

(Session- 2018-19)

Introduction to Bayesian Learning

Introduction

- Allows us to combine observed data and prior knowledge
- Provides practical learning algorithms
- It is a generative (model based) approach, which offers a useful conceptual framework
 - This means that any kind of objects (e.g. time series, trees, etc.) can be classified, based on a probabilistic model specification

Bayes' Rule

$$p(h | d) = \frac{P(d | h)P(h)}{P(d)}$$

Understanding Bayes' rule

d = data

h = hypothesis

Proof. Just rearrange:

$$p(h | d)P(d) = P(d | h)P(h)$$

$$P(d, h) = P(d, h)$$

the same joint probability

on both sides

Who is who in Bayes' rule

$P(h)$:	prior belief (probability of hypothesis h before seeing any data)
$P(d h)$:	likelihood (probability of the data if the hypothesis h is true)
$P(d) = \sum_h P(d h)P(h)$:	data evidence (marginal probability of the data)
$P(h d)$:	posterior (probability of hypothesis h after having seen the data d)

Does patient have cancer or not?

- A patient takes a lab test and the result comes back positive. It is known that the test returns a correct positive result in only 98% of the cases and a correct negative result in only 97% of the cases. Furthermore, only 0.008 of the entire population has this disease.
 - What is the probability that this patient has cancer?
 - What is the probability that he does not have cancer?
 - What is the diagnosis?

$$\begin{aligned}
 P(\text{cancer}) &= .008, P(\neg \text{cancer}) = .992 \\
 P(+ | \text{cancer}) &= .98, P(- | \text{cancer}) = .02 \\
 P(+ | \neg \text{cancer}) &= .03, P(- | \neg \text{cancer}) = .97 \\
 P(\text{cancer} | +) &= \frac{P(+ | \text{cancer})P(\text{cancer})}{P(+)} \\
 P(\neg \text{cancer} | +) &= \frac{P(+ | \neg \text{cancer})P(\neg \text{cancer})}{P(+)}
 \end{aligned}$$

Maximum A Posteriori (MAP) Hypothesis

$$P(h | D) = \frac{P(D | h)P(h)}{P(D)}$$

The Goal of Bayesian Learning: the most probable hypothesis given the training data (Maximum A Posteriori hypothesis)

$$\begin{aligned}
 h_{MAP} &= \arg \max_{h \in H} P(h | D) \\
 &= \arg \max_{h \in H} \frac{P(D | h)P(h)}{P(D)} \\
 &= \arg \max_{h \in H} P(D | h)P(h)
 \end{aligned}$$

Thank you...