Lab Class ML:V

If you have any questions regarding the exercises, feel free to ask them in the Moodle forum.

Until Wednesday, Jan. 21st, 2026, 11:59 pm CET, solutions to the following exercises must be submitted as one zip-file named ml25-ex5-group<your-group-number>.zip via Moodle: 1, 2a–c, 3a, 4a, 5a–b, 6a–b, and 7.

Exercise 1 : Decision Trees (2+1+1+1+1+1=7 Points)

(a) Name these concepts:

(a1) $\mathbf{x}|_A$

(a2) T

(a3) t

(a4) $X(t)$

(a5) $D(t)$

(a6) $\textit{leaves}(T)$

(a7) ι

(a8) Weighted external path length

(b) Name this expression: $X = \{\mathbf{x} \in X : \mathbf{x}|_A \in B\} \cup \{\mathbf{x} \in X : \mathbf{x}|_A \notin B\}$

(c) What are the three requirements of an impurity function?

(d) What is the hypothesis space of decision trees?

(e) What is the search space of the ID3 algorithm?

(f) What is the difference between the inductive bias of the candidate elimination algorithm and that of the ID3 algorithm? Hint: search bias and restriction bias.

Exercise 2 : Decision Trees (1+1+1+0=3 Points)

Construct by hand decision trees corresponding to each of the following Boolean formulas. The examples $(\mathbf{x}, c) \in D$ consist of a feature vector $\mathbf{x}$ where each component corresponds to one of the Boolean variables $(A, B, \ldots)$ used in the formula, and each example corresponds to one interpretation (i.e. assignment of 0/1 to the Boolean variables). The target concept c is the truth value of the formula given that interpretation. Assume the set D contains examples with all possible combinations of attribute values.

Hint: It may be helpful to write out the set D for each formula as a truth table.

(a) $A \land \neg B$

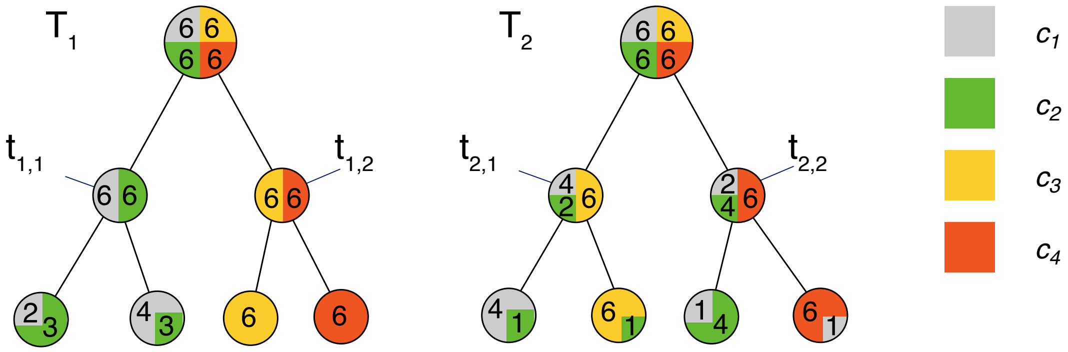
(b) $A \;\textit{XOR}\; B$

(c) $A \lor (B \land C)$

(d) $(A \land B) \lor (C \land D)$

Exercise 3 : Impurity Functions (3+0+0=3 Points)

Let D be a set of examples over a feature space $\mathbf{X}$ and a set of classes $C = \{c_1, c_2, c_3, c_4\}$, with $|D| = 24$. Consider the following illustration of two possible decision trees, T_1 and T_2 – the colors represent the classes present in each subset $D(t_i)$ represented by node $t_{i,j}$ of T_i; the numbers denote how many examples of each class are present.



(a) First, consider only the first split that each of the two trees makes: compute $\Delta\iota(D, \{D(t_{1,1}), D(t_{1,2})\})$ and $\Delta\iota(D, \{D(t_{2,1}), D(t_{2,2})\})$ with (1) the misclassification rate $\iota_{misclass}$ and (2) the entropy criterion $\iota_{entropy}$ as splitting criterion.

Interpret the results: which of $\{D(t_{1,1}), D(t_{1,2})\}$ or $\{D(t_{2,1}), D(t_{2,2})\}$ is the better first split?

(b) If we compare T_1 and T_2 in terms of their misclassification rate on D, which one is the better decision tree?

(c) Assuming the splits shown are the only possibilities, which of T_1 or T_2 would the ID3 algorithm construct, and why?

