# **CSE 521: DATA MINING PROJECT**

# USING WEKA AND ORANGE FOR DESCRIPTIVE AND NON-DESCRIPTIVE CLASSIFIERS ON BAKARY DATA

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## **OUTLINE**

# **TOOL 1: WEKA**

- 1.1 Data Preparation
- 1.2 Data Preprocessing
- 1.3 Experiment 1
- 1.4 Experiment 2
- 1.5 Experiment 3

# **TOOL 2: ORANGE**

- 2.1 Data Preprocessing
- 2.2 Experiment 1
- 2.3 Experiment 2
- 3. Final Analysis of Data and Tools used.

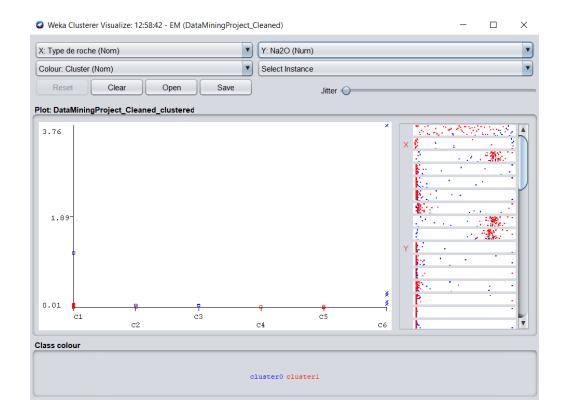
# **Data Preparation**

### 1. File Preparation

- The file contains two extra spreadsheets which were empty, they were removed.
- The initial dataset contains a duplicate of the class "type de roche". This has been removed.
- The attribute "Li" has an instance that contains "<". The value was set as "< 3". This has been changed to 2.99.
- The attribute "U" had a special missing value with "?" entry. This was changed to empty and later dealt with in the "Missing Data" section.
- An empty attribute called "ppms" was found and deleted.
- The first attribute named "Enchillion" was removed as it was found to have no significance with the class prediction. The class "Type de roche" was moved to the end of the attributes.
- It was noticed that since the names of the prediction class "type de roche" were very big, it made things unclear. Hence, the names of the class are changed to C1, C2, C3, C4, C5 and C6 respectively.
- There were also some spelling errors in the name of the "type de roche" attributes which were solved by changing the names with the notations mentioned in the previous point.
- Removed the first row as weka considered it as an empty value.

#### 2. Outlier Detection:

- For outlier detection, we have used Clustering as a method of identification. This can be done using the "Cluster" feature in Weka.
- NOTE: Important point to be noted here is that while clustering, the data needs to be evaluated per class and not over it's range since we are dealing with under-represented classes as well.
- Example:



Here, you can notice that we spotted a clear outlier for class C6 and one outlier for class C1.

Outliers for all the attributes have been cleaned using the same method.

- The values have been removed using the "RemoveWithValues" filter which can be found under "weka.filters.unsupervised.instance".
- The clusters can be visualised using the "Visualize Cluster" feature.
- Given the small number of data, only outliers in "Expert advised important" attributes were strictly evaluated (>3\*sd). For all other attributes, outliers have been removed if they are > 5\*sd. This is because if all the instances appearing to be outliers are removed, then the data is significantly reduced.

### 3. Missing Data:

- In the given data, there are a total of 48 attributes (excluding the prediction class). Many of these attributes have missing values.

### Case Scenario 1:

For the attributes named "Co" and "Mo", the missing values consist of 85% and 89% of the total data. As such, these are too high to have any meaningful contribution to the learning process and are thus dropped.

- Case Scenario 2:

For the rest of the attributes, all of them have missing values. For these attributes, the missing values are replaced with the mean values. In Weka, you can do this by ReplaceMissingValues filter present under filters.unsupervised.attributes.

#### For Dataset: PD

1. Attribute Selection:

Weka provides the ability to select the best possible subset based on user defined criterias. This can be found in filters under "supervised.attribute".

The tool can be divided into two subparts:

- Attribute Evaluator
- Search Method

For our experiment, we used the "CfsSubsetEval" as it evaluates the worth of a subset of attributes by considering the individual predictive ability along with the degree of redundancy between them and the "BestFirst" search method as it uses a greedy hill climbing approach with a backtracking facility.

The motivation behind this is

The final set of attributes selected are: Al2O3, MgO, S, Zn, Cu, Cd, Sr and Rb.

#### For Dataset : PED

1. Attribute Selection:

For this particular dataset, we will use the attributes which are determined as most important by the expert, which are: S, Zn, Pb, Cu, CaO+MgO, CaO, MgO and Fe2O3.

# Data Preprocessing

### For Dataset: PD1 and PED1

1. Data Discretization:

We implemented two methods of Discretization here, namely Equal Width and Equal Frequency Binning.

**Equal Width Binning:** 

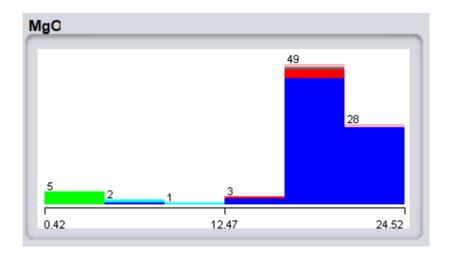
In this method, we decided to apply Equal Width Binning to the attributes which had a comparatively equitable distribution over the range of min to max values.

The idea here is to bin the element with respect to width to create more balanced bins.

This can be done in weka using the Discretize feature under weka.filters.unsupervised.attributes.

NOTE: Weka provides a feature that allows for finding the optimized number of bins for a particular attribute. We set the maximum bins to 3!

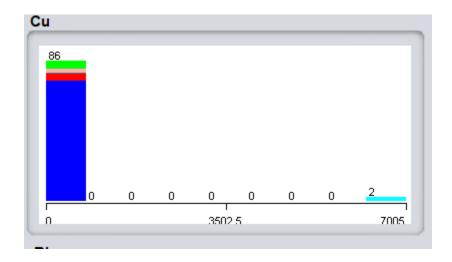
Example of an attribute selected for Equal Width Binning:



### Equal Frequency Binning:

For Equal Frequency Binning, we decided to choose attributes in which the data is highly skewed. In such cases, equal frequency binning should theoretically help with our splits for the tree.

