

Bayesian Learning

20CP401T

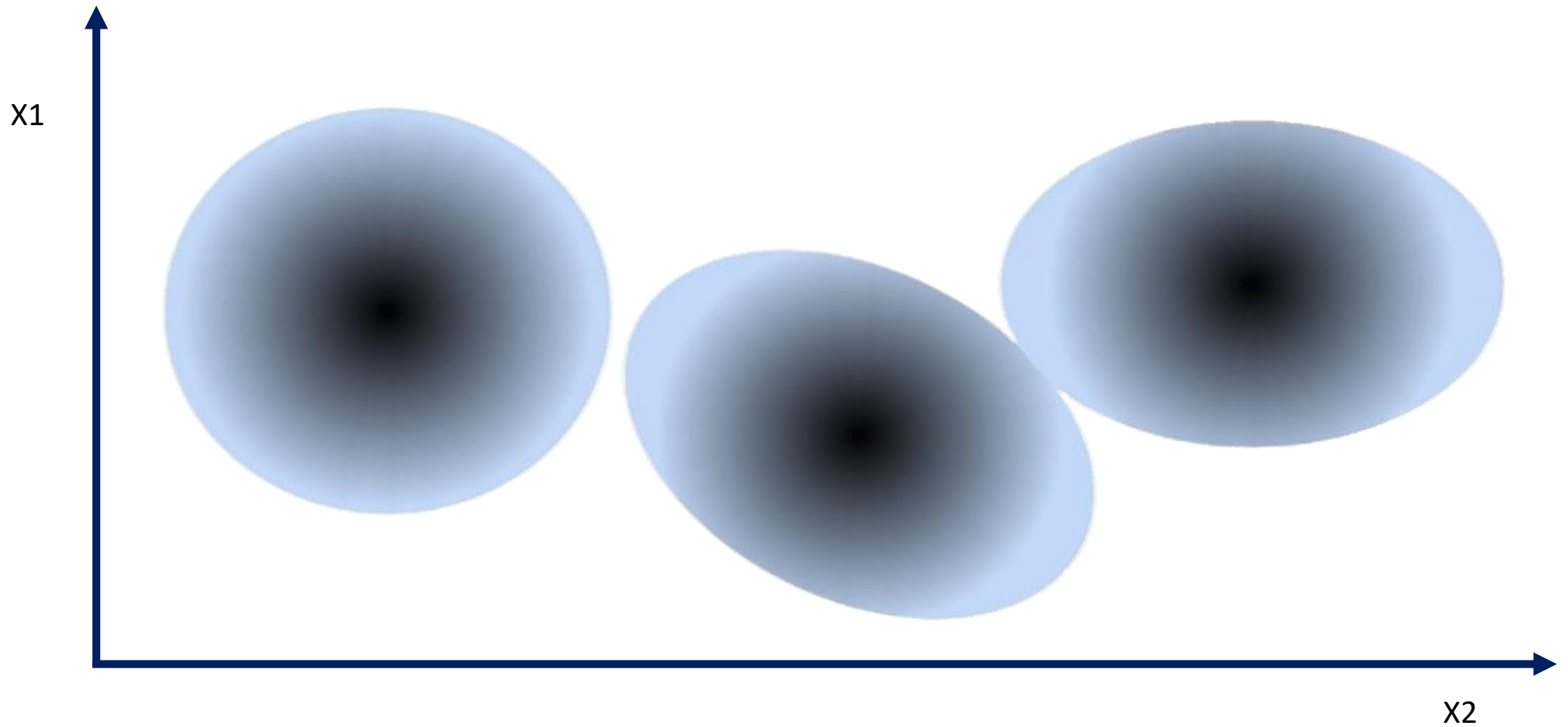
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Feature Space Representation

