

# Practical 2: Classifying Malicious Software

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Public Repository: <https://github.com/tongbaojia/pubcs181>

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In this assignment, we were asked to classify  $\sim 3000$  xml files into 14 malware classes after training on  $\sim 3000$  xml files with known classes. We used this opportunity to explore multiple methods, most notably Random Forest, SVM, MLP, and gradient boosting. We found that Random Forest, combined with feature engineering, produced the best results for this dataset.

## 1 Technical Approach

We found it helpful to preprocess the data before using it to train the model by extracting additional features and rescaling the data. We also performed cross-validation on the training data in order to tune the details of models before making predictions.

### 1.1 Additional Features

We found that the additional features drastically improved our accuracy from 0.666667 to 0.899676. The extra features are:

- number of each kind of tag
- proportion of each kind of tag
- average number of threads per process
- average number of systems calls per section
- average number of system calls per process
- total number of tags

The frequency of different features in the dataset is seen in Figure 1. Notice no extra selection is applied on these features because some malware types are not well represented and we do not want to remove features that are potentially useful for discriminating some specific malwares, even if they often do not appear in other malwares.



Model	Acc.
BASELINE	0.70000
SVM	0.77526
MLP	0.78211
DECISION TREE	0.80632
RANDOM FOREST	0.82421

Table 1: Summary of our best prediction accuracies on the kaggle test dataset.

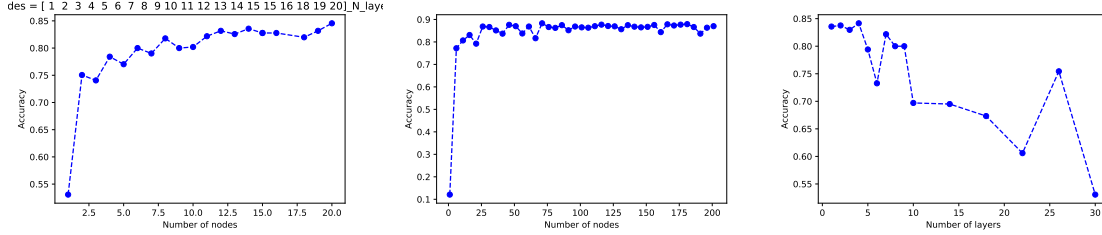


Figure 2: Accuracy achieved with a Multilayer Perceptron algorithm (a) with three hidden layers and up to 20 nodes in each layer; (b) with three hidden layers and up to 203 nodes in each layer (equal to the number of features in the data) (c) with 50 nodes, and a variable number of hidden layers between 1 and 30.

To determine the optimal number of parameters in a MLP model, we varied the number of layers and nodes and recorded cross-validation accuracy. Starting with three hidden layers and varying the number of nodes in each layer, we obtained the accuracy values in figure 2 (a). Since the accuracy didn't seem to saturate at 20 nodes, we extended our search all the way to 203 nodes, which equals the number of our features. It made very little sense to us to create more nodes than dimensions in the data. Despite small fluctuations, we saw an overall trend where the accuracy increases up to 25 nodes, and then stays approximately constant, shown in figure 2 (b).

While adding more nodes improved our accuracy, adding layers beyond three actually hurt the performance (see figure 2 (c)). This could be a reflection of the true nature of the relationships between different features, or it could simply indicate that the amount of data was insufficient to properly tune increasing numbers of layers.

With a small dataset, it is important to avoid overfitting. With this in mind, we explored regularization within the MLP algorithm. This is done by changing the value of a constant  $\alpha$ , with larger  $\alpha$  meaning larger penalty for overfitting. Interestingly, changing  $\alpha$  by multiple orders of magnitude had no effect on our model's accuracy. These data are summarized in table 2.

## 2.2 Decision Tree

Decision Tree method is also tested. To investigate the performance, different maximum depth, maximum number of features, and maximum number of leaf nodes are tested in order, as can be seen in Figure 3. A decision tree with depth greater than 7, with feature greater than 3, and with leaf nodes greater than 50 seems to give us good performance. Interestingly, adding more depth, features or nodes doesn't seem to help us improve the performance. This could be because

$\alpha$	Accuracy
1E-5	0.880259
1E-4	0.899676
1E-3	0.880259
1E-2	0.883495

Table 2: The effect of regularization (quantified by a penalty constant  $\alpha$ ) on the accuracy of MLP predictions.

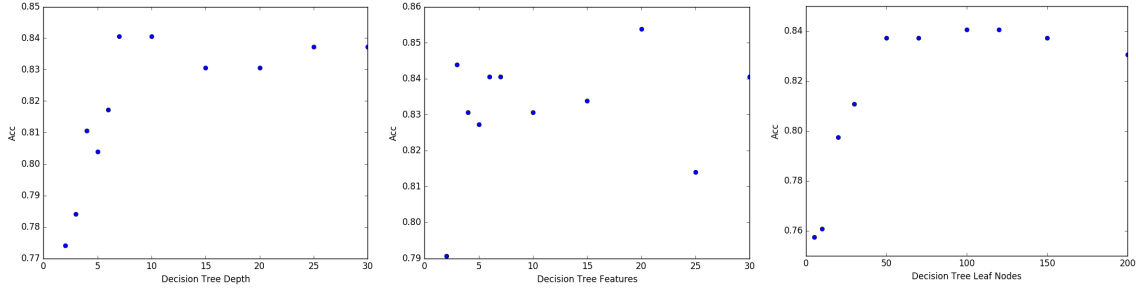


Figure 3: Accuracy achieved with a Decision Tree algorithm (a) with different number of depth; (b) with depth 10 and different number of max features (c) with depth 10, maximum features 5, and different number of of leaf nodes.

our training information is limited. If a large number of maximum depth, features or nodes are used, the risk of overtraining will be significant.

### 3 Discussion

We found that the best results are achieved through a combination of feature engineering and relatively simple methods like the Random Forest. We suspect that simpler methods (with fewer parameters) perform so well here because the data set is small. A neural network would require much more data to tune the parameters.

Different malware classes appear with different frequencies in the training data set. If given more time, we would explore how this affects our accuracy by preselecting particular numbers of data points from each class. Also, more features can possibly be extracted from the information contained in the subprocess commands, which could help further improve the performance.

Since the data are sparse, we could also apply Principal Component Analysis and then examine the feature composition of each component. This would help us gain intuition about the different malware classes. It may also be interesting to firstly train a classifier to distinguish the malware and the None type, and then a second classifier to further classify the different malware types.

Given our testing score is significantly lower than the kaggle final score, overfitting seems to exist. Bagging will help in this case to reduce the variance.