

GENERATIVE APPROACH TO STATISTICAL PATTERN RECOGNITION

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The objective of pattern recognition is to classify a given pattern \mathbf{x} to one of the pre-specified classes, y . For example, in hand-written digit recognition, pattern \mathbf{x} is an image of hand-written digit and class y corresponds to the number the image represents. The number of classes is 10 (i.e., from “0” to “9”). Among various approaches, statistical pattern recognition tries to learn a classifier based on statistical properties of training samples. In [Part 3](#), an approach to statistical pattern recognition based on estimation of the data-generating probability distribution.

After the problem of pattern recognition based on generative model estimation is formulated in [Chapter 11](#), various statistical estimators are introduced. These methods are categorized as either *parametric* or *non-parametric* and either *frequentist* or *Bayesian*.

First, a standard parametric frequentist method called *maximum likelihood estimation* is introduced in [Chapter 12](#), its theoretical properties are investigated in [Chapter 13](#), the issue of model selection is discussed in [Chapter 14](#), and the algorithm for Gaussian mixture models called the *expectation–maximization algorithm* is introduced in [Chapter 15](#). Then, non-parametric frequentist methods called *kernel density estimation* and *nearest neighbor density estimation* are introduced in [Chapter 16](#).

The basic ideas of the parametric Bayesian approach is introduced in [Chapter 17](#), its analytic approximation methods are discussed in [Chapter 18](#), and its numerical approximation methods are introduced in [Chapter 19](#). Then practical Bayesian inference algorithms for *Gaussian mixture models* and *topic models* are introduced in [Chapter 20](#), which also includes a non-parametric Bayesian approach.