.95	1.00	0.98	20079
accuracy			0.98	40158
macro avg	0.98	0.98	0.98	40158
weighted avg	0.98	0.98	0.98	40158

Evaluating model and analysing the results - Scott Tasker

Aim: To evaluate the performance of the proposed intrusion classifiers.

Background / Intro

802.11 wireless networks, commonly known as Wi-Fi, have become the default for wireless local area networks. Securing these networks is critical to protect the networks users from malicious acts. Binary classification of incoming data packets (deciding if each data packet is 'safe' or 'malicious') is a challenging task, as each data packet received by the router has multiple parameters (157 fields), and a malicious signature may consist of only small differences across multiple fields. Machine learning algorithms are an ideal candidate for this application. This is because these algorithms can determine the probability that an unlabeled observation fits into a negative or positive set, based on labelled observations they have previously seen (training data). Labels are assigned based on these probabilities using a threshold for classification (default = 0.5).

To assess the performance of our intrusion detection model, we have utilised the reduced CLS portion of the Aegean Wifi Intrusion Dataset [1]. As this dataset is labelled, we can assess the models predicted classifications against the actual classifications for each observation in the test data. The lower the number of incorrectly classified observations, the higher the classifiers accuracy. For this application, the sensitivity of the classifier (e.g. the ability to correctly identify positive observations) will be given more weight when ranking algorithms than the overall accuracy, as the network must be protected, even at the expense that some 'safe' traffic will be labelled false positive and blocked. Another key metric for intrusion detection is the time required to make predictions. As to work in a real network, the algorithm would need to make predictions as traffic is received. A delay would not be a workable solution.

Methods

The performance of each model was assessed using the equations in figure 1, and receiver operator characteristic curves.

$$Accuracy = \frac{(True\ Positive + True\ Negative)}{(True\ Positive + False\ Positive + True\ Negative + False\ Negative)}$$

$$Sensitivity = \frac{True\ Positive}{(True\ Positive + False\ Negaive)}$$

$$Specificity = \frac{True\ Negative}{(True\ Negative + False\ Positive)}$$

$$Precision = \frac{True\ Positive}{(True\ Positive + False\ Positive)}$$

$$F1\ Score = \frac{2\ x\ True\ Positive}{(2\ x\ True\ Positive) + False\ Positive + False\ Negative}$$

$$Michaels\ Correlation\ Coefficient = \frac{(True\ Positive\ x\ True\ Negative) - (False\ Positive\ x\ False\ Negative)}{\sqrt{(True\ Positive + False\ Positive)\ x\ (True\ Positive + False\ Negative)\ x\ (True\ Negative + False\ Positive)\ x\ (True\ Negative + False\ Negative)}}$$

$$False\ Alarm\ Rate = \frac{False\ Positive}{(True\ Negative + False\ Positive)}$$

Figure 1. Calculation of binary classifier performance from confusion matrix. [2]

To enable high-throughput testing, a function (model_evaluator.py) was built using the Python programming language, and the open source libraries: Numpy, Pandas, SciKit Learn and MatPlotLib.

The function outputs a report for each binary classification model, and the results were compiled in an excel workbook.

Computation time was assessed using a short Python script to record the time required to train the model, and the time required to make predictions when run on an Apple MacBook Pro, 2.7GHz i5, 8GB DDR3 RAM. Results were recorded in an excel workbook.

Results

We evaluated 96 permutations of the intrusion detection classifier using the model_evaulator function. Figure 2 is an example of the evaluation report returned by this function. The 10 best performing models are shown in Table 1. The full database is included in the appendix.

The 5 models with the highest sensitivity scores were taken forward for further analysis. Table 2 shows the computation time required to train each of these models, and the time required to predict unlabeled data. Table 3 compares these models, with the published benchmarks.

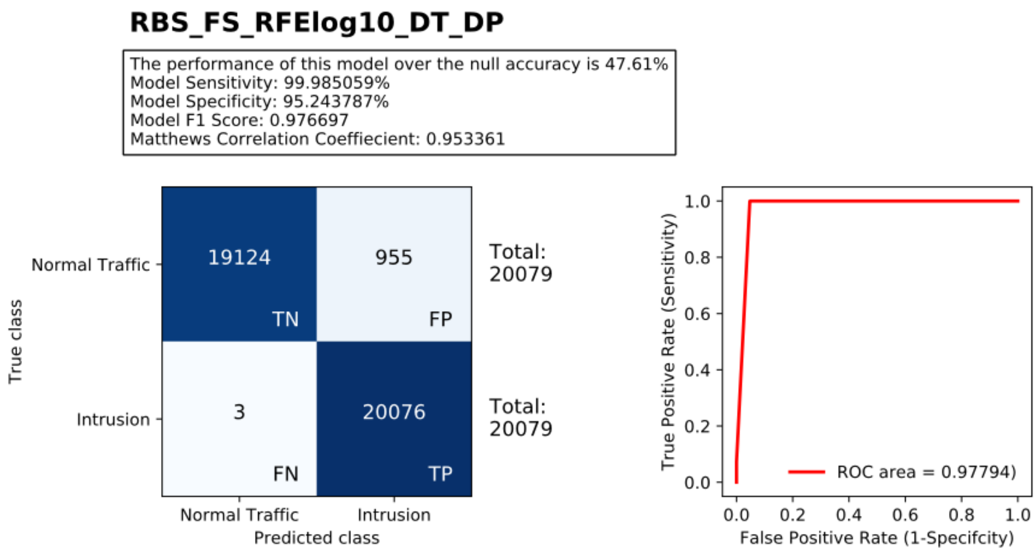

Figure 2. Output from model_evaluator function.