Exercise 4 : Decision Trees (5+0=5 Points)

Given is the following dataset to classifiy whether a dog is dangerous or well-behaved in character:

Color	Fur	Size	Character (C)
brown	ragged	small	well-behaved
black	ragged	big	dangerous
black	smooth	big	dangerous
black	curly	small	well-behaved
white	curly	small	well-behaved
white	smooth	small	dangerous
red	ragged	big	well-behaved

(a) Use the ID3 algorithm with $\iota_{entropy}$ as the impurity function to determine the tree T.

(b) Classify the new example (Color=black, Fur=ragged, Size=small) using T.

Exercise 5 : Decision Tree Pruning (1+2=3 Points)

(a) Define the concept of decision tree pruning and explain why it is important.

(b) Compare the two main approaches to counter overfitting in decision trees:

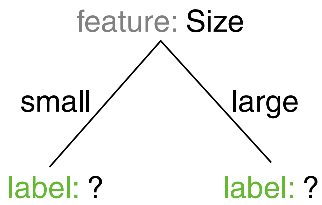
  (i) Stopping during tree construction
  (ii) Pruning after tree construction

  What are the advantages and disadvantages of each approach? Which one is generally more preferred?

Exercise 6 : Cost functions (1+1+0=2 Points)

Consider the set of training examples describing mushrooms, and the simple one-level decision tree given below:

	Color	Size	Points	Edibility
1	red	small	yes	toxic
2	brown	small	no	edible
3	brown	large	yes	edible
4	green	small	no	edible
5	red	large	no	edible



(a) Determine the labels of all nodes using the cost function $\mathit{cost}(c', c)$ (cf. ML:II-185):

$$\mathit{cost}(c', c) = \begin{cases} 1 & \text{if } c' \neq c, c \in C \\ 0 & \text{otherwise} \end{cases}$$

(b) Devise a new cost function that ensures that, for the same tree structure, none of the poisonous mushrooms in the training set are classified as edible.

(c) Compute the misclassification costs of the tree for both cost functions.

Exercise 7 : $\boxed{\text{P}}$ Argument Quality Prediction with CART Decision Trees (1+1+1+1+1+1+1=7 Points)

In this exercise, you will implement the CART algorithm for constructing decision trees for argument quality prediction. To make the implementation less complex, we will assume all features are numeric, and not consider nominal or ordinal features. Submit the file with your predictions for the test set along with your other solutions.

Download and use these files from Moodle (the `tsv` files are the same as in the last sheet):

- `features-train-cleaned.tsv`: Feature vectors for each example in the training set.
- `features-test-cleaned.tsv`: Feature vectors for each example in the test set.
- `quality-scores-train-cleaned.tsv`: Quality scores for each example in the training set.
- `programming_exercise_decision_trees.py`: Template for the programming exercise. It contains function stubs for each function mentioned below. The template contains code from our solution from the last exercise sheet that we can re-use. The program should be used like this with the files above:

```
python3 programming_exercise_decision_trees.py
  features-train-cleaned.tsv quality-scores-train-cleaned.tsv
features-test-cleaned.tsv
```

- `requirements.txt`: Requirements file for the template; can be used to install dependencies.

(a) Implement a function `most_common_class` to find the most common class in the dataset.

(b) Implement a function `gini_impurity` that computes the Gini index for the given set of example classes C (slide ML:VI-79).

(c) Implement a function `gini_impurity_reduction` that computes the Gini impurity reduction of a binary split (slide ML:VI-50).

(d) Implement a function `possible_thresholds` that returns all possible thresholds for splitting the example set X along the given feature. Pick thresholds as the mid-point between all pairs of distinct, consecutive values in ascending order.

(e) Implement a function `find_best_split` that finds the best split based on the Gini impurity reduction for the given set of examples X and the given set of classes C.

(f) Implement the `id3_cart` function to construct a CART decision tree with the modified ID3 algorithm (slides ML:VI-109, ML:VI-22). The function should return the root node of the tree.

(g) Implement a function `train_and_predict`. This function should train the model on the training set and return the predictions for the test set. What is the misclassification rate on the training set?

If you would like to improve your model, here are some hints of what you could try:

- Modify the `train_and_predict` function to split the training set into a training and a validation set. Use the validation set to find the best depth for the CART algorithm.
- Implement a stopping criterion from slide ML:VI-129 to avoid overfitting.
- Implement the pruning algorithm from slide ML:VI-130 to avoid overfitting.