

Machine Learning (Part 1)

(Basic Concepts + Basic Coding)

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DIGITAL EDITION

JULY 02 - 09

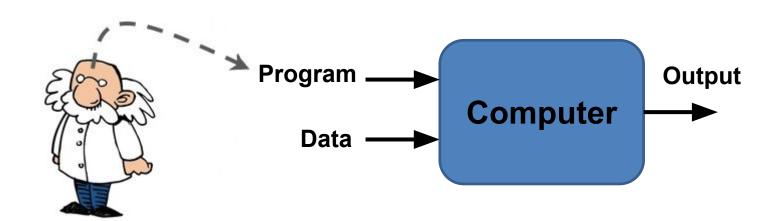


What will we cover?

- What is machine learning?
- What kind of learning settings exist?
- What type of supervised learning problems can you find?
- What type of classifiers are available for you to use?
- How does the learning process work?
- Python basics + Sklearn (the most used toolbox in the realm of machine learning)

AI (expert based)

- Emulates the decision-making process of a human expert
 - "If-then-else" approach
 - What are the advantages and disadvantages of this approach?



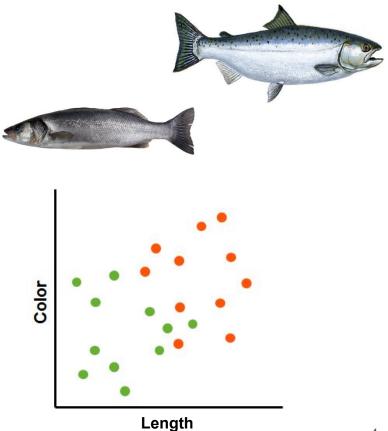
AI (machine learning based)

Step 1:



<u>Step 2:</u>





Al (deep learning based)

Step 1:



Step 2:



Supervised Learning

- In supervised learning, the training data you feed to the algorithm includes the desired solutions, called labels

Input



Label: Real (Bona-fide)

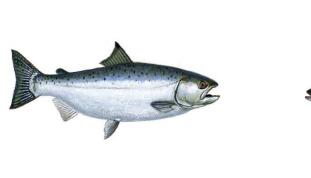
Input



Label: Fake (Attack)

Unsupervised Learning

- In unsupervised learning, as you might guess, the training data is unlabelled. The system tries to learn without a teacher







<u>Semi-supervised Learning</u>

- Some algorithms can deal with partially labelled training data, usually a lot of unlabelled data and a little bit of labelled data
- Most semi-supervised learning algorithms are combinations of unsupervised and supervised algorithms

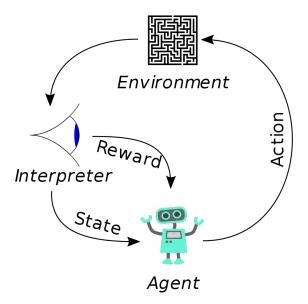
Input 1 Output 1 Input 2

- Weakly-supervised Learning
 - When we have noisy, limited or imprecise sources that are used to provide supervision



Reinforcement Learning

- Reinforcement learning is a different beast



- Classification (binary)
 - System capable of distinguishing between just two classes

Input



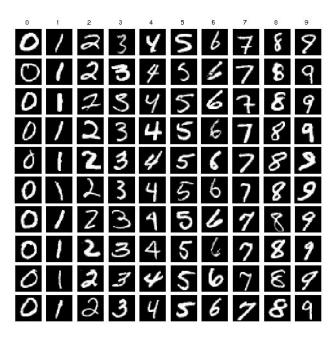
Label: Real (Bona-fide)

Input



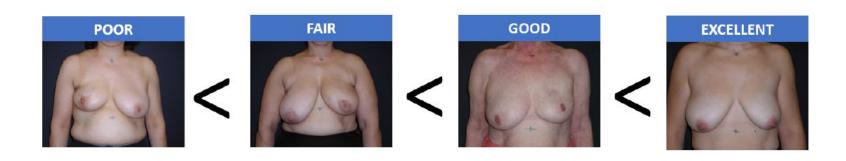
Label: Fake (Attack)

- Classification (multi-class)
 - System capable of distinguishing between more than two classes



Classification (ordinal)

- System capable of distinguishing between more than two classes
- Classes have an inherent natural order



• Regression

- Predicting house price
 - Output: price (a scalar)
 - Inputs: size, orientation, distance to key services, etc.



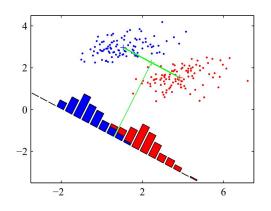
$$y = f(x)$$

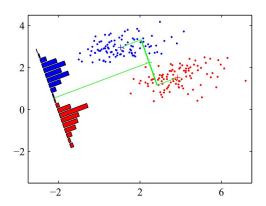
- <u>Training:</u> given a training set of labelled examples {(x1, y1),...,(xn, yn)}, estimate the prediction function f by minimizing the prediction error on the training set
- <u>Testing:</u> apply f to a never seen before test example x and output the predicted value y = f(x)

• <u>Discriminant function</u>

- No computation of posterior probabilities (probability of a certain class given the data).
- Directly map each x onto a class label

Tools: Fisher's Linear Discriminant, SVM, etc.

