Title

INM427 Coursework

Mark Longhurst & Thomas Martin

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Repo: https://github.com/neural-computing/INM427-neural-computing-coursework

TODO: add more references

Abstract

This paper reports on a critical evaluation of two machine learning models in the task of identifying phishing websites. The models considered are a feed-forward neural network and support vector machine classifier. For each model, k-fold cross-validation was performed to determine the best configuration of hyperparameters in training. The performance of each trained model was then checked against a test set, using a confusion matrix and other derived metrics. Against these evaluation metrics, ... concluding statement

I. Introduction

Phishing websites represent a subset of the wider phishing problem [1]. In general, phishing relates to any attempt to fraudulently obtain sensitive personal information in an electronic communication. Phishing websites are websites that trick users into believing they are on an otherwise legitimate website, typically using a range of frontend web technologies in order to gain this information [2]. This is an increasingly important problem due to the increasing reliance on web-based services [1].

This paper aims to evaluate the performance of two models in the task of identifying phishing websites based on 9 features. The models considered in this paper belong to feed-forward neural networks and support vector machine (SVM) family of models. We use cross-validation to perform hyperparameter tuning from the parameter space.

The paper is organised as follows, section 2 provides an exploratory overview of the dataset used in the project, section 3 details the approach taken in the project to train and compare the models, section 4 discusses the results of the previous process, with section 5 providing a final conclusion.

I.I Feed-Forward Neural Network (FNN)

Feed-forward neural networks refer to the generalised, multilayer perceptron model. These model consist of nodes or neurons arranged in input and output layers, typically with one or more hidden layers in between. Individual nodes are connected by edges called "weights", which denote the strength of the relationship between any node pair. During the training process, these weights are adjusted following an algorithm such as gradient descent, which is a systematic process of determine the impact a given node had on the output produced in a forward pass [3]. They are high performing models in supervised tasks especially where the dataset is large, high dimensional, and unstructured [4].

I.II Support Vector Machine (SVM)

Support vector machine (SVM) classifiers determine the classification of data points by finding the hyperplane of maxmimum margin separating the classes of the dataset. SVM is an appropriate for finding nonlinear boundaries, even in case of high-dimensional datasets using a kernel function [5]. Though typically used in binary classification tasks, SMVs can be generalised to non-binary classification problems by following either one-vs-one or one-vs-all classification algorithm [6]. Compared to a feed-forward neural network, SVM classifiers operate similarly to a shallow neural network, however SVMs are generally thought to produce more easily understandable models.

II. Dataset

The dataset used in this study was taken from the UCI Machine Learning Repository, originally collected from the Phishtank data archive [7]. The dataset contains features corresponding to 1353 websites, classed as either legitimate, suspicious, or phishy, encoded as 1, 0, and -1 respectively. There is a slight imbalance between these classes occurring with a frequency of 548, 702 and 103 for legitimate, phishy and suspicious samples respectively. However, this imbalance is not dramatic enough to require additional sampling methods.

III. Methodology

This sections outlines the general approach taken to train and test either model. as well a approaches specific to each model.

III.I General Approach

For both models, the initial dataset was split into a training and testing dataset in a proportion of 70% and 30% respectively.

During the initial training process, grid-search cross-validation was used to select the optimal hyperparameter configuration. The specific process used was k-fold cross validation, where k was taken as 5. Cross-validation is especially useful to get a better understanding of how well the data models remain unbiased and generalise in the case of relatively small datasets - the original dataset has ~1000 rows. Mean test accuracy was used to determine the optimal set of hyperparameters for each model.

To evaluate the performance of the trained models against the test set confusion matrices were plotted. As an additional step the precision for the legitimate class was taken as an optimising metric

... MOVE DISCUSSION TO THIS SECTION ... .

Such an approach also helps given there is a large class imbalance, which accuracy considered alone could lead to a biased classifier.

... Something about evaluating the two models as the test stage ...

III.II Feed-Forward Neural Network (FNN)

Initially a fully connected feed-forward neural network was built utilizing the sigmoid function as the neuron activation function for all nodes. The number of input and output layer nodes was kept consistent, equal to the number of predictor variables plus bias, and classes respectively.

Weights were randomly initialised for each epoch within a given threshold, to ensure that networks weights can reach different minima for each run. The weights of the network were updated following a backpropagation algorithm, updating weights according to the mean squared error of the output layer nodes. An early stopping threshold was also set to ensure the training was stopped for a given epoch if the updated accuracy changed little from its previous value.

