

# Machine Learning

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February 27, 2021

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# 1 Supervised Learning

**input  $\mathbf{x}$**  also called features or attributes

**output  $\mathbf{t}$**  also called targets or labels

**Goal** find a good approximation for  $f : x \rightarrow t$

## 1.1 Tasks

**Classification**  $\mathbf{t}$  is discrete

**Regression**  $\mathbf{t}$  is continuous

**Probability estimation**  $\mathbf{t}$  is a probability

## 1.2 When to use supervised learning?

- Human cannot perform the task
- Human can perform the task but cannot explain how
- Task changes over time
- Task is user-specific

## 1.3 Steps

To approximate  $f$  over the dataset  $\mathcal{D}$

1. Define a loss function  $\mathcal{L}$
2. Choose the hypothesis space  $\mathcal{H}$
3. find  $h \in \mathcal{H}$  that minimizes  $\mathcal{L}$  over  $\mathcal{D}$

## 1.4 Representation, Evaluation, Optimization

**Examples of representation**

- Linear models
- Instance-based
- Decision trees
- Set of rules
- Graphical models
- Neural networks

- Gaussian Processes
- Support vector machines
- Model ensembles

### **Examples of evaluation**

- Accuracy
- Precision and recall
- Squared Error
- Likelihood
- Posterior probability
- Cost/Utility
- Margin
- Entropy
- KL divergence

### **Examples of optimization**

- Combinatorial optimization
  - e.g.: Greedy search
- Convex optimization
  - e.g.: Gradient descent
- Constrained optimization
  - e.g.: Linear programming

## **1.5 Supervised learning taxonomy**

- Parametric vs Nonparametric
  - Parametric: fixed and finite number of parameters
  - Nonparametric: the number of parameters depends on the training set
- Frequentist vs Bayesian
  - Frequentist: use probabilities to model the sampling process
  - Bayesian: use probability to model uncertainty about the estimate

- Empirical Risk Minimization vs Structural Risk Minimization
  - Empirical Risk: Error over the training set
  - Structural Risk: Balance training error with model complexity
- Direct vs Generative vs Discriminative
  - Generative: learns the joint probability distribution  $p(x, t)$
  - Discriminative: learns the conditional probability distribution  $p(t|x)$

## 1.6 Learning approaches

**Direct approach** Learn directly  $f$  from  $D$

**Discriminative approach**

- Model  $p(t|x)$
- Marginalize to find  $E[t|x] = \int t \cdot p(t|x) dt$

**Generative approach**

- Model  $p(x, t)$
- Infer  $p(t|x)$  (Bayes rule)
- Marginalize to find  $E[t|x] = \int t \cdot p(t|x) dt$