Rank	Preprocessing	Feature Selection	Algorithms	Tuning	True Positive	True Negative	False Positive	False Negative	Accuracy	Sensitivity	Specificity	Precision	F1score	False Alarm Rate	Michaels Correlation Coefficient
1	Robust Scaler	RFE, logistic classifier, 10 most important features	DT	default parameters	20076	19124	955	3	0.9761	0.9999	0.9998	0.9546	0.9767	0.0476	0.9770
2	Robust Scaler	RFE, logistic classifier, 10 most important features	DT	tuned parameters	20076	19124	955	3	0.9761	0.9999	0.9998	0.9546	0.9767	0.0476	0.9770
3	Robust Scaler	RFE, logistic classifier, 10 most important features	RF	default parameters	20076	19124	955	3	0.9761	0.9999	0.9998	0.9546	0.9767	0.0476	0.9770
4	Robust Scaler	RFE, logistic classifier, 10 most important features	RF	tuned parameters	20076	19124	955	3	0.9761	0.9999	0.9998	0.9546	0.9767	0.0476	0.9770
5	Robust Scaler	RFE, logistic classifier, 10 most important features	KNN	tuned parameters	20076	19099	980	3	0.9755	0.9999	0.9998	0.9535	0.9761	0.0488	0.9764
6	Robust Scaler	RFE, logistic classifier, 10 most important features	LR	tuned parameters	20076	19082	997	3	0.9751	0.9999	0.9998	0.9527	0.9757	0.0497	0.9760
7	Robust Scaler	RFE, logistic classifier, 10 most important features	LR	default parameters	20076	18584	1495	3	0.9627	0.9999	0.9998	0.9307	0.9640	0.0745	0.9646
8	Robust Scaler	RFE, logistic classifier, 10 most important features	SVC	default parameters	20073	18582	1497	6	0.9626	0.9997	0.9997	0.9306	0.9639	0.0746	0.9645
9	StandardScaler	RFE, logistic classifier, 5 most important features	SVC	tuned parameters	20067	19431	648	12	0.9836	0.9994	0.9994	0.9687	0.9838	0.0323	0.9839
10	StandardScaler	RFE, logistic classifier, 5 most important features	SVC	default parameters	20067	19228	851	12	0.9785	0.9994	0.9994	0.9593	0.9789	0.0424	0.9791

Table 1. Top performing algorithms (10/96). Algorithms ranked according by number of false negatives observed.

Rank	Model	Time taken to build model (s)	Time taken to test model (s)
1	Robust Scaler, RFE logistic classifier 10 features, DT default	0.0407	0.0049
2	Robust Scaler, RFE logistic classifier 10 features, DT tuned	0.0402	0.0059
3	Robust Scaler, RFE logistic classifier 10 features, RF default	0.2026	0.0336
4	Robust Scaler, RFE logistic classifier 10 features, RF tuned	0.2680	0.0389
5	Robust Scaler, RFE logistic classifier 10 features, KNN tuned	0.0109	95.8483

Table 2. Analysis of time required to build model, and time required to test model,

Model	Sensitivity	False Alarm Rate
Robust Scaler, RFE, logistic classifier, 10 features, DT, default	99.985	0.048
Robust Scaler, RFE, logistic classifier, 10 features, DT, tuned	99.985	0.048
Robust Scaler, RFE, logistic classifier, 10 features RF default	99.985	0.048
Robust Scaler, RFE, logistic classifier, 10 features RF tuned	99.985	0.048
Robust Scaler, RFE, logistic classifier, 10 features KNN tuned	99.985	0.049
D-FES-SVM	99.918	0.012
D-FES-ANN	99.877	0.024
D-FES-C4.5	99.549	0.381
ANN+SAE	84.829	2.364
Kolias	22.008	0.021

Table 3. Comparison of the top 5 performing algorithms from our project to published models [1][2][3]

Conclusion

- We identified 2 models, Robust Scaler-RFElog10-Decision Tree, and Robust Scaler FS-RFElog10-Random Forest giving the highest sensitivity (only 3 false negatives of 20079 positive observations).
- Tuning of the Robust Scaler-RFElog10 Decision Tree and Robust Scaler-RFElog10 Random Forest algorithms did not increase the sensitivity or the specificity of the algorithm.
- The Robust Scaler-RFElog10-Decision Tree required the lowest computation to use, as demonstrated in table 2.
- The top performing models had comparable performance to state-of-the-art models [2],[3].
- Future analysis would identify the 3 false-negative observations in the database, to see if the pre-processing, or feature selection could be adjusted to allow correct classification of these samples.

