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

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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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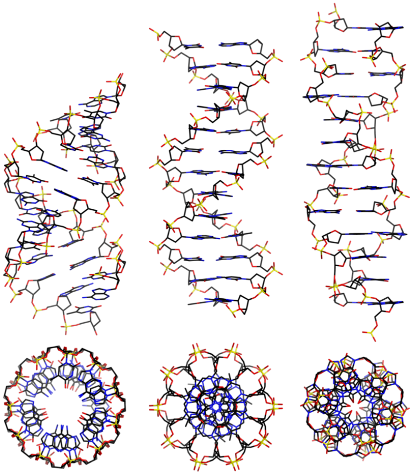

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Examples of Machine Learning Applications [1]

- 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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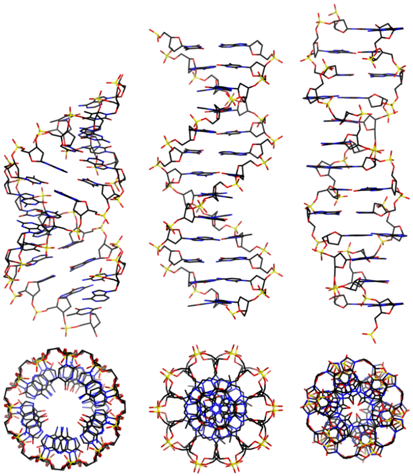

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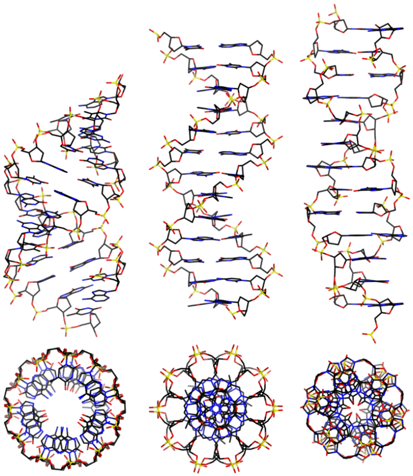

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Unsupervised learning (clustering) task

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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 (real value)
    $\Longrightarrow$ Regression

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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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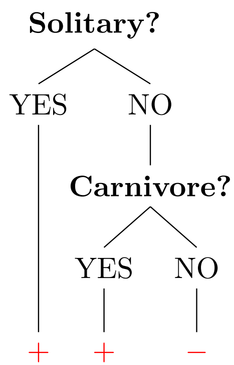

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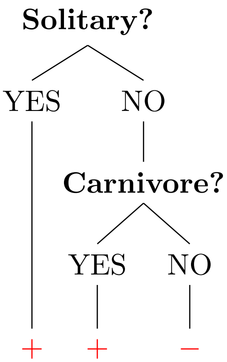

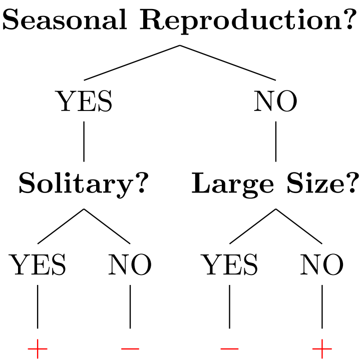

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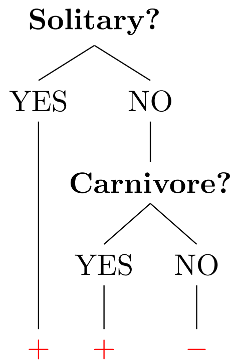

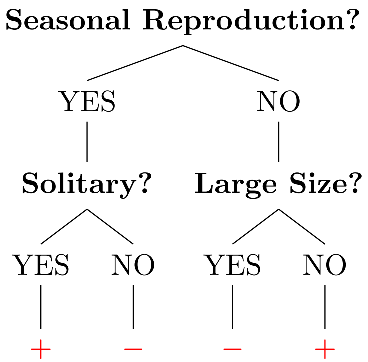

Toy Example: DTs to Predict The Likelihood of Animal Extinction

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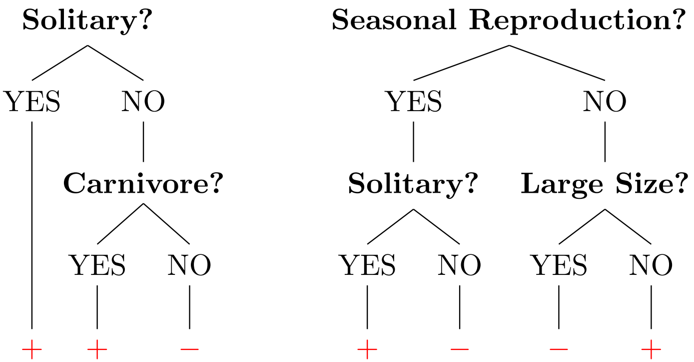