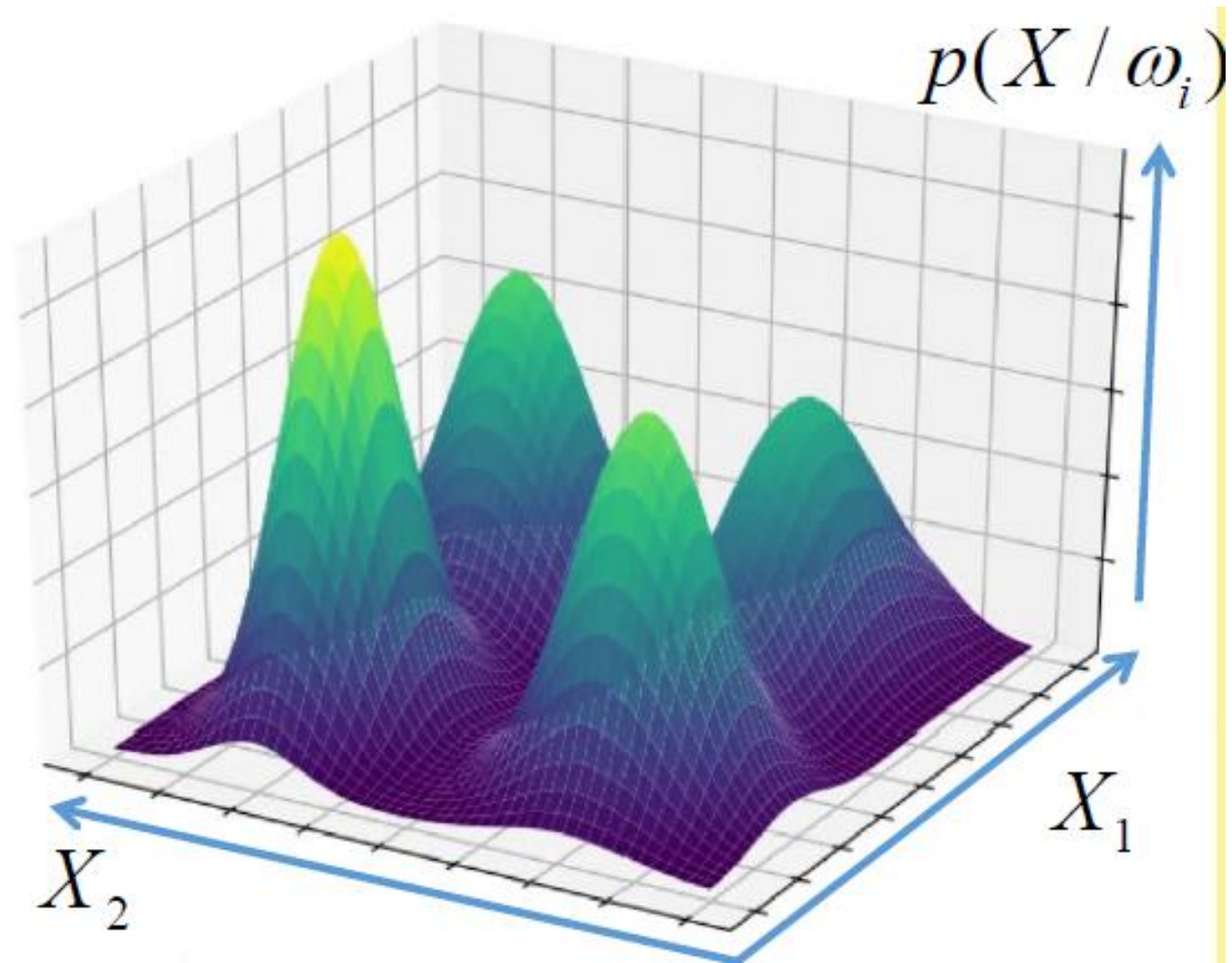


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Feature Space Representation



Feature Space Representation



Feature Space Representation

- Design classifiers to recommend **decisions** that minimize some total expected **"risk"**.
 - The simplest **risk** is the **classification error** (i.e., costs are equal).
 - Typically, the **risk** includes the **cost** associated with different decisions.