Future work - Group section

As discussed in the previous sections of this report, our approach focused on simplicity and speed of computation. The chosen model was also the one that minimized the number of false negatives and therefore minimized the risks of an IoT system being infected.

There are several possible avenues for future development of this work.

Expand number of features / try different feature selection methods

Other methods in the literature on this subject built models using more features than in our best model (which used 10 features). Rezvy et. al built a highly accurate model for a similar purpose using 36 features derived from the same dataset [1]. In light of this, a future development may be to gradually increase the number of features used to train the model and evaluate the performance iteratively to find the optimum number of features. For this project, there was not enough time to carry out the necessary iterations to achieve this. Increasing the number of features may improve the accuracy of the model but at the cost of model speed and simplicity.

Another feature selection method worth exploring would be the use of an auto-encoder (a neural network that compresses a dataset) as this is also very popular in the literature [2]. The trade-off here would be the loss of interpretability from combining / compressing features.

More complex learning algorithms

One potential future development would be to use more complex learning algorithms. The project mostly focused on simpler algorithms such as random forests and KNN. It would be interesting to explore artificial neural networks as a learning approach using this dataset and evaluate the results to compare against the current model. This approach is popular in the literature.

In general, most avenues for future development would be to increase the complexity and assess the impact this has on model accuracy versus speed.

Input from domain experts

The view taken in this project was that it is desirable to look to minimise the number of false negatives and therefore the risk of the system being infected. A next step would be to look for input from domain experts on the trade-off between sensitivity and specificity in the context of this issue. This could allow us to refine our choice of algorithm and give us direction for which avenues to explore further. Further work and deeper reading of the literature could also be informative on this subject.

Bibliography:

References - Feature Selection

[1] Kolias et. al, “Intrusion Detection in 802.11 Networks: Empirical Evaluation of Threats and a Public Dataset”, IEEE Communication Surveys & Tutorials, Vol. 18, No. 1, First Quarter 2016

[2] Parker et. al, “DEMISe: Interpretable Deep Extraction and Mutual Information Selection Techniques for IoT Intrusion Detection” in ACM International Conference on Availability, Reliability and Security (ARES), 26-29 Aug. 2019, U.K

[3] Aminanto et. al, “Wi-Fi Intrusion Detection Using Weighted-Feature Selection for Neural Networks Classifier” in 2017 International Workshop on Big Data and Information Security (IWBIS)

References - Algorithm Comparison

[1] 3.3. Metrics and scoring: quantifying the quality of predictions — scikit-learn 0.22.1 documentation,” *Scikit-learn.org*, 2013. [Online]. Available: https://scikit-learn.org/stable/modules/model_evaluation.html#dummy-estimators. [Accessed: 17-Jan-2020].

[2] Aminanto et. al, “Wi-Fi Intrusion Detection Using Weighted-Feature Selection for Neural Networks Classifier” in 2017 International Workshop on Big Data and Information Security (IWBIS)

[3] Parker et. al, “DEMISe: Interpretable Deep Extraction and Mutual Information Selection Techniques for IoT Intrusion Detection” in ACM International Conference on Availability, Reliability and

Security (ARES), 26-29 Aug. 2019, U.K
[4] Kolias et. al, “Intrusion Detection in 802.11 Networks: Empirical Evaluation of Threats and a Public Dataset”, IEEE Communication Surveys & Tutorials, Vol. 18, No. 1, First Quarter 2016
[5]Scikit-learn: Machine Learning in Python, Pedregosa *et al.*, JMLR 12, pp. 2825-2830, 2011.
[6]M. Sidana, “Types of classification algorithms in Machine Learning,” *Medium*, 28-Feb-2017. [Online]. Available: https://medium.com/@Mandysidana/machine-learning-types-of-classification-9497bd4f2e14. [Accessed: 18-Jan-2020].

References - Model Tuning

[1] P. Probst, A. Boulesteix, B.Bischl, “Tunability: Importance of Hyperparameters of Machine Learning Algorithms”, Journal of Machine Learning Research 20 (2019) 1-32.
[2] Python Scikit Learn documentation. “LogisticRegression”. Available: https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html
[3] Python Scikit Learn documentation. “DecisionTreeClassifier”. Available: https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html
[4] Python Scikit Learn documentation. “RandomForestClassifier”. Available: https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html
[5] Python Scikit Learn documentation. “SVC”. Available: https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html
[6] Python Scikit Learn documentation. “KNeighborsClassifier”. Available: https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html
[7] Python Scikit Learn documentation. “GaussianNB”. Available: https://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.GaussianNB.html
[8] Python Scikit Learn documentation. “Comparing randomized search and grid search for hyperparameter estimation”. Available: https://scikit-learn.org/stable/auto_examples/model_selection/plot_randomized_search.html