Example of an attribute selected for Equal Frequency Binning:



### 2. Principal Component Analysis:

For Experiment 1, we added Principal Component Analysis to check for its impact on performance. Although it improved the performance by a factor of 1-3%, it made understanding the rules of the tree quite difficult.

Thus, we decided to not use this method in our final approach but instead, decided to highlight the use of PCA and its impact on the performance so that if the readability of

the decision trees isn't a requirement, this method can be used to gain a fraction of performance.

PCA can be applied by using the Filter "PrincipalComponents" under weka.filters.unsupervised.attributes.

### 3. Other methods used and considered:

As a means of Normalization of data for our Neural Networks, we decided to experiment with both "Normalize" and "Standardize" filters available in weka. "Normalize", as the name suggests, is used to Normalize the numeric data whereas "Standardize" uses a z-score metric.

We found that for our dataset, both do not have any impact on the performance. These can be found under weka.filters.unsupervised.attributes

# **Experiment 1**

## 1. Decision Tree Classifier Using PD and PED

- Tool 1: WEKA

The two trees used as Descriptive Classifiers are LMT and J48.

Tree 1: LMT

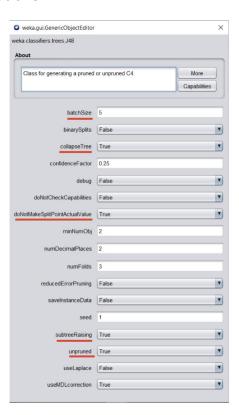
Training method: Cross-Validation with 25 folds.

Tree 2: J48

Training Method: 70-30 dataset split for training and testing.

# **Tree Configurations:**





The red markers indicate the changes made from default configurations.

# In-depth Analysis of both the trees for Dataset PD:

### LMT.

Correctly Classified Instances	83	94.3182 %
Incorrectly Classified Instances	5	5.6818 %
Kappa statistic	0.8016	
Mean absolute error	0.0206	
Root mean squared error	0.1394	
Relative absolute error	19.0318 %	
Root relative squared error	63.087 %	
Total Number of Instances	88	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.986	0.071	0.986	0.986	0.986	0.915	0.994	0.999	C1
	0.750	0.000	1.000	0.750	0.857	0.861	0.991	0.893	C2
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	C3
	0.000	0.023	0.000	0.000	0.000	-0.016	0.207	0.014	C4
	0.000	0.012	0.000	0.000	0.000	-0.016	0.930	0.216	C5
	1.000	0.012	0.833	1.000	0.909	0.907	0.998	0.967	C6
Weighted Avg.	0.943	0.061	0.945	0.943	0.943	0.882	0.984	0.963	

```
a b c d e f <-- classified as
73 0 0 0 0 1 | a = C1
1 3 0 0 0 0 0 | b = C2
0 0 2 0 0 0 | c = C3
0 0 0 0 1 0 | d = C4
0 0 0 2 0 0 0 | e = C5
0 0 0 0 0 0 5 | f = C6
```

## J48.

Correctly Classified Instances	80	90.9091 %
Incorrectly Classified Instances	8	9.0909 %
Kappa statistic	0.6614	
Mean absolute error	0.0252	
Root mean squared error	0.1476	
Relative absolute error	23.2736 %	
Root relative squared error	66.9218 %	
Total Number of Instances	88	

#### === Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.143	0.974	1.000	0.987	0.914	0.959	0.985	C1
	0.750	0.024	0.600	0.750	0.667	0.653	0.872	0.761	C2
	0.000	0.012	0.000	0.000	0.000	-0.016	0.988	0.667	C3
	0.000	0.023	0.000	0.000	0.000	-0.016	0.489	0.011	C4
	0.000	0.012	0.000	0.000	0.000	-0.016	0.988	0.667	C5
	0.600	0.000	1.000	0.600	0.750	0.765	0.888	0.700	C6
Weighted Avg.	0.909	0.122	0.903	0.909	0.903	0.840	0.947	0.933	

a	b	С	d	е	f		< classified	as
74	0	0	0	0	0	I	a = C1	
0	3	1	0	0	0		b = C2	
0	2	0	0	0	0	I	c = C3	
0	0	0	0	1	0	I	d = C4	
0	0	0	2	0	0	I	e = C5	
2	0	0	0	0	2	1	£ = C6	

# In-depth Analysis of both the trees for Dataset PED:

## LMT.

=== Summary ===

Correctly Classified Instances	25	96.1538 %
Incorrectly Classified Instances	1	3.8462 %
Kappa statistic	0.8354	
Mean absolute error	0.0729	
Root mean squared error	0.1545	
Relative absolute error	26.7186 %	
Root relative squared error	42.7578 %	
Total Number of Instances	26	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.250	0.957	1.000	0.978	0.847	1.000	1.000	C1
	0.750	0.000	1.000	0.750	0.857	0.847	1.000	1.000	notC1
Weighted Avg.	0.962	0.212	0.963	0.962	0.959	0.847	1.000	1.000	

=== Confusion Matrix ===

a b <-- classified as
22 0 | a = C1</pre>

1 3 | b = notC1

### J48.

Correctly Classified Instances	81	92.0455 %
Incorrectly Classified Instances	7	7.9545 %
Kappa statistic	0.7308	
Mean absolute error	0.0216	
Root mean squared error	0.1316	
Relative absolute error	21.5468 %	
Root relative squared error	62.3069 %	
Total Number of Instances	88	

### === Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.067	0.986	1.000	0.993	0.960	0.967	0.986	C1
	0.750	0.024	0.600	0.750	0.667	0.653	0.868	0.574	C2
	0.000	0.000	?	0.000	?	?	0.750	0.511	C3
	0.000	0.023	0.000	0.000	0.000	-0.016	0.489	0.011	C4
	0.000	0.012	0.000	0.000	0.000	-0.016	0.988	0.667	C5
	1.000	0.012	0.833	1.000	0.909	0.907	0.992	0.783	C6
	0.000	0.000	?	0.000	?	?	0.483	0.011	c7
Weighted Avg.	0.920	0.058	?	0.920	?	?	0.948	0.916	

a	b	С	d	е	f	g		< classified	as
73	0	0	0	0	0	0	I	a = C1	
1	3	0	0	0	0	0	I	b = C2	
0	2	0	0	0	0	0	I	c = C3	
0	0	0	0	1	0	0	I	d = C4	
0	0	0	2	0	0	0	I	e = C5	
0	0	0	0	0	5	0	I	f = C6	
0	0	0	0	0	1	0	ı	g = C7	

