

Machine Learning Cheatsheet

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1 Introduction

What does it mean "to learn"? We have two different definitions, one from a **statistical perspective**, and one from a **computer science perspective**.

- **Statistical Perspective**

Vast amounts of data are being generated in many fields. The statistician's job is to make sense of all of this data, extract meaningful patterns and trends, and understand "what the data says". This approach is also known as **learning from data**.

- **Computer Science Perspective**

The field of machine learning is concerned with how to construct computer programs that automatically improve with experience.

1.1 Mitchell's Formalisation

A computer program is said to learn from **experience** E – concerning some class of **task** T , and **performance measurement** P – if its performance at task T , as measured by P , improves with experience E .

1.2 Models

1.2.1 White Box Model

In this case, both physical laws and structural parameters of the problem are known. A family equation can be derived.

1.2.2 Grey Box Model

The physical laws are known in this case, and at least one parameter is unknown. A family of equations can be derived, but the parameters need to be identified.

1.2.3 Black Box Model

In this case, the physical laws are unknown. A family of equations cannot be derived.

1.3 Measures and Measurements

The operation of measuring an unknown quantity x_0 can be modeled as taking an instance – i.e., a **measurement** – x_i at time i , with an ad-hoc sensor S .

Although S has been suitably designed and realized, the physical elements that compose it are far from ideal and introduce uncertainties in the measurement process. As a result, x_i only represents an estimate of x_0 .

1.4 Types of Models

1.4.1 Additive Model

The measurement process can be modeled as:

$$x = x_0 + \eta \quad \text{where } \eta = f_n(0, \sigma_\eta^2)$$

Where η is an independent and identically distributed random variable, the model assumes that the i.i.d. noise does not depend on the working point x_0 .

1.5 Multiplicative Model

The measurement process can be modeled as:

$$x = x_0(1 + \eta) \quad \text{where } \eta = f_n(0, \sigma_\eta^2)$$

Where η is an independent and identically distributed random variable, the noise, in this case, depends on the working point x_0 . In absolute terms, the impact of the noise on the signal is $x_0\eta$, but the relative contribution is η – which does not depend on x_0 .

1.6 Supervised Learning

In a supervised learning framework, we have the following elements: a **concept to learn**, a **teacher**, and a **student**.

1.6.1 Regression

The goal of regression is to determine the function that explains the given instances – **measurements**. The student proposes a family of models $f(\theta, x)$, and after a learning procedure, the "best" model $f(\hat{\theta}, x)$ is found.

1.6.2 Classification

The goal of classification is to determine the function – **model** – that partitions the input – **measurements** – into classes. The student proposes a family of models $f(\theta, x)$, and after a learning procedure, the "best" model $f(\hat{\theta}, x)$ is found.

1.6.3 Prediction

The goal of prediction is to tell us which data – **measurements** – will come next, possibly along with a confidence level. The student proposes a family of models $f(\theta, x)$, and after a learning procedure, the "best" model $f(\hat{\theta}, x)$ is found.

1.7 Features

We might want to extract features from the measurements to ease the learning task. The features must:

- Provide a compact representation of inputs
- Be particularly advantageous if we have prior information to take advantage of
- Be reduced to a minimal set before processing them for task solving

1.8 Unsupervised Learning

The goal of unsupervised learning is to build a representation of data. During its operational life, given an input, the machine provides information that can be used for decision-making.