References - Model Evaluation

[1] C. Kolias, G. Kambourakis, A. Stavrou and S. Gritzalis, "Intrusion Detection in 802.11 Networks: Empirical Evaluation of Threats and a Public Dataset", *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 184-208, 2016. Available: 10.1109/comst.2015.2402161 [Accessed 13 January 2020].
[2] M. Aminanto, R. Choi, H. Tanuwidjaja, P. Yoo and K. Kim, "Deep Abstraction and Weighted Feature Selection for Wi-Fi Impersonation Detection", *IEEE Transactions on Information Forensics and Security*, vol. 13, no. 3, pp. 621-636, 2018. Available: 10.1109/tifs.2017.2762828 [Accessed 13 January 2020].
[3] M. Aminanto and K. Kim, "Detecting Impersonation Attack in WiFi Networks Using Deep Learning Approach", *Information Security Applications*, pp. 136-147, 2017. Available: 10.1007/978-3-319-56549-1_12 [Accessed 13 January 2020].

References - Future work section

[1] Rezvy et. al, “An efficient deep learning model for intrusion classification and prediction in 5G and IoT networks” in 53rd Annual Conference on Information Sciences and Systems (CISS), 2019.

[2] Kolias et. al, “Intrusion Detection in 802.11 Networks: Empirical Evaluation of Threats and a Public Dataset”, IEEE Communication Surveys & Tutorials, Vol. 18, No. 1, First Quarter 2016

Appendices

Appendix – Feature Selection

1) Recursive feature elimination

Recursive feature elimination is an algorithm that starts by building a model using all attributes to predict the target. It then removes features (removing the least useful features first) and re-builds a model on the remaining attributes. This is repeated until the specified number of attributes is reached.

<u>Python code – recursive feature elimination using a logistic regression classifier with 10 features</u>

```
# Initiate model
model = LogisticRegression()

# Try 10 features
rfe_log = RFE(model, 10)
fit_rfe_log = rfe_log.fit(X, Y)

# Create list with names of features
rfe_log_features = X.columns[fit_rfe_log.get_support()]
for feature in rfe_log_features:
    print(feature)
radiotap.datarate
wlan.fc.retry
wlan.fc.pwrmgt
wlan.fc.protected
wlan_mgt.fixed.capabilities.preamble
wlan_mgt.fixed.capabilities.short_slot_time
wlan_mgt.fixed.timestamp
wlan_mgt.fixed.auth_seq
wlan_mgt.rsn.akms.type
wlan.wep.key
```

2) Feature importance and decision trees

In this method, a random set of decision trees are fitted to subsets of the data with the results averaged across the trees. The top 10 features by feature importance are selected for the learning phase. Feature importance is calculated as the decrease in “node-impurity” weighted by the probability of reaching that node. Node impurity is a measure of the homogeneity of labels at a node.

Nodes of a decision tree that greatly increase the homogeneity of labels imply that that feature has strong predictive power on the target – it is therefore a more important feature.

<u>Python code – extra trees classifier with top 10 most important feature selected</u>

```
# Initiate model and fit to data
model_tree = ExtraTreesClassifier()
fit_tree = model_tree.fit(X,Y)

# Ensure reproducibility
np.random.seed(999)

# Get feature importances
feature_importance = fit_tree.feature_importances_

# Join feature importances to feature names and rank by importance
feature_ranking_data = {'Feature':X.columns.values, 'Importance': feature_importance}
tree_features_imp = pd.DataFrame(data=feature_ranking_data).nlargest(10,'Importance')

# Get list object of the top 10 features
tree_features = list(tree_features_imp['Feature'])
print(tree_features_imp)
```

```
22	wlan.fc.subtype	0.181461
23	wlan.fc.ds	0.120586
13	radiotap.datarate	0.113596
15	radiotap.channel.type.cck	0.070449
27	wlan.fc.protected	0.064409
28	wlan.duration	0.058927
16	radiotap.channel.type.ofdm	0.056004
2	frame.len	0.047525
11	radiotap.mactime	0.040032
3	frame.cap_len	0.025655
```

3) Principal Component Analysis

Principal Component Analysis compresses a dataset statistically into its principal components. It captures as much of the variance in the dataset as possible at each principal component. These principal components can be used as features in the learning phase.

