

MATH 3338 Probability

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Lecture 5 - Chapter 5. Important Distributions and Densities

Outline

1 Important Distributions

2 Important Densities

Important Distributions

- Describe discrete prob distributions and continuous densities.
- **Discrete Uniform Distribution** RV X is uniformly distributed over n elements in the sample space Ω consisted of n elements, if the distribution function $m(\omega) = 1/n$ for each element $\omega \in \Omega$.
- **Binomial Distribution** A Bernoulli trial is repeated n times independently, each time it has the same prob p to take the value 1 and $1 - p$ to take 0. Then the sum of these n indep trials has the Binomial distribution with the prob of being exactly k with $0 \leq k \leq n$

$$P(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}.$$

Important Distributions

- **Geometric Distribution**

Consider a Bernoulli trials process continued for an infinite number of trials. Let T be the number of trials up to and including the first success. Then,

$$P(T = 1) = p; P(T = 2) = qp; P(T = 3) = q^2p; \dots$$

In general, $P(T = n) = q^{n-1}p$. Fact: $p + qp + q^2p + \dots = 1$.

- In general, if $0 < p < 1$, and $q = 1 - p$, then we say that rv T has a geometric distribution if

$$P(T = j) = q^{j-1}p,$$

for $j = 1, 2, 3, \dots$

Important Distributions

- **Geometric Distribution**

Example 5.1 Consider a queuing or waiting line of customers waiting for service. It is often assumed that, in each small time unit, either 0 or 1 new customer arrives. The prob a customer arrives is p and none arrives is $q = 1 - p$. Then the time T until the next arrival has a geometric distr. It is natural to ask for the prob that no one arrives in the next k time units, or $P(T > k)$.

$$P(T > k) = \sum_{j=k+1}^{\infty} q^{j-1} p = q^k (p + qp + \dots) = q^k.$$

This is exactly the prob of having exactly k failures (no one arrives), thus the prob q^k .

Important Distributions

- **Geometric Distribution**

Consider a different scenario. It's often assumed the length of time required to service a customer also has a geometric distr. but with a different p . Now consider the conditional prob

$$P(T > r + s | T > r) = \frac{P(T > r + s)}{P(T > r)} = \frac{q^{r+s}}{q^r} = q^s.$$

It is implied that the customer's service takes s more time units is indep of the length of time r that (s)he has already been serviced. This is the so-called "memoryless" feature, similar to the one of the exponential distribution, but this one is for discrete RV.

Important Distributions

- **Poisson Distribution**

One of the three most important discrete distr.

Consider the event of traffic accidents. Suppose in a specific district, such as a segment of free way (I-10). We count the number of accidents on one day. Suppose the traffic remains constant (non-rush hour). Three basic assumptions.

- 1) Rare event. Within each small unit time, there is either 1 accident, or no accident. $P(> 1 \text{ accidents}) = 0$.
- 2) Stationary. Within the same length of time window (eg. hour), the intensity of accidents remains the same at different time of the day.
- 3) Independence. The outcome of having accidents in one time interval does not affect the likelihood of having accidents at another time interval that has no time overlapping.

Important Distributions

● Poisson Distribution

Assume the intensity of accidents per unit time is λ . Then the prob of having k accidents in a time interval of length t is

$$P(X = k) = \frac{(\lambda t)^k}{k!} e^{-\lambda t}, \quad k = 0, 1, 2, \dots$$

Often, the time duration t can be absorbed into the intensity, or a large unit $t = 1$. It is simplified as

$$P(X = k) = \frac{\lambda^k}{k!} e^{-\lambda}, \quad k = 0, 1, 2, \dots$$

Note that there is no upper limit of the value k that X may take. In theory, the number can go up as high as possible, but the prob becomes very small, no chance to occur.

