



**University of  
Nottingham**

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# COMP3009 Machine Learning

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## Assignment 2: Report

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Group 18

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# Introduction

In this coursework, we are using decision tree to do both classification and regression. The data sets we used are both from previous coursework.

## Data Set for Classification

This data set consists of 12 features and 1 column of class labels with a total of 299 instances within the data set. The goal is to classify the death event based on the 12 features.

## Data Set for Regression

In this data set, 8 features and a total of 1030 instances were consisted. The goal is to predict the Concrete Compressive Strength based on the 8 features.

# Implementations

## Folder Structure

```
.
├── cw2/
│   ├── datasets/
│   ├── functions/
│   │   ├── data_processing/
│   │   ├── decision_tree/
│   │   └── metrics/
│   ├── demo.m
│   ├── cross_validation_classification.m
│   └── cross_validation_regression.m
```

`demo.m` show both tree are working for the datasets.

`cross_validation_classification.m` show the evaluation of decision tree on the classification task.

`cross_validation_regression.m` show the evaluation of decision tree on the regression task.

`data_processing` for data validation split and normalisation

`decision_tree` for all decision tree related functions

`metrics` for accuracy, f1, confusion matrix etc.

# Decision Tree for Classification

Figure below denoting the acquired decision tree for classification dataset, constructed using the best tuned depth of 2.

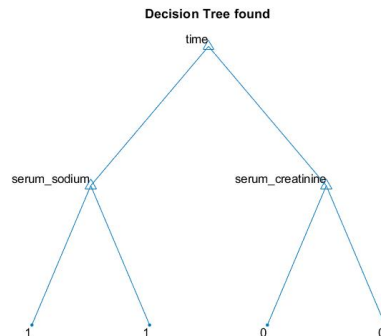


Figure 1: Classification Decision Tree

## Cross-validation classification results

The result below consists of F1 score, recall and precision shown below is acquired from performing cross validation.

```
Inner: 1 TestSize: 54 TrainSize: 215 Accuracy: 0.777778 F1Score: 0.755556 BestD: 9
Inner: 2 TestSize: 54 TrainSize: 215 Accuracy: 0.833333 F1Score: 0.909091 BestD: 2
Inner: 3 TestSize: 54 TrainSize: 215 Accuracy: 0.814815 F1Score: 0.608696 BestD: 6
Inner: 4 TestSize: 54 TrainSize: 215 Accuracy: 0.777778 F1Score: 0.756757 BestD: 4
Inner: 5 TestSize: 53 TrainSize: 216 Accuracy: 0.792453 F1Score: 0.782609 BestD: 2
Outer: 1 TestSize: 30 TrainSize: 269 Accuracy: 0.733333 F1Score: 0.500000 Precision: 0.571429 Recall: 0.444444 MostDepth: 2
Inner: 1 TestSize: 54 TrainSize: 215 Accuracy: 0.722222 F1Score: 0.600000 BestD: 2
Inner: 2 TestSize: 54 TrainSize: 215 Accuracy: 0.777778 F1Score: 0.909091 BestD: 2
Inner: 3 TestSize: 54 TrainSize: 215 Accuracy: 0.833333 F1Score: 0.636364 BestD: 7
Inner: 4 TestSize: 54 TrainSize: 215 Accuracy: 0.777778 F1Score: 0.705882 BestD: 4
Inner: 5 TestSize: 53 TrainSize: 216 Accuracy: 0.830189 F1Score: 0.782609 BestD: 2
Outer: 2 TestSize: 30 TrainSize: 269 Accuracy: 0.733333 F1Score: 0.714286 Precision: 0.909091 Recall: 0.588235 MostDepth: 2
Inner: 1 TestSize: 54 TrainSize: 215 Accuracy: 0.722222 F1Score: 0.680851 BestD: 6
Inner: 2 TestSize: 54 TrainSize: 215 Accuracy: 0.796296 F1Score: 0.838710 BestD: 2
Inner: 3 TestSize: 54 TrainSize: 215 Accuracy: 0.777778 F1Score: 0.600000 BestD: 2
Inner: 4 TestSize: 54 TrainSize: 215 Accuracy: 0.796296 F1Score: 0.685714 BestD: 5
Inner: 5 TestSize: 53 TrainSize: 216 Accuracy: 0.754717 F1Score: 0.782609 BestD: 2
Outer: 3 TestSize: 30 TrainSize: 269 Accuracy: 0.866667 F1Score: 0.818182 Precision: 1.000000 Recall: 0.692308 MostDepth: 2
Inner: 1 TestSize: 54 TrainSize: 215 Accuracy: 0.777778 F1Score: 0.717949 BestD: 7
Inner: 2 TestSize: 54 TrainSize: 215 Accuracy: 0.796296 F1Score: 0.800000 BestD: 2
Inner: 3 TestSize: 54 TrainSize: 215 Accuracy: 0.851852 F1Score: 0.733333 BestD: 4
Inner: 4 TestSize: 54 TrainSize: 215 Accuracy: 0.777778 F1Score: 0.702703 BestD: 5
Inner: 5 TestSize: 53 TrainSize: 216 Accuracy: 0.698113 F1Score: 0.782609 BestD: 2
Outer: 4 TestSize: 30 TrainSize: 269 Accuracy: 0.966667 F1Score: 0.923077 Precision: 1.000000 Recall: 0.857143 MostDepth: 2
Inner: 1 TestSize: 54 TrainSize: 215 Accuracy: 0.666667 F1Score: 0.652174 BestD: 7
Inner: 2 TestSize: 54 TrainSize: 215 Accuracy: 0.685185 F1Score: 0.812500 BestD: 2
Inner: 3 TestSize: 54 TrainSize: 215 Accuracy: 0.796296 F1Score: 0.645161 BestD: 8
Inner: 4 TestSize: 54 TrainSize: 215 Accuracy: 0.722222 F1Score: 0.648649 BestD: 3
Inner: 5 TestSize: 53 TrainSize: 216 Accuracy: 0.754717 F1Score: 0.782609 BestD: 2
```