<u>Python code – PCA with top 5 principal components selected</u>

```
pca = PCA(n_components=5)
fit_pca = pca.fit(X)
```

```
# summarize components
print("Explained Variance: %s" % fit_pca.explained_variance_ratio_)
print("Total variance explained by first 5 components: %s" % sum(fit_pca.explained_variance_ratio_))
Explained Variance: [0.80629725 0.12093112 0.02414355 0.0183569  0.01252285]
Total variance explained by first 5 components: 0.9822516621351488
```

Appendix - Model Evaluation (next page)

Preprocessing	FeatureSelection	Algorithms	Tuning	Accuracy	True Positive	True Negative	False Positive	False Negative	specificity = TN/(TN+FP)	recall (or sensitivity) = TP / (TP + FN)	precision = TP / (TP + FP)	F1score = (2* True Positive)/((2*True Positive)+False Positive+False Negative)	False Positives Rate = FP/(FP+TN)	MCC
RobustScaler	RFE, logistic classifier, 10 features	DT	default parameters	0.97614423	20076	19124	955	3	0.999843154	0.99985059	0.954590842	0.976696667	0.04756213	0.976951366
RobustScaler	RFE, logistic classifier, 10 features	DT	tuned parameters	0.97614423	20076	19124	955	3	0.999843154	0.99985059	0.954590842	0.976696667	0.04756213	0.976951366
RobustScaler	RFE, logistic classifier, 10 features	RF	default parameters	0.97614423	20076	19124	955	3	0.999843154	0.99985059	0.954590842	0.976696667	0.04756213	0.976951366
RobustScaler	RFE, logistic classifier, 10 features	RF	tuned parameters	0.97614423	20076	19124	955	3	0.999843154	0.99985059	0.954590842	0.976696667	0.04756213	0.976951366

RobustScaler	RFE, logistic classifier, 10 features	KNN	tuned parameters	0.97552169	20076	19099	980	3	0.999842948	0.99985059	0.953457447	0.976103075	0.048807212	0.976371021
RobustScaler	RFE, logistic classifier, 10 features	LR	tuned parameters	0.97509836	20076	19082	997	3	0.999842808	0.99985059	0.952688274	0.975699844	0.049653867	0.975976977
RobustScaler	RFE, logistic classifier, 10 features	LR	default parameters	0.96269735	20076	18584	1495	3	0.999838597	0.99985059	0.930693987	0.964033613	0.074455899	0.964641156
RobustScaler	RFE, logistic classifier, 10 features	SVC	default parameters	0.96257284	20073	18582	1497	6	0.999677211	0.99970118	0.930598053	0.963912699	0.074555506	0.964507733
StandardScaler	RFE, logistic classifier, 5 features	SVC	tuned parameters	0.983564919	20067	19431	648	12	0.999382811	0.999402361	0.96871832	0.98382115	0.032272524	0.983921116
StandardScaler	RFE, logistic classifier, 5 features	SVC	default parameters	0.978509886	20067	19228	851	12	0.999376299	0.999402361	0.959317334	0.978949679	0.042382589	0.979128827

StandardScaler	Decision tree classifier, 10 most important features	LR	default parameters	0.927411724	20064	17179	2900	15	0.999127603	0.999252951	0.873715381	0.932277025	0.144429503	0.934260305
RobustScaler	Decision tree classifier, 10 most important features	KNN	default parameters	0.98819662	20053	19631	448	26	0.998677316	0.998705115	0.978147407	0.988319369	0.022311868	0.988343569
StandardScaler	RFE, logistic classifier, 5 features	LR	tuned parameters	0.965187509	20052	18708	1371	27	0.998558847	0.998655312	0.936003361	0.966314876	0.068280293	0.96672657
StandardScaler	Decision tree classifier, 10 most important features	LR	tuned parameters	0.929354051	20047	17274	2805	32	0.99815093	0.998406295	0.877253632	0.933917216	0.139698192	0.935628964
StandardScaler	RFE, logistic classifier, 10 features	LR	tuned parameters	0.98055182	20032	19345	734	47	0.99757632	0.997659246	0.964653761	0.980878933	0.036555605	0.980930375

StandardScaler	RFE, logistic classifier, 10 features	LR	default parameters	0.980003984	20032	19323	756	47	0.997573567	0.997659246	0.963632865	0.980350894	0.037651277	0.980408459
StandardScaler	RFE, logistic classifier, 5 features	LR	default parameters	0.960779919	20024	18559	1520	55	0.997045235	0.99726082	0.929446714	0.962160344	0.075700981	0.962540291
RobustScaler	Decision tree classifier, 10 most important features	KNN	tuned parameters	0.98142338	19911	19501	578	168	0.991458641	0.991633049	0.971789741	0.981611122	0.028786294	0.981415759
StandardScaler	RFE, logistic classifier, 5 features	NBC	tuned parameters	0.940659395	19698	18077	2002	381	0.979358544	0.981024951	0.907741935	0.942961775	0.099706161	0.941650897
RobustScaler	Decision tree classifier, 10 most important features	NB	default parameters	0.9558992	18613	19774	305	1466	0.930979284	0.926988396	0.983877788	0.95458625	0.01519	0.953849383

