Lecture 12: Order Statistics; Conditional Expectation

Relevant textbook passages:
- Pitman [5]: Section 4.6
- Larsen–Marx [2]: Section 3.11

12.1 Order statistics

Given a random vector \((X_1, \ldots, X_n)\) on the probability space \((S, \mathcal{E}, P)\), for each \(s \in S\), sort the components into a vector \((X_1(s), \ldots, X_n(s))\) satisfying

\[
X_1(s) \leq X_2(s) \leq \cdots \leq X_n(s).
\]

The vector \((X_1, \ldots, X_n)\) is called the vector of order statistics of \((X_1, \ldots, X_n)\).

Equivalently,

\[
X_k = \min \left\{ \max \{X_j : j \in J\} : J \subset \{1, \ldots, n\} \text{ and } |J| = k \right\}.
\]

Order statistics play an important role in the study of auctions, among other things.

12.2 Marginal Distribution of Order Statistics

\[-3pt\]

From here on, we shall assume that the original random variables \(X_1, \ldots, X_n\) are independent and identically distributed.

Let \(X_1, \ldots, X_n\) be independent and identically distributed random variables with common cumulative distribution function \(F\), and let \((X_1, \ldots, X_n)\) be the vector of order statistics of \(X_1, \ldots, X_n\). By breaking the event \((X_k \leq x)\) into simple disjoint subevents, we get

\[
(X_k \leq x) = (X_1 \leq x) \bigcup (X_n > x, X_{n-1} \leq x) \bigcup \cdots \bigcup (X_n > x, \ldots, X_{j+1} > x, X_j \leq x) \bigcup \cdots \bigcup (X_n > x, \ldots, X_{k+1} > x, X_k \leq x).
\]
Each of these subevents is disjoint from the ones above it, and each has a binomial probability:

\[(X_{(n)} > x, \ldots, X_{(j+1)} > x, X_{(j)} \leq x) = (n-j \text{ of the random variables are } > x \text{ and } j \text{ are } \leq x),\]

so

\[P(X_{(n)} > x, \ldots, X_{(j+1)}>x, X_{(j)} \leq x) = \binom{n}{j} (1-F(x))^{n-j} F(x)^j.\]

Thus:

The cdf of the \(k\)th order statistic from a sample of \(n\) is:

\[F_{(k,n)}(x) = P(X_{(k)} \leq x) = \sum_{j=k}^{n} \binom{n}{j} (1-F(x))^{n-j} F(x)^j. \tag{1}\]

### 12.3 Marginal Density of Order Statistics

If \(F\) has a density \(f = F'\), then we can calculate the marginal density of \(X_{(k)}\) by differentiating the CDF \(F_{(k,n)}\):

\[
\frac{d}{dx} F_{(k,n)}(x) = \frac{d}{dx} \sum_{j=k}^{n} \binom{n}{j} F(x)^j (1-F(x))^{n-j} \]

\[= \sum_{j=k}^{n} \binom{n}{j} \frac{d}{dx} F(x)^j (1-F(x))^{n-j} \]

\[= \sum_{j=k}^{n} \binom{n}{j} \left(j F(x)^{j-1} (1-F(x))^{n-j} F'(x) - (n-j) F(x)^j (1-F(x))^{n-j-1} F'(x)\right) \]

\[= \sum_{j=k}^{n} \binom{n}{j} \left(j F(x)^{j-1} (1-F(x))^{n-j} - (n-j) F(x)^j (1-F(x))^{n-j-1}\right) f(x) \]

\[= \sum_{j=k}^{n} \binom{n}{j} \frac{n!}{(j-1)!(n-j)!} F(x)^{j-1} (1-F(x))^{n-j} f(x) \]

\[= \sum_{j=k}^{n} \frac{1}{n!} \frac{n!}{(n-j-1)!} (1-F(x))^{n-j-1} F(x)^j f(x) \]

\[+ \sum_{j=k+1}^{n} \frac{n!}{(j-1)!(n-j)!} (1-F(x))^{n-j} F(x)^{j-1} f(x) \]

\[= \frac{n!}{(k-1)!(n-k)!} (1-F(x))^{n-j} F(x)^{k-1} f(x) \]

\[+ \sum_{j=k+1}^{n} \frac{n!}{(j-1)!(n-j)!} (1-F(x))^{n-j} F(x)^{j-1} f(x) \]

\[= \sum_{j=k}^{n-1} \frac{n!}{j!(n-j-1)!} (1-F(x))^{n-j} F(x)^j f(t). \]
The last two terms above cancel, since using the change of variables $i = j - 1$,

$$
\sum_{j=k+1}^{n} \frac{n!}{(j-1)!(n-j)!} (1 - F(x))^{n-j} F(x)^{j-1} = \sum_{i=k}^{n-1} \frac{n!}{i!(n-i-1)!} (1 - F(x))^{n-i} F(x)^{i}.
$$

