1 Supervised learning

Method where you train the program by feeding the learning algorithm with a mapping of inputs to correct outputs.

1.1 Regression

Regression is curve fitting: learn a continuous input $\rightarrow$ output mapping from a set of examples.

1.2 Classification

Outputs are discrete variables (category labels). Learn a decision boundary that separates one class from the other. Generally, a confidence is also desired, i.e., how sure are we that the input belongs to the chosen category.

1.3 Training set

The training set is a set of m $(X,\, y)$ pairs, where:

$$\begin{aligned} X \in \mathbb{R}^d &\quad \text{models the input.} \\ y \in \{0, 1\} &\quad \text{models the output.} \end{aligned}$$

1.4 Error function

The error function for a model $f : X \mapsto y$ parameterized by W applied to a dataset $\{(X,\, y)\}$ of size m is:

$$\min_W \sum_{i=1}^{m} \left(f_W(X_i) - y_i\right)^2$$

1.5 Perceptron

Perceptron is the trivial neural network. The model for a parameter $W = (\text{threshold},\, w_1,\, \ldots,\, w_d)$ and inputs of the form $(1,\, x_1,\, \ldots,\, x_d)$ is given by

$$f_W(X) = \text{sign}(W^\top X)$$

If x_i is evidence for approval, then w_i should be high.
If x_i is evidence for denial, then w_i should be low.

1.5.1 Learning algorithm

The learning algorithm of the Perceptron is quite simple. The learning rate $\in (0,\, 1]$ is used to scale each step. the For a training set $S = \{\, (X_1,\, y_1),\ \ (X_1,\, y_1),\ \ \ldots\,\}$

- Starting with random weights, show each sample in sequence repetitively.
- If the output is correct, do nothing.
- If the produced output is negative, and the correct output is positive, increase the weights.
- If the produced output is positive, and the correct output is negative, decrease the weights.
- The amount to increase/decrease is given by the current sample scaled by the learning rate.

1.6 Error

The error function for a model f in a **training** sample is

$$E_{\text{in}}(f)$$

This function is known and calculable.

The error function for a model f in a **test** sample is

$$E_{out}(f)$$

This function is **not** known, and only **approachable**.

Given a model f in a set of M models, the bound for the probability of the error deviation surpassing a given ϵ is

$$\mathbb{P}\left(\left|E_{\text{in}}(f) - E_{out}(f)\right| > \epsilon\right) \leq 2Me^{-2N\epsilon^2}$$

Notably, $E_{\text{in}}(f)$ and $E_{\text{out}}(f)$ deviates as f becomes complex.

1.6.1 Empirical error minimization

During the learning algorithm, always conserve the weights that produce the lower error.
This has a disadvantage: It memorizes the training set.

1.7 Ensemble learning

Ensemble learning consists in combining several simple models to form a more complex model.

Bagging: Each model training with a different dataset

Boosting: Same dataset, but instrumented for each model to mitigate the weakness of others

1.8 Learning decision trees

Each layer in the tree consists of an attribute that splits the data into subsets that are ideally disjoint.
The entropy of the subsets produced is a measure of how disjoint they are.

For a set containing p positive and n negatives, the entropy is

$$H\left(\frac{p}{p+n}, \frac{n}{p+n}\right) = -\frac{p}{p+n}\log\left(\frac{p}{p+n}\right) - \frac{n}{p+n}\log\left(\frac{n}{p+n}\right)$$

A given attribute A, with k distinct values, divides the training set S into subsets $S_1, S_2, \ldots, S_k$.
The expected entropy remaining after applying A is

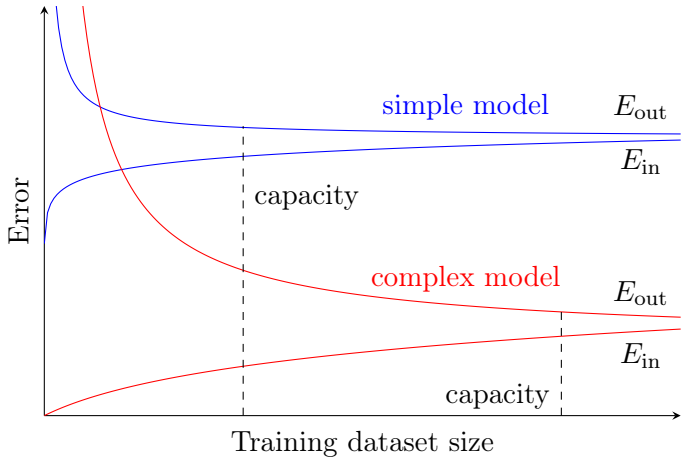
$$EH(A) = \sum_{i=1}^{k}\left[\frac{p_i + n_i}{p+n} \cdot H\left(\frac{p_i}{p_i+n_i}, \frac{n_i}{p_i+n_i}\right)\right]$$

The information gain, i.e. the reduction in entropy for A, is

$$I(A) = H\left(\frac{p}{p+n}, \frac{n}{p+n}\right) - EH(A)$$

1.8.1 Capacity

The capacity is a measure of when the training error is a good approximation for the test error.



2 Reinforcement learning

Method where you train the program by rewarding the learning algorithm positively or negatively according to the produced results. This method is similar to how we teach animals.

3 Unsupervised learning

Given only inputs as training, find a pattern: discover clusters, manifolds, embedding.