APPLIANCES ENERGY PREDICTION & BANK TERM LOAN DEPOSIT PREDICTION USING SUPPORT VECTOR MACHINES AND DECISION TREES

SUDHARSANA RAJASEKARAN
APPLIED MACHINE LEARNING
Assignment 2

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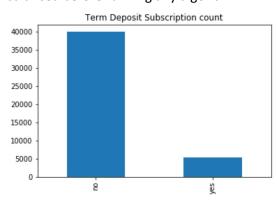
Introduction:

The data is related with direct marketing campaigns of a Portuguese banking institution and the <u>dataset</u> was derived from the UCI Machine learning repository. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be ('yes') or not ('no') subscribed.

Exploratory Data Analysis:

Initial dataset analysis yielded the following results,

- 1. Number of Transactions: The dataset contains 45211 observation and 17 variables.
- 2. Missing Values: Fortunately, there are no missing values in the dataset.
- 3. Distribution of Classes: It can be observed that the distribution of classes is imbalanced. Therefore, the dataset must be balanced before running any algorithm.



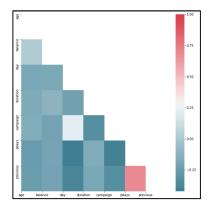


Figure 1. Term Deposit Subscription Count

Figure 2. Correlation Plot

- 4. Correlation Plot: The correlation plot tells us how far the dependent variables are correlated. It can be observed from the correlation plot that campaign and duration are highly negatively correlated with one another. The campaign and number of days since a client was last contacted are negatively correlated with one another.
- 5. Dataset Imbalance: The distribution of negative classes is high causing an imbalance in the distributions of classes. Hence to avoid this sample of the majority class is taken to make both the classes equally balanced.

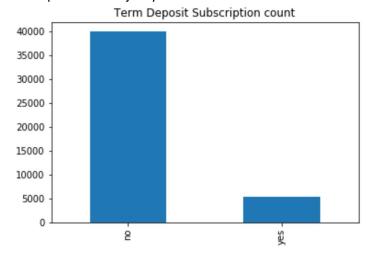


Figure 3. Distribution of Term deposit subscription

Term Deposit Subscription

SUPPORT VECTOR MACHINES

Linear Kernel

SVM with linear model has an accuracy of 63%. Although linear kernel can identify customers who have subscribed for term deposit with good accuracy, it does poorly in identifying customers who have not. It is important identifying these customers who have not subscribed any misclassification to that class is missed business opportunity for term deposit.

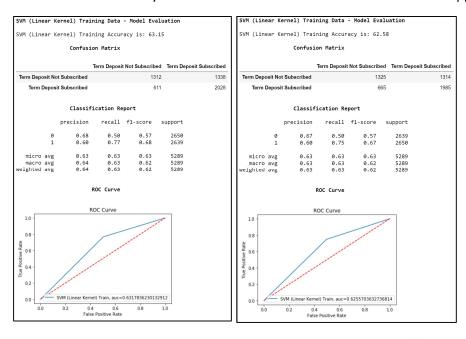


Figure 3. SVM Training and Test – Model Evaluation (Linear Kernel)

Sigmoid Kernel

Sigmoid kernel performs poorly over linear kernel. It can be observed from the ROC curve that the roc line of the sigmoid is almost the same as the default line, thus telling the model is not good for identifying the term deposit subscription.

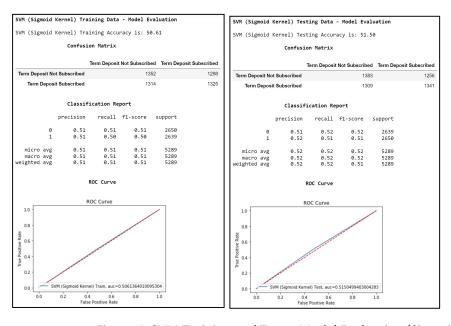


Figure 4. SVM Training and Test – Model Evaluation (Sigmoid Kernel)

Gaussian Kernel

Gaussian kernel of SVM overcomes the drawback of linear kernel by showing an improved performance of identifying the subscribers who have not subscribed for term deposit. Thus, adding to an overall training accuracy of 73%.