# 2. Neural Network Classifier Using PD and PED

Network 1: MultiLayer Perceptron

Network Details: Batch Size: 100 Hidden Layers: 100 learningRate: 0.4 Decay: True

Seed: 10 Epoch: 500

Cross Validation Folds: 10

Network 2: MultiClassClassifier

Network Details: Batch Size: 10

Underlying Classifier: MultiLayer Perceptron

logLossDecoding: True

Method: Random correction code

Seed: 10

Activation function: Sigmoid

# In depth Analysis of the MultiLayer Perceptron on PD:

Correctly Classified Instances	82	93.1818 %
Incorrectly Classified Instances	6	6.8182 %
Kappa statistic	0.7459	
Mean absolute error	0.0243	
Root mean squared error	0.1269	
Relative absolute error	22.3938 %	
Root relative squared error	57.5336 %	
Total Number of Instances	88	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.143	0.974	1.000	0.987	0.914	0.997	0.999	C1
	0.750	0.012	0.750	0.750	0.750	0.738	0.982	0.850	C2
	0.500	0.000	1.000	0.500	0.667	0.703	1.000	1.000	C3
	0.000	0.023	0.000	0.000	0.000	-0.016	0.345	0.017	C4
	0.000	0.012	0.000	0.000	0.000	-0.016	0.895	0.141	C5
	0.800	0.000	1.000	0.800	0.889	0.889	1.000	1.000	C6
Weighted Avg.	0.932	0.121	0.932	0.932	0.929	0.868	0.987	0.962	

```
a b c d e f <-- classified as
74 0 0 0 0 0 0 | a = C1
1 3 0 0 0 0 | b = C2
1 0 1 0 0 0 | c = C3
0 0 0 0 1 0 | d = C4
0 0 0 2 0 0 | e = C5
0 1 0 0 0 4 | f = C6
```

# In depth Analysis of the MultiClass Classifier on PD:

84	95.4545 %
4	4.5455 %
0.8362	
0.0159	
0.1207	
14.5992 %	
54.687 %	
88	
	4 0.8362 0.0159 0.1207 14.5992 % 54.687 %

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.071	0.987	1.000	0.993	0.957	0.992	0.998	C1
	0.750	0.000	1.000	0.750	0.857	0.861	0.958	0.806	C2
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	C3
	0.000	0.023	0.000	0.000	0.000	-0.016	0.908	0.111	C4
	0.000	0.012	0.000	0.000	0.000	-0.016	0.733	0.069	C5
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	C6
Weighted Avg.	0.955	0.061	0.955	0.955	0.954	0.923	0.984	0.959	

```
a b c d e f <-- classified as
74 0 0 0 0 0 0 | a = C1
1 3 0 0 0 0 | b = C2
0 0 2 0 0 0 | c = C3
0 0 0 0 1 0 | d = C4
0 0 0 2 0 0 0 | e = C5
0 0 0 0 0 0 5 | f = C6
```

# In depth Analysis of the MultiLayer Perceptron on PED:

Correctly Classified Instances	83	94.3182 %
Incorrectly Classified Instances	5	5.6818 %
Kappa statistic	0.7878	
Mean absolute error	0.0189	
Root mean squared error	0.1074	
Relative absolute error	17.3803 %	
Root relative squared error	48.6513 %	
Potal Number of Instances	88	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.143	0.974	1.000	0.987	0.914	0.993	0.999	C1
	0.750	0.024	0.600	0.750	0.667	0.653	0.976	0.833	C2
	0.000	0.000	?	0.000	?	?	1.000	1.000	C3
	0.000	0.000	?	0.000	?	?	0.632	0.030	C4
	1.000	0.012	0.667	1.000	0.800	0.812	1.000	1.000	C5
	0.800	0.000	1.000	0.800	0.889	0.889	1.000	1.000	C6
Weighted Avg.	0.943	0.121	?	0.943	?	?	0.989	0.980	

```
a b c d e f <-- classified as
74 0 0 0 0 0 0 | a = C1
1 3 0 0 0 0 | b = C2
1 1 0 0 0 0 | c = C3
0 0 0 0 1 0 | d = C4
0 0 0 0 0 2 0 | e = C5
0 1 0 0 0 4 | f = C6
```

### In depth Analysis of the MultiClass Classifier on PED:

```
Correctly Classified Instances 84
Incorrectly Classified Instances 4
Kappa statistic 0.83
Mean absolute error 0.0158
Root mean squared error 0.1236
                                                               95.4545 %
                                                                4.5455 %
Mean absolute error
Root mean squared error
                                              0.1236
                                           14.6238 %
Relative absolute error
Root relative squared error
                                          56.015 %
Total Number of Instances
=== Detailed Accuracy By Class ===
                   TP Rate FP Rate Precision Recall F-Measure MCC
                                                                                    ROC Area PRC Area Class
                   1.000 0.143 0.974 1.000 0.987 0.914 0.965 0.993 C1
                   0.750 0.024 0.600 0.750 0.667 0.653 0.872 0.709 C2
0.000 0.000 ? 0.000 ? 0.983 0.700 C3
0.000 0.000 ? 0.000 ? ? 0.920 0.125 C4
1.000 0.000 1.000 1.000 1.000 1.000 1.000 1.000 C5
1.000 0.000 1.000 1.000 1.000 1.000 1.000 1.000 C6
Weighted Avg. 0.955 0.121 ? 0.955 ? ? 0.964 0.964
=== Confusion Matrix ===
  a b c d e f <-- classified as
  74 0 0 0 0 0 | a = C1
  1 3 0 0 0 0 | b = C2
  1 1 0 0 0 0 | c = c3
  0 1 0 0 0 0 | d = C4
  0 0 0 0 2 0 | e = C5
   0 \ 0 \ 0 \ 0 \ 0 \ 5 \ | \ f = C6
```

### Summary and Analysis of Experiment 1:

Here is the summary of our results for Experiment 1.

