Foundations of Machine Learning Al2000 and Al5000

FoML-03 Probability - Expectation, Variance and Gaussian Distribution

> <u>Dr. Konda Reddy Mopuri</u> Department of AI, IIT Hyderabad July-Nov 2025





So far in FoML

- What is ML and the learning paradigms
- Probability refresher
 - o Sum rule, product rule, Random variables, Bayes Theorem, Independence



Expectation, Variance and the Gaussian Distribution





Expectation

• Random variable X and a function $f: X \to \mathbb{R}$

$$\mathbb{E}[f] = \mathbb{E}_{x \sim p(X)}[f(x)]$$





Expectation

• For N points drawn from $\rho(X)$

$$\mathbb{E}[f] =$$





Expectation

Conditional expectation

$$\mathbb{E}[f/y] = \mathbb{E}_{x \sim p(X/Y=y)}[f(x)]$$





Variance

ullet Expected quadratic distance between f and its mean ${\mathbb E}[f]$

var(f)





Covariance

 Measures the extent to which two random variables X and Y vary together

cov[X,Y]





Covariance

- X and Y are vectors of random variables
- Covariance matrix





Covariance

Between independent variables

cov[X,Y]



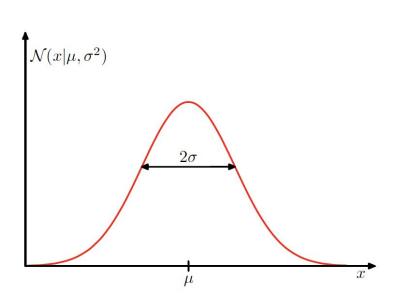


Gaussian Distribution





Gaussian Distribution



$$\mathcal{N}(x|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2}$$

$$x \sim \mathcal{N}(x|\mu, \sigma^2)$$

$$\mathbb{E}[x] = \mu \qquad \text{Var}(x) = \sigma^2$$

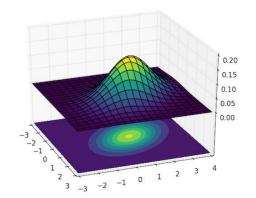




Multivariate Gaussian Distribution

ullet D-dimensional vector ${f x}=(x_1,x_2,\dots x_D)^T$

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







Next Maximum Likelihood Principle



