

Statistics Lecture

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Conditional Distribution and Expectation

Let A and B be two events and $P(B) \neq 0$. The conditional probability of the event A , given that event B is realized, is by definition

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

Let X be a random variable and define B to be the event that $X = x$. The conditional probability $P(A | X = x)$ of the event A is then

$$P(A | X = x) = \frac{P(A \text{ and } X = x)}{P(X = x)} = \frac{P(A \cap [X = x])}{P(X = x)} =$$

provided of course that $P(X = x) \neq 0$.

Conditional Distribution and Expectation

Definition

1) Conditional pmf. Let X and Y be discrete random variables with joint pmf $p(x, y)$. The conditional pmf of Y given X is

$$\begin{aligned} p_{Y|X}(y | x) &= P(Y = y | X = x) \\ &= \frac{P(Y = y, X = x)}{P(X = x)} = \frac{p(x, y)}{p_X(x)} \end{aligned}$$

if $p_X(x) \neq 0$ and 0 otherwise.

2) The conditional distribution function of a random Variable Y (not necessarily discrete) given a discrete random variable X is

$$F_{Y|X}(y | x) = P(Y \leq y | X = x) = \frac{P(Y \leq y \text{ and } X = x)}{P(X = x)}$$

for all y and all x such that $P(X = x) \neq 0$.

Example

- Server cluster with two servers labeled A and B .
- Incoming jobs are independently routed to A and B with probability p and $q = 1 - p$, respectively.
- The number X of arriving jobs per unit of time is Poisson distributed with intensity λ .
- Determine the number of jobs, Y , received by server A , per unit of time.

$$P_{Y|X}(k, n) = \begin{cases} P_{Y|X}(Y = k, X = n) = \binom{n}{k} p^k q^{n-k}, & 0 \leq k \leq n. \\ 0 & \text{otherwise.} \end{cases}$$

Example

(Continued) Recall that $P(X = n) = e^{-\lambda} \lambda^n / n!$ so that

$$\begin{aligned} p_Y(k) &= \sum_{n=k}^{\infty} p_{Y|X}(k | n) p_X(n) \\ &= \sum_{n=k}^{\infty} \binom{n}{k} p^k q^{n-k} \frac{e^{-\lambda} \lambda^n}{n!} \\ &= \lambda^k p^k e^{-\lambda} \sum_{n=k}^{\infty} \binom{n}{k} \frac{1}{n!} q^{n-k} \lambda^{n-k} \\ &= \frac{(\lambda p)^k}{k!} e^{-\lambda} \sum_{n=k}^{\infty} \frac{(q\lambda)^{n-k}}{(n-k)!} \end{aligned}$$

so that finally $p_Y(k) = \frac{(\lambda p)^k}{k!} e^{-\lambda} e^{q\lambda} = \frac{(\lambda p)^k}{k!} e^{-\lambda p}$, i.e. Y is Poisson distributed with intensity λp .

Conditional Distribution and Expectation

If X is a continuous random variable then $P(X = x) = 0$ for all $x \in \mathbb{R}$ so that the previous definition $\frac{P(Y=y, X=x)}{P(X=x)}$ of conditional probability is not satisfactory.

However when X and Y are jointly continuous we can define the conditional pdf of Y given X :

Definition

Let X and Y be continuous r.v. with joint pdf $f(x, y)$. The conditional density $f_{Y|X}$ is

$$f_{Y|X}(y | x) = \begin{cases} \frac{f(x, y)}{f_X(x)}, & \text{if } 0 < f_X(x) < \infty, \\ 0 & \text{otherwise.} \end{cases}$$

Conditional Distribution and Expectation

From the definition of conditional density it follows that

$$f(x, y) = f_{Y|X}(y | x)f_X(x) = f_{X|Y}(x | y)f_Y(y),$$

and if X and Y are independent, then

$$f(x, y) = f_X(x)f_Y(y).$$

Furthermore,

$$f_Y(y) = \int_{-\infty}^{\infty} f(x, y)dx = \int_{-\infty}^{\infty} f_{Y|X}(y | x)f_X(x)dx$$

which is the continuous analog of the theorem of total probability.

Conditional Distribution and Expectation

- The conditional pdf can be used to obtain the conditional probability:

$$P(a \leq Y \leq b \mid X = x) = \int_a^b f_{Y|X}(y \mid x) dy, \quad a \leq b.$$

- The conditional distribution function is defined analogously

$$\begin{aligned} F_{Y|X}(y \mid x) &= P(Y \leq y \mid X = x) \\ &= \frac{\int_{-\infty}^y f(x, t) dt}{f_X(x)} \\ &= \int_{-\infty}^y f_{Y|X}(t \mid x) dt. \end{aligned}$$

Example

Consider a series system of two *independent* components with respective lifetime distributions $X \sim \text{EXP}(\lambda_1)$ and $Y \sim \text{EXP}(\lambda_2)$. We are interested in the probability of event A that component 2 causes the system failure, i.e.

$$P(A) = P(X \geq Y).$$

The conditional pdf is $F_{X|Y}(t, t) = P(X \leq t \mid Y = t) = F_X(t)$ by the independence of X and Y . By the total prob. theorem (continuous version)

$$\begin{aligned} P(A) &= \int_0^\infty P(X \geq t, Y = t) f_Y(t) dt \\ &= \int_0^\infty [1 - F_X(t)] f_Y(t) dt = \frac{\lambda_2}{\lambda_1 + \lambda_2}. \end{aligned}$$

Conditional Distribution and Expectation

Exercise

Consider the three-dimensional vector $X = (X_1, X_2, X_3)$ having the following joint density function

$$f_X(x_1, x_2, x_3) = \begin{cases} 6x_1x_2^2x_3, & \text{if } 0 \leq x_1 \leq 1, 0 \leq x_2 \leq 1, 0 \leq x_3 \leq \sqrt{2}. \\ 0, & \text{otherwise.} \end{cases}$$

- 1 Compute the conditional density functions $f_{X_1, X_2 | X_3}(x_1, x_2 | x_3)$ and $f_{X_3 | X_1}(x_3 | x_1)$.
- 2 Verify if the three random variables X_1, X_2, X_3 are independent.

