



Probability Revisited

Discrete Random Variable, Continuous Random Variable,
Joint Probability, Conditional Probability, Probability
Distribution

Discrete Random Variable

- Discrete random variable: the expression $p(A)$ denotes the probability that the event A is true.
- A discrete random variable take any value from a finite or countably infinite set X .
- $p(X = x)$ denotes the probability mass function for the rv X and $\sum p(x) = 1$

Joint Probability

- We define probability of the joint event A and B as follows:
- $p(A, B) = p(A \cap B) = p(A|B)p(B)$
- This is sometimes called product rule.
- Given a joint distribution on two events $p(A, B)$, the marginal distribution is
- $p(A) = \sum_b p(A, B) = \sum_b p(A|B = b)p(B = b)$
- This is called sum rule or rule of total probability.

Joint Probability

- The product rule or chain probability can be written as
- $p(X_{1:N}) = p(X_1)p(X_2|X_1)p(X_3|X_2, X_1) \dots p(X_N|X_1, X_2 \dots X_{N-1})$

Conditional Probability

- The conditional probability for the event A , given that the event B is true
- $p(A|B) = \frac{p(AB)}{p(B)}$ if $p(B) > 0$
- Bayes Rule:
- $$p(X = x|Y = y) = \frac{p(X=x,Y=y)}{p(Y=y)} = \frac{p(Y = y|X = x)p(X=x)}{\sum_{\hat{x}} p(Y = y|X = \hat{x})p(X=\hat{x})}$$

Example:

- Suppose you are a woman in your 40s, and you decide to have a medical test for breast cancer called a mammogram. If the test is positive, what is the probability you have cancer? Suppose you are told the test has a sensitivity of 80%, which means, if you have cancer, the test will be positive with probability 0.8. the prior probability of having breast cancer is 0.004.

Generative Classifier

- We can generalize the medical diagnosis example to classify feature vectors x of arbitrary type as follows:

- $$p(y = c|x, \theta) = \frac{p(x|y = c, \theta)p(y=c|\theta)}{\sum_{\hat{c}} p(x|y = \hat{c}, \theta)p(y=\hat{c}|\theta)}$$

Mean and Variance

- The mean or expected value of X is denoted as $E(X)$ or μ
- $E(x) = \sum xp(x)$
- $E(x) = \int xp(x)dx$
- The variance of X is a measure of dispersion, denoted as σ^2
- $E[(X - \mu)^2] = \int (x - \mu)^2 p(x)dx$

Continuous Random Variable

- If X is some uncertain continuous quantity. The probability that X lies in any interval can be written as $P(a \leq X \leq b)$
- We define the cumulative density function of X as $F(a)$
- $P(a \leq X \leq b) = F(b) - F(a)$
- $p(a \leq x \leq b) = \int_a^b f(x)dx$, where $f(x)$ is pdf of X

Discrete Distribution

- Bernoulli Distribution
- Binomial Distribution
- Poisson Distribution
- The empirical Distribution

Bernouli Distribution

- A discrete random variable only having two outcome success with probability p and failure with probability $(1-p)$ follows Bernoulli distribution.
- $P(X = 1) = p$
- And $P(X = 0) = 1 - p$
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Binomial Distribution

- The binomial distribution is n repetition of the identical experiment, each experiment has only two outcomes: success and failure.
- $P(X = x) = {}^nC_x p^x (1 - p)^{n-x}$

Poisson Distribution

- $P(X = x) = \frac{\lambda^x e^{-\lambda}}{x!}$
- Where $x = 0, 1, 2, 3, 4, \dots$
- And λ is the long-run average

Empirical Distribution

- The empirical distribution for the dataset $D = \{x_1, x_2, \dots, x_n\}$ of n observation is the function $[0,1] \rightarrow \mathbb{R}$
- $F(x) = \frac{1}{n} \sum \mathbb{I}_n$

Gaussian Distribution

- The widely used distribution in machine learning is the Gaussian distribution. The probability distribution of x is
- $$(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$
- Where $\mu = E[x]$ and $\sigma^2 = \text{var}(x)$

Some Continuous Distribution

- Gaussian(Normal) Distribution
- Degenerate pdf
- The Laplace Distribution
- The gamma distribution
- Beta Distribution

Covariance and Correlation

- $COV(X, Y) = E[(X - E(X))(Y - E(Y))] = E(XY) - E(X)E(Y)$
- $Corr(X, Y) = \frac{COV(X, Y)}{\sqrt{var(X)Var(Y)}}$

Multivariate Gaussian

- The probability distribution function(pdf) for the multivariate Gaussian in \$D\$ dimension is defined as

- $$\mathcal{N}(x|\mu, \Sigma) = \frac{1}{(2\pi)^{\frac{D}{2}} |\Sigma|^{1/2}} \exp\left[-\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu)\right]$$