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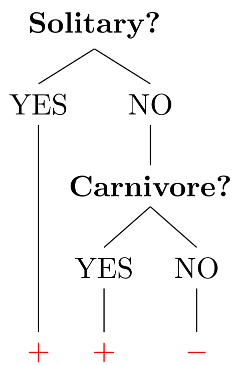

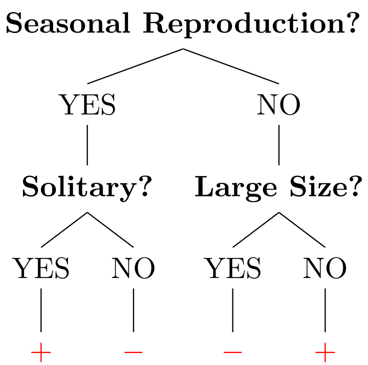

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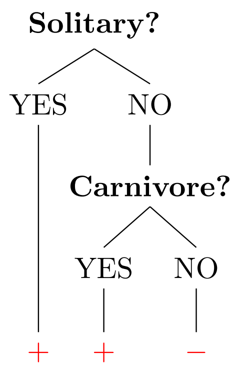

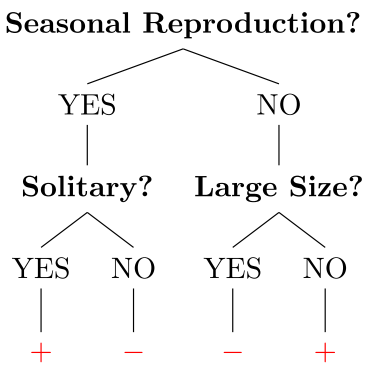

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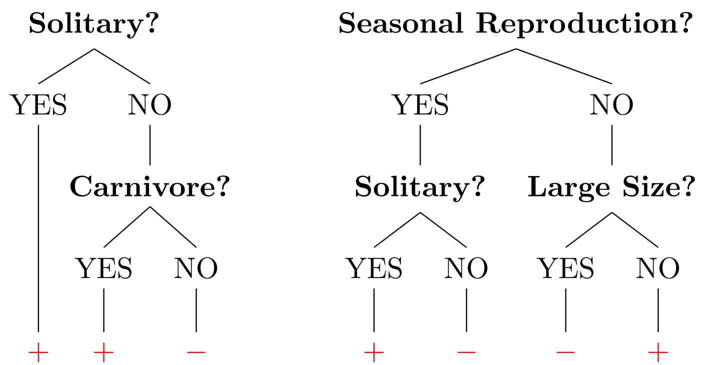

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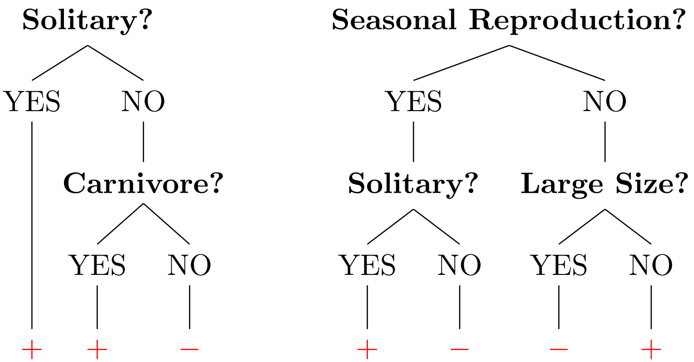

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- We need an error function that take into account a notion of distance between true values and predicted values

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- Consider a dataset with n examples where y is the vector of the true values and $\hat{y}$ is the vector of predicted values:

$$MAE = \frac{1}{n} \sum |y_i - \hat{y}_i|$$

$$MSE = \frac{1}{n} \sum (y_i - \hat{y}_i)^2$$

$$RMSE = \sqrt{MSE}$$

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- In this case the objective function is slightly different from the standard accuracy (weighted sum)

Computational Hardness

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

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- $g(n) = O(k \times f(n))$: We can solve Question 3 by solving Question 2 iteratively by increasing/decreasing the height
- Different objective functions can be defined (i.e., the training problem itsetf can have different definitions)
- The definition of the objective function with the hypothesis space has an impact on the complexity of training

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- The way the optimisation problem is defined impacts its computational complexity

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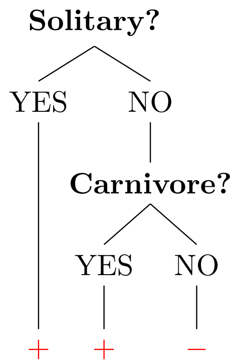