Dataset/Netwo rk Accuracy	LMT	J48	NN1	NN2
PD	94.32%	90.9%	93.18%	95.45%
PED	96.15%	92.04%	93.32%	95.45%

Initially, we approached the problem by working on all the attributes provided in the dataset. But we quickly realized that there was a big gap between the performance of PD and PED dataset.

Thus, we decided to modify the PD dataset by selecting a better set of attributes using methods discussed in the Data Preprocessing subpart and found our results to be much closer to the dataset with expert provided attributes.

In our experiment, we found that LMT does a much better job than J48. LMT uses a classification model with logistic regression functions at the leaves. We found that the rules of LMT were better suited.

The reason for such a conclusion is that after checking the models over various dataspliting methods, we noticed that both the trees do a very good job at classifying the class "C1", with no misclassifications noticed. However, J48 made more errors when it comes to underrepresented classes. This is where LMT outperformed J48.

In the case of our Neural Networks, we noticed that the results were surprisingly very similar even though the datasets in question here had quite different attributes. This shows that although the expert data is still better, using machine learning techniques to define a better subset of attributes for classification can provide for an accurate result in the absence of an expert.

# **Experiment 2**

### 3. Decision Tree Contrast Classifier Using PD and PED

- The two trees used as Descriptive Classifiers are LMT and J48.

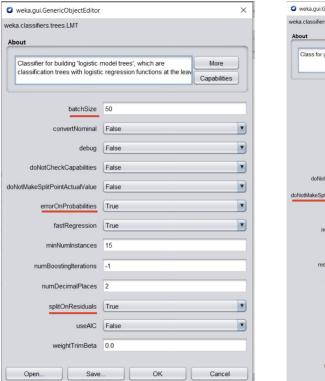
Tree 1: LMT

Training method: 70-30 dataset split for training and testing.

Tree 2: J48

Training Method: Cross-Validation with 25 Folds.

# **Tree Configurations:**





The red markers indicate the changes made from default configurations.

# In-depth Analysis of both the trees for Dataset PD:

### **LMT**

Correctly Classified Instances	26	100	8
Incorrectly Classified Instances	0	0	8
Kappa statistic	1		
Mean absolute error	0.042		
Root mean squared error	0.1076		
Relative absolute error	15.4039 %		
Root relative squared error	29.7804 %		
Total Number of Instances	26		

#### === Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	C1
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	notC1
Weighted Avg.	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	

=== Confusion Matrix ===

a b <-- classified as
22 0 | a = C1
0 4 | b = notC1</pre>

### **J48**

Correctly Classified Instances	85	96.5909 %
Incorrectly Classified Instances	3	3.4091 %
Kappa statistic	0.8688	
Mean absolute error	0.0376	
Root mean squared error	0.1849	
Relative absolute error	13.7289 %	
Root relative squared error	50.3119 %	
Total Number of Instances	88	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.986	0.143	0.973	0.986	0.980	0.870	0.986	0.996	C1
	0.857	0.014	0.923	0.857	0.889	0.870	0.986	0.881	notC1
Weighted Avg.	0.966	0.122	0.965	0.966	0.965	0.870	0.986	0.978	

=== Confusion Matrix ===

a b <-- classified as
73 1 | a = C1</pre>

2 12 | b = notC1

# In-depth Analysis of both the trees for Dataset PED:

### LMT.

=== Summary =	==
---------------	----

Correctly Classified Instances	25	96.1538 %
Incorrectly Classified Instances	1	3.8462 %
Kappa statistic	0.8354	
Mean absolute error	0.0729	
Root mean squared error	0.1545	
Relative absolute error	26.7186 %	
Root relative squared error	42.7578 %	
Total Number of Instances	26	

#### === Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.250	0.957	1.000	0.978	0.847	1.000	1.000	C1
	0.750	0.000	1.000	0.750	0.857	0.847	1.000	1.000	notC1
Weighted Avg.	0.962	0.212	0.963	0.962	0.959	0.847	1.000	1.000	

=== Confusion Matrix ===

a b <-- classified as

22 0 | a = C1

1 3 | b = notC1

### J48.

Correctly Classified Instances	84	95.4545 %
Incorrectly Classified Instances	4	4.5455 %
Kappa statistic	0.8079	
Mean absolute error	0.0512	
Root mean squared error	0.2145	
Relative absolute error	18.7116 %	
Root relative squared error	58.3655 %	
Total Number of Instances	88	

### === Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.286	0.949	1.000	0.974	0.823	0.914	0.969	C1
	0.714	0.000	1.000	0.714	0.833	0.823	0.914	0.827	notC1
Weighted Avg.	0.955	0.240	0.957	0.955	0.951	0.823	0.914	0.946	

=== Confusion Matrix ===

a b <-- classified as

74 0 | a = C1

4 10 | b = notC1

# 4. Neural Network Contrast Classifier Using PD and PED

Network 1: MultiLayer Perceptron

Network Details: Batch Size: 100 Hidden Layers: 100 learningRate: 0.4 Decay: True

Seed: 10 Epoch: 500

Cross Validation Folds: 10

Network 2: MultiClassClassifier

Network Details: Batch Size: 10

Underlying Classifier: MultiLayer Perceptron

logLossDecoding: True

Method: Random correction code

Seed: 10

# In depth Analysis of the MultiLayer Perceptron for contrast classification on PD:

Correctly Classified Instances			87		98.8636	8			
Incorrectly Clas	ssified In	nstances	1		1.1364	8			
Kappa statistic			0.95	63					
Mean absolute error		0.01	.91						
Root mean square	ed error		0.10	86					
Relative absolut	te error		6.98	32 %					
Root relative so	quared err	or	29.56	511 <del>%</del>					
Total Number of	Instances	3	88						
=== Detailed Acc	curacy By	Class ===	:						
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.071	0.987	1.000	0.993	0.957	1.000	1.000	C1
	0.929	0.000	1.000	0.929	0.963	0.957	1.000	1.000	notC1
Weighted Avg.	0.989	0.060	0.989	0.989	0.988	0.957	1.000	1.000	
=== Confusion Ma	atrix ===								
a b < cla	assified a	as							
74 0   a = C1									
1 13   b = notC1									

