

3.4 Indicator method (Ince formula)

$$X = \sum_{i=1}^n I_{A_i}, \quad X^2 = \sum_{i=1}^n I_{A_i} + 2 \sum_{i < j} I_{A_i} I_{A_j}$$

$$(1) E(X) = \sum_{i=1}^n P(A_i), \quad E(X^2) = \sum_{i=1}^n P(A_i) + 2 \sum_{i < j} P(A_i A_j)$$

$$\text{Var}(X) = E(X^2) - (E(X))^2$$

$$(2) \text{Var}(X) = \sum_{i=1}^n \text{Var}(I_{A_i}) + 2 \sum_{i < j} \text{Cor}(I_{A_i}, I_{A_j}), \text{ where}$$

$$\text{Var}(I_{A_i}) = P(A_i) - P(A_i)^2$$

$$\text{Cor}(I_{A_i}, I_{A_j}) = E(I_{A_i} I_{A_j}) - E(I_{A_i})E(I_{A_j}) = P(A_i A_j) - P(A_i)P(A_j)$$

This week:

3.7 Conditional expectation

3.8 Sums of r.v.

3.5 Examples

3.7 Conditional expectations

Def. Conditional prob of Y given $X=x$,
is the prob

$$f(y|x) = f_{Y|X}(y|x) = P(Y=y | X=x) = \frac{P(X=x, Y=y)}{P(X=x)}$$

$$= \frac{f(x,y)}{f_X(x)} \quad \text{if } f_X(x) = P(X=x) > 0, \quad \text{where}$$

$f(x,y)$ is joint prob of (X,Y)

Some formulas:

$$a) f(y|x) = \frac{f(x,y)}{f_X(x)}$$

$$b) f(x,y) = f(y|x) f_X(x) \quad (\text{multiplication rule})$$

$$c) f_Y(y) = \sum_x f(y|x) f_X(x) \quad (\text{total probability law})$$

$$d) f(x|y) = \frac{f(y|x) f_X(x)}{f_Y(y)} \quad (\text{Bayes formula})$$

Def. Conditional expectation of Y given $X=x$ is the expectation

$$E(Y|X=x) = \sum_j y P(Y=j|X=x) = \sum_j y f(y|x).$$

Def. For an event A we define

$$E(Y|A) = \sum_j y P(Y=j|A)$$

Def. $E(Y|X)$ is discrete r.v. defined as a function of X .

$$E(Y|X) = h(X), \text{ where } h(x) = E(Y|X=x), -\infty < x < \infty.$$

Properties of $E(Y|X)$

1. $E(Y)$ can be computed using conditioning:

$$(1) E(Y) = E[E(Y|X)] = \sum_x \underbrace{E(Y|X=x)}_{h(x)} P(X=x)$$

Also, if $\Omega = \bigcup_i A_i$, and A_i are disjoint, then

$$E(Y) = \sum_i E(Y|A_i) P(A_i).$$

Note (1) is equivalent to

$$(1') E(Y) = E[h(X)], \text{ where } h(x) = E(Y|X=x).$$

$$\text{Proof of } (1) \quad E(Y) = E[E(Y|X)] = \sum_x E(Y|X=x) P(X=x)$$

$$\text{Indeed, } E(Y) = \sum_y y P(Y=y) = \sum_y y \sum_x P(Y=y|X=x) P(X=x)$$

$$= \sum_x \left(\sum_y y P(Y=y|X=x) \right) P(X=x) = \sum_x E(Y|X=x) P(X=x).$$

$$\text{Application of } \left[E(Y) = \sum_x E(Y|X=x) P(X=x) \right] = E[E(Y|X)]$$

Ex1. Population is divided into r groups whose proportions are p_1, \dots, p_r ($p_1 + \dots + p_r = 1$). Average weight of i th group member is w_i .

What is expected weight of a randomly chosen member of the population?

Answer. Let W be weight of a member

X be the group of a member

$$\text{We know } P(X=i) = p_i, \quad i = 1, \dots, r$$

$$E(W|X=i) = w_i, \quad i = 1, \dots, r.$$

$$E(W) = \sum_{i=1}^r E(W|X=i) P(X=i) = \sum_{i=1}^r w_i p_i$$

Application of (1'). $E(Y) = E[h(X)]$, where $h(x) = E(Y|X=x)$.

Application of (i'). $E(Y) = E[h(X)]$, where $h(x) = E(Y|X=x)$.

Ex 2. Number N of fish caught is $\text{Poisson}(\lambda)$.
Let Y be the number of H's in N tosses of a coin with $P(H) = p$.

(i) Find $E(Y|N=n)$, $E(Y|N)$, $E(Y)$.

Answer. We know: a) Given $N=n$, Y is $\text{binomial}(n, p)$:

$$P(Y=k|N=n) = \binom{n}{k} p^k q^{n-k}, \quad k=0, 1, \dots, n.$$

(In such a case, we say Y is $\text{binomial}(N, p)$)

b) N is $\text{Poisson}(\lambda)$

$$\text{Thus } E(Y|N=n) = np, \quad E(Y|N) = pN$$

$$E(Y) = E(pN) = p E(N) = \boxed{p\lambda}.$$

(ii) Find $E(Y^2|N)$.

$$\text{Answer. } E(Y^2|N=n) = npq + (np)^2 = pqn + p^2 n^2$$

$$E(Y^2|N) = pqN + p^2 N^2$$

$$\text{Note } E(Y^2) = pq E(N) + p^2 E(N^2).$$

Remark 1. In Ex 2, Y can be described as

a) Y is $\text{binomial}(N, p)$: given $N=n$, Y is $\text{binomial}(n, p)$

b) Alternatively to a) Y can be modeled as

$$(3) \quad \boxed{Y = \sum_{i=1}^N X_i}, \quad \text{where } X_i \text{ are independent Bernoulli}(p), \\ \text{independent of } N.$$

According to (3), given $N=n$, $Y = \sum_{i=1}^n X_i$ is binomial (n, p) .

Prediction property of $E(Y|X)$

2. $h(X) := E(Y|X)$ is the unique solution to the following minimization problem.

Find a function of X (denoted $l(X)$) so that

$$E[(Y - l(X))^2] \leq E[(Y - g(X))^2] \text{ for any other } g(X)$$

We use $g(X)$ to predict (estimate) Y ;

$E[(Y - g(X))^2]$ is the mean square error of our estimate (prediction)

Answer. $l(X) = E(Y|X)$ is the best mean square estimate (prediction) of Y based on X .

Comment. In Ex 2., we found $E(Y|N) = pN$.
Assume $p = \frac{1}{2}$, $N=10$. The best mean square estimate prediction of Y is $\frac{1}{2} \cdot 10 = 5$.

Why $l(X) = E(Y|X)$ is the best?