So the density of the $k$th order statistic from a sample of $n$ is:

$$
f_{(k,n)}(x) = \frac{n!}{(k-1)!(n-k)!} (1 - F(x))^{n-k} F(x)^{k-1} f(x) = n \binom{n-1}{k-1} (1 - F(x))^{(n-1)-(k-1)} F(x)^{k-1} f(x). \quad (2)
$$

Note: I could have written $n-k$ instead of $(n-1) - (k-1)$, but then the binomial coefficient would have seemed more mysterious.

### 12.4 The war of attrition

In the 1970s, the ethologist John Maynard Smith [3] began to apply game theory to problems of animal behavior. One application was to the settlement of intraspecies conflict. In some species (e.g., peafowl), conflicts are not settled by violent means, but by means of displays. The rivals will fan their tails, and eventually one will depart, leaving to the other whatever was the source of the conflict. Maynard Smith modeled this as a “war of attrition.”

In the war of attrition game there are two rival contestants $i = 1, 2$ for a prize of value $V$. Each chooses a length of time $T_i$ at random according to a common probability distribution with cumulative distribution function $F$. Waiting is costly, and the cost of waiting a length of time $T$ is $cT$. The rivals continue their displays, until the lesser time elapses and that animal leaves. The distribution is an equilibrium distribution if it has the following properties. (i) Each rival, knowing that the opponent has drawn a time $T_i$ from the distribution specified by $F$, is also willing to choose a time specified by $F$. (ii) When the time $T_i$ has elapsed, and contestant $i$’s opponent has not left, then $i$ does not have an incentive to stay longer, and so will leave.

Suppose contestant $i$ independently chooses a time $T_i$ to wait at random according to an exponential distribution with parameter $\lambda$. Suppose contestant 2 chooses $\lambda$ so that the expected waiting cost for 1 is equal to the value of the prize,

$$
c = \frac{\lambda}{\lambda} \iff \lambda = \frac{c}{V}.
$$

The expected value of waiting 2 out is $V - (c/\lambda) = 0$, so 1 does not care if he waits out 2 or not.

Suppose some length of time $t$ passes and neither contestant has dropped out. How much longer does contestant 1 expect 2 to wait? The answer, which we just calculated is still $1/\lambda$, so 1’s expected value of staying until 2 leaves is zero, just as it was at the start. Thus he is happy to leave at time $T_1$. If both contestants choose $T_i$ according to this $\lambda$, then each is best responding to the other, and we have an equilibrium.

The theoretical length of the contest is $\min\{T_1, T_2\}$. Now $\min\{T_1, T_2\} \leq t$ if and only if it is not the case that $T_1 > t$ and $T_2 > t$. Thus

$$
P(\min\{T_1, T_2\} \leq t) = 1 - P(T_1 > t \& T_2 > t)
= 1 - P(T_1 > t) P(T_2 > T) = 1 - e^{\lambda t} e^{\lambda t}
= 1 - e^{2\lambda t},
$$
which is an exponential survival function with parameter $2\lambda$. Thus the expected length of the contest is $1/(2\lambda)$. So the winner and loser both expect to wait $1/(2\lambda)$ and the expected total cost incurred is equal to $V$, the value of the prize.

Note that this model implies that the length of contest durations should be exponentially distributed. The noted game theorist Robert Rosenthal once told me that in fact the duration of display contests among dung flies is exponentially distributed. Indeed Parker and Thompson [4] find qualified support for this distribution, but argue that an asymmetric model would fit better.

### 12.5 Uniform order statistics and the Beta function

For a Uniform[0,1] distribution, $F(t) = t$ and $f(t) = 1$ on [0,1]. In this case equation (2) tells us:

The density $f_{(k,n)}$ of the $k^{th}$ order statistic for $n$ independent Uniform[0,1] random variables is

$$f_{(k,n)}(t) = n\binom{n-1}{k-1}(1-t)^{n-k}t^{k-1}.$$  

Since $f_{(k,n)}$ is a density,

$$\int_0^1 f_{(k,n)}(t) \, dt = n\binom{n-1}{k-1} \int_0^1 (1-t)^{n-k}t^{k-1} = 1,$$

or

$$\int_0^1 (1-t)^{n-k}t^{k-1} = \frac{1}{n\binom{n-1}{k-1}} = \frac{(k-1)!(n-k)!}{n!}.$$

Now change variables by setting $r = k$ and $s = n - r + 1$ (so $s - 1 = n - r$ and $n = r + s - 1$).