During the training stage, the following hyperparameter were tuned:

- Hidden nodes - number of fully connected nodes within the hidden layer, varied at increments of 5 between 10 and 60
- Learning rate - rate at which the models weights are updated during the back-propagation, varied at increments of 0.05, between 0.001 and 0.1
- Momentum - level of inertia added when modifying the models weights, varied at increments of 0.025, between 0.005 and 0.05
- Early stopping threshold - smallest delta allowed when updating the models weights before training is halted, this varid as increments of 0.05, between 0.001 and 0.1

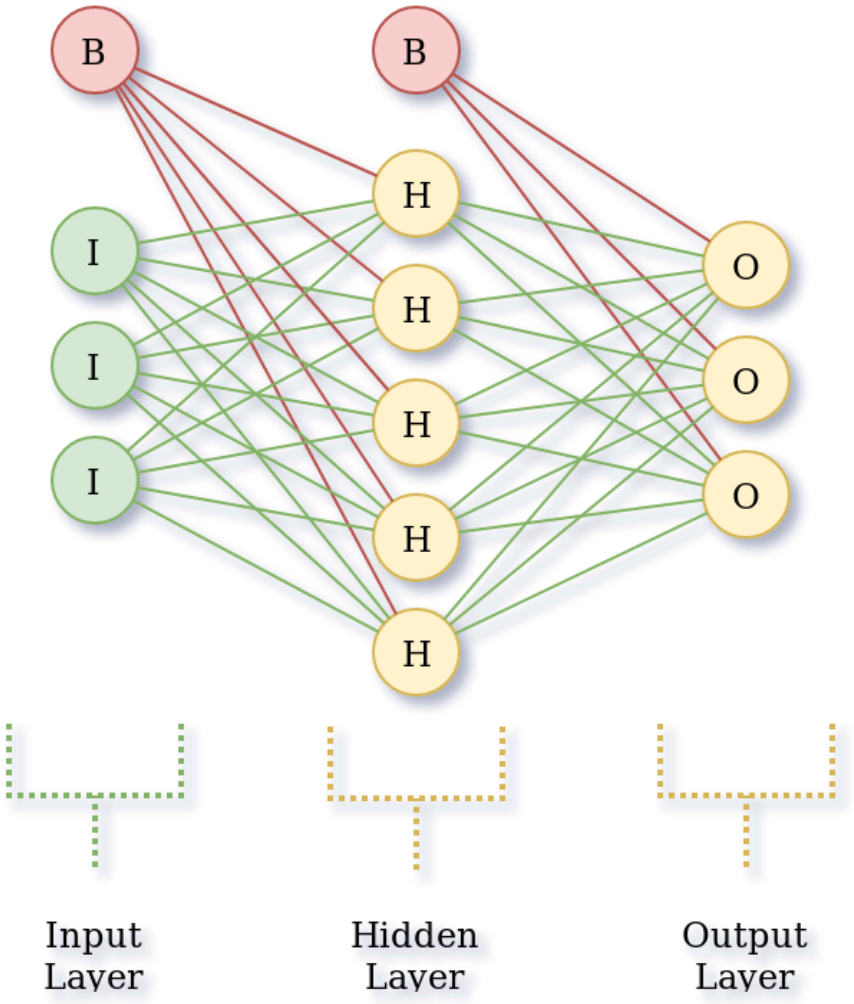


Figure 1: Feed Forward Neural Network

III.III Support Vector Machine (SVM)

Next a multiclass SVM model was constructed using MATLAB's "fitcecoc" method. The SVM state is completely defined by the initial hyperparameter set. Given that the task is a mutliclass classification problem, a one-vs-all algorithm was used to produce the classifications.

The following hyperparameters were tuned:

TODO Define kernel_scale and shrinkage_period

- Kernel - this determines how the SVM performs comparisons between datapoints to determine the hyperplane of maximum margin. The selection available consisted of linear, RBF, and polynomial kernels
- Box Constraint - this controls the penalty on data-points that are misclassfied by the margin and overall helps with overfitting. Increasing the box constraint will reduce the number of support vectors the SVM margin uses. This was varied between 0.05 and 1, at increments of 0.3
- Kernel scale - ... This was varied between 0.1 and 1, at increments of 0.3
- Shrinkage period - ... This was varied between 1 and 10, at increments of 3

IV. Results

IV.I Model Selection

In total, 128 models were run for both the Neural Net and SVM. The following tables reproduces the top ten configurations for both models, ordered by test accuracy.

