# STAT 2593 Formula Sheet

# Measures of Location and Variability

 $\overline{x} = \frac{\sum_{i=1}^{n} x_i}{n} = \frac{x_1 + x_2 + \dots + x_n}{n}$ If n is even then  $\tilde{x} = \frac{(\frac{n}{2})^{\text{th}} \operatorname{obs.} + (\frac{n+1}{2})^{\text{th}} \operatorname{obs.}}{2}$ Mean: Median: If n is odd then  $\tilde{x} = \frac{n+1}{2}^{\text{th}}$  obs. Range:  $x_{\max} - x_{\min}$  $s^{2} = \frac{\sum_{i=1}^{n} (x_{i} - \overline{x})^{2}}{n-1} = \frac{\sum_{i=1}^{n} x_{i}^{2} - n\overline{x}^{2}}{n-1}$ Variance: IQR: IQR = Q3 - Q1

## **Discrete Random variables**

**Probability Mass Function** (pmf): p(x) = P(X = x)

- 1.  $1 \ge p(x) \ge 0$  for all x in X
- 2.  $\sum_{x} p(x) = 1$

Cumulative Distributive Function (cdf):  $F(x) = P(X \le x) = \sum_{k \le x} f(k)$ 

Mean  $(\mu)$ : SD  $(\sigma)$ :

 $E(X) = \sum_{x} x f(x)$ Expected value:  $E(g(X)) = \sum_{x} g(x) f(x)$ Variance  $(\sigma^2)$ :  $\operatorname{var}(X) = \sum_{x} (x - \mu)^2 f(x) = E(X^2) - [E(X)]^2$  $SD(X) = \sqrt{\operatorname{var}(X)}$ 

# Basic Probability Rules

- General Addition Rule:  $P(A \cup B) = P(A) + P(B) P(A \cap B)$
- Complement Rule:  $P(A^c) = 1 P(A)$
- $P(\emptyset) = 0$  and P(S) = 1
- 0 < P(A) < 1 for all A
- $P(A|B) = \frac{P(A \cap B)}{P(B)}$  and  $P(B|A) = \frac{P(A \cap B)}{P(A)}$
- Multiplication Rule:  $P(A \cap B) = P(B) \times P(A|B) = P(A) \times P(B|A)$
- Law of Total Probability:  $P(B) = P(B|A_1)P(A_1) + \cdots + P(B|A_k)P(A_k)$ where  $A_1, \ldots, A_k$  form a partition of the sample space.
- $A \perp B$  if and only if  $P(A \cap B) = P(A)P(B)$
- Bayes' Theorem:  $P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_{i=1}^{n} P(A_i)P(B|A_i)}$

# **Counting Rules**

- Product rule for counting:  $n_i$  choices for decision  $j; n_1 \times \cdots \times n_k$  total choices.
- Permutations are given by  $P_{k,n} = \frac{n!}{(n-k)!}$ .

• Combinations are given by 
$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$
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# **Continuous Random variables**

**Probability Density Function** (pdf):  $P(a \le X \le b) = \int_a^b f(x) dx = F(b) - F(a)$ 

- 1. f(x) > 0 for all x
- 2.  $\int_{-\infty}^{\infty} f(x) dx = 1$

**Cumulative Distributive Function** (cdf):  $F(x) = P(X \le x) = \int_{-\infty}^{x} f(t) dt$ 

Median: x such that F(x) = 0.5x such that F(x) = 0.25 and x such that F(x) = 0.75 $Q_1$  and  $Q_3$ :  $\begin{array}{ll} \text{Mean } (\mu): & E(X) = \int_{-\infty}^{\infty} xf(x)dx \\ \text{Expected value:} & E(g(X)) = \int_{-\infty}^{\infty} g(x)f(x)dx \\ \text{Variance } (\sigma^2): & \text{var}(X) = \int_{-\infty}^{\infty} (x-\mu)^2 f(x)dx = E(X^2) - [E(X)]^2 \end{array}$  $SD(X) = \sqrt{\operatorname{var}(X)}$ SD  $(\sigma)$ :

## **Expectation and Variance Rules**

- E(aX+b) = aE(X) + b, for  $a, b \in \mathbb{R}$
- E(X + Y) = E(X) + E(Y), for all pairs of X and Y
- $\operatorname{var}(aX + b) = a^2 \operatorname{var}(X)$ , for  $a, b \in \mathbb{R}$
- $\operatorname{var}(X+Y) = \operatorname{var}(X) + \operatorname{var}(Y)$ , for independent X and Y

## Uniform and Exponential

 $X \sim \text{Unif}(a, b)$  $\mu = E(X) = \frac{a+b}{2}$ Mean: Variance:  $\sigma^2 = \operatorname{var}(X) = \frac{(b-a)^2}{12}$ pdf of X  $\frac{\text{pdf of A}}{f(x) = \begin{cases} \frac{1}{b-a} & a \le x \le b\\ 0 & \text{otherwise} \end{cases}} \qquad \qquad F(x) = \begin{cases} 0 & x < a\\ \frac{x-a}{b-a} & a \le x \le b\\ 1 & x > b \end{cases}$ 

 $X \sim \operatorname{Exp}(\lambda)$ Mean:  $\mu = E(X) = \frac{1}{\lambda}$ Variance:  $\sigma^2 = \operatorname{var}(X) = \frac{1}{\lambda^2}$ 

