

MATH 3338 Probability

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Test 1 Review

Date of Test and Covered Chapters

- Dates: Feb 22, 2024
- Chapters: 1, 2, 3 and 4 and part of Ch 5 on discrete distributions

Chapter 1

- Probability function, sample space, set, etc.

Given $A \subset \Omega$, $P(A) = \sum_{\omega \in A} m(\omega)$.

- Operation of sets.

A, B are sets in sample space Ω .

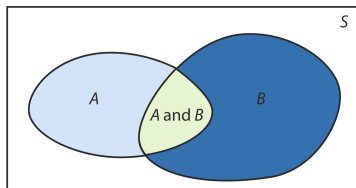
$$A \subset B$$

$$A \cup B$$

$$A \cap B$$

$$\overline{A}$$

- Venn diagram



Chapter 2

- Properties of probability

1. $P(E) \geq 0$ for every $E \subset \Omega$.
2. $P(\Omega) = 1$.
3. If $E \subset F \subset \Omega$, then $P(E) \leq P(F)$.
4. If A and B are disjoint subsets of Ω , then $P(A \cup B) = P(A) + P(B)$.
5. $P(\bar{A}) = 1 - P(A)$ for every $A \subset \Omega$.

- **Theorem 1.2** If A_1, \dots, A_n are pairwise disjoint subsets of Ω (i.e. no two of the A_i 's have an element in common), Then

$$P(A_1 \cup \dots \cup A_n) = \sum_{i=1}^n P(A_i).$$

Theorem 1.3 Let A_1, \dots, A_n be disjoint events with $\Omega = A_1 \cup \dots \cup A_n$, and let E be any event. Then

$$P(E) = \sum_{i=1}^n P(E \cap A_i)$$

- **Corollary 1.1** For any two events A and B ,

$$P(A) = P(A \cap B) + P(A \cap \bar{B})$$

Theorem 1.4 If A and B are two subsets of Ω , then

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

Chapter 2

- Continuous density function

- Prob density function of continuous RVs.

A density function for X is a real-valued function f which satisfies

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

for all $a, b \in \mathbb{R}$. The Probability is equal to the area under the density function.

- Uniform Density

Other forms of density function, e.g. $f(x) = 2x$ on $[0, 1]$.

- The cumulative distribution function for a random variable X is defined as $F(x) = \int_{-\infty}^x f(x)dx$ for any given $x \in \mathbb{R}$
The CDF $F(x)$ is an increasing and right continuous function.

$$0 \leq F(x) \leq 1, \text{ and } \frac{d}{dx}F(x) = f(x).$$

Chapter 3 Combinatorics

- **Counting Problems** When a task requires a few steps (r) to finish, the first step has n_1 ways to complete, the second step has n_2 ways to complete, ..., the r -th step has n_r ways to complete, the total number of ways to complete the task is $N = n_1 \dots n_r$.
- Permutation number, when the order of selected matters
 $P_r^n = n(n-1)\dots(n-r+1)$
- Combination number, when the order of selected does not matter.

$$C_r^n = \binom{n}{r} = n(n-1)\dots(n-r+1)/r!$$

- Properties.

1) $P_r^n = C_r^n r! > C_r^n$

2) Adding all binomial coefficients together we have

$$\binom{3}{0} + \binom{3}{1} + \binom{3}{2} + \binom{3}{3} = 2^3.$$

$$\binom{n}{0} = \binom{n}{n} = 1; \quad \binom{n}{1} = \binom{n}{n-1} = n$$

Chapter 3 Combinatorics

● Theorem 3.4

For integers n and j , with $0 < j < n$, the binomial coefficients satisfy:

$$\binom{n}{j} = \binom{n-1}{j} + \binom{n-1}{j-1}.$$

● Theorem 3.5

For integers n and j , with $0 < j < n$, the binomial coefficients satisfy:

$$\binom{n}{j} = \frac{P_j^n}{j!} = \frac{n!}{j!(n-j)!};$$

It is easy to see that

$$\binom{n}{j} = \binom{n}{n-j}$$

Chapter 3 Combinatorics

- Bernoulli Trials. Binary outcome, success (1) or failure (0) with Prob $P(X = 1) = p$, and $P(X = 0) = 1 - p = q$.
- Binomial prob of having exact k successes out of n trials is

$$P(X = k) = b(n, p, k) = \binom{n}{k} p^k (1 - p)^{n-k}, \quad k = 0, 1, \dots, n$$

A sum of n indep Bernoulli trials.