We noticed that despite the tree can fit perfectly to the training set, the model doesn't perform well in testing set, which indicates it is overfitting. Result shows the only important feature is time, the others may not be as important because pruning the tree to only 1 node leads to better prediction as high as 89% accuracy(Figure: ??).



it take a lot of node splitting for it to fit the regression line if it is not perpendicular to the axis. Worst case happened when the line decision tree trying to fit is a complicated polynomial line. For these 2 reasons, decision tree may not be so ideal for complicated regression task.

## Cross-validation regression results

The below result which consist of RMSE shown below is acquired from performing cross validation.

```

Inner: 1 TestSize: 185 TrainSize: 742 RMSE: 5.836764 BestD: 14
Inner: 2 TestSize: 185 TrainSize: 742 RMSE: 6.324395 BestD: 17
Inner: 3 TestSize: 185 TrainSize: 742 RMSE: 6.335310 BestD: 18
Inner: 4 TestSize: 185 TrainSize: 742 RMSE: 6.135024 BestD: 15
Inner: 5 TestSize: 187 TrainSize: 740 RMSE: 6.389585 BestD: 16
Outer: 1 TestSize: 103 TrainSize: 927 RMSE: 5.771021 MostDepth: 14
Inner: 1 TestSize: 185 TrainSize: 742 RMSE: 6.211833 BestD: 9
Inner: 2 TestSize: 185 TrainSize: 742 RMSE: 6.145389 BestD: 11
Inner: 3 TestSize: 185 TrainSize: 742 RMSE: 6.649158 BestD: 13
Inner: 4 TestSize: 185 TrainSize: 742 RMSE: 6.219018 BestD: 18
Inner: 5 TestSize: 187 TrainSize: 740 RMSE: 6.915477 BestD: 11
Outer: 2 TestSize: 103 TrainSize: 927 RMSE: 5.204744 MostDepth: 11
Inner: 1 TestSize: 185 TrainSize: 742 RMSE: 6.004376 BestD: 10
Inner: 2 TestSize: 185 TrainSize: 742 RMSE: 6.214803 BestD: 16
Inner: 3 TestSize: 185 TrainSize: 742 RMSE: 7.870636 BestD: 12
Inner: 4 TestSize: 185 TrainSize: 742 RMSE: 6.549546 BestD: 9
Inner: 5 TestSize: 187 TrainSize: 740 RMSE: 7.846672 BestD: 8
Outer: 3 TestSize: 103 TrainSize: 927 RMSE: 5.678429 MostDepth: 9
Inner: 1 TestSize: 185 TrainSize: 742 RMSE: 7.015569 BestD: 12
Inner: 2 TestSize: 185 TrainSize: 742 RMSE: 6.229615 BestD: 17
Inner: 3 TestSize: 185 TrainSize: 742 RMSE: 6.360509 BestD: 11
Inner: 4 TestSize: 185 TrainSize: 742 RMSE: 5.926373 BestD: 19
Inner: 5 TestSize: 187 TrainSize: 740 RMSE: 7.551650 BestD: 10
Outer: 4 TestSize: 103 TrainSize: 927 RMSE: 5.023550 MostDepth: 11
Inner: 1 TestSize: 185 TrainSize: 742 RMSE: 6.847550 BestD: 10
Inner: 2 TestSize: 185 TrainSize: 742 RMSE: 6.021640 BestD: 12