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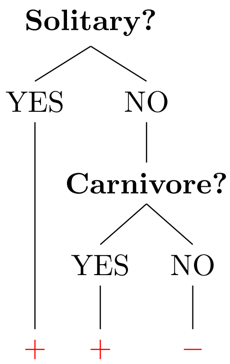

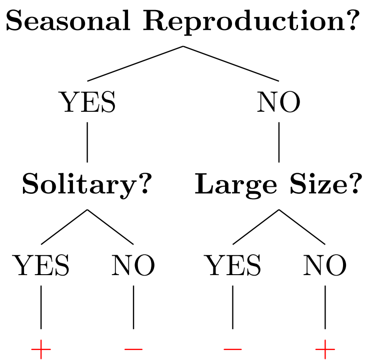

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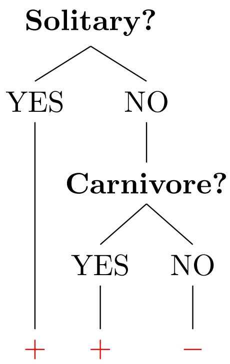

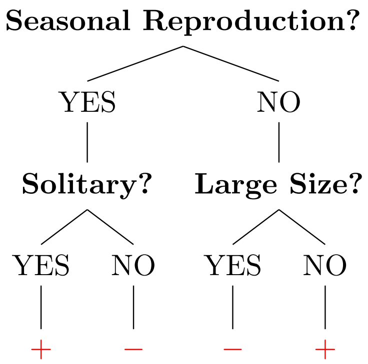

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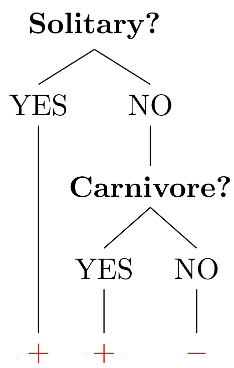

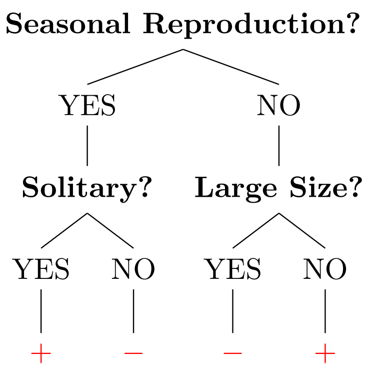

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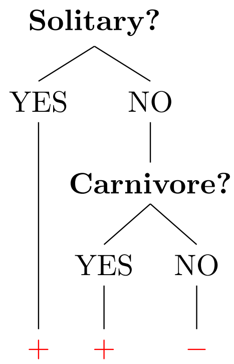

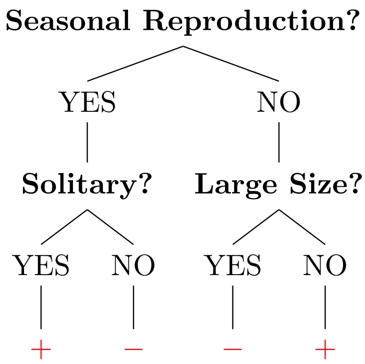

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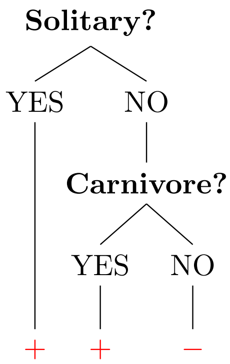

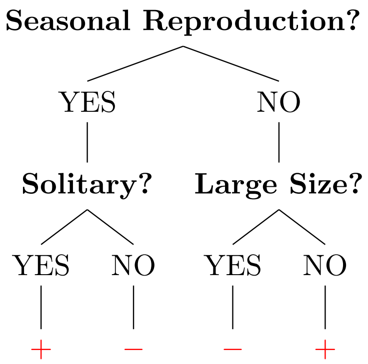

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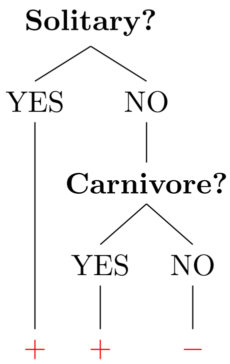