Important Distributions

- **Negative Binomial Distribution**

Recall that we learned Geometric distribution. In tossing a coin with prob p to get a head. We ask the prob of having the k -th toss to get the first head. The prob is a geometric distribution

$$P(X = k) = (1 - p)^{k-1} p$$

Now consider the prob of getting the k -th head at the x -th toss. Notice that there are $k - 1$ heads in the previous $x - 1$ tosses. So for each set of tossing, the probability of having a total of k heads out of x tosses is $q^{x-k} p^k$. But since there are $k - 1$ heads out of the first $x - 1$ tosses, there are C_{k-1}^{x-1} sets of different arrangements. Hence we have the Negative Binomial distribution

$$P(X = x) = \binom{x-1}{k-1} p^k q^{x-k}$$

The negative binomial RV X is the sum of k indep geometrically distributed RV Y_i with prob p , i.e. $X = \sum_{i=1}^k Y_i$.

Important Distributions

- **Hypergeometric Distribution**

Suppose there are a total of N balls, with k red balls and $N - k$ blue balls. We choose n balls without replacement. Then the prob of having exact x red balls is

$$P(X = x) = \frac{\binom{k}{x} \binom{N-k}{n-x}}{\binom{N}{n}}$$

Remark 1. This prob distribution uses the combination number and the number of ways to complete a task in 2 steps.

Remark 2. Let $k, N \rightarrow \infty$, and $k/n \rightarrow p$ and $0 < p < 1$. Then the hypergeometric prob converges to the Binomial prob with prob p , i.e. $Bin(n, p)$.

The definition of hypergeometric distribution has many applications (e.g Defect products). The distribution can be also extended to more than two types of objects.

Important Densities

- **Continuous Uniform Distribution**

Recall that we have defined continuous uniform distribution over an interval $[a, b]$. The density $f(x)$ is defined as

$$f(x) = \frac{1}{b-a} I_{[a,b]}$$

where $I_{[a,b]} = 1$ for $x \in [a, b]$, and 0 otherwise, is an indicator function of the interval $[a, b]$.

Exponential and Gamma Densities The exponential density function is defined by

$$f(x) = \begin{cases} \lambda e^{-\lambda x}, & \text{if } 0 \leq x < \infty, \\ 0, & \text{otherwise.} \end{cases}$$

Where $\lambda > 0$.

The CDF function $F(x)$

$$F(x) = \int_{-\infty}^x \lambda e^{-\lambda t} dt = 1 - e^{-\lambda x}.$$

- **Exponential Distribution**

The exponential distribution has the memoryless property

$$\begin{aligned}P(T > r + s | T > r) &= \frac{P(T > r + s)}{P(T > r)} = \frac{1 - F(r + s)}{1 - F(r)} = 1 - F(s) \\&= P(T > s) = e^{-\lambda s}\end{aligned}$$

Important Densities

- **Functions of a Random Variable**

Theorem 5.1 Let X be a continuous RV, and $\phi(x)$ is a strictly increasing function on the range of X . Define $Y = \phi(X)$. Suppose that X and Y have CDFs F_X, F_Y . then we have

$$F_Y(y) = F_X(\phi^{-1}(y)).$$

If $\phi(x)$ is strictly decreasing on the range of X , then

$$F_Y(y) = 1 - F_X(\phi^{-1}(y))$$

Proof Assume ϕ is strictly increasing, then

$$F_Y(y) = P(Y \leq y) = P(\phi(X) \leq y) = P(X \leq \phi^{-1}(y)) = F_X(\phi^{-1}(y))$$

Assuming ϕ is strictly decreasing.

$$\begin{aligned} F_Y(y) &= P(Y \leq y) = P(\phi(X) \leq y) = P(X \geq \phi^{-1}(y)) \\ &= 1 - F_X(\phi^{-1}(y)) \end{aligned}$$

Important Densities

- **Functions of a Random Variable**

Corollary 5.1 Let X be a continuous RV, and $\phi(x)$ is a strictly increasing function on the range of X . Define $Y = \phi(X)$. Suppose the density functions of X and Y are f_X and f_Y , respectively. Then

$$f_Y(y) = f_X(\phi^{-1}(y)) \frac{d}{dy} \phi^{-1}(y).$$

If $\phi(x)$ is strictly decreasing on the range of X , then

$$f_Y(y) = -f_X(\phi^{-1}(y)) \frac{d}{dy} \phi^{-1}(y)$$

Proof Take derivative on both sides of equation in Theorem 5.1.