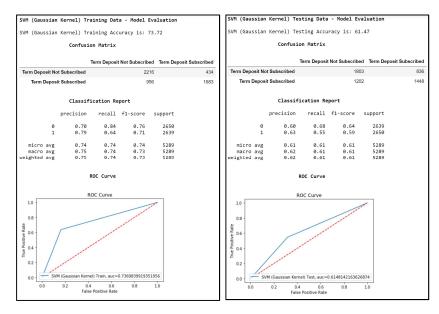


Figure 5. SVM Training and Test – Model Evaluation (Gaussian Kernel)

K-fold Cross validated SVM

10-fold cross validated SVM model was built using gaussian kernel and the final mean accuracy of the model was found to be 60.74%.

```
[0.59357278 0.59357278 0.64461248 0.63705104 0.58412098 0.62192817 0.61625709 0.5879017 0.60491493 0.59090909]
Accuracy of Model with Cross Validation is: 60.74841037979033
```

Figure 7. SVM Training and Test – Model Evaluation (K-Fold)

Decision Trees:

Entropy based Decision Tree

A decision tree without any pruning constraint was constructed for the term deposit classification. It can be observed that the tree grows without any constraint overfitting the training dataset. Thus, it poorly performs on the testing dataset. The model of decision tree has a training accuracy of 81% and testing accuracy of 64%.

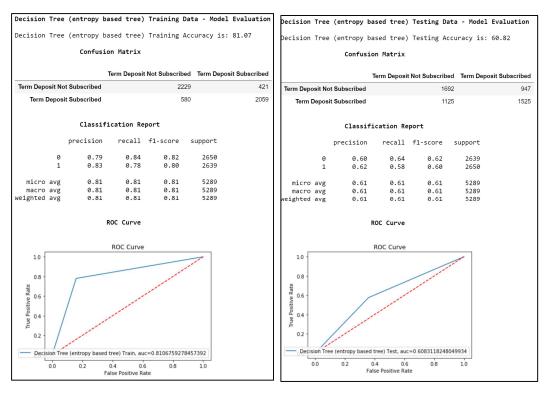


Figure 8. Decision Tree Training and Test – Model Evaluation (Entropy based)

Pruned Decision Tree

Pruning are important part of decision tree modelling. Pruning avoids overfitting of the model. It can be observed that the training and testing accuracies are almost the same. This tells us that the model is able to generalize well on the testing data set.

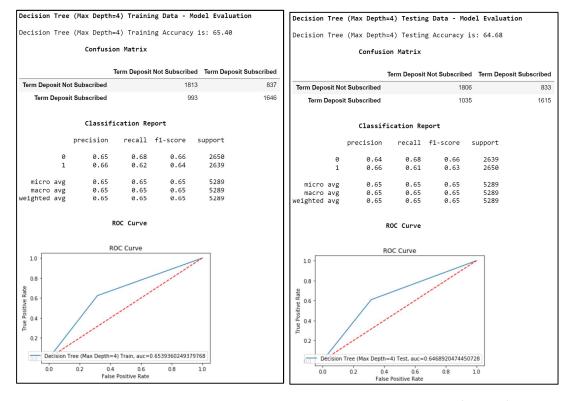


Figure 9. Decision Tree Training and Test – Model Evaluation (Pruned)

Ada Boosted Decision Tree

Boosting improves the performance of decision trees. The data boosted decision tree has an overall training accuracy of 99%. But however, it does poorly on the test dataset.

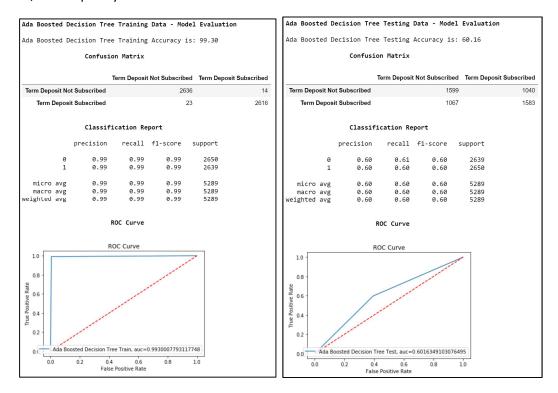


Figure 10. Decision Tree Training and Test – Model Evaluation (Ada Boosted)

Cross Validated Decision Trees:

10-fold cross validated decision scored an overall mean accuracy of 59%.

```
[0.56710775 0.56521739 0.56899811 0.61814745 0.59546314 0.60869565 0.60491493 0.61625709 0.60113422 0.59848485]
Accuracy of Model with Cross Validation is: 59.444205762731286
```

Figure 11. Decision Tree Training and Test – Model Evaluation (K-Fold)

Appliances Energy Prediction

The Appliances Energy prediction dataset was derived from the UCI Machine learning repository. The dataset consists of house temperature and humidity conditions that were monitored with a ZigBee wireless sensor network. Each wireless node transmitted the temperature and humidity conditions around 3.3 min. Then, the wireless data was averaged for 10 minutes periods, which then becomes each of the rows in the dataset. The aim of the project is predicting the energy usage of the appliances using Linear and Logistic Regression by hyperparameter tuning of parameters

SUPPORT VECTOR MACHINES

Linear Kernel

The most basic kernel is the linear kernel. With linear as the kernel there is a training accuracy of 79% and a test error of 80.42%. From the confusion matrix, it can be observed that the misclassification rate for "Energy consumed" is high and hence could be mitigated by using different kernels.

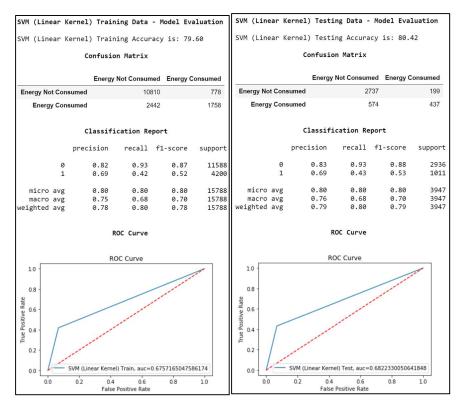


Figure 12. SVM Training and Test – Model Evaluation (Linear Kernel)

Sigmoid Kernel

The sigmoid kernel shows and improvement over linear in identifying "Energy not consumed" class. But on the other hand, it is totally bad no identifying the "Energy consumed" classes. This model's weakness for identifying the "energy consumed" classes can be handled by using Gaussian kernel.

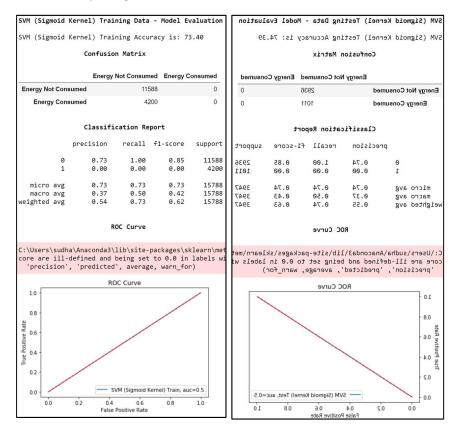


Figure 13. SVM Training and Test – Model Evaluation (Sigmoid Kernel)

Gaussian Kernel

Gaussian kernel shows an improvement in identifying both linear and sigmoid kernels. Hence gaussian model here is good for energy consumption classification.

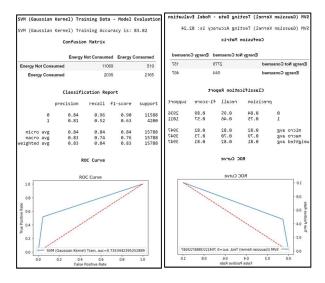


Figure 14. SVM Training and Test – Model Evaluation (Gaussian Kernel)

Grid Search SVM:

Using the Grid search method, the best parameters for this classification is found to be Gaussian kernel, C=1000, gamma=0.0001. Grid search has helped us fine tune our classification model in improving the performance of our model. The model shows an improved performance after parameter tuning and showed an improved accuracy of 87% in training set and 86% in test set.