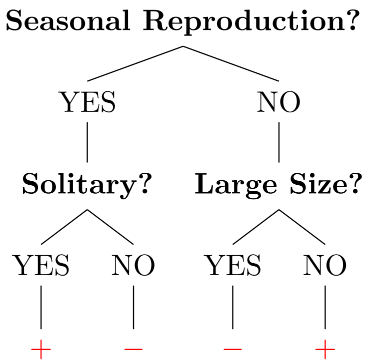

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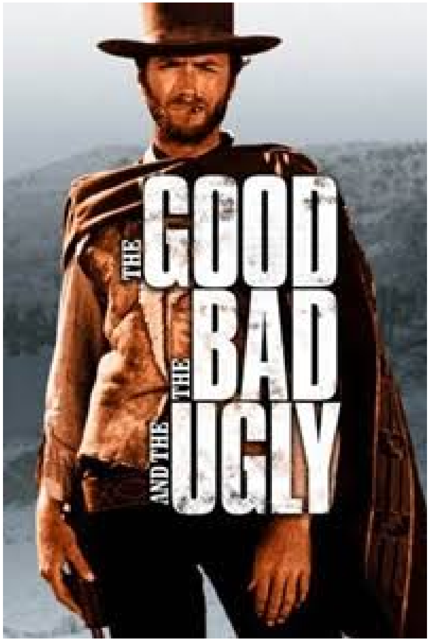
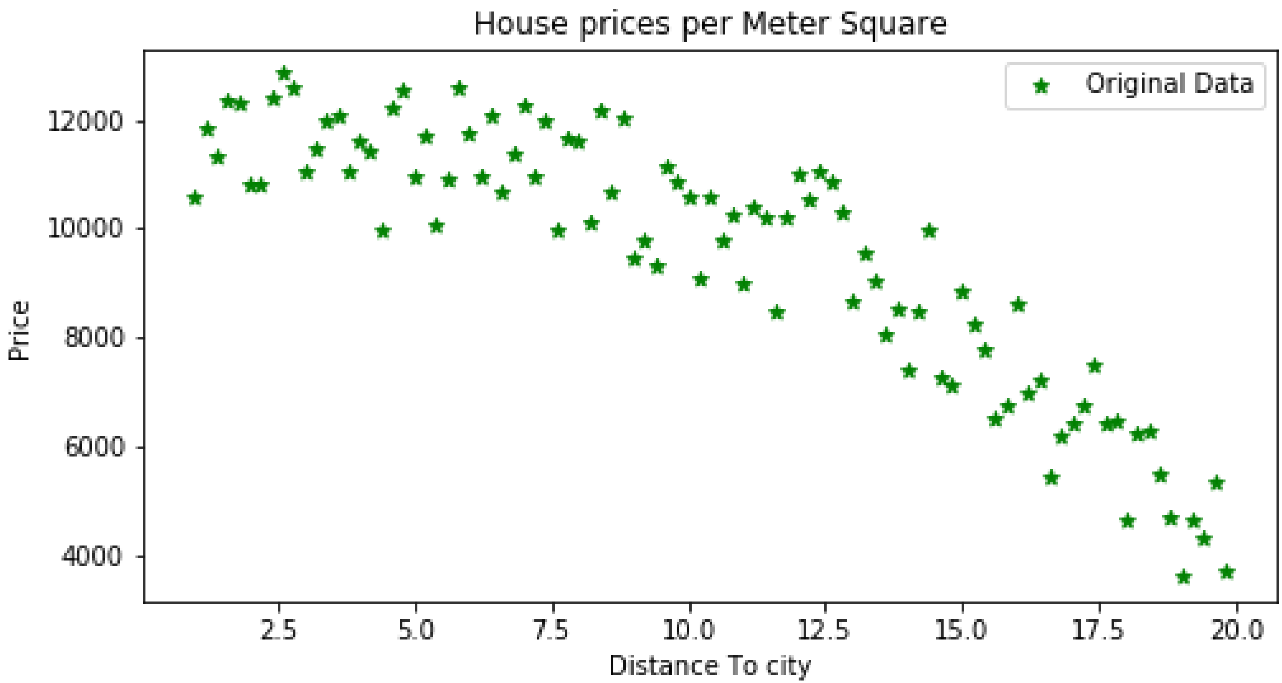
Chapter 3: Deeper Evaluations