Chapter 4 Conditional Probability

- **Conditional Probability** $P(F|E)$

$$P(F|E) = \frac{P(F \cap E)}{P(E)}$$

- Independent events E, F .

$$P(F|E) = P(F); \quad P(E|F) = P(E); \quad P(F \cap E) = P(F)P(E)$$

- Mutually independent events A_1, A_2, \dots, A_n if for any subsets $\{A_i, A_j, \dots, A_m\}$ of these events,

$$P(A_i \cap A_j \cap \dots \cap A_m) = P(A_i)P(A_j)\dots P(A_m),$$

or equivalently, their complement events $\overline{A_i}, \dots$, satisfy the above equation.

Joint distributions

1. Joint discrete RVs are also provided with a table or tables that display the prob of each joint coordinates (x, y) . How to use the table to explain or demonstrate the independence ?

Mutually independent The random variables X_1, X_2, \dots, X_n are mutually independent if

$$\begin{aligned}P(X_1 = r_1, X_2 = r_2, \dots, X_n = r_n) \\ = P(X_1 = r_1)P(X_2 = r_2) \dots P(X_n = r_n)\end{aligned}$$

for any choice of r_1, r_2, \dots, r_n . Thus if X_1, X_2, \dots, X_n are mutually independent, then the joint distribution function of the random variable $X = (X_1, X_2, \dots, X_n)$ is just the product of individual distribution functions.

2. Marginal distributions. Take the prob of event on only 1 RV, and ignore the others.

- **Bayes Probabilities** Suppose a set of events H_1, H_2, \dots, H_m that are pairwise disjoint and exhaustive (mutually exclusive and exhaustive):

$$\Omega = H_1 \cup H_2 \cup \dots \cup H_m; \quad H_i \cap H_j = \emptyset \quad \forall i \neq j$$

Bayes' Formula

$$P(H_i|E) = \frac{P(H_i)P(E|H_i)}{\sum_{j=1}^m P(H_j)P(E|H_j)}$$

CH 4 Continuous Conditional Probability

- **Conditional Density Function**

Normalize the density function by dividing it with prob of condition, $f(x)/P(E)$.

$$f(x|E) = \begin{cases} f(x)/P(E), & \text{if } x \in E, \\ 0, & \text{if } x \notin E. \end{cases}$$

For joint distribution of RVs X_1, \dots, X_n , the CDF is

$$F(x_1, x_2, \dots, x_n) = P(X_1 \leq x_1, X_2 \leq x_2, \dots, X_n \leq x_n).$$

The joint density function of X satisfies the following equation

$$F(x_1, \dots, x_n) = \int_{-\infty}^{x_1} \int_{-\infty}^{x_2} \cdots \int_{-\infty}^{x_n} f(t_1, t_2, \dots, t_n) dt_n dt_{n-1} \dots dt_1.$$

It can be shown that

$$f(x_1, x_2, \dots, x_n) = \frac{\partial^n F(x_1, \dots, x_n)}{\partial x_1 \partial x_2 \dots \partial x_n}.$$

Chapter 4 Continuous Conditional Probability

- **Definition 4.7** Let X_1, \dots, X_n be continuous rvs with CDFs $F_1(x_1), \dots, F_n(x_n)$. Then these RVs are mutually indep if

$$F(x_1, x_2, \dots, x_n) = F_1(x_1)F_2(x_2)\dots F_n(x_n)$$

for any choice of x_1, \dots, x_n .

- If RVs are mutually indep, then the CDF of $X = (X_1, \dots, X_n)$ is the product of individual CDFs of X_1, \dots, X_n .
- **Theorem 4.2** Let X_1, \dots, X_n be continuous rvs with density functions $f_1(x_1), \dots, f_n(x_n)$. Then the RVs are mutually indep iff

$$f(x_1, \dots, x_n) = f_1(x_1)\dots f_n(x_n)$$

for all choice of x_1, \dots, x_n .

Chapter 4 Continuous Conditional Probability

- **Theorem 4.3** Let X_1, \dots, X_n be mutually indep continuous rvs and let $\phi_1(x), \dots, \phi_n(x)$ be continuous functions. Then $\phi_1(X_1), \dots, \phi_n(X_n)$ are mutually indep.