## Foundations of Artificial Intelligence

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# Exercise Sheet 10 — Solutions

**Exercise 10.1** (Decision Trees)

| No | Age | Engine power [kW] | **Risk** |
|---|---|---|---|
| 1 | $< 25$ | $< 100$ | low |
| 2 | $< 25$ | $> 200$ | high |
| 3 | $\geq 25$ | $> 200$ | high |
| 4 | $\geq 25$ | $100 - 200$ | low |
| 5 | $< 25$ | $100 - 200$ | high |
| 6 | $\geq 25$ | $< 100$ | low |

Consider the data on car insurance risk in the table above. Produce a decision tree, which correctly classifies the insurance risk for the examples given, using the attributes *Age* and *Engine Power* in order of decreasing *information gain*. Give detailed calculations that justify the order in which the attributes are tested.
You can make use of the following values:
$\log_2(\frac{1}{3}) \approx -\frac{3}{2}$, $\log_2(\frac{2}{3}) \approx -\frac{1}{2}$, $\log_2(\frac{1}{2}) = -1$, $\log_2(1) = 0$.

**Solution:**

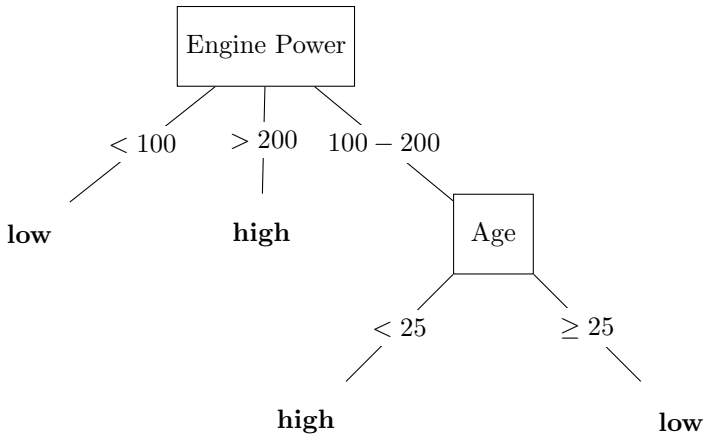
Entropy of the root node: $I(Risk) = I(\frac{1}{2}, \frac{1}{2}) = 1$
Remaining uncertainties after splitting on the different attributes:

$$R(EnginePower) = \frac{1}{3} \cdot I(1,0) + \frac{1}{3} \cdot I(0,1) + \frac{1}{3} \cdot I(\frac{1}{2}, \frac{1}{2}) = \frac{1}{3}$$
$$R(Age) = \frac{1}{2} \cdot I(\frac{1}{3}, \frac{2}{3}) + \frac{1}{2} \cdot I(\frac{2}{3}, \frac{1}{3}) = I(\frac{1}{3}, \frac{2}{3}) = -\frac{1}{3}\log_2(\frac{1}{3}) - \frac{2}{3}\log_2(\frac{2}{3}) = \frac{5}{6}$$

Gains are then:

$$Gain(EnginePower) = 1 - \frac{1}{3} = \frac{2}{3}$$
$$Gain(Age) = 1 - \frac{5}{6} = \frac{1}{6}$$

So the first split should be on attribute *Engine Power*. After that, splitting on *Age* will result in a clean split with no entropy left.




**Exercise 10.2** (Best practices in ML)

When doing machine learning, it is good practice to split the dataset into a training/validation/test set.

- Which subset(s) should you use for the following tasks:
  (a) training models (R & D)[1]
  (b) guard against overfitting (R & D)
  (c) model selection (R & D)
  (d) progress reports (R & D)
  (e) train the model (product)[2]
  (f) evaluating the model (product)
- Which of these subsets should always be fixed a priori (before even looking at the data)?

**Solution:**

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| **task** | **phase** | **training set** | **validation set** | **test set** |
|---|---|---|---|---|
| training models | R & D | yes | no | no |
| guard against over-fitting | R & D | no | yes | no |
| model selection | R & D | no | yes | no |
| progress reports | R & D | no | yes | no |
| training the model | product | yes | maybe | no |
| evaluating the model | product | no | no | yes |

- The test set should always be fixed a priori (and used only once, to evaluate the final model). Instances in validation/training sets may vary during R & D. However, having a sparsely-used, fixed subset that acts as a 'pseudo' test-set can be useful (e.g. for internal progress reports). Also, if examples in the validation set are frequently used (e.g during training, hyper-parameter tuning, etc.) failing to detect overfitting is a real risk.

[1] R & D: During research and development
[2] product: For the final product/publication