Overfitting, Underfitting, and Goodfitting

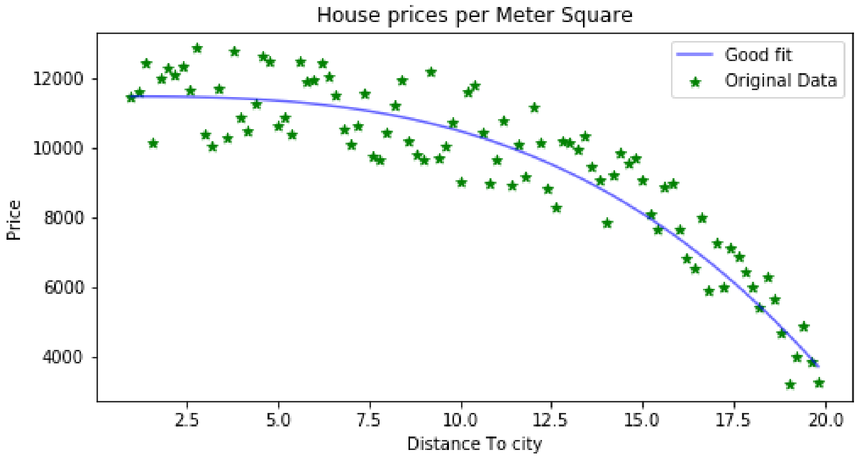


The Housing Prices Example



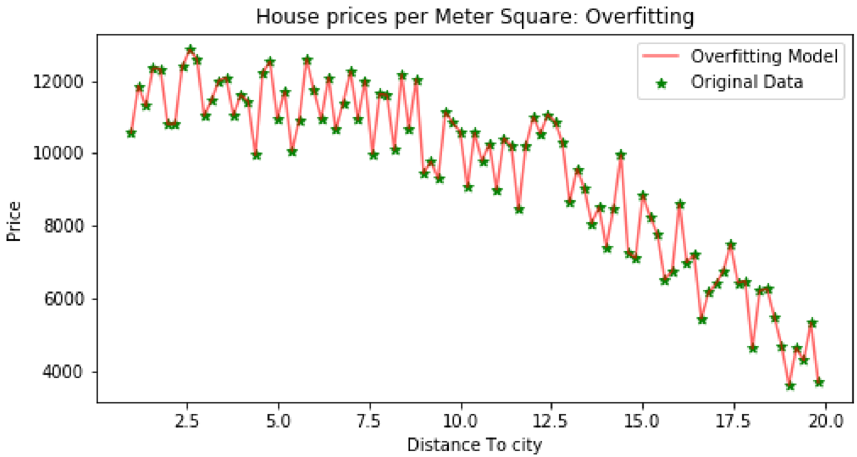
This data includes some **noise**. That is, points that are not correctly collected (which is often the case in real applications)

The Housing Prices Example: The Good



We can make an analogy to a smart student who has a good understanding of a lecture

The Housing Prices Example: The Bad (Overfitting)



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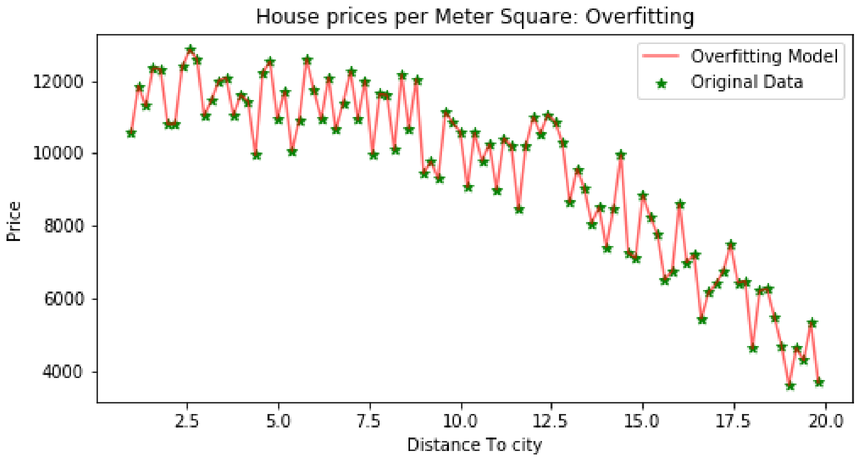
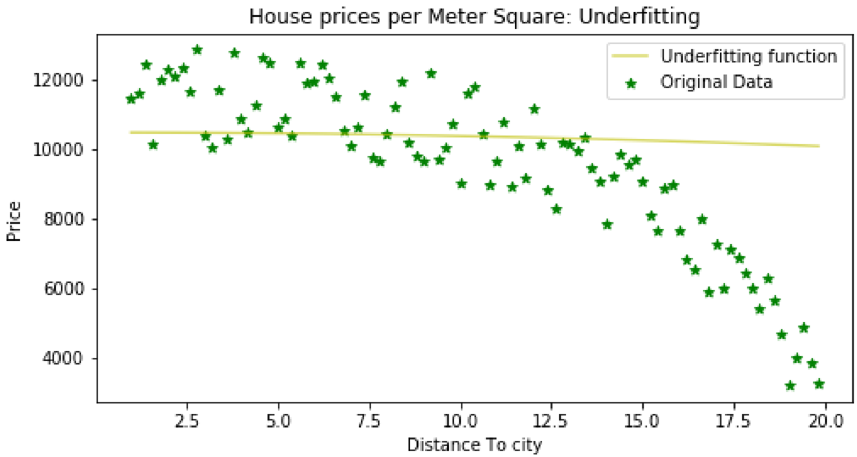


We can make an analogy to the student who "learns" the lecture mechanically without a real understanding.