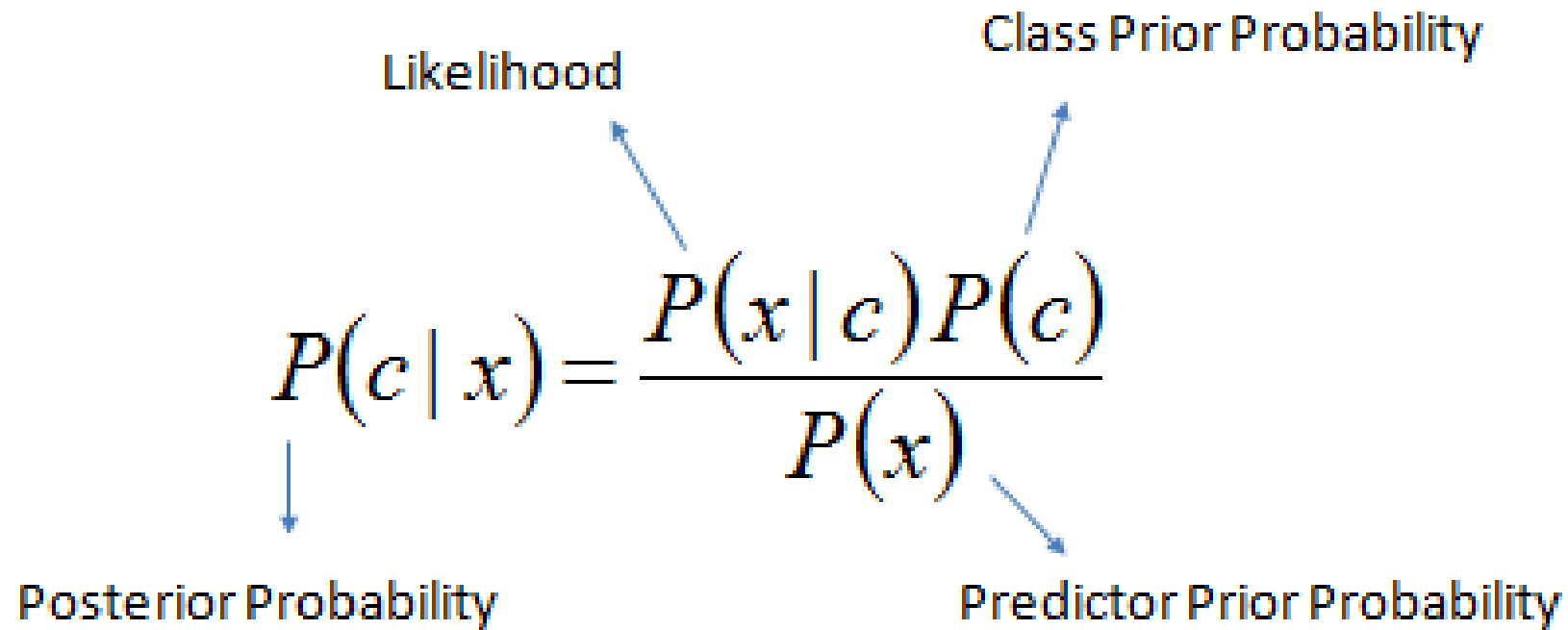
Terminology

- State of nature ω (*random variable*):
 - e.g., ω_1 for car, ω_2 for bird
- Probabilities $P(\omega_1)$ and $P(\omega_2)$ (*priors*):
 - e.g., prior knowledge of how likely is to get a bird or a car
- Probability density function $p(x)$ (*evidence*):
 - e.g., how frequently we will measure a pattern with feature value x (e.g., x corresponds to lightness)

Terminology

- Conditional probability density $p(x/\omega_j)$ (**likelihood**) :
 - e.g., how frequently we will measure a pattern with feature value x given that the pattern belongs to class ω_j
- Conditional probability $P(\omega_j / x)$ (**posterior**) :
 - e.g., the probability that the fish belongs to class ω_j given measurement x .

Terminology



A diagram illustrating the components of Bayes' theorem. The central equation is $P(c | x) = \frac{P(x | c) P(c)}{P(x)}$. Four blue arrows point from the labels to the corresponding parts of the equation: 'Likelihood' points to $P(x | c)$, 'Class Prior Probability' points to $P(c)$, 'Posterior Probability' points to $P(c | x)$, and 'Predictor Prior Probability' points to $P(x)$.

$$P(c | x) = \frac{P(x | c) P(c)}{P(x)}$$

Likelihood

Class Prior Probability

Posterior Probability

Predictor Prior Probability

$$P(c | X) = P(x_1 | c) \times P(x_2 | c) \times \cdots \times P(x_n | c) \times P(c)$$

Decision Rule Using Prior Probabilities

Decide ω_1 if $P(\omega_1) > P(\omega_2)$; otherwise decide ω_2

$$P(\text{error}) = \begin{cases} P(\omega_1) & \text{if we decide } \omega_2 \\ P(\omega_2) & \text{if we decide } \omega_1 \end{cases}$$

or $P(\text{error}) = \min[P(\omega_1), P(\omega_2)]$

Favors the most likely class.

- This rule will be making the same decision all times.
i.e., optimum if no other information is available

Decision Rule Using Conditional Probabilities

Using Bayes' rule, the posterior probability of category ω_j given measurement x is given by:

$$P(\omega_j / x) = \frac{p(x / \omega_j)P(\omega_j)}{p(x)} = \frac{\textit{likelihood} \times \textit{prior}}{\textit{evidence}}$$

where $p(x) = \sum_{j=1}^2 p(x / \omega_j)P(\omega_j)$ (i.e., scale factor – sum of probs = 1)

Decide ω_1 if $P(\omega_1 / x) > P(\omega_2 / x)$; otherwise **decide** ω_2

or

Decide ω_1 if $p(x/\omega_1)P(\omega_1) > p(x/\omega_2)P(\omega_2)$ otherwise **decide** ω_2