5/7/19

Tuesday, May 7, 2019 1:35 PM

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

→ you (X,Y) discrete have $f_{X,Y}(x,y)$

$$f_X(x) = \sum_{\text{all } y} f_{XY}(x,y)$$

marginal PDF of X

$$f_X(x) = \int_{-\infty}^{\infty} f_{XY}(x,y)\,dy$$ ← (marginalizing out y)

similarly,

$$f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x,y)\,dx$$ ← (marginalizing out x)

independent if:

$$f_{XY}(x,y) = f_X(x) \cdot f_Y(y)$$

there is one situation in which the marginals do uniquely determine the joint, when X and Y independent.

X, Y independent $\overset{\text{iff}}{\longleftrightarrow}$ $f_{XY}(x,y) = f_X(x) \cdot f_Y(y)$

discrete:

$$f_{Y|X}(y|x) \triangleq \frac{f_{XY}(x,y)}{f_X(x)}$$

$$= P(Y=y \mid X=x)$$

continuous:

$$f_{Y|X}(y|x) = \frac{f_{XY}(x,y)}{f_X(x)}$$

joint density, marginal pdf, conditional pdf

$$f_{XY}(x,y) = f_X(x)\, f_{Y|X}(y|x)$$

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

Bayes's with random variables:

$$P(\theta|\underset{\sim}{D}) = \frac{P(\theta)\, P(\underset{\sim}{D}|\theta)}{P(\underset{\sim}{D})}$$

$$\updownarrow$$

$$P(\theta|N) = \frac{p(\theta)\, p(N|\theta)}{P(N)}$$ ← info about θ internal to data set

total info about θ; prior distribution; normalizing constant