

Probability and Random Variables Test # 2 Note Sheet

DeMoivre-Laplace Theorem: Many distributions approach a gaussian when certain conditions are met.

$$\binom{n}{k} p^k q^{n-k} \approx \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(k-m)^2/(2\sigma^2)}$$

where $n \gg 1$, $m = np$, and $\sigma^2 = npq$

RV Transformations: $f_Y(y) = f_X(x) \left| \frac{dx}{dy} \right|_{x=g^{-1}(y)}$

Generation of Random Numbers:

- Generate a uniform RV outcome x_i
- Calculate the outcome y_i using the mapping

$$y_i = F_Y^{-1}(x_i)$$

Linear Transformations:

$$Y = g(X) = aX + b$$

$$f_Y(y) = \frac{1}{|a|} f_X\left(\frac{Y-b}{a}\right)$$

Expectation Operator: $E\{g(X)\} = \int_{-\infty}^{\infty} g(x) f_X(x) dx$

$$\text{Mean} \equiv E\{X\} = \int_{-\infty}^{\infty} x f_X(x) dx = m$$

$$\text{Variance} \equiv E\{X^2\} - m^2 = \int_{-\infty}^{\infty} x^2 f_X(x) dx = \sigma^2$$

$$\text{Standard deviation} \equiv \sqrt{\sigma^2} = \sigma$$

$$E\{\alpha\} = \alpha \text{ for } \alpha \text{ constant}$$

$$E\{\alpha g(X)\} = \alpha E\{g(X)\}$$

$$E\{g_1(X) + g_2(X)\} = E\{g_1(X)\} + E\{g_2(X)\}$$

$$\text{For discrete pdfs: } E\{g(X)\} = \sum_k g(x_k) p_k$$

Normalizing: $Y = \frac{X-m}{\sigma}$

Moments of an RV: $M_X(v) = E\{e^{jvX}\}$

$$E\{X^n\} = (-j)^n \left[\frac{d^n}{dv^n} M_X(v) \right] \bigg|_{v=0}$$

Conditional CDFs & PDFs:

$$F_X(x|B) = P(X \leq x|B) = \frac{P(X \leq x, B)}{P(B)}$$

$$F_X(x|a < X \leq b) = \begin{cases} 0 & x \leq a \\ \frac{F_X(x) - F_X(a)}{F_X(b) - F_X(a)} & a < x \leq b \\ 1 & x > b \end{cases}$$

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$$F_X(x|X > a) = \begin{cases} 0 & x \leq a \\ \frac{F_X(x) - F_X(a)}{1 - F_X(a)} & x > a \end{cases}$$

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Conditional CDF and Total Prob. Theorem: Given the sample space partitioning

$$S = \{A_1, A_2, \dots, A_n\}$$

$$\text{then } F_X(x) = \sum_{k=1}^n F_X(x|A_k) P(A_k)$$

Chebyshev's Inequality:

$$P(|X - m| \geq k\sigma) \leq \frac{1}{k^2} \text{ or } P(|X - m| \leq k\sigma) \geq 1 - \frac{1}{k^2}$$

Markov's Inequality:

$$P(X \geq \delta) \leq \frac{m}{\delta} \text{ or } P(X \leq \delta) \geq 1 - \frac{m}{\delta}$$

Monte Carlo Method: Given

$$A = \int_a^b f(x)g(x)dx \text{ where } \int_a^b g(x)dx = 1$$

generate set of outcomes, x_i from RV X with pdf $g(x)$

$$A \approx \frac{1}{n} \sum_{i=1}^n f(x_i)$$

Weak Law of Large Numbers: As the number of samples increases, the sample mean is close to the true mean

Strong Law of Large Numbers: As the number of samples increases, the sample mean approaches the true mean

Joint CDFs: Given two RVs X and Y , the joint CDF is

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

Properties:

- $F_{XY}(-\infty, y) = F_{XY}(x, -\infty) = F_{XY}(-\infty, -\infty) = 0$
- $F_{XY}(\infty, \infty) = 1$
- $F_{XY}(x, \infty) = F_X(x)$ and $F_{XY}(\infty, y) = F_Y(y)$
- Positive-side continuous
- Monotonically non-decreasing along the positive direction

Joint PDFs: Given a joint CDF

$$f_{XY}(x, y) = \frac{\partial}{\partial x} \frac{\partial}{\partial y} F_{XY}(x, y)$$

Properties:

- $f_{XY}(x, y) \geq 0$ for all x, y
- $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{XY}(x, y) dx dy = 1$
- $f_X(x) = \int_{-\infty}^{\infty} f_{XY}(x, y) dy$ and $f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x, y) dx$

Joint Conditional Probability:

$$F_{X|Y}(x|B) = \frac{P(X \leq x, B)}{P(B)}$$

$$F_{X|Y}(X|a < Y \leq b) = \frac{F_{XY}(x, b) - F_{XY}(x, a)}{F_Y(b) - F_Y(a)}$$

$$F_{X|Y}(x|Y \leq b) = \frac{F_{XY}(x, b)}{F_Y(b)}$$

$$f_{X|Y}(x|Y \leq b) = \frac{1}{F_Y(b)} \left[\frac{\partial}{\partial x} F_{XY}(x, b) \right]$$

$$F_{X|Y}(x|Y = a) = \frac{\frac{\partial}{\partial y} F_{XY}(x, y) \big|_{y=a}}{f_Y(a)}$$

$$f_{X|Y}(x|a) = \frac{f_{XY}(x, a)}{f_Y(a)}$$