Applied Stats Formula Sheet

Chapter 1

**Def 1.1)** The mean of a sample of *n* measured responses y1, y2, … yn is given by The corresponding population mean is defined µ.

**Def 1.2)** The *variance* of a sample of measurements y1, y2, …, yn is the sum of the square of the differences between the measurements and their mean, divided by *n* – 1, symbolically, the sample variance is The corresponding population variance is denoted by the symbol ∂2

**Def 1.3)** The *Standard Deviation* of a sample of measurements is the positive square root of the variance; that is, The corresponding *population* standard deviation is denoted by .

Chapter 2

**Def 2.6)** Suppose *S* is a sample space associated with an experiment. To every event *A* in *S* (*A* is a subset of *S*), we assign a number, *P(A)*, called the *probability of A*, so that the following axioms hold:

Axiom 1: *P(A) >= 0*.

Axiom 2: *P(S) = 1.*

Axiom 3: If *A*1, *A*2, *A3*, … form a sequence of pairwise mutually exclusive events in *S* (that is, *Ai ∩ A*j = ∅ if *I* ≠ *j*), then

**Def 2.7 / Theorem 2.2:** Permutations (order matters) Use: To get the ordered arrangements of distinct objects

**Theorem 2.3)** The number of ways of partitioning n distinct objects into k distinct groups containing n1, n2​,…,nk​ objects respectively, where each object appears in exactly one group and

N=

**Def 2.8 and Theorem 2.4)** The number of combinations of n objects taken r at a time is the number of subsets, each of size r, that can be formed from the n objects.

() = =

**Def 2.9)** The *conditional probability of an event* A, given that an event *B* has occurred, is equal to Provided *P(B) > 0.* [The symbol *P(A|B)* is read “probability of *A* given *B.”*]

**Def 2.10)** Two events *A* and *B* are said to be *independent* if any one of the following holds:

*P(A|B)* = *P(A),*

*P(B|A)* = *P(B),*

*P(A ∩ B) = P(A)P(B).*

Otherwise, the events are said to be *dependent.*

**Theorem 2.5**) The probability of the intersection of two events A and B is

P(A∩B) = P(A)P(B|A) = P(B)P(A|B)

If A and B are independent events, then  
  
P(A∩B) = P(A)P(B)

**Theorem 2.6)** The probability of the union of two events A and B is

P(AUB) = P(A) + P(B) – P(A∩B)

If A and B are exclusive  
P(A∩B) = 0 and P(AUB) =P(A) + P(B)

**Theorem 2.7)** If A is an event, then  
P(A) = 1-P(

**Def 2.11)** For some positive integer *k,* let the sets *B*1, *B*2, …, *B*k be such that

1. *S* = *B1* ∪ *B2* ∪ … ∪ *B*k.
2. *Bi ∩ B*j = ∅, for i ≠ *j*.

Then the collection of sets (*B1, B2, …, Bk)* is said to be a *partition* of *S*.

**Theorem 2.8)** Assume that {B1,B2,...,Bk}is a partition of S such that P(Bi)>0, for I = 1,2,...,k. Then for any event A

**Theorem 2.9)** Bayes’ Rule Assume that { B 1 , B 2 ,...,B k } is a partition of S such that P (Bi ) >0, for i = 1 , 2 ,...,k .Then

Chapter 3

**Def 3.4)** Let *Y* be a discrete random variable with the probability function *p(y)*. Then the *expected value* of *Y*, *E(Y)* is defined to be:

**Theorem 3.2)** Let Y be a discrete random variable with probability function p(y) and g(Y) be a real-valued function of Y. Then the expected value of g(Y)is given by

**Def 3.5)** If *Y*, is a random variable with mean *E(Y)* = µ, the variance of a random variable *Y* is defined to be the expected value of (*Y* - µ)2. That is,

The *standard deviation* of *Y* is the positive square root of *V(Y)*.

**Theorem 3.4)** Let Y be a discrete random variable with probability function p(y), g(Y) be a function of Y, and c be a constant. Then

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

**Theorem 3.5)** Let Y be a discrete random variable with probability function p(y) and let g₁(Y), g₂(Y), ..., gₖ(Y) be functions of Y. Then

  E[g₁(Y) + g₂(Y) + ··· + gₖ(Y)] = E[g₁(Y)] + E[g₂(Y)] + ··· + E[gₖ(Y)].

**Theorem 3.6**) Let Y be a discrete random variable with probability function p(y) and mean E(Y) = μ; then

V(Y) = σ² = E[(Y − μ)²] = E(Y²) − μ².

**Def 3.6)** A binomial experiment possesses the following properties:

1. The experiment consists of a fixed number, n, of identical trials.
2. Each trial results in one of two outcomes: success, S, or failure, F.
3. The probability of success on a single trial is equal to some value p and remains the same from trial to trial. The probability of a failure is equal to q=1−pq = 1 - pq=1−p.
4. The trials are independent.
5. The random variable of interest is Y, the number of successes observed during the n trials.

**Def 3.7)** A random variable *Y* is said to have a *binomial distribution* based on *n* trials with success *p* if and only if

**Theorem 3.7)** Let Y be a binomial random variable based on n trials and success probability p. Then

μ = E(Y) = np and σ² = V(Y) = npq

**Def 3.8)** A random variable *Y* is said to have a *geometric probability distribution* if and only if

**Theorem 3.8)** is a random variable with a geometric distribution,

AND

**Def 3.9)** A random variable Y is said to have a negative binomial probability distribution if and only if its probability mass function can be written in the form

Y= r, r+1, r+2,…. 0 ≤p≤1.

**Theorem 3.9)** Let Y be a random variable with a negative binomial distribution. Then the mean and variance are given by

μ = E(Y) = r / p

  σ² = V(Y) = r(1 – p) / p²

**Def 3.10)** A random variable Y is said to have a hypergeometric probability distribution if and only if where Y is an integer 0, 1, 2, …. n, subject to restrictions y ≤ r and n-y ≤ N-r.

**Theorem 3.10)** If Y is a random variable with a hypergeometric distribution.

μ= E(Y) = and