Inner: 3 TestSize: 185 TrainSize: 742 RMSE: 6.596329 BestD: 12
Inner: 4 TestSize: 185 TrainSize: 742 RMSE: 6.225894 BestD: 12
Inner: 5 TestSize: 187 TrainSize: 740 RMSE: 7.239258 BestD: 11

Inner: 5 TestSize: 187 TrainSize: 740 RMSE: 6.950056 BestD: 6
Outer: 10 TestSize: 103 TrainSize: 927 RMSE: 6.035104 MostDepth: 10
FinalRMSE: 5.682935 FinalD: 10

Outer: 5 TestSize: 103 TrainSize: 927 RMSE: 5.453350 MostDepth: 12
Inner: 1 TestSize: 185 TrainSize: 742 RMSE: 6.421334 BestD: 7
Inner: 2 TestSize: 185 TrainSize: 742 RMSE: 7.282734 BestD: 7
Inner: 3 TestSize: 185 TrainSize: 742 RMSE: 5.963037 BestD: 12
Inner: 4 TestSize: 185 TrainSize: 742 RMSE: 6.127547 BestD: 10
Inner: 5 TestSize: 187 TrainSize: 740 RMSE: 7.403905 BestD: 11
Outer: 6 TestSize: 103 TrainSize: 927 RMSE: 5.324208 MostDepth: 12
Inner: 1 TestSize: 185 TrainSize: 742 RMSE: 6.175456 BestD: 10
Inner: 2 TestSize: 185 TrainSize: 742 RMSE: 6.143625 BestD: 10
Inner: 3 TestSize: 185 TrainSize: 742 RMSE: 5.915851 BestD: 14
Inner: 4 TestSize: 185 TrainSize: 742 RMSE: 7.319395 BestD: 17
Inner: 5 TestSize: 187 TrainSize: 740 RMSE: 6.390718 BestD: 10
Outer: 7 TestSize: 103 TrainSize: 927 RMSE: 5.507387 MostDepth: 10
Inner: 1 TestSize: 185 TrainSize: 742 RMSE: 7.508725 BestD: 10
Inner: 2 TestSize: 185 TrainSize: 742 RMSE: 6.681730 BestD: 7
Inner: 3 TestSize: 185 TrainSize: 742 RMSE: 6.109656 BestD: 16
Inner: 4 TestSize: 185 TrainSize: 742 RMSE: 7.539876 BestD: 13
Inner: 5 TestSize: 187 TrainSize: 740 RMSE: 6.263431 BestD: 11
Outer: 8 TestSize: 103 TrainSize: 927 RMSE: 6.275347 MostDepth: 10
Inner: 1 TestSize: 185 TrainSize: 742 RMSE: 6.607116 BestD: 9
Inner: 2 TestSize: 185 TrainSize: 742 RMSE: 5.410458 BestD: 20
Inner: 3 TestSize: 185 TrainSize: 742 RMSE: 6.279138 BestD: 15
Inner: 4 TestSize: 185 TrainSize: 742 RMSE: 5.963944 BestD: 16
Inner: 5 TestSize: 187 TrainSize: 740 RMSE: 6.668170 BestD: 10
Outer: 9 TestSize: 103 TrainSize: 927 RMSE: 6.556206 MostDepth: 10
Inner: 1 TestSize: 185 TrainSize: 742 RMSE: 7.660379 BestD: 9
Inner: 2 TestSize: 185 TrainSize: 742 RMSE: 7.319591 BestD: 13
Inner: 3 TestSize: 185 TrainSize: 742 RMSE: 6.652584 BestD: 16
Inner: 4 TestSize: 185 TrainSize: 742 RMSE: 7.187244 BestD: 13

```

Figure 5: Result of the regression cross validation

Despite that, this decision tree still have impressive result with RMSE around 6, which is better than the SVM with linear kernel. SVM with polynomial kernel and gaussian kernel still yields better results with RMSE around 3 to 5.

