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Pattern Recognition Theory

Recitation 2: Probability and Statistics

Topics To Be Covered

- Basic Probability Theory
 - Elementary Stuff
 - Bayes Rule
- Random Variables (RVs)
 - PDFs and CDFs
 - Mean and Variance
 - Commonly Used PDFs
- Joint Distributions (>1 RV)
- Conditional Probability Revisited
- MATLAB functions

The Basic Stuff

- Define probability of an event as $P(A)$

$$P(A) = \lim_{n \rightarrow \infty} \frac{n_A}{n}$$

- Axioms of probability
 - $0 \leq P(A) \leq 1$
 - $P(\text{Certain Event}) = 1$, $P(\text{Impossible Event}) = 0$
 - If A and B are **Mutually Exclusive** i.e.

$$P[A \cap B] = 0 \text{ then } P[A \cup B] = P[A] + P[B]$$

- A and B are **Independent Events** if $P(AB) = P(A)P(B)$

Conditional Probability

$$P(A|B) = \frac{P(AB)}{P(B)} = \frac{P(B|A)P(A)}{P(B)}$$

Bayes Rule

$$P(B) = P(B|A_1)P(A_1) + \dots P(B|A_n)P(A_n)$$

Total Probability Rule

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{P(B)} = \frac{P(B|A_i)P(A_i)}{P(B|A_1)P(A_1) + \dots P(B|A_n)P(A_n)}$$

Bayes Rule + Total Probability Rule

Random Variable Preliminaries

- An RV represents the probability of different events and hence takes on different values with probabilities that sum up to 1
- An RV can be Continuous, Discrete or Mixed
- Cumulative Distribution Function (CDF) – Non Decreasing Function

$$F_X(x) = P(X \leq x)$$

$$F(+\infty) = 1, F(-\infty) = 0$$

$$F(x_2) - F(x_1) = P(x_2 < x \leq x_1)$$

- Probability Density (Mass) Function (PDF or PMF)

$$f_X(x) = \frac{d}{dx}(F_X(x))$$

$$\int_{-\infty}^{+\infty} f_X(x) dx = 1$$

$$F_X(x) = \int_{-\infty}^x f_X(x) dx$$

$$F_X(x) = \sum_{x \leq x_i} f_X(x_i)$$

Mean and Variance

- Mean is also known as expected value or expectation

$$\mu = E(X) = \int_{-\infty}^{+\infty} x f_X(x) dx$$

Continuous RV

$$\sum_{-\infty}^{+\infty} x f_X(x)$$

Discrete RV

- Variance is second moment about mean

$$\sigma^2 = E[(X - E(X))^2] = E(X^2) - E^2(X)$$

$$\int_{-\infty}^{+\infty} (x - \mu)^2 f_X(x) dx$$

Continuous RV

$$\sum_{-\infty}^{+\infty} (x - \mu)^2 f_X(x)$$

Discrete RV

Properties of Mean and Variance

- Expectation is a linear operator
- $E(X + c) = E(X) + E(c) = E(X) + c$
- $E(cX) = cE(X)$
- $E(X + Y) = E(X) + E(Y)$
- $E(XY) = E(X)E(Y)$ only if X and Y are uncorrelated or independent
- $\text{var}(aX) = a^2\text{var}(X)$

Discrete Densities

Bernoulli

$$f_X(x) = x^p(1-x)^{(1-p)} \quad X = 0, 1$$

Binomial

$$P(X = k) = \binom{n}{k} p^k q^{n-k} \quad p + q = 1 \quad k = 0, 1, 2 \dots n$$

Geometric

$$P(X = k) = pq^{k-1} \quad k = 1, 2, 3 \dots \infty$$

Poisson

$$P(X = k) = e^{-\lambda} \frac{\lambda^k}{k!} \quad k = 0, 1, 2 \dots \infty$$

Continuous Densities

Uniform

$$f_X(x) = \frac{1}{b-a} \quad a \leq x \leq b$$

$$= 0 \quad \text{otherwise}$$

Normal

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2} \quad -\infty \leq x \leq +\infty$$

$$F_X(x) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}\sigma} e^{-(y-\mu)^2/2\sigma^2} dy \triangleq G\left(\frac{x-\mu}{\sigma}\right)$$

$$G(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-y^2/2} dy$$

Exponential

$$f_X(x) = \lambda e^{-\lambda x} \quad x \geq 0$$

$$= 0 \quad \text{otherwise}$$

Joint Distributions – Bivariate

$$F_{X,Y}(x,y) = P(X \leq x, Y \leq y)$$

CDF

$$f_{X,Y}(x,y) = \frac{\delta^2 F_{X,Y}(x,y)}{\delta x \delta y}$$

PDF

$$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy$$

$$f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx$$

Marginal PDFs

Joint Distributions – Bivariate

$$\text{cov}(X, Y) = E[(X - E(X))(Y - E(Y))] = E(XY) - E(X)E(Y)$$

Covariance

$$\rho_{X,Y} = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y}$$

Correlation Coefficient

$$E(X, Y) = E(X)E(Y)$$

Uncorrelated

$$f_{X,Y}(x, y) = f_X(x)f_Y(y)$$

Independent

Joint Distributions – Multivariate

$$F_{\underline{X}}(\underline{x}) = F_{X_1, X_2 \dots X_n}(x_1, x_2 \dots x_n) = P(X_1 \leq x_1 \dots X_n \leq x_n) = \int_{-\infty}^{x_n} \dots \int_{-\infty}^{x_1} f_{X_1, X_2 \dots X_n}(x_1, x_2 \dots x_n) dx_1 \dots dx_n$$

$$F_{\underline{X}}(-\infty \dots -\infty) = 0 \quad F_{\underline{X}}(\infty \dots \infty) = 1$$