# In depth Analysis of the MultiClass Classifier for contrast classification on PD:

a b <-- classified as

74 0 | a = C1 5 9 | b = notC1

Correctly Classi	fied Inst	ances	83		94.3182	8			
Incorrectly Clas	sified In	stances	5		5.6818	8			
Kappa statistic		0.7517							
Mean absolute error			0.06	3					
Root mean squared error			0.23	17					
Relative absolute error			23.01	.04 %					
Root relative squared error			63.19	18 %					
Total Number of Instances			88						
=== Detailed Accuracy By Class ===									
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.357	0.937	1.000	0.967	0.776	0.784	0.874	C1
	0.643	0.000	1.000	0.643	0.783	0.776	0.784	0.805	notC1
Weighted Avg.	0.943	0.300	0.947	0.943	0.938	0.776	0.784	0.863	
=== Confusion Ma	=== Confusion Matrix ===								

# In depth Analysis of the MultiLayer Perceptron for contrast classification on PED:

Correctly Classified Instances			86		97.7273	8			
Incorrectly Cla	ssified In	nstances	2		2.2727	8			
Kappa statistic	:		0.90	98					
Mean absolute error			0.03	57					
Root mean squar	Root mean squared error			86					
Relative absolu	te error		13.05	61 %					
Root relative s	quared er	or	43.15	47 %					
Total Number of	Instances	3	88						
=== Detailed Ad	curacy By	Class ===	:						
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.143	0.974	1.000	0.987	0.914	0.994	0.999	C1
	0.857	0.000	1.000	0.857	0.923	0.914	0.994	0.974	notC1
Weighted Avg.	0.977	0.120	0.978	0.977	0.977	0.914	0.994	0.995	
=== Confusion N	Matrix ===								
	assified a	as							
74 0   a = 0									
2 12   b = r	iotC1								

## In depth Analysis of the MultiClass Classifier for contrast classification on PED:

Correctly Classi	fied Inst	ances	85		96.5909	8			
Incorrectly Clas	sified In	stances	3		3.4091	8			
Kappa statistic			0.86	05					
Mean absolute error 0.0			0.04	27					
Root mean squared error 0.1792			92						
Relative absolute error			15.50	24 %					
Root relative squared error			48.91	.33 %					
Total Number of Instances			88						
=== Detailed Acc	ursen Bu	Class ===							
Detailed Acc	uracy by	Class							
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.214	0.961	1.000	0.980	0.869	0.926	0.953	C1
	0.786	0.000	1.000	0.786	0.880	0.869	0.926	0.920	notC1
Weighted Avg.	0.966	0.180	0.967	0.966	0.964	0.869	0.926	0.948	
=== Confusion Ma	trix ===								
a b < cla	eeified s								
		.5							
74 0   a = C1									
3 11   b = no	tC1								

# Summary and Analysis of Experiment 2:

Here is the summary of our results for Experiment 2.

Dataset/Netwo rk Accuracy	LMT	J48	NN1	NN2
Contrast PD	100%	96.6%	98.86%	94.31%
Contrast PED	96.17%	95.45%	97.72%	96.59%

To our surprise, LMT provided a perfect accuracy score for the contrast PD classification. As we noticed in the previous segment, LMT was working perfectly with class C1 but had a few errors when it came to under-represented classes. Now that those classes have been grouped together, it shows perfect results.

This is what the tree looks like:

```
LM_1:

Class C1:

1.25 +

[MgO] * 0.11 +

[S] * -0 +

[Zn] * -0 +

[Rb] * -0.03

Class notC1:

-1.25 +

[MgO] * -0.11 +

[S] * 0 +

[Zn] * 0 +

[Rb] * 0.03
```

Now, J48, although a few errors in class "notC1" were expected, it makes an error for class "C1" as well.

Again, for Neural Networks, we notice that the MultiClass Classifier performs worse. This was a surprise as it is built on MultiLayer Perceptron with additional functionalities like "1 against 1" or "1 against all" functionalities. However, for multilayer perceptron, we again notice a close accuracy between the PD and PED dataset indicating the effectiveness of the chosen attributes for PD.

# **Experiment 3**

# 5. Decision Tree Classifier Using PD1 and PED1:

The two trees used as Descriptive Classifiers are LMT and J48.

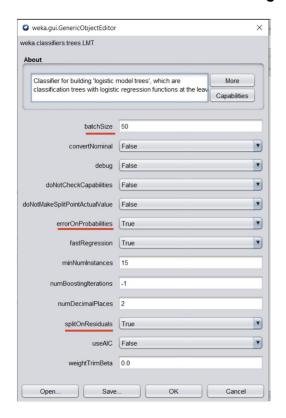
Tree 1: LMT

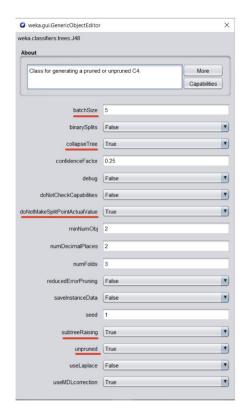
Training method: Cross-Validation with 25 folds.

Tree 2: J48

Training Method: 70-30 dataset split for training and testing.

### **Tree Configurations:**





The red markers indicate the changes made from default configurations.

# In-depth Analysis of both the trees for Dataset PD1:

### M1 Classifier: J48 with Cross-Validation.

=== Sum	mary	=	_
---------	------	---	---

Correctly Classified Instances	85	96.5909 %
Incorrectly Classified Instances	3	3.4091 %
Kappa statistic	0.8688	
Mean absolute error	0.0553	
Root mean squared error	0.1845	
Relative absolute error	20.1976 %	
Root relative squared error	50.2063 %	
Total Number of Instances	88	

#### === Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.986	0.143	0.973	0.986	0.980	0.870	0.857	0.945	C1
	0.857	0.014	0.923	0.857	0.889	0.870	0.857	0.814	notC1
Weighted Avg.	0.966	0.122	0.965	0.966	0.965	0.870	0.857	0.924	

=== Confusion Matrix ===

a b <-- classified as
73 1 | a = C1</pre>

2 12 | b = notC1

# M2 Classifier: J48 with Binary Splits.

#### === Summary ===

Correctly Classified Instances	85	96.5909 %
Incorrectly Classified Instances	3	3.4091 %
Kappa statistic	0.8688	
Mean absolute error	0.0624	
Root mean squared error	0.19	
Relative absolute error	22.811 %	
Root relative squared error	51.7134 %	
Total Number of Instances	88	

#### === Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.986	0.143	0.973	0.986	0.980	0.870	0.858	0.941	C1
	0.857	0.014	0.923	0.857	0.889	0.870	0.858	0.799	notC1
Weighted Avg.	0.966	0.122	0.965	0.966	0.965	0.870	0.858	0.919	

=== Confusion Matrix ===

a b <-- classified as

73 1 | a = C1

2 12 | b = notC1

Discriminant Rules of both the trees for Dataset PD1:

### M1 Classifier: J48 with Cross-Validation.

```
Al203 = '(-inf-4.52]'

| Zn = '(-inf-826.333333]'

| S = '(-inf-12955.666667]': C1 (76.0/2.0)

| S = '(12955.666667-25873.3333333]': notC1 (2.0)

| S = '(25873.333333-inf)': notC1 (2.0)

| Zn = '(826.333333-inf)': notC1 (3.0)

Al203 = '(4.52-inf)': notC1 (5.0)
```

An easier way to interpret this is:

Note that the rules of the tree should be represented as in the image, the second interpretation is for ease of understanding.

### M2 Classifier: J48 with Binary Splits.

```
s = '(-inf-12955.666667]'
| Al203 = '(-inf-4.52]'
| Zn = '(-inf-826.333333]': C1 (76.0/2.0)
| Zn != '(-inf-826.333333]': notC1 (3.0)
| Al203 != '(-inf-4.52]': notC1 (3.0)
s != '(-inf-12955.666667]': notC1 (6.0)
```

An easier way to interpret this is:

Note that the rules of the tree should be represented as in the image, the second interpretation is for ease of understanding.

## In-depth Analysis of both the trees for Dataset PED1:

# M1 Classifier: J48 with Cross-Validation.

Correctly Classified Instances	84	95.4545 %
Incorrectly Classified Instances	4	4.5455 %
Kappa statistic	0.8197	
Mean absolute error	0.0565	
Root mean squared error	0.1998	
Relative absolute error	20.6378 %	
Root relative squared error	54.3802 %	
Total Number of Instances	88	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.986	0.214	0.961	0.986	0.973	0.823	0.854	0.943	C1
	0.786	0.014	0.917	0.786	0.846	0.823	0.854	0.804	notC1
Weighted Avg.	0.955	0.182	0.954	0.955	0.953	0.823	0.854	0.921	

```
a b <-- classified as
```

<sup>73 1 |</sup> a = C1

<sup>3 11 |</sup> b = notC1

### M2 Classifier: J48 with Binary Splits.

```
=== Summary ===
Incorrectly Classified Instances 3
Kappa statistic
                                                         96.5909 %
                                       3
0.8688
                                                           3.4091 %
Kappa statistic
                                         0.0567
Mean absolute error
                                         0.1902
Root mean squared error
Relative absolute error
                                        20.7056 %
Root relative squared error
                                       51.7713 %
Total Number of Instances
=== Detailed Accuracy By Class ===
                 TP Rate FP Rate Precision Recall F-Measure MCC ROC Area PRC Area Class 0.986 0.143 0.973 0.986 0.980 0.870 0.857 0.945 C1 0.857 0.014 0.923 0.857 0.889 0.870 0.857 0.799 notC1
                                                                                       0.799
Weighted Avg. 0.966 0.122 0.965 0.966 0.965 0.870 0.857 0.921
=== Confusion Matrix ===
  a b <-- classified as
 73 1 | a = C1
  2 12 | b = notC1
```

Discriminant Rules of both the trees for Dataset PED1:

### M1 Classifier: J48 with Cross-Validation.

```
s = '(-inf-12955.666667]'
| CaO+MgO = '(-inf-19.836667]': notC1 (3.0)
| CaO+MgO = '(19.836667-39.193333]': C1 (3.0/1.0)
| CaO+MgO = '(39.193333-inf)'
| Zn = '(-inf-826.333333]': C1 (73.0/1.0)
| Zn = '(826.333333-inf)': notC1 (3.0)
s = '(12955.666667-25873.333333]': notC1 (3.0)
```

An easier way to interpret this is:

Note that the rules of the tree should be represented as in the image, the second interpretation is for ease of understanding.

### M2 Classifier: J48 with Binary Splits.

```
s = '(-inf-12955.666667]'
| MgO = '(-inf-8.453333]': notC1 (5.0/1.0)
| MgO != '(-inf-8.453333]'
| Zn = '(-inf-826.333333]': C1 (74.0/1.0)
| Zn != '(-inf-826.333333]': notC1 (3.0)
s != '(-inf-12955.666667]': notC1 (6.0)
```

An easier way to interpret this is:

Note that the rules of the tree should be represented as in the image, the second interpretation is for ease of understanding.

Summary and Analysis of Experiment 3:

Here is the summary of our results for Experiment 3.

Dataset/Network Accuracy	M1	M2
PD1	96.6%	96.4%
PED1	95.45%	96.6%

The interesting conclusion of this was to see the use of different attributes be used as a result of using binary splits or not. The broader conclusion based on discriminant rules is that since the notC1 classes, despite being pooled together, are still underrepresented, the tree makes error in differentiating between them.

It is also interesting to note the changes in the attributes still lead to a misclassification in the same class subgroup.

### **TOOL 2: ORANGE**

# Data Preprocessing

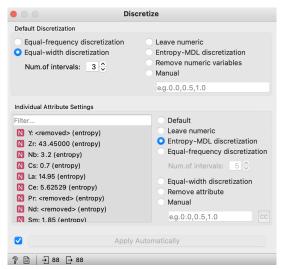
# Descriptive Classifier For Dataset: PD1 and PED1

1. PD1: Data Discretization

Method 1: Equal-width discretization

Evenly splits the range between the smallest and the largest observed value.