Top 10 Configurations for SVM

TODO: Out of "Train Accuracy" and "K-fold Accuracy", which makes most sense to keep? I think they should be reporting the same kind of thing if I understand correctly

Box Constraint	Kernel Scale	Shrinkage Period	Kernel	Train Accuracy	Test Accuracy	K-fold Accuracy
0.65	1	10	rbf	0.9398	0.8768	0.8877
0.95	1	10	rbf	0.9535	0.8818	0.8847
0.65	1	1	rbf	0.9398	0.8768	0.8840
0.95	1	7	rbf	0.9535	0.8818	0.8840
0.95	1	4	rbf	0.9535	0.8818	0.8832
0.95	1	1	rbf	0.9535	0.8818	0.8825
0.65	1	7	rbf	0.9398	0.8768	0.8810
0.95	0.7	4	rbf	0.9609	0.8768	0.8766

Box Constraint	Kernel Scale	Shrinkage Period	Kernel	Train Accuracy	Test Accuracy	K-fold Accuracy
0.65	1	4	rbf	0.9398	0.8768	0.8721
0.95	0.7	7	rbf	0.9609	0.8768	0.8707

Top 10 Configurations for FNN

Hidden Layer Nodes	Learning Rate	Momentum	Early Stopping Threshold	Train Accuracy	Test Accuracy
26	0.046	0.005	0.001	0.9496	0.8926
26	0.046	0.03	0.001	0.9398	0.8926
34	0.046	0.005	0.001	0.9498	0.8926
34	0.031	0.03	0.001	0.9452	0.8911
18	0.046	0.03	0.001	0.9411	0.8911
34	0.046	0.03	0.001	0.9435	0.8911
30	0.046	0.005	0.001	0.9491	0.8904
22	0.046	0.005	0.001	0.9428	0.8889
30	0.046	0.03	0.001	0.9459	0.8889
22	0.031	0.005	0.001	0.9431	0.8881

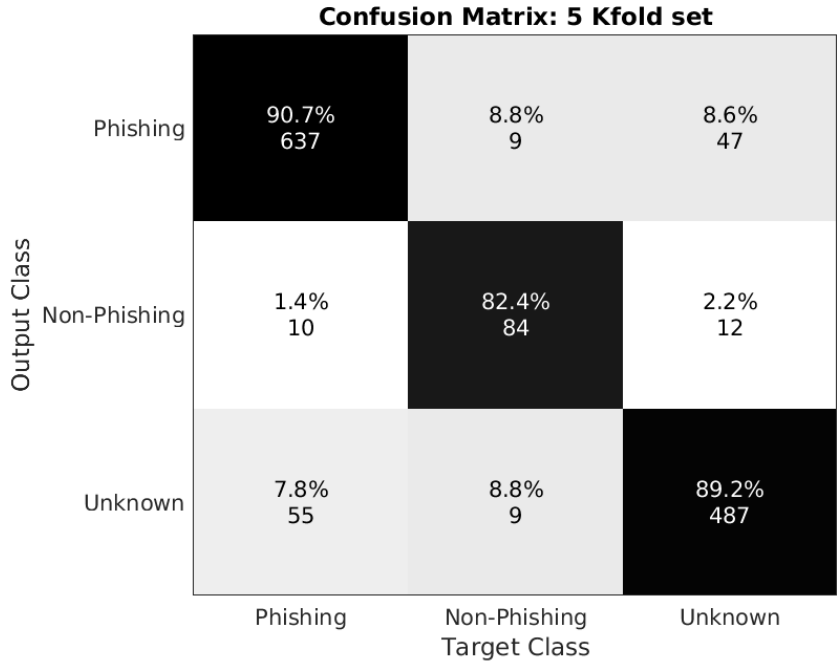
From these tables we can see that all of the best performing SVM models used a radial basis function (rbf) kernel with a kernel scale of 1. Coupling this with a box constraint of 0.65 and shrinkage period of 10 built the best SVM model and this will be carried forward into the model comparison. Similarly with the FNN we can see that the top 3 models all achieved almost identical test accuracy. This suggests that either 26 or 34 hidden nodes, a momentum of either 0.005 and 0.03, a learning rate of 0.046 and a stopping threshold of 0.001 delivers the best performance. We selected 26 hidden nodes instead of 34 to try and reduce the training time of the model.

