An Introduction to Supervised Machine Learning

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- The course is articulated around three parts: introduction, interpretable machine learning (myself), and neural networks (Arthur Bit Monnot)

References

T. Hastie, R. Tibshirani, and J. H. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd Edition.*
Springer Series in Statistics, Springer, 2009.

S. J. Russell and P. Norvig, *Artificial Intelligence - A Modern Approach, Third International Edition.*
Pearson Education, 2010.

Part 1: Introduction

Chapter 1: Context

[1] Image from https://en.wikipedia.org/wiki/Cycling

Figure 1: How to cycle? [1]

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[2] Image from https://en.wikipedia.org/wiki/Global_biodiversity

Figure 2: How to teach a child animal recognition? [2]

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Figure 3: How to predict a player's performance? [3]

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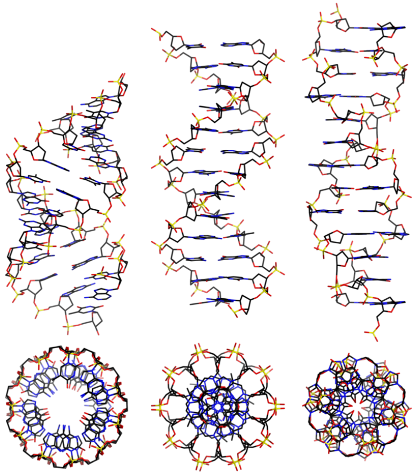

Figure 4: Analysis of evolutionary biology based on DNA patterns [4]

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Examples of Machine Learning Applications [1]

- Autonomous cars
- Flying drones
- Face recognition
- Computer vision
- Natural language processing
- Music/movie recommendation
- Dating apps
- Friends recommendation
- Weather prediction
- Trading
- ...

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2. **Unlabelled data**: For instance, when using clustering to evaluate the density of a population. The data can simply be a set of coordinates with no labels.
3. **Continuously updated data**: The data is continuously updated according to previous experiences: For instance, a robot that tries to ride a bicycle learns how to bike by a sequence of trials

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- Unsupervised Learning: The task is to figure out patterns presented in the data (unlabelled data)
- Reinforcement learning: learning from a series of rewards /punishments
- But also, depending on the problem, data could be both labelled/non labelled, etc.. (semi-supervised learning)

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Classification task

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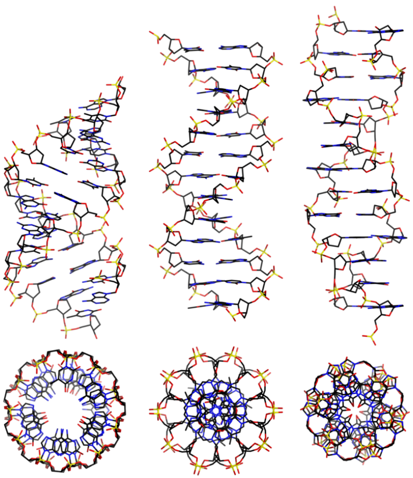

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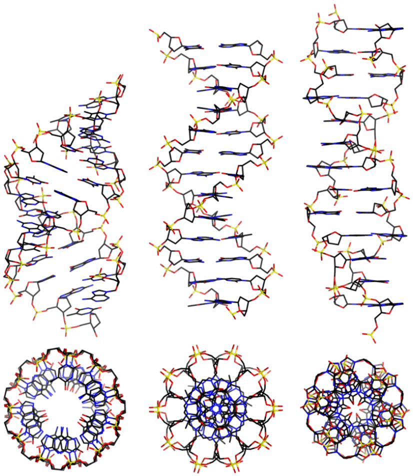

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Unsupervised learning (clustering) task

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Chapter 2: Supervised Machine Learning

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  - Precipitation prediction: (loosely speaking) the data is a collection of sequential weather conditions and the purpose is to predict the Precipitation chance (float value)
    $\Longrightarrow$ Regression

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- Given a historical data (**training set**) in the form of input-output examples: $\{(x_1, y_1), \ldots (x_n, y_n)\}$ where x_i is an input, y_i is the output of x_i drawn from an unknown function f

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- Find a function f_h (called a hypothesis or model) that approximates the true function f
- The approximation criterion can be defined in different ways. We can consider it as a function minimizing some error.

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- Examples of hypothesis space (family of functions) include polynomial functions, trigonometry functions, decision trees, decision lists, neural networks, ...