CDF

$$f_{\underline{X}}(\underline{x}) = P(X_1 = x_1 \dots X_n = x_n) = f_{X_1, X_2 \dots X_n}(x_1, x_2 \dots x_n) = \frac{dF_{\underline{X}}(\underline{x})}{d\underline{X}} = \frac{\delta^n F_{X_1, X_2 \dots X_n}(x_1, x_2 \dots x_n)}{\delta x_1 \dots \delta x_n}$$

$$f_{\underline{X}}(\underline{x}) \geq 0$$

$$\int_{-\infty}^{+\infty} \dots \int_{-\infty}^{+\infty} f_{X_1, X_2 \dots X_n}(x_1, x_2 \dots x_n) dx_1 \dots dx_n = 1$$

PDF

Joint Distributions – Multivariate

$$\underline{\mu} = E[\underline{X}] = E[X_1 \dots X_n]^T = [E[X_1] \dots E[X_n]]^T$$

Mean Vector

$$\underline{\Sigma} = \begin{bmatrix} \text{cov}(X_1, X_1) & \text{cov}(X_1, X_2) & \dots & \text{cov}(X_1, X_n) \\ \text{cov}(X_2, X_1) & \text{cov}(X_2, X_2) & \dots & \text{cov}(X_2, X_n) \\ \vdots & \vdots & \ddots & \vdots \\ \text{cov}(X_n, X_1) & \text{cov}(X_n, X_2) & \dots & \text{cov}(X_n, X_n) \end{bmatrix} = \begin{bmatrix} \sigma_{X_1}^2 & \text{cov}(X_1, X_2) & \dots & \text{cov}(X_1, X_n) \\ \text{cov}(X_2, X_1) & \sigma_{X_2}^2 & \dots & \text{cov}(X_2, X_n) \\ \vdots & \vdots & \ddots & \vdots \\ \text{cov}(X_n, X_1) & \text{cov}(X_n, X_2) & \dots & \sigma_{X_n}^2 \end{bmatrix}$$

$$\underline{\Sigma} = E[(\underline{X} - E(\underline{X}))(\underline{X} - E(\underline{X}))^T] = E[(\underline{X} - \underline{\mu})(\underline{X} - \underline{\mu})^T] = E[\underline{X}\underline{X}^T] - \underline{\mu}\underline{\mu}^T$$

Covariance Matrix

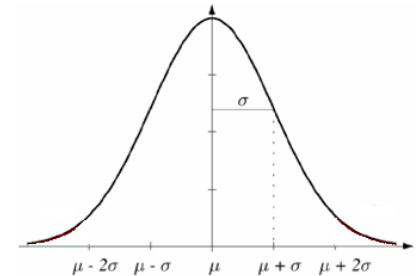
$$f_{X_1 \dots X_n}(x_1 \dots x_n) = \prod_i^n (f_{X_i}(x_i))$$

Independence

Gaussian (Normal) Distribution

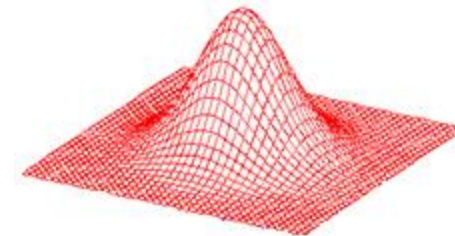
Univariate Normal Distribution

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/2\sigma^2}$$



Multivariate Normal Distribution

$$f_{\underline{X}}(\underline{x}) = \frac{1}{(2\pi)^{n/2} |\underline{\Sigma}|^{1/2}} \exp\left[-\frac{(\underline{x} - \underline{\mu})^T \underline{\Sigma}^{-1} (\underline{x} - \underline{\mu})}{2}\right]$$



If \underline{X} is $N(\underline{\mu}, \underline{\Sigma})$ then $\underline{Y} = \underline{A}\underline{X}$ is $N(\underline{A}\underline{\mu}, \underline{A}\underline{\Sigma}\underline{A}^T)$

Conditional Probability Revisited

$$f_{X|Y}(x|y) = P(X = x|Y = y) = f_{X,Y}(x, y)/f_Y(y) = P(X = x, Y = y)/P(Y = y)$$

Bayes Rule

$$f(y|x) = f(x, y)/f(x)$$

$$f(x|y) = f(x, y)/f(y)$$

$$f(x, y) = f(x|y)f(y) = f(y|x)f(x)$$

Simplified Notation

$$f(x|y) = \frac{f(x, y)}{f(y)} = \frac{f(x|y)f(y)}{f(y)} = \frac{f(y|x)f(x)}{f(y)} = \frac{f(y|x)f(x)}{\int_{-\infty}^{\infty} f(y|x)f(x)dx}$$

The Grand Scheme

Useful MATLAB Functions

- rand/randn
- randperm
- pdf
- normpdf
- mvnpdf
- cdf
- erf, erfc, erfinv, erfcinv

References

- Useful Denitions and Results in Probability Theory - Notes By Prof. Vijaykumar Bhagavatula for Pattern Recognition
- Athanasios Papoulis, S. Unnikrishna Pillai, “Probability, Random Variables and Stochastic Processes,” TMH 4th edition, 2002
- Richard O. Duda, Peter E. Hart, David G. Stork, “Pattern Classification,” Wiley 2nd edition, 2007
- MATLAB Help