

1. Introduction – Supervised Learning

Deep Learning

Prof. Dr. Christoph Lippert

based on the material at <https://d2l.ai>

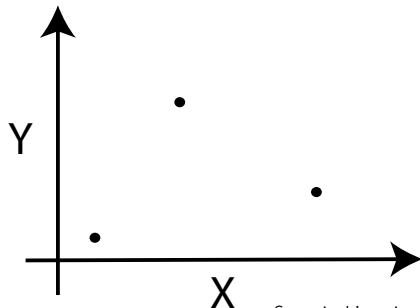
Key concepts

Data

- Let \mathcal{D} denote a **dataset**, consisting of N **datapoints** $\mathcal{D} = \{ \underbrace{\mathbf{x}_i}_{\text{Inputs}}, \underbrace{y_i}_{\text{Outputs}} \}_{i=1}^N$.
- Typical (this course)
 - $\mathbf{x} = \{x_1, \dots, x_D\}$ multivariate, spanning D features for each observation (age, image pixels etc.).
 - y
 - univariate (disease status, price, etc.).
 - multivariate (image segmentation, bounding box)

- Notation:

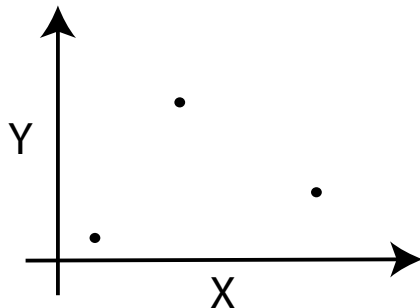
- x : A scalar
- \mathbf{x} : A vector
- \mathbf{X} : A matrix
- $x_i, [\mathbf{x}]_i$: The i^{th} element of vector \mathbf{x}
- $x_{ij}, [\mathbf{X}]_{ij}$: The element of matrix \mathbf{X} at row i and column j



Key concepts

Predictions

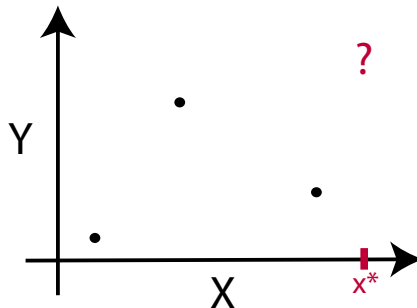
- Observed training dataset $\mathcal{D} = \{ \underbrace{\mathbf{x}_n}_{\text{Inputs}}, \underbrace{y_n}_{\text{Outputs}} \}_{n=1}^N$.
- Given \mathcal{D} , what can we say about y^* at an unseen test input \mathbf{x}^* ?



Key concepts

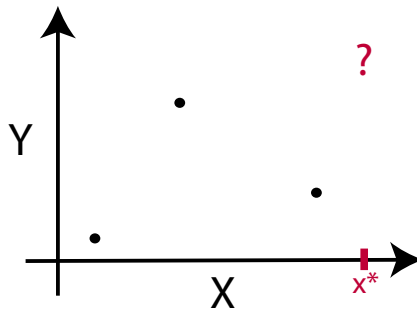
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Model

- Observed **dataset** $\mathcal{D} = \left\{ \underbrace{\mathbf{x}_n}_{\text{Inputs}}, \underbrace{y_n}_{\text{Outputs}} \right\}_{n=1}^N$.
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- To make **predictions** we need to make **assumptions**.
- A **model** encodes these assumptions and often depends on some parameters θ .

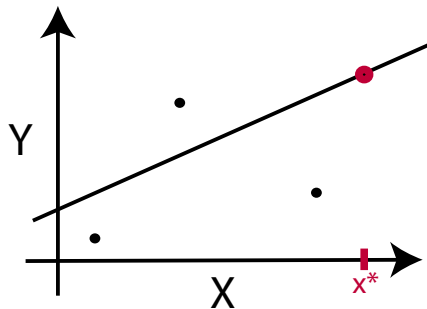


Model

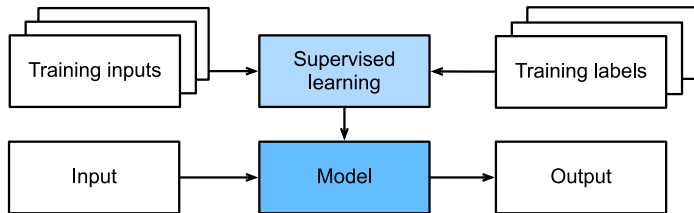
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- Curve fitting: the model relates x to y ,

$$\begin{aligned} y &= f(x; \underbrace{(w, b)}_{\theta}) \\ &= \underbrace{b + w \cdot x}_{\text{example: a linear model}} \end{aligned}$$



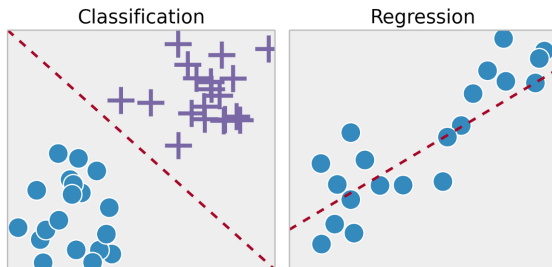
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Classification vs. regression

Classification:

- Categorize data into discrete categories (e.g. disease vs healthy)

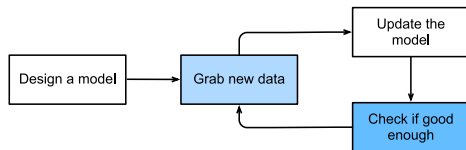


Regression:

- Predict continuous output variable (e.g. insulin level)

Loss and optimization

Training process



- In order to **optimize** our parameters, we need an **objective function** to score different models and parameter settings.
- Based on our training data, we find the model that minimizes the loss using an **optimization algorithm**.
 - Training Error:
The error on that data on which the model was trained.
 - Test Error:
This is the error incurred on an unseen test set.
Can deviate significantly from the training error.

Loss and optimization

Regression

- L1 loss

$$l(y, y') = \sum_i |y_i - f'_i|$$

- squared loss, or L2 loss

$$l(y, y') = \sum_i (y_i - f'_i)^2.$$

Classification

Predict (probability P of) a category given the input

- Negative **log likelihood** of the labels y_i

$$\sum_i -\log P(y_i|x_i; \theta)$$

Better known as **cross entropy** loss

$$P(y = \text{deathcap}|\text{image}) = 0.2$$

$$L(\text{action}|x) = E_{y \sim p(y|x)}[\text{loss}(\text{action}, y)].$$



Supervised Learning Summary

For supervised learning, we need

- Labeled training data
- A model with parameters that encodes my assumptions
- An objective function (loss function)
- An optimization algorithm to find the best parameter values