RobustScaler	Decision tree classifier, 10 most important features	NB	tuned parameters	0.9558992	18613	19774	305	1466	0.930979284	0.926988396	0.983877788	0.95458625	0.01519	0.953849383
StandardScaler	Decision tree classifier, 10 most important features	NBC	tuned parameters	0.944842871	18613	19330	749	1466	0.929505674	0.926988396	0.96131598	0.943840166	0.037302655	0.9411152
RobustScaler	RFE, logistic classifier, 10 features	NB	tuned parameters	0.91715225	18613	18218	1861	1466	0.925523268	0.926988396	0.90910423	0.917959214	0.092683899	0.910616797
RobustScaler	RFE, logistic classifier, 5 features	RF	default parameters	0.93821903	18609	19068	1011	1470	0.928425358	0.926789183	0.948470948	0.937504723	0.050351113	0.933640556
RobustScaler	RFE, logistic classifier, 5 features	KNN	tuned parameters	0.93821903	18609	19068	1011	1470	0.928425358	0.926789183	0.948470948	0.937504723	0.050351113	0.933640556
RobustScaler	RFE, logistic classifier, 5 features	DT	default parameters	0.93821903	18609	19068	1011	1470	0.928425358	0.926789183	0.948470948	0.937504723	0.050351113	0.933640556

RobustScaler	RFE, logistic classifier, 5 features	DT	tuned parameters	0.93821903	18609	19068	1011	1470	0.928425358	0.926789183	0.948470948	0.937504723	0.050351113	0.933640556
RobustScaler	Decision tree classifier, 10 most important features	SVM	tuned parameters	0.96331989	18606	20079	0	1473	0.931653675	0.926639773	1	0.961923226	0	0.962621303
RobustScaler	Decision tree classifier, 10 most important features	RF	tuned parameters	0.96331989	18606	20079	0	1473	0.931653675	0.926639773	1	0.961923226	0	0.962621303
RobustScaler	Decision tree classifier, 10 most important features	LR	default parameters	0.95634743	18606	19799	280	1473	0.930754043	0.926639773	0.985174203	0.955010907	0.013944918	0.954389107
RobustScaler	Decision tree classifier, 10 most important features	SVM	default parameters	0.95231336	18606	19637	442	1473	0.930222643	0.926639773	0.976795464	0.951056815	0.022013048	0.94969183

RobustScaler	Decision tree classifier, 10 most important features	LR	tuned parameters	0.95099358	18606	19584	495	1473	0.930047015	0.926639773	0.974085126	0.949770291	0.024652622	0.948165213
StandardScaler	RFE, logistic classifier, 10 features	NBC	tuned parameters	0.940759002	18606	19173	906	1473	0.928654461	0.926639773	0.953567036	0.939910586	0.045121769	0.936490423
RobustScaler	RFE, logistic classifier, 5 features	SVC	default parameters	0.9376961	18606	19050	1029	1473	0.928226867	0.926639773	0.947593583	0.936999547	0.051247572	0.933050951
RobustScaler	RFE, logistic classifier, 5 features	LR	default parameters	0.9376214	18606	19047	1032	1473	0.928216374	0.926639773	0.947448824	0.936928771	0.051396982	0.932967365
RobustScaler	RFE, logistic classifier, 5 features	LR	tuned parameters	0.9376214	18606	19047	1032	1473	0.928216374	0.926639773	0.947448824	0.936928771	0.051396982	0.932967365
RobustScaler	RFE, logistic classifier, 10 features	SVC	tuned parameters	0.85756263	15339	19099	980	4740	0.801166156	0.763932467	0.939947301	0.842848508	0.048807212	0.833945818

RobustScaler	RFE, logistic classifier, 5 features	NB	default parameters	0.8055182	15337	17011	3068	4742	0.782007079	0.76383286	0.833306167	0.797058518	0.152796454	0.753325122
RobustScaler	RFE, logistic classifier, 5 features	NB	tuned parameters	0.79710145	15337	16673	3406	4742	0.778566425	0.76383286	0.818278824	0.790119005	0.169629962	0.740652653
RobustScaler	RFE, logistic classifier, 10 features	NB	default parameters	0.81866627	15336	17540	2539	4743	0.787147153	0.763783057	0.857958042	0.808136165	0.12645052	0.77326187
RobustScaler	RFE, logistic classifier, 5 features	SVC	tuned parameters	0.82025997	13872	19068	1011	6207	0.754421365	0.690871059	0.932070147	0.79354728	0.050351113	0.783421334
RobustScaler	RFE, logistic classifier, 5 features	RF	tuned parameters	0.82025997	13872	19068	1011	6207	0.754421365	0.690871059	0.932070147	0.79354728	0.050351113	0.783421334
StandardScaler	PCA, top 5 features	KNN	tuned parameters	0.335997809	14473	12020	8059	18606	0.39247698	0.073360227	0.154532102	0.099490054	0.40136461	-0.795236456
StandardScaler	PCA, top 5 features	KNN	default parameters	0.335524678	14472	12002	8077	18607	0.392106897	0.073310424	0.154152267	0.099365465	0.402261069	-0.798015436

