Data ▪ Model ▪ Loss

An open resource from the Aalto Dictionary of ML

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October 7, 2025

At a glance — goals

- Understand the three components of machine learning (ML): data, model, loss.
- Identify features vs labels in common modalities (image, audio).
- Explain how a hypothesis maps $\mathcal{X} \to \mathcal{Y}$.
- Compare common loss functions and when to use them.

Data point = An Image $\mathbf{z}$

Features:

- $x_1, \ldots, x_d$: Colour intensities of all image pixels.
- x_{d+1}: Time-stamp of the image capture.
- x_{d+2}: Spatial location of the image capture.

Labels:

- y_1: Number of cows depicted.
- y_2: Number of wolves depicted.
- y_3: Condition of the pasture (e.g., healthy, overgrazed).

Data point = An Audio Recording $\mathbf{z}$

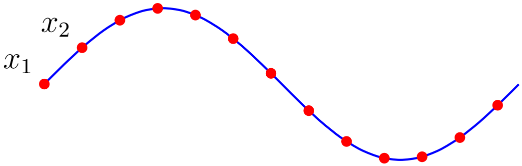
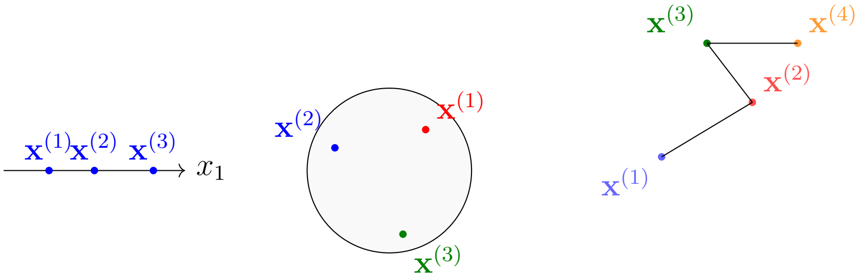


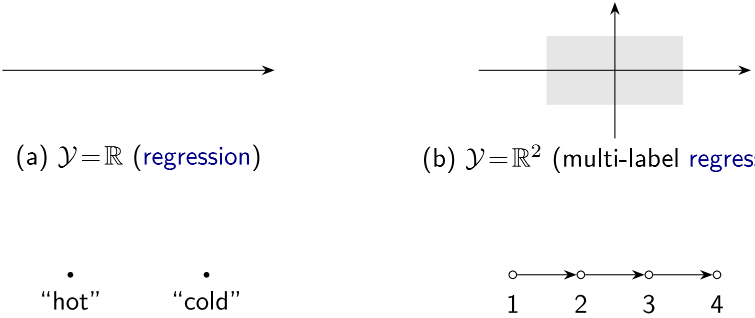
Figure: An audio signal (blue waveform) $\mathbf{z}$ and its discretized signal samples (red dots) which can be used as its features $x_1, \ldots, x_d$.

Feature space

- often we use a fixed number $d \in \mathbb{N}$ of features
- stack them into a feature vector $\mathbf{x} = \big(x_1, \ldots, x_d\big)$
- feature vectors belong to some feature space $\mathcal{X}$
- most widely-used (by far) choice is $\mathcal{X} = \mathbb{R}^d$



Label space



(a) $\mathcal{Y} = \mathbb{R}$ (regression)

(b) $\mathcal{Y} = \mathbb{R}^2$ (multi-label regression)

(c) $\mathcal{Y} = \{y_1, y_2\}$ (binary classification)

(d) $\mathcal{Y} = \{1, 2, 3, 4\}$ (ordinal regression)

Figure: Examples of label spaces and corresponding ML flavours.

Goal of ML: Predict Label from Features

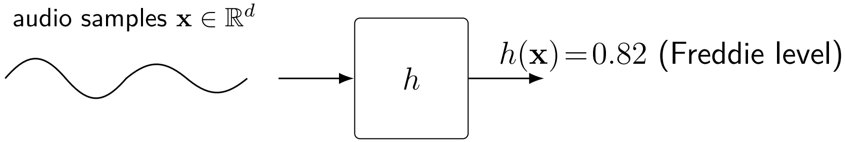


Figure: A hypothesis $h : \mathcal{X} \rightarrow \mathcal{Y}$ maps the features $\mathbf{x} \in \mathcal{X}$ of a data point to a prediction $h(\mathbf{x}) \in \mathcal{Y}$ of the label. For example, the ML application `https://freddiemeter.withyoutube.com/` uses the samples of an audio recording as features predict how closely a person's singing resembles that of Freddie Mercury.

From Features to Prediction

$$\boxed{\mathbf{x} \in \mathcal{X}} \longrightarrow \boxed{h} \longrightarrow \boxed{\hat{y} = h(\mathbf{x})}$$

Core Problem of ML given data $\{(\mathbf{x}^{(r)}, y^{(r)})\}_{r=1}^{m}$ and model $\mathcal{H}$, learn (or find) $\widehat{h} \in \mathcal{H}$ such that $\widehat{h}(\mathbf{x}) \approx y$ for any data point with features $\mathbf{x}$ and label y.

Model = A Set of Hypothesis Maps

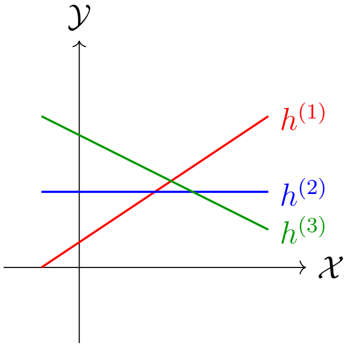
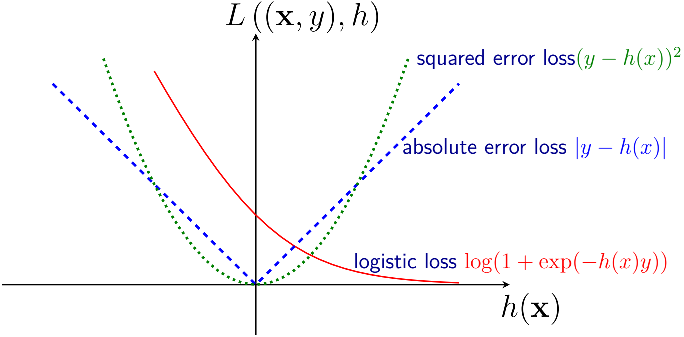


Figure: A hypothesis space $\mathcal{H} = \{h^{(1)}, h^{(2)}, h^{(3)}\}$ consisting of three linear maps.

Which one of the hypothesis maps is the best?

Loss function



A loss function $L\left((\mathbf{x}, y), h\right)$ measures the error (or "loss"), incurred by predicting the label y of a data point with feature vector $\mathbf{x}$.

Which Loss function should we use?

The choice of loss function influences

- computational aspects,
- statistical aspects (robustness, generalization, . . .), and
- interpretability

of the resulting ML method.

Reuse & Citation

Source and updates: `https://github.com/AaltoDictionaryofML/AaltoDictionaryofML.github.io`