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

Section 4: Monte Carlo Approximation

Section 5: Entropy

Section 6: Mutual Information

Section 1: Conditional Independence

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

<u>Def</u>

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)

<u>Notation</u>

X $\perp$ Y | 2 : X and Y are ***Conditionally Independent*** **(CI)** given 2

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

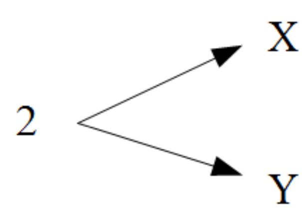

Figure 1: X and Y are CI given 2

<u>P</u>(X, Y) : Joint Distribution of X and Y

$\{w \in S \mid X(w) = a\}, \{w \in S \mid Y(w) = b\}$

Can extend to <u>P</u>($X_1, \ldots, X_D$) : CDF, PDF/PMF

$$\begin{aligned} COV(X, Y) &\triangleq E[(X\text{-}E(X))(Y\text{-}E(Y))] \\ &= E[XY - XE(Y) - YE(X) + E(X)E(Y)] \\ &= E(XY) = E(X)E(Y) \end{aligned}$$

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