20CS6037 Machine Learning

MLE, MAP, Bayesian Reasoning - Chapter 3 & 5 (Lecture 5: 9/9/14)

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Section 1:

Conditional Independence

Section 2:

Transformation of Random Variables

Section 3:

General Transformations

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Monte Carlo Approximation

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Entropy

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Mutual Information

Section 1: Conditional Independence

X,Y r.v. $X \perp Y : X$ and Y are independent

Def

$$X \perp Y \Leftrightarrow P(X,Y) = P(X)P(Y)$$

This really means $\{w \in S \mid X(w) = a\}, \{w \in S \mid Y(w) = b\}$
are independent event for all $a \in Range(x)$; $b \in Range(Y)$

Notation

 $X \perp Y \mid 2 : X \text{ and } Y \text{ are } Conditionally Independent (CI) given 2$

$$P(X \perp Y \mid 2) \Leftrightarrow P(X, Y \mid 2) = P(X \mid 2)P(Y \mid 2)$$

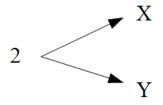


Figure 1: X and Y are CI given 2

$$\begin{split} \underline{P}(X, Y) &: \text{Joint Distribution of } X \text{ and } Y \\ \{w \in S \mid X(w) = a\}, \ \{w \in S \mid Y(w) = b\} \\ \text{Can extend to } \underline{P}(X_1, \dots, X_D) &: \text{CDF, PDF/PMF} \\ \text{COV}(X, Y) &\triangleq E[(X\text{-}E(X))(Y\text{-}E(Y))] \\ &= E[XY - XE(Y) - YE(X) + E(X)E(Y)] \\ &= E(XY) = E(X)E(Y) \end{split}$$

For a vector $X = (X_1, X_2, X_3)$

$$Cov[X] = \begin{bmatrix} Var(X_1) & Cov(X_1, X_2) & Cov(X_1, X_3) \\ Cov(X_2, X_1) & Var(X_2) & Cov(X_2, X_3) \\ Cov(X_3, X_1) & Cov(X_3, X_2) & Var(X_3) \end{bmatrix}$$

 $Cov \in (0, \infty)$

Correlation
$$\rho(X,Y) = \frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}} \in [-1,1]$$

X, Y independent
$$\Rightarrow$$
 Cov(X,Y) = 0 \Rightarrow ρ (X,Y) = 0 (Uncorrelated)

Independence \rightleftharpoons Uncorrelated

ex)
$$X \sim u(\text{-}1,1) \; ; \; Y = X^2 \Rightarrow X, \; Y \; \text{are dependent} \\ \rho(X,Y) = 0$$

$$E(X) = \frac{-1+1}{2} = 0 \text{ Var}(X) = \frac{(1-(-1)^2)}{12} = \frac{4}{12} = \frac{1}{3}$$

E(Y)
$$= \int_{-1}^{1} x^{2} f(x) dx$$

$$= \int_{-1}^{1} x^{2} (\frac{1}{2}) dx = \frac{1}{2} \frac{x^{4}}{4} \Big|_{-1}^{1} = \frac{2}{6} = \frac{1}{3}$$

$$E(XY) = \int_{-1}^{1} x^{3} \frac{1}{2} dx = \frac{1}{2} \frac{x^{4}}{4} \Big|_{-1}^{1} = \frac{1}{2} \cdot 0$$

$$\mathrm{Cov}(X,Y) = \mathrm{E}(XY)$$
 - $\mathrm{E}(X)\mathrm{E}(Y) = 0$ - $0 \cdot \frac{1}{3} = 0$ - $0 = 0$

Section 2:

Transformation of Random Variables

$$X \sim P(X) p:pdf$$

Y = f(X) What is the distribution of Y?

$$P_Y(Y \le y) = P_Y(f(X) \le y) = \underline{P}_X(X \le f^{-1}(y)) = P(f^{-1}(y))$$

ex)
$$Y = aX + b \Rightarrow f(x) = aX + b$$

$$f^{-1}(y) = \frac{y-b}{a}$$
 $X = -1$ $Y = b-a$; $X = 1$ $Y = a+b$

$$P_Y(y) = P_X\left(\frac{y-b}{a}\right)$$

ex)
$$X \sim u(-1,1)$$

$$P_X(x) = \begin{cases} 0 & x \le -1\\ \frac{1}{1 - (2 - 1)} & -1 < X < 1\\ 0 & x \ge 1 \end{cases}$$

$$P_X(\frac{y-b}{a}) = \begin{cases} 0 & \frac{y-b}{a} \le -1\\ \frac{1}{1-(2-1)} & -1 < \frac{y-b}{a} < 1\\ 0 & x \ge 1 \end{cases} = \begin{cases} 0 & \frac{y-b}{a} \le -1\\ \frac{1}{1-(2-1)} & -1 < \frac{y-b}{a} < 1\\ 0 & x \ge 1 \end{cases}$$

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