

UNIT I – Review of Statistics: Jointly normal variables

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Jointly Gaussian random variables

X and Y are jointly Gaussian r.v., is they are normal and the joint p.d.f. is

$$f_{XY}(x,y) = \frac{1}{2\pi\sigma_X \sigma_Y \sqrt{1-\rho^2}} e^{\frac{-1}{2(1-\rho^2)} \left(\frac{(x-\mu_X)^2}{\sigma_X^2} - \frac{2\rho(x-\mu_X)(y-\mu_Y)}{\sigma_X \sigma_Y} + \frac{(y-\mu_Y)^2}{\sigma_Y^2} \right)},$$

$$-\infty < x < +\infty, -\infty < y < +\infty, |\rho| < 1.$$

where ρ is the correlation coefficient of X and Y

Random signals: 1-3: Multiple Random Variables



Jointly Gaussian random variables

• If X and Y are uncorrelated, then $\rho = 0$

$$\begin{split} f_{XY}(x,y) &= \frac{1}{2\pi\sigma_{X}\sigma_{Y}\sqrt{1-\rho^{2}}} e^{\frac{-1}{2(1-\rho^{2})}\left(\frac{(x-\mu_{X})^{2}}{\sigma_{X}^{2}} - \frac{2\rho(x-\mu_{X})(y-\mu_{Y})}{\sigma_{X}\sigma_{Y}} + \frac{(y-\mu_{Y})^{2}}{\sigma_{Y}^{2}}\right)} \\ &= \frac{1}{2\pi\sigma_{X}\sigma_{Y}} e^{\frac{-1}{2}\left(\frac{(x-\mu_{X})^{2}}{\sigma_{X}^{2}} + \frac{(y-\mu_{Y})^{2}}{\sigma_{Y}^{2}}\right)} & \text{X and Y are independent!} \\ &= \frac{1}{\sqrt{2\pi\sigma_{X}^{2}}\sqrt{2\pi\sigma_{Y}^{2}}} e^{\frac{-(x-\mu_{X})^{2}}{2\sigma_{X}^{2}}} e^{\frac{-(y-\mu_{Y})^{2}}{2\sigma_{Y}^{2}}} = f_{X}(x)f_{Y}(y) \end{split}$$

Two uncorrelated jointly Gaussian r.v. are **independent** (and vice versa)

Random signals: 1-3: Multiple Random Variables



Jointly Gaussian random variables

- Normal r.v. are completely defined by their **mean** and **variance**
- Two uncorrelated jointly gaussian r.v. are independent

Random signals: 1-3: Multiple Random Variables

- Any linear transformation of several normal r.v. leads to a normal r.v.
- Given a jointly Gaussian p.d.f., any marginal function will be normal