StandardScaler	PCA, top 5 features	RF	default parameters	0.262737188	1470	9081	10998	18609	0.327952329	0.073210817	0.117901829	0.090330906	0.547736441	-1.331498602
StandardScaler	PCA, top 5 features	LR	tuned parameters	0.112580308	1469	3052	17027	18610	0.140891884	0.073161014	0.079422578	0.076163318	0.848000398	-5.311306526
StandardScaler	PCA, top 5 features	LR	default parameters	0.112480701	1469	3048	17031	18610	0.140733216	0.073161014	0.079405405	0.076155421	0.848199612	-5.319068958
StandardScaler	RFE, logistic classifier, 5 features	DT	tuned parameters	0.533019573	1468	19937	142	18611	0.517199336	0.073111211	0.911801242	0.135368159	0.007072065	0.234877717
StandardScaler	RFE, logistic classifier, 5 features	DT	default parameters	0.532745655	1468	19926	153	18611	0.517061525	0.073111211	0.905613819	0.135299539	0.007619901	0.232265742
RobustScaler	RFE, logistic classifier, 10 features	KNN	default parameters	0.5364062	1467	20074	5	18612	0.518895725	0.073061407	0.996603261	0.136142174	0.000249016	0.268986564
StandardScaler	RFE, logistic classifier, 10 features	DT	tuned parameters	0.533293491	1467	19949	130	18612	0.517336169	0.073061407	0.91859737	0.135357077	0.006474426	0.237645097

StandardScaler	RFE, logistic classifier, 10 features	RF	default parameters	0.533094278	1467	1941	138	1862	0.517236013	0.073061407	0.914018692	0.135307139	0.006872852	0.235728216
StandardScaler	RFE, logistic classifier, 10 features	DT	default parameters	0.533044474	1467	1939	140	1862	0.517210967	0.073061407	0.912881145	0.13529466	0.006972459	0.235250552
StandardScaler	RFE, logistic classifier, 5 features	RF	tuned parameters	0.532994671	1467	1937	142	1862	0.517185919	0.073061407	0.911746426	0.135282184	0.007072065	0.234773507
StandardScaler	RFE, logistic classifier, 10 features	RF	tuned parameters	0.531600179	1467	1881	198	1862	0.516483516	0.073061407	0.881081081	0.134933775	0.009861049	0.221659994
StandardScaler	PCA, top 5 features	DT	tuned parameters	0.510508491	1467	1034	1045	1862	0.505604845	0.073061407	0.583996815	0.129874729	0.052044425	0.06268211
StandardScaler	RFE, logistic classifier, 5 features	RF	default parameters	0.532895064	1464	1936	143	1865	0.517133148	0.072911998	0.911014312	0.135017984	0.007121869	0.234222113
StandardScaler	RFE, logistic classifier, 5 features	KNN	default parameters	0.52492654	1463	1617	462	1866	0.513090785	0.072862194	0.76	0.132975823	0.023009114	0.164799981

StandardScaler	RFE, logistic classifier, 5 features	KNN	tuned parameters	0.525673589	1461	19649	430	18618	0.513471137	0.072762588	0.772607086	0.132999545	0.021415409	0.170979282
StandardScaler	RFE, logistic classifier, 10 features	KNN	default parameters	0.535011704	1444	20041	38	18635	0.518176647	0.071915932	0.974358974	0.13394555	0.001892525	0.258233672
StandardScaler	RFE, logistic classifier, 10 features	KNN	tuned parameters	0.534762687	1444	20031	48	18635	0.518052035	0.071915932	0.967828418	0.133883455	0.002390557	0.255663904
StandardScaler	RFE, logistic classifier, 10 features	SVC	default parameters	0.521788934	1444	19510	569	18635	0.511469393	0.071915932	0.717337308	0.130726055	0.028338065	0.141644572
StandardScaler	PCA, top 5 features	DT	default parameters	0.479032882	1438	17799	2280	18641	0.488446762	0.071617112	0.386767079	0.12085557	0.113551472	-0.109934204
StandardScaler	Decision tree classifier, 10 most important features	RF	tuned parameters	0.49818218	1395	18611	1468	18684	0.499021317	0.069475571	0.487251135	0.121611019	0.073111211	-0.010387559

StandardScaler	Decision tree classifier, 10 most important features	DT	tuned parameters	0.51200259	1394	19167	912	18685	0.506366903	0.069425768	0.604509974	0.124547688	0.045420589	0.07420519
StandardScaler	Decision tree classifier, 10 most important features	KNN	default parameters	0.511380049	1351	19185	894	18728	0.506026956	0.067284227	0.601781737	0.121035657	0.04452413	0.07123891
StandardScaler	Decision tree classifier, 10 most important features	KNN	tuned parameters	0.511529459	1346	19196	883	18733	0.506103509	0.067035211	0.603858232	0.120674198	0.043976294	0.07239128
StandardScaler	Decision tree classifier, 10 most important features	SVC	default parameters	0.503013098	1332	18868	1211	18747	0.501608401	0.066337965	0.523790798	0.117761471	0.060311769	0.018020107