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#### Normal Distribution

 $X \sim N(\mu, \sigma^2)$ Standard Normal:  $Z \sim N(0, 1)$  where  $Z = \frac{X - \mu}{\sigma}$ ; cdf denoted as  $\Phi(z)$ Empirical Rule:

- approximately 68% of observations fall within  $\sigma$  of  $\mu$
- approximately 95% of observations fall within  $2\sigma$  of  $\mu$
- approximately 99.7% of observations fall within  $3\sigma$  of  $\mu$

#### Bernoulli and Binomial Random variables

 $X \sim \text{Bernoulli}(p)$ <u>pmf</u>:  $P(X = x) = p^x (1 - p)^{1-x}$  for x = 0, 1Mean:  $\mu = E(X) = p$ Variance:  $\sigma^2 = \text{var}(X) = p(1 - p)$   $X \sim \text{Bin}(n, p)$ pmf:  $P(X = x) = {n \choose x} p^x (1 - p)^{n-x}$  for x = 0, 1, 2, ..., n

Mean:  $\mu = E(X) = np$ Variance:  $\sigma^2 = \operatorname{var}(X) = np(1-p)$ 

## Geometric Distribution

 $\begin{array}{ll} X \sim \operatorname{Geo}(p) \\ \underline{\mathrm{pmf}} \colon P(X=x) = p(1-p)^{x-1} \text{ for } x=1,2,3,\dots \\ \\ \text{Mean:} & \mu = E(X) = \frac{1}{p} \\ \text{Variance:} & \sigma^2 = \operatorname{var}(X) = \frac{1-p}{p^2} \end{array}$ 

#### Hypergeometric Distribution

 $X \sim \text{Hypgeo}(N, M, n)$   $\underline{\text{pmf:}} P(X = x) = \frac{\binom{M}{x}\binom{N-M}{n-x}}{\binom{N}{n}} \text{ for } x = \max\{0, n - N + M\}, \dots, \min\{n, M\}.$   $\text{Mean:} \quad \mu = E(X) = n\frac{M}{N}$   $\text{Variance:} \quad \sigma^2 = \operatorname{var}(X) = \frac{N-n}{N-1} \cdot n \cdot \frac{M}{N} \cdot \left(1 - \frac{M}{N}\right)$ 

# Negative Binomial Distribution

 $\begin{array}{l} X \sim \mathrm{NB}(r,p) \\ \underline{\mathrm{pmf:}} \ P(X=x) = {x+r-1 \choose r-1} p^r (1-p)^x \ \mathrm{for} \ x=0,1,2,3,\ldots \\ \overline{\mathrm{Mean:}} \qquad \mu = E(X) = \frac{r(1-p)}{p} \\ \mathrm{Variance:} \quad \sigma^2 = \mathrm{var}(X) = \frac{r(1-p)}{p^2} \end{array}$ 

#### Poisson Distribution

 $\begin{array}{l} X \sim \operatorname{Poi}(\lambda) \ \underline{\mathrm{pmf:}} \ P(X=x) = \frac{\lambda^x e^{-\lambda}}{x!} \ \mathrm{for} \ x=0,1,2,3,\ldots \\ \underline{\mathrm{cdf:}} \ P(X \leq x) = \sum_{i=0}^x \frac{\lambda^i e^{-\lambda}}{i!} \ \mathrm{for} \ x=0,1,2,3,\ldots \end{array}$ 

Mean:  $\mu = E(X) = \lambda$ Variance:  $\sigma^2 = \operatorname{var}(X) = \lambda$ 

#### Central Limit Theorem

Let  $X_1, X_2, ..., X_n$  be a random sample from an arbitrary population/distribution with mean  $\mu$  and Variance  $\sigma^2$ . When n is large  $(n \ge 30)$  then

 $\overline{X} = \frac{X_1 + X_2 + \dots + X_n}{n} \sim N(\mu, \frac{\sigma^2}{n}), \text{ approx.}$ 

## Point Estimators

- Bias =  $E[\hat{\theta}] \theta$ .
- $MSE(\hat{\theta}) = E[(\hat{\theta} \theta)^2]$
- $MSE(\hat{\theta}) = Bias(\hat{\theta})^2 + var(\hat{\theta})$

#### Confidence Interval for Mean

General Form: point estimate  $\pm$  margin of error When  $\sigma^2$  is **known**:  $\overline{x} \pm z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}$ When  $\sigma^2$  is **unknown** (Z):  $\overline{x} \pm Z_{\frac{\alpha}{2}} \frac{s}{\sqrt{n}}$ When  $\sigma^2$  is **unknown** (t):  $\overline{x} \pm t_{\frac{\alpha}{2},n-1} \frac{s}{\sqrt{n}}$ 

#### Pooled Variance

Requires assumptions that population Variances are equal:  $\sigma_1^2 = \sigma_2^2 = \sigma^2$  $s_p^2 = \frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1+n_2-2}$ 

# **Critical Values**

- $\Phi(-2.58) = 0.005;$
- $\Phi(-1.96) = 0.025;$
- $\Phi(-1.645) = 0.05;$
- $\Phi(1.645) = 0.95;$
- $\Phi(1.96) = 0.975;$
- $\Phi(2.58) = 0.995$