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- The model bias can be easily seen: For instance, one can answer statistical queries such as: is the error evenly distributed? to which class the model is likely to predict? ...

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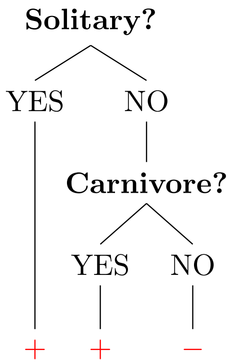

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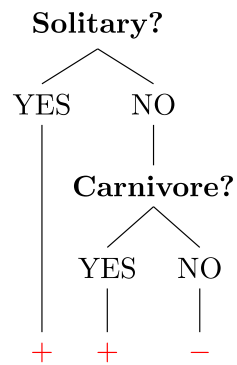

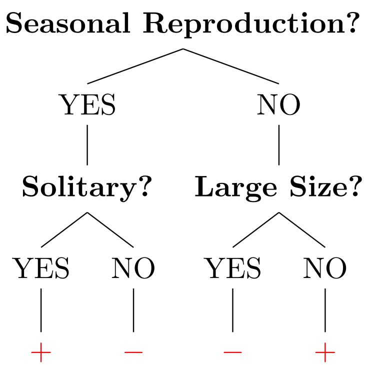

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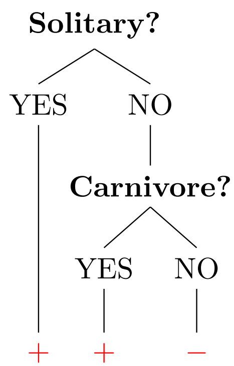

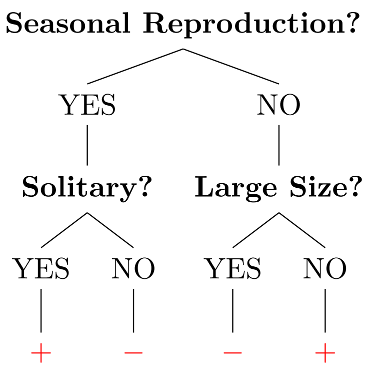

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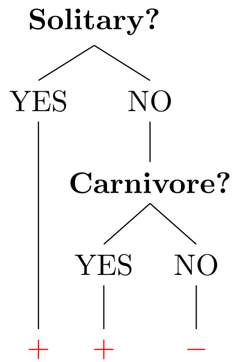

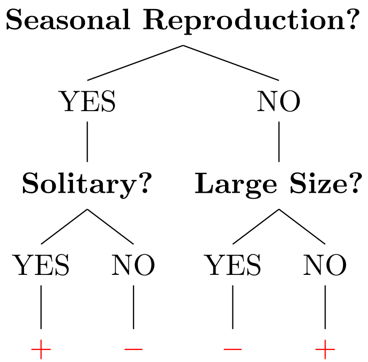

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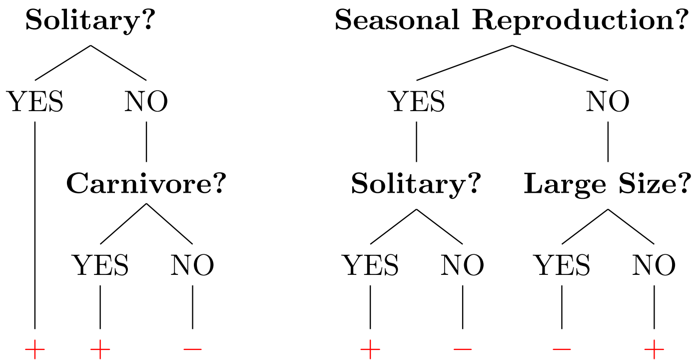

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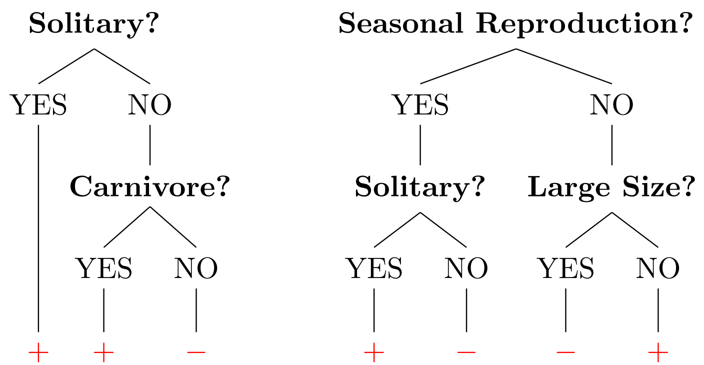