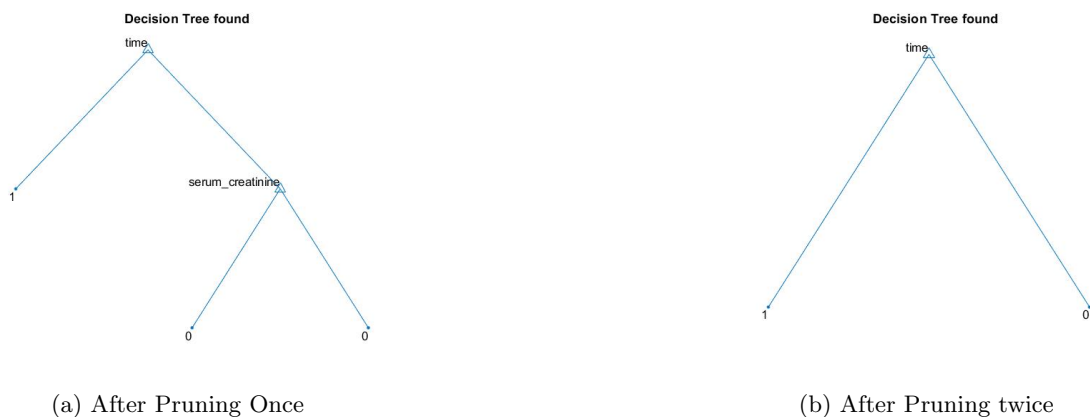
## Additional Questions

1. Pruning is an important issue in trees. Explain what pruning does and find the node(s) that would be pruned first for one of your learned trees. Explain the difference between the original and the pruned tree.

**Answer:**

Pruning is a method that is used to reduce the size and depth of the decision trees that does not impact much on the classifying of the instances. Pruning a decision tree also help with reducing the overfitting and hence the model able to predict better with the unseen data. We will be implementing our pruning using post-pruning, reduced error pruning algorithm.

Pruning our first classification tree, we are able to observe that both children are leading to the same type of labels, meaning that removing them won't affect the performance and the accuracy of before and after will be the same. Figures below demonstrating the removal of nodes without impacting the accuracy.



**Accuracy: 89.83%**

(c) Acc. Before & After Pruning

Figure 6: Pruning two Nodes

The pruned tree should be higher or equal in performance and smaller in size.

2. In this assignment, you trained a binary tree. Explain how you would use a single decision tree to learn to predict multiple independent binary class labels. Explain how to make decisions in leaf nodes, and how you would have to change your query search algorithm for any node.

**Answer:**

Since this is a multi binary class problem and there is no relation between each binary classes. For example, we have 3 independent binary classes for each instances, usually we will simply construct 3 trees to solve that. However to merge 3 problems into 1, we will need some tricks to turn it into a multi class problem. we can simply concatenate 3 labels into one turning them into  $\{ [0,0,0], [0,0,1], [0,1,0], \dots, [1,1,1] \}$  of multi class, then construct the tree using the same functions we have. The prediction label at the leaf node will be assign with the maximum occurrence of the label. Here's the catch, the multi class isn't merge into one as strings but as arrays, so that we can calculate the max occurrence of each bit when the leaf node is reached. (e.g. take multi class labels, calculate max occurrence of the first bit, then the 2nd bit, then the 3rd, assign the array to leaf).

We also need to change the calculation of impurity. Here we present similar method which still use the same information entropy. In the following equations.  $i$  represent the label number (We have 3 independent classifier),  $j$  represent the distinct value of a label(We got 2 because we are having binary classification.)

$$I(\frac{p}{p+n}, \frac{n}{p+n}) = -\frac{p}{p+n} \log_2 \frac{p}{p+n} - \frac{n}{p+n} \log_2 \frac{n}{p+n}$$

$$Remainder(A) = \frac{1}{3} \sum_{i=1}^3 \sum_{j=1}^2 \frac{p_{ij} + n_{ij}}{p_i + n_i} I(\frac{p_{ij}}{p_{ij} + n_{ij}} + \frac{n_{ij}}{p_{ij} + n_{ij}})$$

$$Gain(A) = \frac{1}{3} \sum_{i=1}^3 I(\frac{p_i}{p+n} + \frac{n_i}{p+n}) - Remainder(A)$$

Now with this, we can predict 3 binary labels at once using one training dataset that constructed this single tree. The traversal of the tree will work as the way it is without changing anything.

## Conclusion

Decision Tree is able to find decisive features for classification in a short time. In our experiment, decision tree with depth 2 performs the best overall with the features time, serum sodium and serum creatinine. However, we know that after pruning the tree layer 1 decisions are all leading to the same class for each of them meaning they can be removed. After all, time is what separate the label the most for our classification dataset.

Decision Tree also more capable on reasoning, we can see the decision process and try to change the decision by changing the threshold of a node. In the other hand, SVM is harder to interpret with the prediction, we can only rely on the training set it fit is a good generalization of data set of the task.