Exercise

X_1 and X_2 are independent r. v. with Poisson distribution, having respective parameters α_1 and α_2 . Show that the conditional pmf of X_1 given $X_1 + X_2$, $p_{X_1 | X_1 + X_2}(X_1 = x_1 | X_1 + X_2 = y)$, is binomial. Determine its parameters.

Exercise

Let the execution times X and Y of two independent parallel processes be uniformly distributed over $(0, t_X)$ and $(0, t_Y)$, respectively, with $t_X \leq t_Y$. Find the probability that the former process finishes execution before the later.

Conditional Distribution and Expectation

- If X and Y are continuous random variables, we can for instance compute the conditional density $f_{Y|X}$.
- Since $f_{Y|X}$ has all properties of a density function of a continuous random variable, we can talk about its moments.
- Its mean (if exists) is called the conditional expectation of Y given $X = x$ and is denoted $E[Y | X = x]$ or $E[Y | x]$:

$$E[Y | x] = \begin{cases} \int_{-\infty}^{\infty} yf(y | x)dy, & \text{if } 0 < f(x) < \infty \\ 0 & \text{otherwise.} \end{cases}$$

- In case the random variables X and Y are discrete, $E[Y | x]$ is defined as

$$E[Y | X = x] = \sum_y yP(Y = y | X = x) = \sum_y yp_{Y|X}(y | x).$$

Theorem

(Chebyshev) Let X be a random variable with expected value μ and finite variance $\sigma^2 < \infty$. The, for all $t > 0$, the following inequality holds

$$P(|X - \mu| \geq t) \leq \frac{\sigma^2}{t^2}.$$

Definition

(Convergence in probability) Let $\{X_n\}_{n \in \mathbb{N}}$ be a sequence of random variables. We say that the sequence converges in probability to $c \in \mathbb{R}$, write $X_n \xrightarrow{p} c$ or $p\lim X_n = c$, if, for all $\varepsilon > 0$

$$\lim_{n \rightarrow \infty} P(|X_n - c| \geq \varepsilon) = 0.$$

Limit Theorems

Theorem

Let $\{X_n\}_{n \in \mathbb{N}}$ be a sequence of random variables with common expectation μ and finite variance $\sigma_n^2 < \infty$. If $\lim_{n \rightarrow \infty} \sigma_n^2 = 0$, then

$$X_n \xrightarrow{p} \mu.$$

Proof.

Apply Chebyshev inequality. □

Example

Let $\{X_n\}_{n \in \mathbb{N}}$ be an *i.i.d.* $\sim (\mu, \sigma^2)$ (independent and identically distributed) sequence of random variables. Define the sequence $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$. From the linearity of the expectation and the properties of the variance we know that $\bar{X}_n \sim (\mu, \frac{\sigma^2}{n})$. The sequence $\{\bar{X}_n\}_{n \in \mathbb{N}}$ converges in probability to μ :
 $\text{plim } \bar{X}_n = \mu.$

Limit Theorems

The result in the previous Example is also known as the **weak law of large numbers** (WLLN). In order for the WLLN to apply the existence of the second moment (the variance) is not required. The WLLN holds just under the assumption that the $\{X_n\}_{n \in \mathbb{N}}$ i.i.d. sequence have finite expected value μ .

Theorem

Consider two sequences $\{X_n\}_{n \in \mathbb{N}}$ and $\{Y_n\}_{n \in \mathbb{N}}$ of random variables converging in probability to $a < \infty$ and $b < \infty$, respectively. Then

① $p\lim (X_n + Y_n) = p\lim X_n + p\lim Y_n = a + b.$

② $p\lim (X_n \cdot Y_n) = p\lim X_n \cdot p\lim Y_n = a \cdot b.$

③ $b \neq 0,$

$$p\lim \left(\frac{X_n}{Y_n} \right) = \frac{p\lim X_n}{p\lim Y_n} = \frac{a}{b}.$$

④ Function g continuous in a : $p\lim g(X_n) = g(p\lim X_n) = g(a).$

Theorem

The Central Limit Theorem (CLT). Let $\{X_n\}_{n \in \mathbb{N}}$ be independent random variables with a finite mean $E[X_n] = \mu_n$ and a finite variance $\text{Var}(X_n) = \sigma_n^2$. Define the normalized random variable

$$Z_n = \frac{\sum_{i=1}^n X_i - \sum_{i=1}^n \mu_i}{\sqrt{\sum_{i=1}^n \sigma_i^2}}$$

so that $E[Z_n] = 0$ and $\text{Var}(Z_n) = 1$ for all n . Then under regularity conditions the limiting distribution of Z_n is standard normal, denoted $Z_n \rightarrow N(0, 1)$, i.e.

$$\lim_{n \rightarrow \infty} F_{Z_n}(t) = \lim_{n \rightarrow \infty} P(Z_n \leq t) = \int_{-\infty}^t \frac{1}{\sqrt{2\pi}} e^{-y^2/2} dy.$$

Remark: the special condition $\text{Var}(X_n) = \sigma^2$ for all n is sufficient for the CTL to apply.

exercises ...