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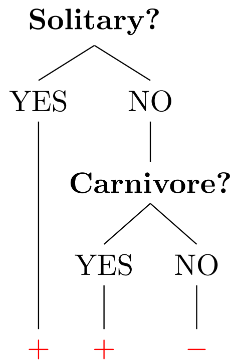
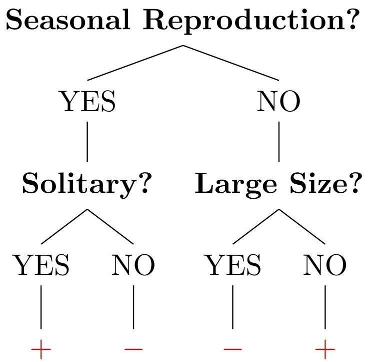
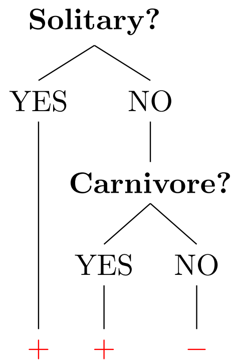


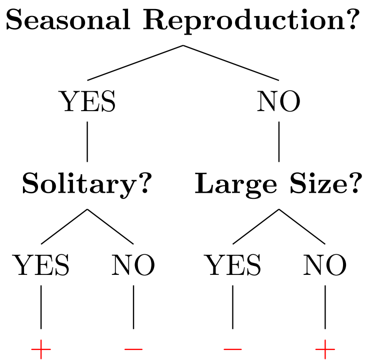


- Tabular data
- Hypothesis space: Decision trees
- Left tree: accuracy 2/5
- Right tree: accuracy 2/5

Toy Example: DTs to Predict The Likelihood of Animal Extinction

Big Size	Carnivore	Seasonal Reproduction	Solitary	Extinct
0	1	0	1	yes
1	0	0	1	yes
0	0	0	1	no
1	1	1	0	no
0	0	1	0	yes





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Ockham's Razor Principle

[9] Philosopher https://en.wikipedia.org/wiki/William_of_Ockham

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- When using polynomials (as a hypothesis space), lower degrees seems to be simpler
- In other cases it is very hard to define simplicity

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  1. Split the data into k folds
  2. Perform the training k times. At each iteration, a different fold is chosen as a testing set and the rest is used for training.

Questions & Exercises

Out of these three questions, which one is the hardest and which one is the easiest (computationally)?

1. Building a perfect decision tree 100% accuracy ?
2. Building the best decision tree within a height h ?
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Question 3 is the hardest (we need a proof) and question 1 is the easiest (we can keep splitting until a perfect classification)

Questions & Exercises

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0	1	0	1	yes
1	0	0	1	yes
0	0	0	1	no
1	1	1	0	no
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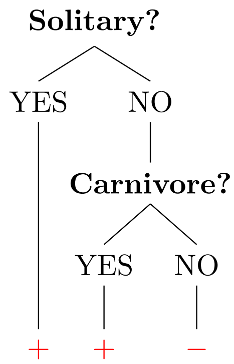

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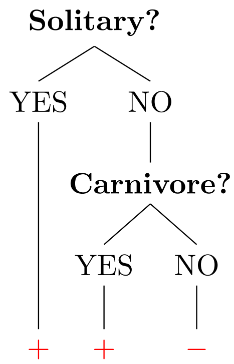