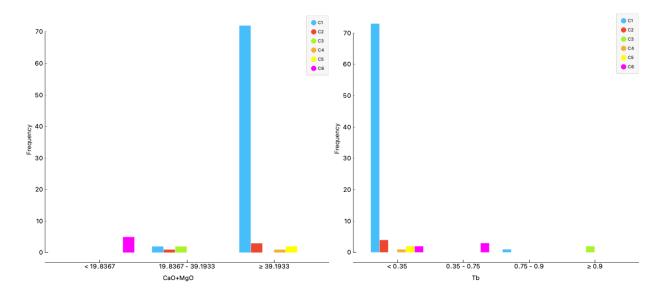
**Method 2:** Entropy-MDL discretization (top-down discretization) Recursively splits the attribute at a cut maximizing information gain, until the gain is lower than the minimal description length of the cut.



We used the above two methods to create a set PD1 with no more than 4 bins. For the first half of these total 46 attributes(from CaO+MgO to Li), we applied method 1, the Equal-width discretization, and set the intervals as 3. For the rest half of these attributes, we applied method 2, the Entropy-MDL discretization.

In the end, we got our new set PD1, and each attribute has at most 3 bins. Following are 2 examples from method1 and 2.

Method 1:	Method 2:



2. **PED1:** By using the "Select Columns" tool in ORANGE, we simply picked out the most important 8 attributes and created the new subset PED1.

# Non - Descriptive Classifier

### For Dataset: PD and PED

ORANGE uses the default method of normalization, it normalizes the data by centering to mean and scaling to standard deviation of 1.

Therefore, we can simply create datasets PD and PED.

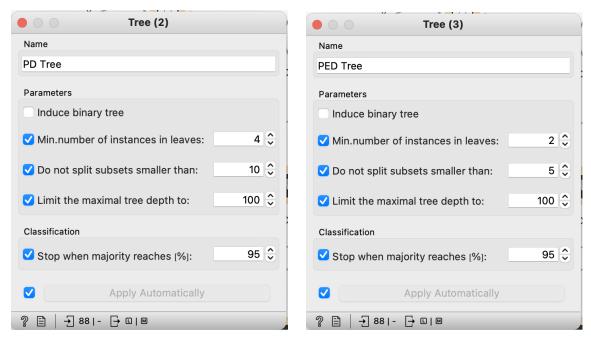
# Experiment 1

# 1. Decision Tree Classifier Using PD and PED

Tool: ORANGE

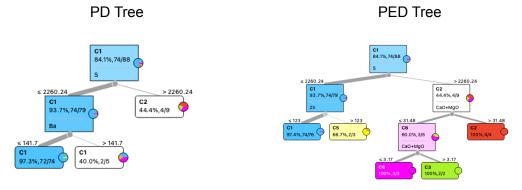
- Testing Method: 10-folds Cross-Validation

Parameters setting:

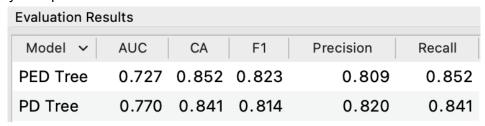


Simply changed the minimum number of instances in leaves and the split point, to see how these factors will impact the accuracy of classifiers.

### - Tree Viewer:



### - Accuracy Compare:



AUC: Area under ROC curve CA: Classification Accuracy

From the table we can see that PED Tree with lower number of instances in leaves and split point has better accuracy than PD Tree.

- Confusion Matrix:

C1 C2 C3 C4 C5 C6 C1 C2 СЗ C4 C5 C6 Σ C1 97.3 % 2.7 % 0.0 % 74 0.0 % 0.0 % 0.0 % 98.6 % 0.0 % 0.0 % 0.0 % 75.0 % 25.0 % 0.0 % 0.0 % 0.0 % 75.0 % 0.0% 0.0 % 0.0 % СЗ 0.0 % 100.0 % 0.0 % 0.0 % 0.0 % 0.0 % 0.0 % 0.0 % 0.0 % 0.0 % 50.0 % 100.0 % C4 0.0 % 0.0 % 0.0 % 0.0 % 0.0 % C4 100.0 % 0.0 % 0.0 % 0.0 % 0.0 % 0.0 %

88

**C**5

100.0 %

0.0 %

20.0 %

PED Tree

0.0 %

0.0 %

0.0 %

0.0 %

0.0 %

88

# 2. Neural Network Classifier Using PD and PED

0.0 %

0.0 %

PD Tree

0.0 %

Network Topology 1:

2

80

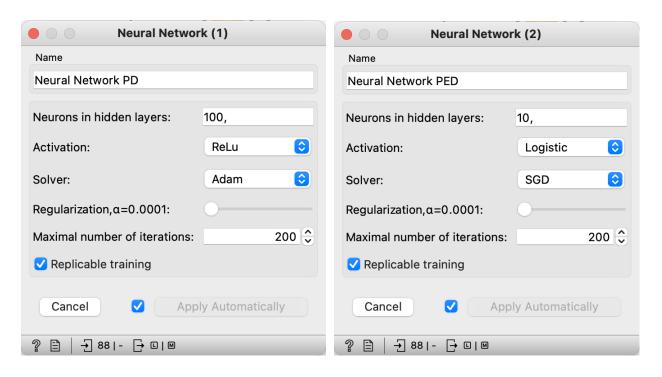
Neurons in hidden layers: 100

Activation: ReLu Solver: Adam (default)

Network Topology 2:

Neurons in hidden layers: 10,

Activation: Logistic Solver: SGD



- Testing Method: 10-folds Cross-Validation

Random Sampling(repeat train: 10; training set size: 90%)

- Accuracy Compare:

10-folds Cross-Validation:

Evaluation Results									
Model ~	AUC	CA	F1	Precision	Recall				
Neural Network PED	0.755	0.841	0.768	0.707	0.841				
Neural Network PD	0.835	0.909	0.889	0.880	0.909				

Random Sampling(repeat train: 10; training set size: 90%):

Evaluation Results									
Model ~	AUC	CA	F1	Precision	Recall				
Neural Network PED	0.606	0.844	0.773	0.713	0.844				
Neural Network PD	0.887	0.911	0.892	0.883	0.911				

- Confusion Matrix:

				Р	D							Р	FD			
				Р	redicted							Р	redicted			
		C1	C2	СЗ	C4	C5	C6	Σ		C1	C2	СЗ	C4	C5	C6	Σ
	C1	100.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	76	C1	100.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	76
	C2	66.7 %	33.3 %	0.0 %	0.0 %	0.0 %	0.0 %	6	C2	100.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	6
_	СЗ	0.0 %	100.0 %	0.0 %	0.0 %	0.0 %	0.0 %	1	_ сз	100.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	1
Actual	C4	100.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	1	C4	100.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	1
	C5	0.0 %	0.0 %	0.0 %	0.0 %	100.0 %	0.0 %	1	C5	100.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	1
	C6	20.0 %	20.0 %	0.0 %	0.0 %	0.0 %	60.0 %	5	C6	100.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	5
	Σ	82	4	0	0	1	3	90	Σ	90	0	0	0	0	0	90

# 3. Compare Descriptive with Non-Descriptive

- Accuracy Compare:

Evaluation Results								
Model	AUC	CA ~	F1	Precision	Recall			
Neural Network PD	0.835	0.909	0.889	0.880	0.909			
PED Tree	0.727	0.852	0.823	0.809	0.852			
PD Tree	0.770	0.841	0.814	0.820	0.841			
Neural Network PED	0.755	0.841	0.768	0.707	0.841			

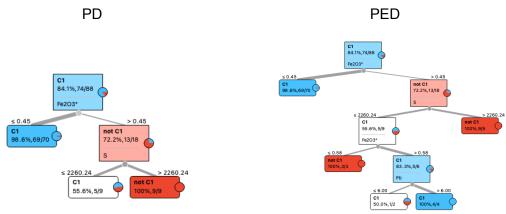
# **Experiment 2**

In order to perform the contrast classification for class **C1** with a class **notC1** that contains other classes, we first changed all the names of classes C2 to C6 into a new class named **notC1**, and this made things much easier for our next move.

Thanks to the design of Orange, we only need to change the dataset in the file widget and don't have to do anything else. All the remaining steps were automatically done in Orange since they were already done in the previous Experiment 1. Following are the results:

### 1. Decision Tree Classifier Using PD and PED

- Testing Method: 10-folds Cross-Validation
- Parameters setting: Same as Experiment 1
- Tree Viewer:



Accuracy Compare:

Evaluation Results								
Model ^	AUC	CA	F1	Precision	Recall			
PD Tree	0.875	0.864	0.854	0.850	0.864			
PED Tree	0.749	0.875	0.873	0.872	0.875			

- Confusion Matrix:

PD PED

Predicted Predicted C1 not C1 Σ C1 not C1 Σ C1 93.2 % 6.8 % 74 94.6 % C1 5.4 % 74 not C1 42.9 % 57.1 % 14 not C1 57.1 % 42.9 % 14 Σ 75 **78** 10 13 88 Σ 88

## 2. Neural Network Classifier Using PD and PED

- Network Topology: Same as Experiment 1
- Testing Method: Same as Experiment 1
- Accuracy Compare:

10-folds Cross-Validation:

Evaluation Results								
Model ^	AUC	CA	F1	Precision	Recall			
Neural Network PD	0.851	0.943	0.938	0.947	0.943			
Neural Network PED	0.776	0.841	0.768	0.707	0.841			

Random Sampling(repeat train: 10; training set size: 90%):

Evaluation Results									
Model	^	AUC	CA	F1	Precision	Recall			
Neural Network PD	)	0.923	0.922	0.915	0.920	0.922			
Neural Network PE	D	0.849	0.844	0.773	0.713	0.844			

### - Confusion Matrix:



## 3. Compare Descriptive with Non-Descriptive

- Accuracy Compare:

Evaluation Results								
Model	AUC	CA ~	F1	Precision	Recall			
Neural Network PD	0.851	0.943	0.938	0.947	0.943			
PED Tree	0.749	0.875	0.873	0.872	0.875			
PD Tree	0.875	0.864	0.854	0.850	0.864			
Neural Network PED	0.776	0.841	0.768	0.707	0.841			

# Analysis

### Of the data:

- Attribute selection plays an important role.
- Out of 49 attributes, only 12 attributes in total were deemed to be useful.
- PCA has a strong impact on performance but makes it difficult to interpret.
- The data is skewed i.e Class C1 has higher representation which leads to accurate prediction for that class but poor performance when it comes to other classes.
- Even after pooling the other classes as "notC1", it's still underrepresented leading to more errors in the "notC1" class.

### Of tools used:

- 1. The tools we used are WEKA and Orange. Both of them are good toolkits for learners to study data visualization and machine learning.
- 2. Compare the accuracy of WEKA and Orange in Experiment 1 and 2, we got the following results:

		WEKA		ORANGE	
		PD	PED	PD	PED
Ex1	Decistion Tree	94.30%	96.20%	84.10%	85.20%
		90.90%	92.10%	86.70%	84.40%
	Neural Network	93.20%	94.32%	90.90%	84.10%
		95.50%	95.50%	91.90%	84.40%
Ex2	Decistion Tree	100.00%	96.20%	86.40%	87.50%
		96.60%	95.50%	87.80%	87.80%
	Neural Network	98.90%	97.70%	94.30%	84.10%
		94.30%	96.60%	92.20%	84.40%

From the above table it is clear that WEKA tool estimates higher accuracy for both Decision Tree and Neural Network than Orange.

For Orange, the accuracy of Neural Network is better than Decision Tree when we use the PD dataset, and it shows the opposite situation when we use the PED dataset. For WEKA, although different algorithms and topologies lead to some accuracy changes, the overall accuracy rate is quite high, basically reaching over 95%. This can be attributed to the multitude of in-built features that provide for optimization techniques at various points in training.

- 3. In general, the experience with Orange is good, because the interface of Orange is nicely designed and the analytics workflow is easy to create with the use of drag and drop of its widgets. But compared with WEKA, Orange has fewer classifiers and adjustable parameters, which makes it impossible to perform more in-depth and specific analysis.
  - For instance, you cannot see how the neural network classifier looks like in Orange, but WEKA provides a clear picture to show you how it looks, therefore when you change the parameters you can notice the difference in the network. Also, the random forest widget does not allow the user to see which variables have the highest information gain.
- 4. As for preference, when dealing with complicated algorithms and huge datasets in real life, WEKA seems to be a better choice than Orange, since it has larger capabilities, more complicated algorithms and adjustable parameters which can meet users' requirements.