









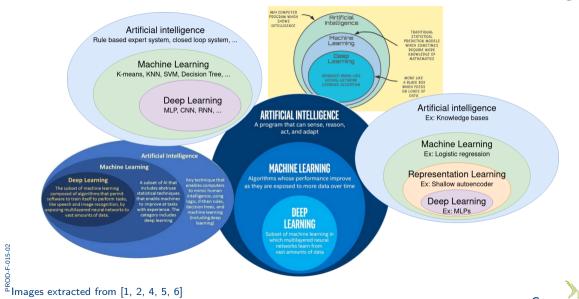


MARTA

Machine leARning TutoriAl 9-10 March 2023, Belgium

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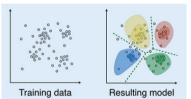
Machine Learning can be further classified in three categories:

Supervised Lion Cow Dog = Labels

Semi-supervised

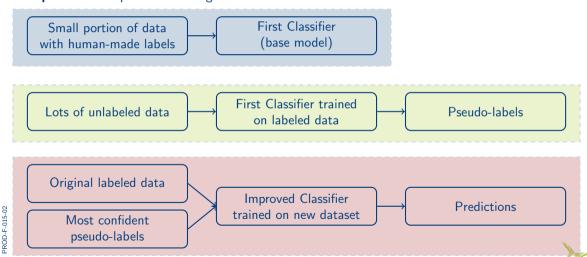
Uses a small set of **labeled** data and a larger set of **unlabeled** data, happy compromise between the two previous categories.

Unsupervised



PCA and POD are also examples of unsupervised learning (=dimensionality reduction) and can also be performed with neural networks

Example of semi-supervised learning



Examples of common Machine Learning algorithms:

- Linear regression is now part of ML techniques, even if it is used for many decades now
- Logistic regression is a supervised learning used to make predictions for categorical response variables
- Clustering is an unsupervised learning that identifies patterns in data to group them
- Decision trees are used both for regression problems (prediction of numerical values) and for classification (branching sequence of linked decisions)
- Random forests predict a value or category by combining the results from several decision trees.
- Neural networks can be seen as "the way the human brain works"

Speech recognition

- to conduct voice search (e.g., Siri)
- to translate human speech into a written format

Computer vision

- facial recognition
- radiology imaging in healthcare
- self-driving cars in the automotive industry

Applications into Physics

- Space ablation model (Tool: LSTM)
- Wall models and improvement of RANS models based on Direct Numerical Simulations (DNS) and Large Eddy Simulations (LES) data (Tool: CNN, MDN, MLP, ...)
- Ice accretion model (Tool: well-chosen combination of MLP)
- Prediction of the temperature evolution in additive manufacturing (Tool: Graph Neural Network)

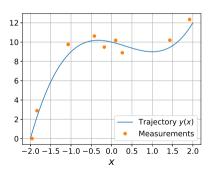
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Let's start with a basic example of machine learning

Database

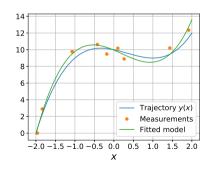
Assuming a phenomena y that is controlled by a single variable x (e.g. the trajectory of a moving object with y(x) the instantaneous position at time x). Let us construct a database of n pairs of values $\{(x_i, y(x_i)), i = 0, \ldots, n\}$, being a set of y measurements for different values of x.



Let's start with a basic example of machine learning

Model

The database on itself is not useful. However, as an engineer, we are interested to predict the value of the phenomena y at any value of the control variable x. We want to build a model $\hat{y}(x)$ that "fits" (i.e., according to a given risk) the values of the real phenomena $y(x_i)$ as recorded in the database but with generalization capabilities allowing to predict \hat{y} for any x value.