The Housing Prices Example: The Ugly (Underfitting)



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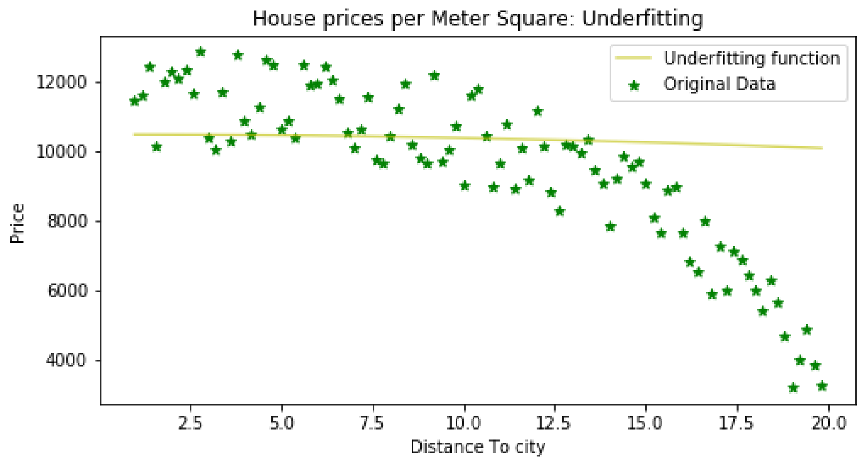
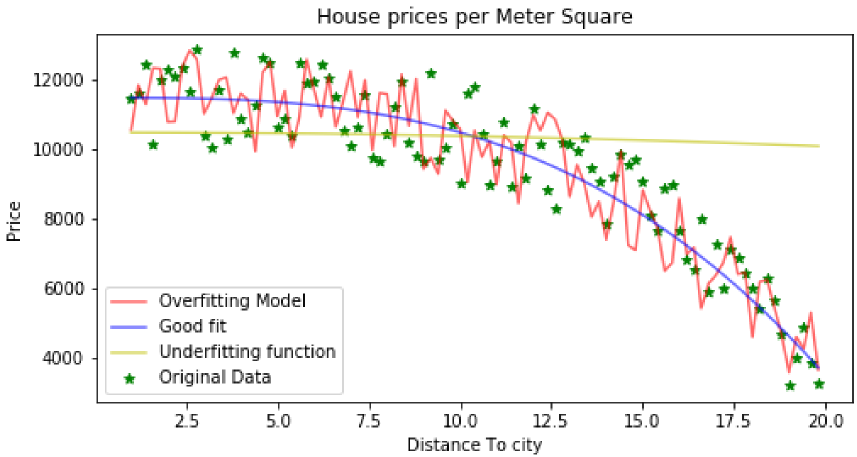


We can make an analogy to a lazy student who barely remember the lecture without any understanding

The Housing Prices Example: All Together



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- A good fit happens when the model approximates well the true distribution without being disturbed by noise (good generalisation)

Overfitting with Decision Trees as an Example

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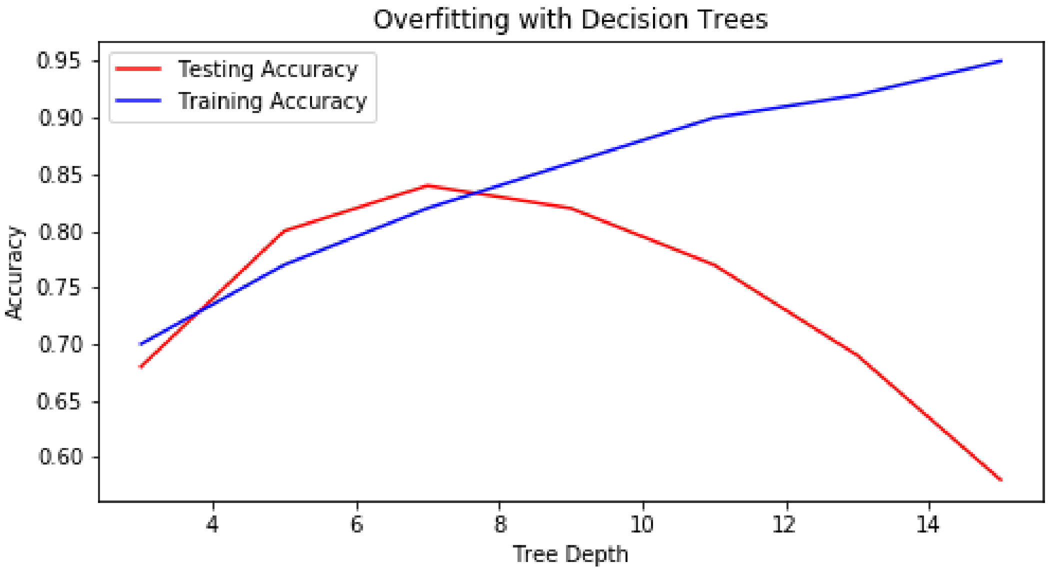

