Exam 2 Notes Name: Cooper Morris

### C2S4:

Random Variable: X, assigns a numeric value to outcomes in a sample space.

Discrete Random Variable: Possible values are countable, sum of two dice.

Continuous Random Variable: Possible values continuous, weight of random person.

Probability Mass Function: P(X = x) = p(x)Cumulative Distribution Function:  $P(X \le x)$ 

Denoted by F(x)

$$0 \le p(x) \le 1$$

$$\sum_{x} p(x) = 1$$

**Support:** the set of values such that f(x) > 0

**Percentile:**  $x_p$  such that  $P(X \le x_p) = \frac{p}{100}$ 

$$F(x_p) = \int_{-\infty}^{x_p} f(x) dx = \frac{p}{100}$$

C2S6:

Jointly Distributed Random Variable: Two or more random variables that are related when considering "individuals" in a population.

Joint Probability Mass Function: P(X = $(x, Y = y) = p(x, y) P(X = x \cap Y = y)$ 

Probability Marginal Mass Function:

$$P_x(x) = \sum_y p(x, y)$$
  
$$f_x(x) = \int_{-\infty}^{\infty} f(x, y) dy$$

$$f_x(x) = \int_{-\infty}^{\infty} f(x, y) \, dy$$

Summing or integrating out the opposite variable gives you the marginal probability mass function for the variable you desire.

### Discrete Random Variables:

$$\begin{aligned} \mu_x &= \mathbb{E}[X] = \sum_x x \cdot p(x) \\ \sigma^2 &= \sum_x x^2 \cdot p(x) - \mu_x^2 \\ \mathbb{E}[g(X)] &= \sum_x g(x) \cdot p(x) \end{aligned}$$

Continuous Random Variables:  

$$P(a \le X \le b) = \int_a^b f(x) dx$$

$$\mu_x = \mathbb{E}[X] = \int_{-\infty}^{\infty} x \cdot f(x) dx$$

$$\sigma^2 = \int_{-\infty}^{\infty} x^2 \cdot f(x) dx - \mu_x^2$$

$$\mathbb{E}[g(X)] = \int_{-\infty}^{\infty} g(x) \cdot f(x) dx$$

$$(\mu \pm k\sigma_x)$$

$$P(|X - \mu_x| > k\sigma_x) = \frac{1}{k^2}$$

## C2S5:

**Linear Functions of Random Variables** 

**Linear Function:** Y = aX + bExpected Value:  $a\mathbb{E}[X] + b$ 

Variance:  $a^2 \cdot Var(X)$ 

Standard Deviation:  $|a| \cdot \sigma_x$ 

# Linear Combinations of Random Variables

Linear Combinations:  $\sum_{i=1}^{n} c_i X_i$ 

Expected Value:  $\sum_{i=1}^{n} c_i \mathbb{E}[X_i]$ Variance:  $\sum_{i=1}^{n} c_i^2 \text{Var}(X)$  where  $X_i$ s are indepen-

dent

$$Var(x+y) = Var(x) + Var(y)$$
  
 $Var(x-y) = Var(x) + Var(y)$ 

# Simple Random Samples

$$\bar{x} = \sum_{i=1}^{n} \frac{1}{n} \cdot x_i$$

$$\mu_{\bar{x}} = \mathbb{E}[\bar{x}] = \mu$$

$$\sigma_x^2 = \operatorname{Var}(\bar{x})$$

$$\sigma_{\bar{x}} = \frac{\sigma_x}{\sqrt{n}}$$
C2S6:

$$\frac{\mathbf{C2S6:}}{0 \le p(x,y)} \le 1$$

$$\sum_{x} \sum_{y} p(x,y) = 1$$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) \, dx \, dy = 1$$

$$P(a \le x \le b, c \le y \le d) = \int_{c}^{d} \int_{a}^{b} f(x,y) \, dx \, dy$$

$$\mathbb{E}[h(X,Y)] = \sum_{x} \sum_{y} h(x,y)p(x,y)$$

$$\mathbb{E}[h(X,Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x,y)f(x,y) \, dx \, dy$$

$$\operatorname{Cov}(X,Y) = \mu_{XY} - \mu_{x}\mu_{y}$$

$$\rho_{X,Y} = \frac{\operatorname{Cov}(X,Y)}{\sqrt{\operatorname{Var}(X)\operatorname{Var}(Y)}}$$