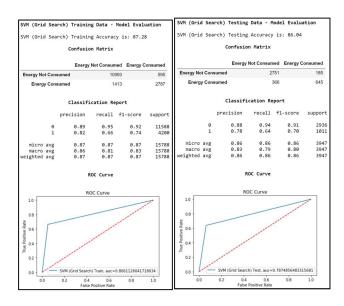


Figure 15. SVM Training and Test – Model Evaluation (Grid Search CV)

K-fold Cross validated SVM

With 20-fold cross validation we can achieve an accuracy of 84%

```
[0.85316456 0.84556962 0.83670886 0.8556962 0.85189873 0.85443038 0.84303797 0.84556962 0.84917617 0.83776933 0.85931559 0.83396705 0.85171103 0.85931559 0.85678074 0.85297845 0.85171103 0.84790875 0.86692015 0.84157161]
Accuracy of Model with Cross Validation is: 84.97600712326128
```

Figure 16. SVM Training and Test – Model Evaluation (K-Fold)

Decision Trees:

Entropy based Decision Tree

Decision Tree Algorithm choose the highest Information gain to *split/construct* a Decision Tree. Here in this model the decision tree can grow relentlessly without any constraint. In general decision trees tend to over fit the test data and hence the decision tree that can grow without any condition perform poorly on the test data, since it will not be able to generalize well on the test data. Here in this model, even though the decision tree has an accuracy of 95% on the training data, it does not generalize well on the test data and thus produces a test accuracy of only 86%.

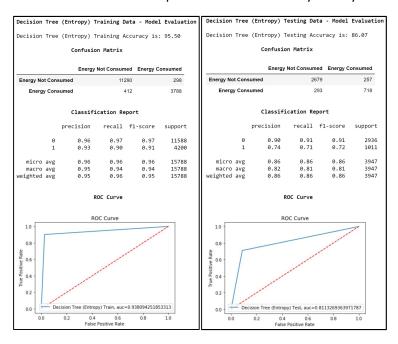


Figure 17. Decision Tree Training and Test – Model Evaluation (Entropy based)

Pruned Decision Tree

Pruning decision trees are very important as this could possibly avoid overfitting the training data. Here in the model the tree is pruned at a maximum depth of 4. Pruning makes the model generalize well on the training data. This additional flexibility comes with a price of training and testing accuracies being less that of an un-pruned tree. Here in the pruned decision tree, the training and testing accuracies are closer to each other, letting know the goodness of fit of the model.

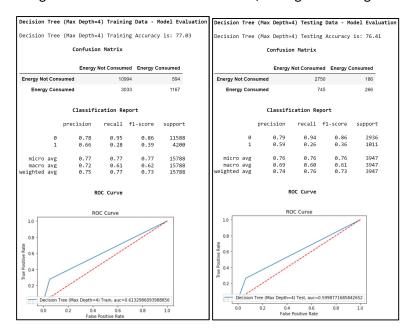


Figure 18. Decision Tree Training and Test – Model Evaluation (Pruned)

Ada Boosted Decision Tree

Boosting is another ensemble technique to create a collection of predictors. In this technique, learners are learned sequentially with early learners fitting simple models to the data and then analyzing data for errors. AdaBoost was the first successful boosting algorithm developed for binary classification. Ada boost has a training accuracy of 100%, that is the model is correctly able to identify all the observations in the training data set, it can also be seen that the test accuracy of boosted decision tree is 88% and ROC is 0.835 which is high when compared to decision tree with just pruning.

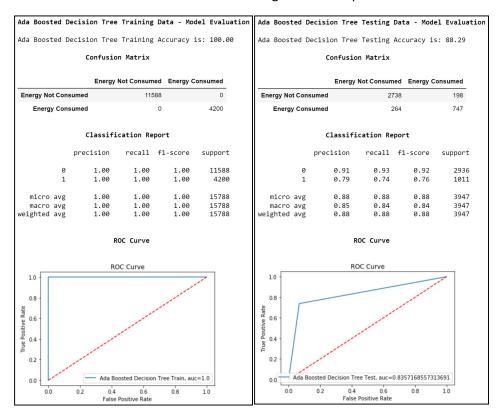


Figure 19. Decision Tree Training and Test – Model Evaluation (Ada Boosted)

Cross Validated Decision Trees:

Cross-validation is a statistical technique for testing the performance of a Machine Learning model. A good cross validation method gives us a comprehensive measure of our model's performance throughout the whole dataset.

Here in the model, designed a 20-fold cross validation and the average training accuracy was found to be 87% which high when compared with a decision tree with pruning.

[0.89043699 0.88157061 0.86637112 0.86827106 0.87080431 0.87143762 0.8809373 0.87903737 0.87072243 0.88149556]
Accuracy of Model with Cross Validation is: 87.61084368586107

Figure 20. Decision Tree Training and Test – Model Evaluation (K-Fold)