University of Science - VNUHCM

FACULTY OF INFORMATION TECHNOLOGY

LAB 02 REPORT

Topic: Decision Tree

Course: Artificial Intelligence

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Mục lục

1	Information					
	1.1	Student information	2			
	1.2	Check list	2			
2	Requirements					
	2.1	Preparing the data sets	2			
	2.2	Building the decision tree classifiers	3			
	2.3	Evaluating the decision tree classifiers	3			
		2.3.1 Classification report	3			
		2.3.2 Confusion Matrix	5			
	2.4	Evaluating the decision tree classifiers	6			
	2.5	The depth and accuracy of a decision tree	6			
\mathbf{R}_{0}	efere	ence	8			

1 Information

1.1 Student information

Name	ID		
Võ Hữu Tuấn	22127439		

Bång 1: student information

1.2 Check list

No.	Task	Completion (%)
1	Preparing the data sets	100%
2	Building the decision tree classifiers	100%
3	Evaluating the decision tree classifiers	100%
	Classification report and confusion matrix	
	Comments	
4	The depth and accuracy of a decision tree	100%
	Trees, tables, and charts	
	Comments	
5	Report	100%

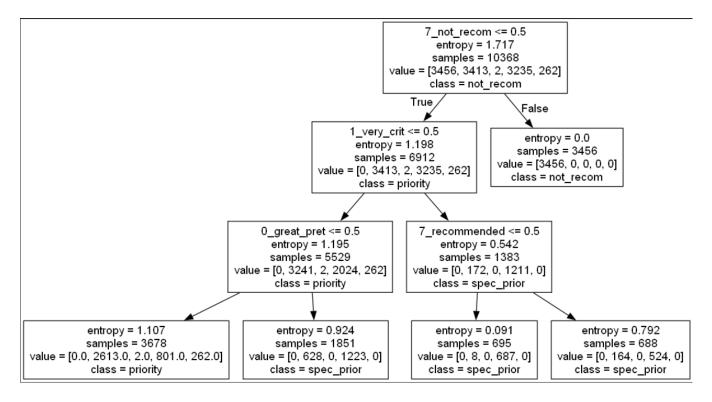
Bång 2: Check list

2 Requirements

2.1 Preparing the data sets

- Prepare "nursery.data.csv" and read data from it.
- Use shuffle_and_split_data function to create training and testing datasets.

2.2 Building the decision tree classifiers



Hình 1: Example of decision tree with ratio 80/20 and max depth = 2

2.3 Evaluating the decision tree classifiers

2.3.1 Classification report

* Classification report provides the following information:

- Precision: The ratio of true positive predictions to the total number of positive predictions
 (true positive + false positive).
- Recall: The ratio of true positive predictions to the total number of actual positive instances (true positive + false negative).
- F1-score: The harmonic mean of precision and recall.
- Support: The number of actual samples in each class.
- Accuracy: The ratio of correct predictions to the total number of samples.

* Example:

Classification report with 40/60:							
precision		recall f1-scor		support			
not_recom	1.00	1.00	1.00	2592			
priority	0.97	0.98	0.97	2560			
recommend	0.33	1.00	0.50	1			
spec_prior	0.98	0.97	0.97	2426			
very_recom	0.97	0.96	0.96	197			
accuracy			0.98	7776			
macro avg	0.85	0.98	0.88	7776			
weighted avg	0.98	0.98	0.98	7776			

Hình 2: Classification report with ratio 40/60

• Comment:

- The "not_recom" class has perfect precision, recall, and F1-score (=1.00 mean 100%),
 indicating that the model performs exceptionally well in identifying instances of this class
- The "priority" and "spec_prior" classes also have high precision, recall, and F1-scores, indicating good performance.
- The "recommend" class has lower precision but perfect recall, suggesting that the model identifies all instances of this class correctly but may misclassify other instances as "recommend".
- The "very_recom" class has a slightly lower precision, recall, and F1-score compared to other classes but is still reasonably high.
- Accuracy: The overall accuracy of the model is reported as 98%, indicating that the model correctly predicts the class label for 98% of the instances in the test set.

2.3.2 Confusion Matrix

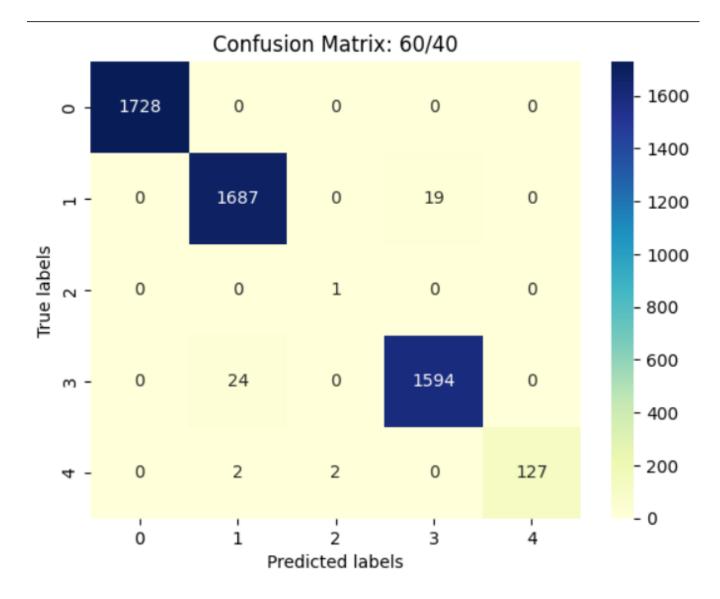
- * The confusion matrix provides a visual representation of the performance of the classifiers.
 - Each row of the matrix represents the instances in the actual class:

```
- \ "not \ recom"
```

- "recommend"

- Each column represents the instances in the predicted class.
- The diagonal elements represent the instances that were correctly classified.
- The off-diagonal elements represent misclassification.

* Example:



Hình 3: Confusion Matrix with ratio 60/40

2.4 Evaluating the decision tree classifiers

The decision tree classifier demonstrates strong performance across different train/test ratios

2.5 The depth and accuracy of a decision tree

$Max_d epth$	None	2	3	4	5	6	7
Accuracy	1.00	0.77	0.82	0.84	0.87	0.88	0.91

Bång 3: Statistical tables

* Comment:

- The accuracy score increases steadily as the max_depth parameter increases.
- With max_depth = None, the accuracy reaches 100% (=1.00), indicating potential overfitting due to perfect fitting of the training data.
- With max_depth from 2 to 7, the accuracy steadily improves, which shows that setting an appropriate depth helps prevent overfitting and enhances the model's generalization capability. * In summary, these statistics highlight the importance of controlling the max_depth parameter to strike a balance between model complexity and performance. While a deeper tree may capture intricate patterns in the training data, it risks overfitting, whereas a shallower tree might generalize better to unseen data but could overlook certain nuances in the training data.

Reference

- 1. Graph Plotting in Python | Set 1
- 2. Graph Plotting in Python | Set 2
- 3. Graph Plotting in Python | Set 3
- 4. Introduction to Scikit-Learn (sklearn) in Python
- 5. Graphviz