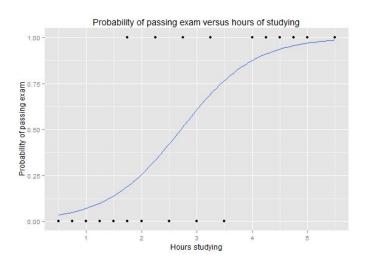




- Probabilistic Discriminative Models
- Computation of posterior probabilities: p(C = k | x)
- Model posterior probabilities directly

Tools: Logistic Regression

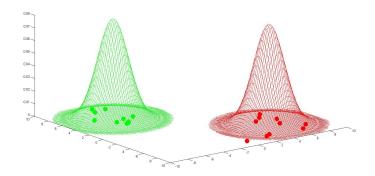
$$p = \frac{1}{1 + e^{-\omega_0 + \omega_1 x}}$$



- Probabilistic Generative Models
- Model class priors, p(C = k), and class-conditional densities, $p(x \mid C = k)$
- Use Bayes theorem to compute posterior probability, $p(C = k \mid x)$

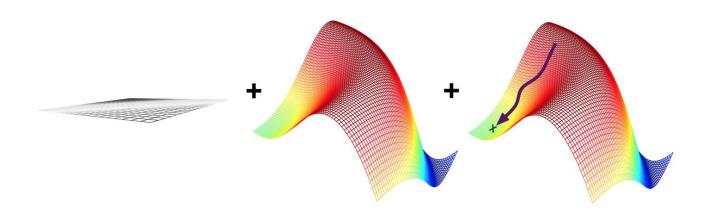
Tools: Bayes

$$p(C = k|x) = \frac{p(x \mid C = k) p(C = k)}{p(x)}$$



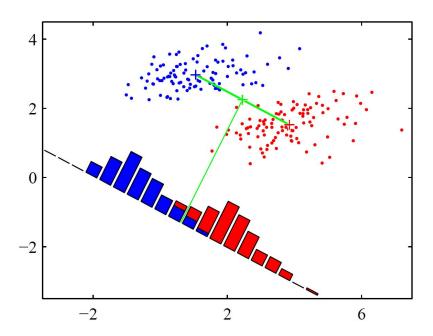
Common steps in all approaches

- The learning of a model from the data entails:
- Model representation
- Evaluation
- Optimization



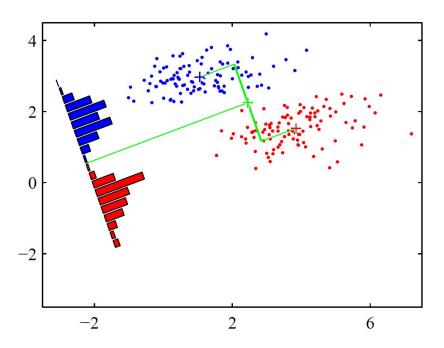
Design of a classifier (example)

- Use the (hyper-) plane orthogonal to the line joining the means
 - Project the data in the direction given by the line joining the class means



Design of a classifier (example)

 Project the data in the direction that maximizes the ratio between class variance to within class variance (Fisher)



Design of a classifier (example)

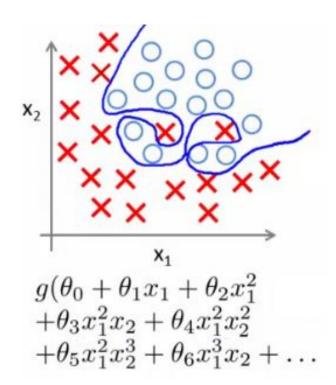
- Fisher's linear discriminant
 - Model representation: class of linear models
 - Evaluation: find the direction w that maximizes J(w)

$$J(\omega) = \frac{(m_2 - m_1)^2}{s_1^2 + s_2^2} \qquad J(\omega) = \frac{\omega^T S_B \omega}{\omega^T S_W \omega}$$

- Optimization:

$$\omega^* \infty S_w^{-1} (m_2 - m_1)$$

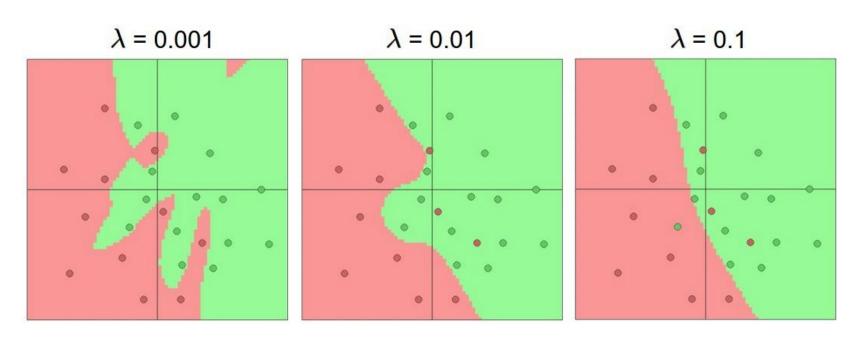
Avoid overfitting and data memorization



Avoid overfitting and data memorization

Evaluation:

- Minimize (error in data) + λ (model complexity)





Machine Learning (Part 2)

(Basic Concepts + Basic Coding)

https://colab.research.google.com/drive/1ZXYpsBx6y74LULldLLgwcFNdHRkoixtf?usp=sharing

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