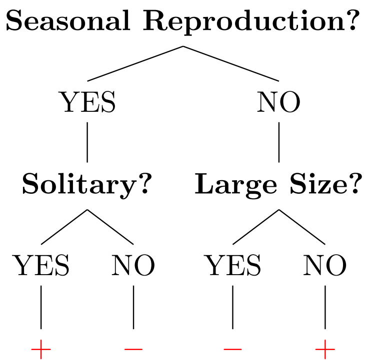

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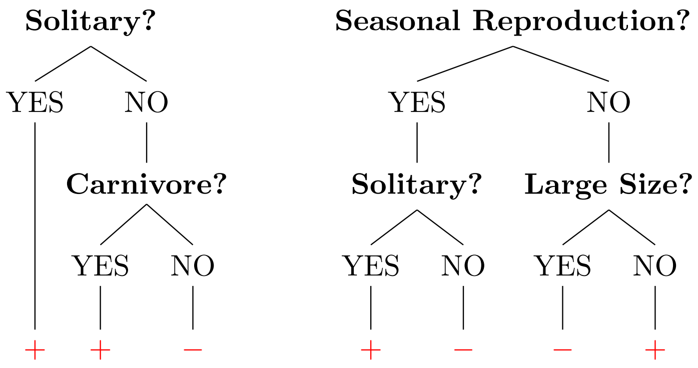

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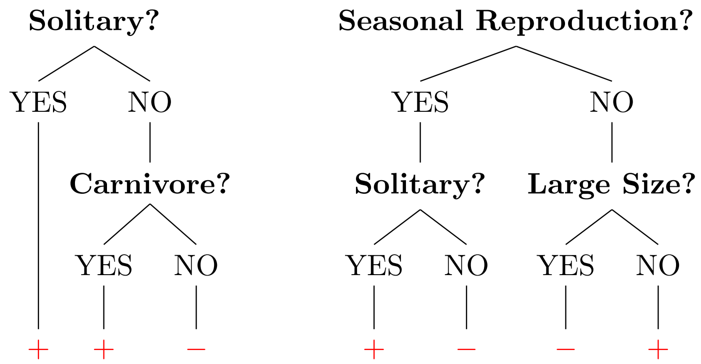

- Find a perfect tree

Questions & Exercises

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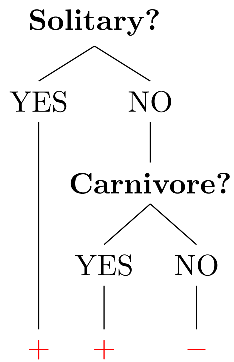

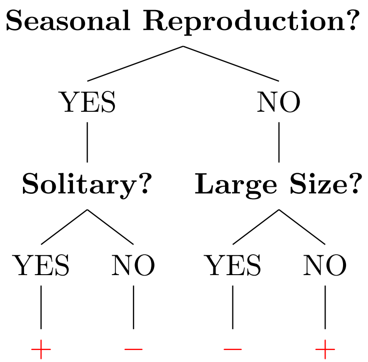

- Find a perfect tree
- Find a perfect tree with a minimum weight

Questions & Exercises

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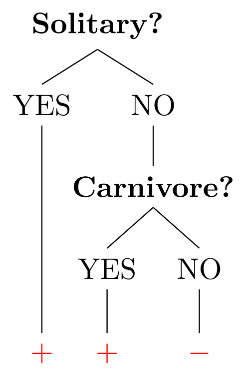
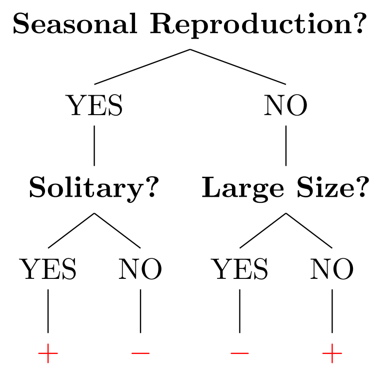
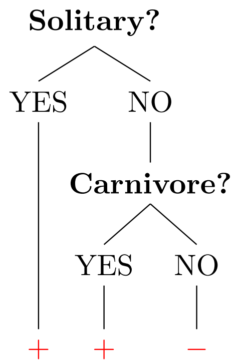


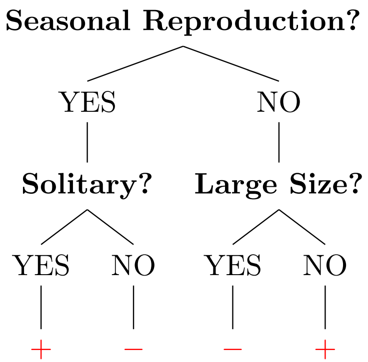


- Find a perfect tree
- Find a perfect tree with a minimum weight
- Find a best tree with height 2

Questions & Exercises

Big Size	Carnivore	Seasonal Reproduction	Solitary	Extinct
0	1	0	1	yes
1	0	0	1	yes
0	0	0	1	no
1	1	1	0	no
0	0	1	0	yes





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