Note: The model is here all polynomial functions of order 3 defined as

$$\hat{y}(x) = p_3 x^3 + p_2 x^2 + p_1 x + p_0$$

Method

- 1. Database creation: build, clean, and organize the available data in an adapted format
- 2. **Model definition:** the example above uses a polynomial fitting of order 3 such that we try to fit the four coefficients in $\hat{y}(x) = p_3 x^3 + p_2 x^2 + p_1 x + p_0$ according to a given risk
- 3. **Training the model on the database:** an optimization method is used to adjust the values of the four model parameters p_i such that $\hat{y}(x)$ is "close" (according to a given metric) to the measured value y(x) for each of the point (x, y(x)) in the database
 - ▶ Define a minimization function \mathcal{L} (e.g., MSE)
 - ▶ Setup an optimization method to adapt the four model parameters (e.g., gradient descent):

$$p_{i,t+1} = p_{i,t} - \gamma \left(\frac{\partial \mathcal{L}}{\partial p_i} \right)_t$$
 where γ is the learning rate .

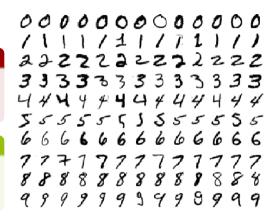
- ► Loop over the database to reach the desired model accuracy
- Save the 'trained model' for future use
- 4. **Test** the 'trained model' on unseen data

Remark

The previous example was an easy one-to-one relation. However, real-world problems are not as simple as that.

Question

How can an algorithm be implemented to recognise low-resolution handwritten digits (see figure on the right [3])?



More complicated example of machine learning

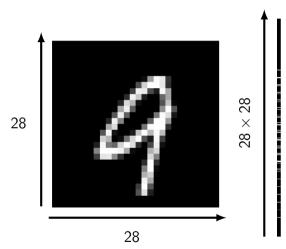
Digits classification using (deep) neural network

The human brain can quickly distinguish a three, a one, or a nine, but how can a machine make the same distinction as us? This is where deep learning appears as *almost miraculous*. Deep neural networks are large artificial neural networks (ANN) that claim to combine both

- automatic feature engineering, and,
- universal approximation capabilities.

Thanks to their hidden and activation layers, ANN are able to identify relevant features and their functional relationships with limited human intervention. However, the remaining **drawback** is the size of the database that needs to be large enough to capture the relevant phenomena. You will also have to deal with a list of **hyperparameters** to tune.

More complicated example of machine learning



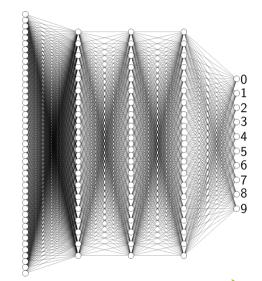


Image extracted from MNIST database and neural network generated on https://alexlenail.me/NN-SVG/

After this brief introduction about Machine Learning, we can dive into the tutorial which is constructed according to six sections:

1. The **first** section is dedicated to the Pytorch data structures. Through this section, we will see how to construct a tensor and how to perform operations on them.

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- 6. The **sixth** section ... it's your turn.

- Input is a p-dimensional vector of features or descriptors.
- Output is the prediction of a model (e.g., a scalar value, a label, an image, a signal, ...).
- Target is the feature of a dataset about which you want to gain a deeper underdstanding.
- **Epoch** is a *N*/batch size training iterations, where *N* is the size of training database (i.e., number of training samples). A full training pass over the entire training set such that each sample of the training database is visited.
- Batch is a set of samples used in one training iteration.
- Batch size corresponds to the number of samples contained in a batch.
- Learning rate is a floating point which is multiplied to the gradient to adjust the weights and biases on each iteration.
- Layer is a set of neurons in a neural network. There exist three common layers: the input layer, the hidden layer and the output layer.



¹Inspired by https://developers.google.com/machine-learning/glossary\$#\$h

- **Backpropagation** is an algorithm that implements the gradient descent based on the chain rule for a neural network.
- Neuron is the basic unit of computation in a neural network, also called node or unit.
- Weights and Biases are model's parameters learned during the training.
- Hyperparameter is a parameter whose value is used to control the learning process (e.g. the learning rate).
- Loss function measures how far the model's prediction is from its target value (i.e., its label) according to a given metric (e.g. MSE, Cross Entropy, ...).
- Activation function is the key ingredient to help neural network to learn nonlinear (complex) relationship between the features (=inputs) and the label (=targets).
- Overfitting A model overfits the training data if the predictions on it are so closely that it fails to make correct predictions on unseen data.
- Underfitting A model underfits the training data if it has poor prediction abilities because it has not fully captured the training data complexity.

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