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- The longer the tree, the better the training accuracy gets, however, this is not necessarily the case for the testing accuracy
- Testing accuracy increases at the beginning until a certain value (depth $= 7$), the it decreases afterwards
- This happens because with longer trees, the model can classify correctly more examples in the training set, however, this includes noise.

Overfitting Based on the Complexity of the Model

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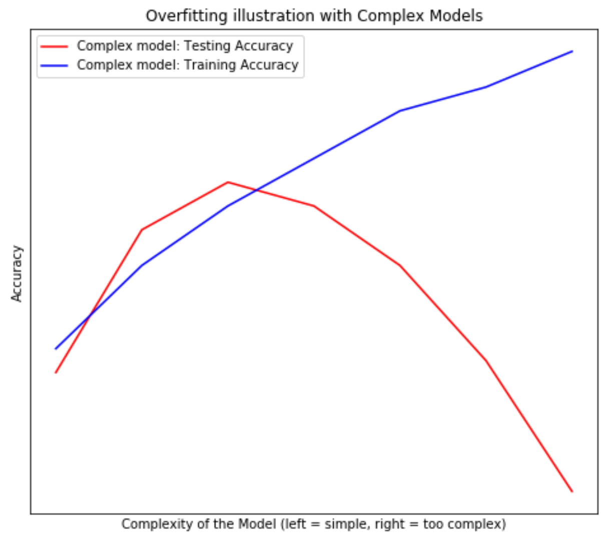

- When the model is too simple, there is a risque of underfitting
- When the model is too complex, there is a risque of overfitting
- We need a Model that is somehow in between
- ML libraries offer parameters for regulation to avoid overfitting/underfitting

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- A common way is to use the $k-$fold cross validation:
  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
  3. Typical values for k are 5 and 10

Overcome Overfitting

- How to avoid overfitting?

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- The testing set is inaccessible at the moment of training
- We can sacrifice a part of the training set as a 'validation set' to evaluate the generalisation of the model.
- Basically, the training set has a subset for training and a subset for validation (evaluation)
- A common way is to use $k-$cross validation on the training set to overcome overfitting
- Also, we can restrict the hypothesis space with simple models

Complexity/Quality Tradeoff

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- Most ML libraries offer the possibility to control the complexity with a regularization parameter

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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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- Simple models might underfit
- Ideally, we look for a hypothesis that is ‘easy’ to compute and simple enough to be a good fit

Chapter 4: Interpretable Models

The COMPAS Tool

MIT Technology Review

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AI is sending people to jail—and getting it wrong

Using historical data to train risk assessment tools could mean that machines are copying the mistakes of the past.

By Karen Hao

January 21, 2019

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Increasing Number of Real Life and Social AI Applications

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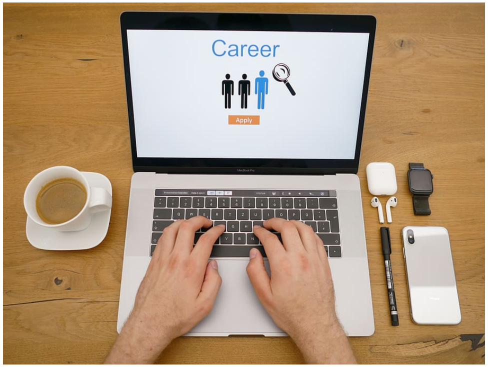
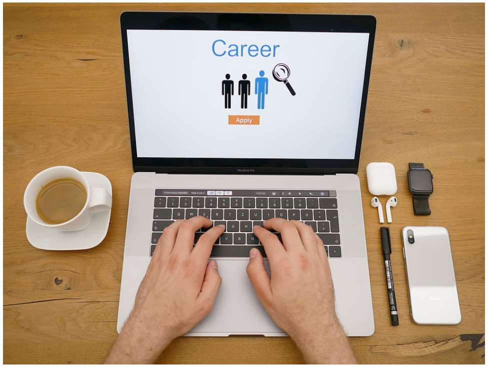