IV.II Model Comparison

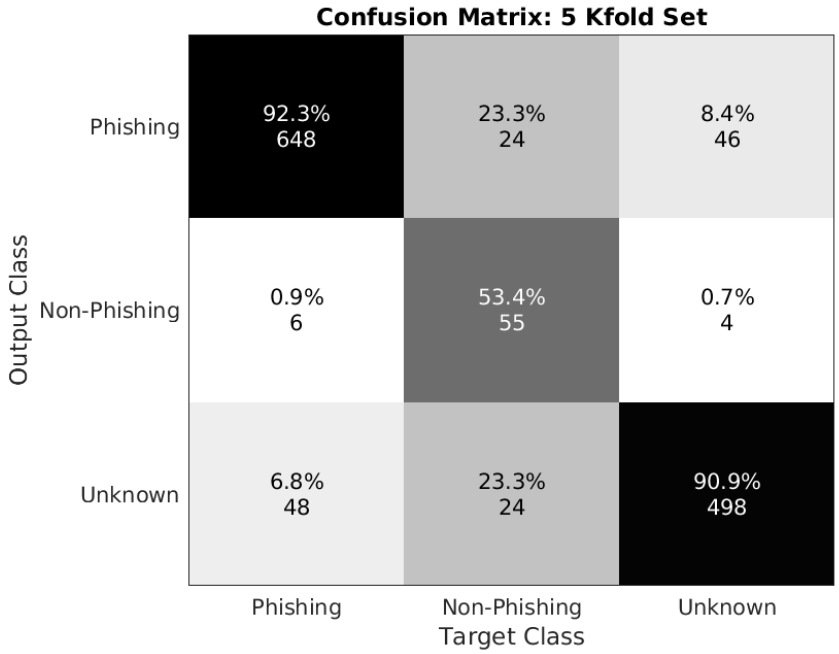
The reported training accuracy for the most successful configurations for both models indicates that FNN performed better overall, if only slightly: 94.96% v 93.89%. More interesting perhaps is the choice of hyperparameters that produced the top performing models. In particular, the RBF kernel was the best kernel choice for the SVM classifier. The FNN demonstrated a high variability in the number of hidden layer nodes which produced the best performance.

To determine the most effective model for this dataset a confusion matrix was produced using the best model choice on the test data. Accuracy is reported for

the test set only, which is defined as the percentage of true positives identified over all classes out of the total samples considered.



Neural Net



SVM

Considering the accuracy alone, we see very comparable performances between the two models as shown in the table below.

	Accuracy
FNN	89.3%
SVM	88.8%

The feedforward network out performs the SVM model by about 0.5% and it appears to be significantly better at correctly identifying emails as "non-phishing".However when determining whether a website is phishy or not, it can be considered that the best model is the one that minimises the number of web sites wrongly classified as legitimate i.e. minimises number of false negatives for legitimate/non-phishy class. This is precisely because, in optimising for the lowest number of websites wrongly classfied as non-phishy we can ensure the safest experience for a user: a website classified as phishy/suspicious can always be investigated further.

TODO: Discuss recall

	Phishy Class Recall
FNN	90.7%
SVM	92.3%

	Legitimate Class Precision
FNN	82.4%
SVM	53.4%

From this perspective, it can be argued that the SVM model performed much better than the FNN model

V. Conclusion

In this paper, we considered the performance of two types of models, SVMs and FFNs, to correctly classify websites as either legitimate, phishy, or suspicious.

Conclusion of two model comparison ... need to discuss

Given that this is a multiclass classification problem, a confusion matrix proved to be the most immediate and effective means to make meaningful comparison between the two trained model. From consideration of the problem domain, the precision of the legitimate class can be considered as a single optimising metric for either model.

Extensions ...

models were selected based on the test accuracy achieved during the kfold training process. The dataset used within this study contains a fairly large class imbalance with the "non-phishing" class under represented by a ratio of roughly 7-1. This may mean that using accuracy for model selection is unfairly biased towards models that are able to better predict "phishing" websites at the expense of "non-phishing" websites. Whilst this may not be a problem to an end user,

Ensemble methods generally give better performance - rather than comparing, maybe the two methods could be used in conjunction to achieve a better overall performance.

VI. References

[1] Phishing https://en.wikipedia.org/wiki/Phishing [2] Phishing Web Site Methods https://www.webcitation.org/5w9Z2iACi?url=http://www.fraudwatchinternational.com/phishing-fraud/phishing-web-site-methods/ [3] https://cs.stanford.edu/people/eroberts/courses/soco/projects/neural-networks/Architecture/feedforward.html [4] https://towardsdatascience.com/introduction-to-neural-networks-advantages-and-applications-96851bd1a207 [5] https://core.ac.uk/download/pdf/6302770.pdf [6] https://nlp.stanford.edu/IR-book/html/htmledition/multiclass-svms-1.html [7] Website Phishing Data Set, https://archive.ics.uci.edu/ml/datasets/Website+Phishing