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CSCI 3327 Formula Sheet

Chapter 1

Sample Mean

$$\bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i$$

Population Mean

$$\mu = \frac{1}{N} \sum_{i=1}^{N} y_i$$

Sample Variance

$$s^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (y_{i} - \bar{y})^{2}$$

Population Variance

$$\sigma^{2} = \frac{1}{N} \sum_{i=1}^{N} (y_{i} - \mu)^{2}$$

Sample Standard Deviation

$$s = \sqrt{s^2}$$

Population Standard Deviation

$$\sigma = \sqrt{\sigma^2}$$

Emprical Rule

 $\mu \pm \sigma$ contains approximately 68% of all the measurements $\mu \pm 2\sigma$ contains approximately 95% of all the measurements $\mu \pm 3\sigma$ contains almost all (99.7%) of all measurements

Chapter 2

Distributive Laws (Set Theory)

$$A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$$

$$A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$$

DeMorgan's Laws

$$\overline{(A\cap B)}=\bar{A}\cup\bar{B}$$

$$\overline{(A \cup B)} = \bar{A} \cap \bar{B}$$

Axioms for Probability of A

- 1. $P(A) \ge 0$
- 2. P(S) = 1
- 3. If A_1, A_2, A_3, \ldots form a sequence of pairwise mutually exclusive events in S (that is, $A_i \cap A_j = \emptyset$ if $i \neq j$), then

$$P(A_1 \cup A_2 \cup A_3 \cup \dots) = \sum_{l=1}^{\infty} P(A_l)$$

mn Rule

$$mn = m \times n$$

Permutation Formula

$$P_r^n = \frac{n!}{(n-r)!}$$

Combination Formula

$$C_r^n = \frac{n!}{r! (n-r)!}$$

Multinomial Coefficient Formula

$$N = \binom{n}{n_1 \ n_2 \dots \ n_k} = \frac{n!}{n_1! \ n_2! \cdots n_k!}$$

Conditional Probability

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

As long as
$$P(B) > 0$$

Independence Equations

Two events A and B are considered independent if any of the following statements hold:

$$P(A|B) = P(A)$$

$$P(B|A) = P(B)$$

$$P(A \cap B) = P(A)P(B)$$

Multiplicative Law of Probability (Dependent)

$$P(A \cap B) = P(A)P(B|A)$$
$$= P(B)P(A|B)$$

Multiplicative Law of Probability (Independent)

$$P(A \cap B) = P(A)P(B)$$

Additive Law of Probability

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

If A and B are mutually exclusive events, where $P(A \cap B) = 0$

$$P(A \cup B) = P(A) + P(B)$$

Probability of event A

$$P(A) = 1 - P(\bar{A})$$

Partition of S

Let the sets B_1, B_2, \ldots, B_k be such that

$$1. S = B_1 \cup B_2 \cup \ldots \cup B_k$$

2.
$$B_i \cap B_j = \emptyset$$
, for $i \neq j$

Then the collection of sets is said to be a partition of S.

The Law of Total Probability

$$P(A) = \sum_{i=1}^{k} P(A|B_i)P(B_i)$$

Bayes' Rule

$$P(B_j|A) = \frac{P(A|B_j)P(B_j)}{\sum_{i=1}^k P(A|B_i)P(B_i)}$$

Chapter 3

Probability Distribution statements

1.
$$0 \le p(y) \le 1$$
 for all of y

2. $\sum_{y} p(y) = 1$, where the summation is over all values of y with nonzero probability

Expected value of Y

$$E(Y) = \sum_{y} y p(y)$$

Expected value of g(Y)

$$E[g(Y)] = \sum_{all \ y} g(y)p(y)$$

Variance of a Random Variable

$$V(Y) = E[(Y - \mu)^2]$$

$$V(Y) = \sigma^2 = E[(Y - \mu)^2] = E(Y^2) - \mu^2$$

Standard Deviation of a Random Variable

$$\sigma = \sqrt{\sigma^2} = \sqrt{V(Y)}$$

Theorems for Mean or Expected Value

$$E(c) = c$$

$$E[cg(Y)] = cE[g(Y)]$$

$$E[g_1(Y) + g_2(Y) + ... + g_k(Y)] = E[g_1(Y)] + E[g_2(Y)] + ... + E[g_k(Y)]$$

Binomial Distribution

$$p(y) = P(Y = y) = \binom{n}{y} p^y q^{n-y}, y = 0, 1, 2, ..., n \text{ and } 0 \le p \le 1$$

Expected Value of a Binomial Distribution

$$\mu = E(Y) = np$$

Variance of a Binomial Distribution

$$\sigma^2 = V(Y) = npq$$

Standard Deviation of a Binomial Distribution

$$\sigma = \sqrt{\sigma^2} = \sqrt{V(Y)}$$

Geometric Distribution

$$p(y) = P(Y = y) = q^{y-1}p$$

Expected Value of a Geometric Distribution

$$\mu = E(Y) = \frac{1}{p}$$

Variance of a Geometric Distribution

$$\sigma^2 = V(Y) = \frac{1-p}{p^2}$$

Standard Deviation of a Geometric Distribution

$$\sigma = \sqrt{\sigma^2} = \sqrt{V(Y)}$$

Negative Binomial Probability Distribution

$$p(y) = p(Y = y) = {y-1 \choose r-1} p^r q^{y-r}$$

Expected Value of Negative Binomial Distribution

$$\mu = E(Y) = \frac{r}{p}$$

Variance of Negative Binomial Distribution

$$\sigma^2 = V(Y) = \frac{r(1-p)}{p^2}$$

Standard Deviation of Negative Binomial Distribution

$$\sigma = \sqrt{\sigma^2} = \sqrt{V(Y)}$$