Increasing Number of Real Life and Social AI Applications



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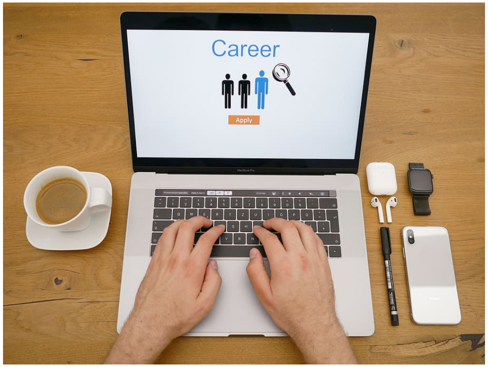

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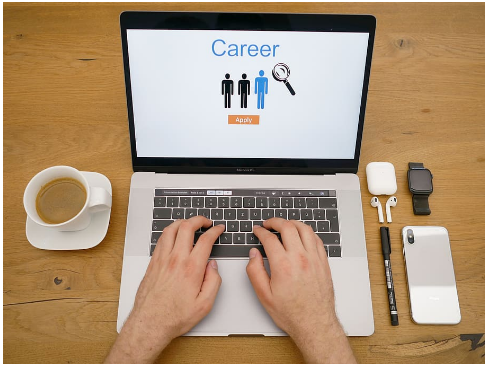

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  - Credit scoring: AI that gives a credit score (for bank loans and credit applications) that recommends people from a particular geographical region, specific gender, social class, etc
  - Compass tool: (2016) used by judges in the US to predict which criminals are likely to re-offend is found to be biased by the ethnicity (African-American/Caucasian).

COMPASS data and Rule-based Predictions

Sex	Age	Priors	Juvenile Felonies	Juvenile Crimes	Ethnicity
Male	15	1	0	1	Caucasian
Male	15	1	0	1	African-American
Female	33	1	0	1	African-American
Female	27	0	1	0	Caucasian
Male	41	0	1	0	Caucasian
...	...	...	...	...	...

The problem is to predict recidivism. That is, the tendency of a convicted criminal to re-offend.

Black-Box vs Interpretable Models

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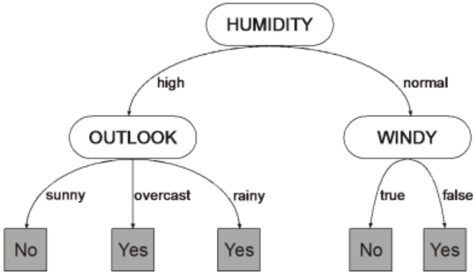

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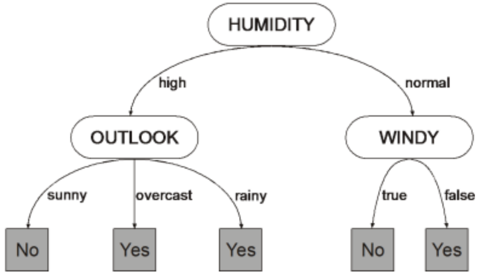

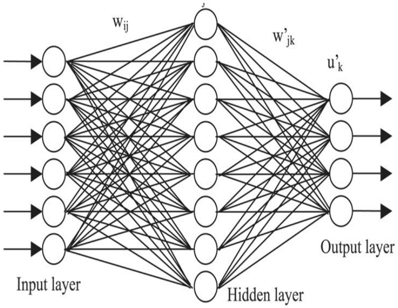

Definitions [3]

- **Black-box model** : A formula that is either too complicated for any human to understand, or proprietary, so that one cannot understand its inner workings
- **Interpretable model** obeys a domain-specific set of constraints to allow it (or its predictions, or the data) to be more easily understood by humans. These constraints can differ dramatically depending on the domain.

Why Interpretable Models?

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- **Mandatory criteria in high-stake decision making**

- We consider in this course tabular data (but extensions to other types is possible)
- Models:Decision trees, decision lists, decision rules, and linear functionns . . .

Decision rules & Decision Sets

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Example of Rule List found by FairCORELS

- Data : `https://www.kaggle.com/danofer/compass`
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```
if [priors:>3] then [recidivism]
else if [age:21-22 && gender:Male] then [recidivism]
else if [age:18-20] then [recidivism]
else if [age:23-25 && priors:2-3] then [recidivism]
else [no recidivism]
```

Rule list 5. Example of an unconstrained rule list found by `FairCORELS` on COMPAS dataset, with Accuracy $= 0.681$, $\mathrm{UNF}_{\mathrm{EOdds}} = 0.217$ and $\mathrm{UNF}_{\mathrm{CUAE}} = 0.046$