StandardScaler	Decision tree classifier, 10 most important features	SVC	tuned parameters	0.504382688	1321	18934	1145	18758	0.502334713	0.065790129	0.53568532	0.117187847	0.057024752	0.026524353
RobustScaler	PCA, top 5 features	LR	tuned parameters	0.28783804	666	10893	9186	19413	0.359433775	0.033168983	0.067600487	0.044502355	0.457492903	-1.116608497
RobustScaler	PCA, top 5 features	LR	default parameters	0.287887843	662	10899	9180	19417	0.359513128	0.032969769	0.067262751	0.044249858	0.457194083	-1.116298501
RobustScaler	Decision tree classifier, 10 most important features	DT	default parameters	0.48585587	459	19052	1027	19620	0.492656185	0.022859704	0.308882907	0.042568978	0.051147966	-0.109589614
RobustScaler	Decision tree classifier, 10 most important features	DT	tuned parameters	0.48585587	459	19052	1027	19620	0.492656185	0.022859704	0.308882907	0.042568978	0.051147966	-0.109589614

StandardScaler	Decision tree classifier, 10 most important features	DT	default parameters	0.490412869	148	19546	533	19931	0.495123743	0.0073708885	0.21732746	0.014258189	0.026545147	-0.10695481
RobustScaler	PCA, top 5 features	DT	default parameters	0.35063997	140	13941	6138	19939	0.414814817	0.006972459	0.022300096	0.010623364	0.305692515	-0.769436736
RobustScaler	PCA, top 5 features	DT	tuned parameters	0.37367399	127	14879	5200	19952	0.42717694	0.006325016	0.023840811	0.009997638	0.258977041	-0.661943328
StandardScaler	Decision tree classifier, 10 most important features	RF	default parameters	0.495443	89	19807	272	19990	0.497700832	0.004432492	0.246537396	0.008708415	0.013546491	-0.068904856
StandardScaler	PCA, top 5 features	RF	tuned parameters	0.456546641	78	18256	1823	20001	0.477193716	0.003884656	0.041031036	0.007097361	0.090791374	-0.310648875
RobustScaler	PCA, top 5 features	RF	default parameters	0.49681259	12	19939	140	20067	0.49840024	0.000597639	0.078947368	0.001186298	0.006972459	-0.073782921

StandardScaler	Decision tree classifier, 10 most important features	NBC	default parameters	0.499551771	7	20054	25	20072	0.499775707	0.000348623	0.21875	0.000696136	0.001245082	-0.022483688
RobustScaler	Decision tree classifier, 10 most important features	RF	default parameters	0.5000249	1	20079	0	20078	0.500012451	4.98033E-05	1	9.96016E-05	0	0.007057144
RobustScaler	PCA, top 5 features	RF	tuned parameters	0.47920713	1	19243	836	20078	0.489382264	4.98033E-05	0.001194743	9.56206E-05	0.04163554	-0.212530863
RobustScaler	PCA, top 5 features	SVM	default parameters	0.5	0	20079	0	20079	0.5	0	#DIV/0!	0	0	0
RobustScaler	PCA, top 5 features	SVM	tuned parameters	0.5	0	20079	0	20079	0.5	0	#DIV/0!	0	0	0
RobustScaler	PCA, top 5 features	NB	default parameters	0.5	0	20079	0	20079	0.5	0	#DIV/0!	0	0	0

RobustScaler	PCA, top 5 features	NB	tuned parameters	0.5	0	20079	0	20079	0.5	0	#DIV/0!	0	0	0
RobustScaler	PCA, top 5 features	KNN	default parameters	0.5	0	20079	0	20079	0.5	0	#DIV/0!	0	0	0
RobustScaler	PCA, top 5 features	KNN	tuned parameters	0.5	0	20079	0	20079	0.5	0	#DIV/0!	0	0	0
StandardScaler	RFE, logistic classifier, 10 features	NBC	default parameters	0.5	0	20079	0	20079	0.5	0	#DIV/0!	0	0	0
StandardScaler	RFE, logistic classifier, 5 features	NBC	default parameters	0.5	0	20079	0	20079	0.5	0	#DIV/0!	0	0	0
RobustScaler	RFE, logistic classifier, 5 features	KNN	default parameters	0.5	0	20079	0	20079	0.5	0	#DIV/0!	0	0	0
StandardScaler	RFE, logistic classifier, 10 features	SVC	tuned parameters	0.496563574	0	19941	138	20079	0.498275862	0	0	0	0.006872852	-0.083476388

StandardScaler	PCA, top 5 features	NBC	default parameters	0.487673689	0	19584	495	20079	0.493759927	0	0	0	0.024652622	-0.160980117
StandardScaler	PCA, top 5 features	NBC	tuned parameters	0.487673689	0	19584	495	20079	0.493759927	0	0	0	0.024652622	-0.160980117
StandardScaler	PCA, top 5 features	SVC	default parameters	0.48070123	0	19304	775	20079	0.490160729	0	0	0	0.03859754	-0.204349972
StandardScaler	PCA, top 5 features	SVC	tuned parameters	0.446137756	0	17916	2163	20079	0.471535728	0	0	0	0.107724488	-0.3678394