Important Densities

- **Functions of a Random Variable**

Example RV X has a density function $f(x) = 3x^2$ over the interval $[0, 1]$. Let $Y = X^3$. Find the density of Y .

Solution $\forall y \in [0, 1]$, $Y = X^3$. Then $X = Y^{1/3}$.

$$f_Y(y) = f_X(y^{1/3}) \frac{d}{dy} y^{1/3} = 3(y^{1/3})^2 \frac{1}{3} y^{-2/3} = 1$$

Hence Y has a uniform distribution over $[0, 1]$.

- **Simulation** Theorem 5.1 informs that if we take a special function of a RV X , and X has a CDF $F(x)$. Then $Y = F^{-1}(X)$ follows a uniform distribution over $[0, 1]$.

The implication of this fact is, if we want to generate random variates X_i of a distribution with CDF F , we need to generate random variates Y_i following *Unif* $[0, 1]$, and then take

$X_i = F^{-1}(Y_i)$. We know that X_i follows a distribution with CDF $F(x)$.

Important Densities

- **Functions of a Random Variable**

Corollary 5.2 If $F(y)$ is a given CDF that is strictly increasing when $0 < F(y) < 1$ and if U is a random variable with uniform distribution on $[0, 1]$, then $Y = F^{-1}(U)$ has the CDF $F(y)$.

- **Normal Density** The normal density function with parameters μ and σ is defined as follows.

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2}$$

The parameter μ is the center or mean of the distribution, σ is the standard deviation. The CDF is

$$F_X(x) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}\sigma} e^{-(u-\mu)^2/2\sigma^2} du$$

Important Densities

- **Functions of a Random Variable**

- Normal Distribution and Standard Normal Distribution**

Let Z be a RV following a normal distribution with parameter $\mu = 0, \sigma = 1$. Let $X = \sigma Z + \mu$, then X follows a normal distribution with parameters mean μ and standard deviation σ , ie. $N(\mu, \sigma^2)$.

- Similarly, suppose a RV X following a normal distribution with parameters mean μ and standard deviation σ , then we can always standardize X to make a RV following a standard normal distribution $Z = \frac{X - \mu}{\sigma} \sim N(0, 1)$.
- Since standard normal distribution plays a major role in calculating probability, we name a function $\Phi(z) = F(z)$, CDF of $N(0, 1)$.
 $\Phi(0) = 0.5$, $\Phi(1) = 0.841$, $\Phi(1.96) = 0.975$, $\Phi(2) = .9772$ and $\Phi(3) = .99865$. This means that within 1 and 2 standard deviation, $P(|Z| \leq 1) = .682$, $P(|Z| \leq 2) = .954$, $P(|Z| \leq 3) = .997$.

Important Densities

- **Functions of a Random Variable**

Normal Distribution and Standard Normal Distribution

With the standardization, $X = \sigma Z + \mu$,

$P(|X - \mu|/\sigma \leq s) = P(|Z| \leq s)$. Hence

$P(|X - \mu|/\sigma \leq 1) = .682$, $P(|X - \mu|/\sigma \leq 2) = .954$, and

$P(|X - \mu|/\sigma \leq 3) = .997$

- **A Rule of Thumb.** For any distribution, except for strange distributions, the prob mass is .68 within 1 sd, .95 within 2 sd, and 99 within 3 sd.

Example 5.8 Suppose $X \sim N(10, 3^2)$, Find $P(4 < X < 16)$.

$P(4 < X < 16) = P((4 - 10)/3 < (X - \mu)/\sigma < (16 - 10)/3) =$

$P(-2 < Z < 2) = .954$

- **Functions of a Random Variable**

- Chi-squared Distribution**

For a given RV $Z \sim N(0, 1)$, we define RV $X = Z^2$. Then X is said to follow a Chi-squared distribution with 1 degree of freedom, χ_1^2 .

For a given sequence of indep RV $Z_1, \dots, Z_n \sim N(0, 1)$, we define a RV $Y = Z_1^2 + \dots + Z_n^2$. Then Y is said to follow a Chi-squared distribution with n degrees of freedom, χ_n^2 .