Then rewrite (3) as

$$\int_0^1 (1-t)^{s-1}t^{r-1} = \frac{(r-1)!(s-1)!}{(s+r-1)!} = \frac{\Gamma(s)\Gamma(r)}{\Gamma(r+s)}.$$

(Recall that the Gamma function is a continuous version of the factorial, and has the property that $\Gamma(s+1) = s\Gamma(s)$ for every $s > 0$, and $\Gamma(m) = (m-1)!$ for every natural number $m$. See Definition 11.2.1.)

This fact suggests (to at least some people) the following definition:

**12.5.1 Definition** The Beta function is defined for $r, s > 0$ (not necessarily integers), by

$$B(r, s) = \int_0^1 t^{r-1}(1-t)^{s-1} \, dt = \frac{\Gamma(s)\Gamma(r)}{\Gamma(r+s)}.$$  

**12.5.2 Definition** The beta$(r, s)$ distribution has the density

$$f(x) = \frac{1}{B(r, s)}x^{r-1}(1-x)^{s-1}$$

on the interval [0,1] and zero elsewhere.
The mean of a beta \((r, s)\) distribution is
\[
\frac{r}{r + s}.
\]

**Proof:**
\[
\int_0^1 x f(x) \, dx = \frac{1}{B(r, s)} \int_0^1 x x^{r-1}(1-x)^{s-1} \, dx
\]
\[= \frac{1}{B(r, s)} \int_0^1 x^{r+1-1}(1-x)^{s-1} \, dx\]
\[= \frac{B(r + 1, s)}{B(r, s)}\]
\[= \frac{\Gamma(s)\Gamma(r + 1)}{\Gamma(r + s + 1)} = \frac{\Gamma(s)\Gamma(r)}{\Gamma(s + r + 1)}\]
\[= \frac{r}{r + s}.
\]

Thus for a Uniform\([0,1]\) distribution, the \((k, n)\) order statistic has a beta\((k, n - k + 1)\) distribution and so has mean
\[
\frac{k}{n + 1}.
\]

[Application to breaking a unit length bar into \(n + 1\) pieces by choosing \(n\) breaking points. The expectation of the \(k^{th}\) breaking point is at \(k/(n + 1)\), so each piece has expected length \(1/n\).]

### 12.6 * The \(\sigma\)-algebra of events generated by random variables

Recall that the Borel sets of the real numbers are the members of the smallest \(\sigma\)-algebra that contains all the intervals. Given a set \(X_1, \ldots, X_n\) of random variables defined on the probability space \((S, \mathcal{E}, P)\) and intervals \(I_1, \ldots, I_n\),
\[(X_1 \in I_1, X_2 \in I_2, \ldots X_n \in I_n) \text{ is an event.}\]

The smallest \(\sigma\)-algebra that contains all these events, as the intervals \(I_i\) range over all intervals, is called the **\(\sigma\)-algebra of events generated by \(X_1, \ldots, X_n\)**, and is denoted \(\sigma(X_1, \ldots, X_n)\).

A function \(g: S \to \mathbb{R}\) is \(\sigma(X_1, \ldots, X_n)\)-measurable if for every interval \(I\), the set \(g^{-1}(I)\) belongs to \(\mathcal{E}\). The following theorem is beyond the scope of this course, but may be found, for instance, in Aliprantis–Border [1, Theorem 4.41] or M. M. Rao [6, Theorem 1.2.3, p. 4].

**12.6.1 Theorem** Let \(X = (X_1, \ldots, X_n)\) be a random vector on \((S, \mathcal{E}, P)\) and let \(g: S \to \mathbb{R}\). Then the function \(g\) is \(\sigma(X_1, \ldots, X_n)\)-measurable if and only if there exists a Borel function \(h: \mathbb{R}^n \to \mathbb{R}\) such that \(g = h \circ X\).
This means there is a one-to-one correspondence between $X$-measurable functions and functions that depend only on $X$. As a corollary we have:

12.6.2 Corollary The set of $X$-measurable functions is a vector subspace of the space of random variables.

12.7 Conditioning on the value of a Random Variable: The discrete case

Let $X$ and $Y$ be discrete random variables with joint pmf $p(x, y)$, and let $p_X$ and $p_Y$ be the respective marginals. Then $(Y = y)$ and $(X = x)$ are events so the conditional probability of $(Y = y)$ given $(X = x)$ is

$$P(Y = y \mid X = x) = \frac{P(Y = y, X = x)}{P(X = x)} = \frac{p(x, y)}{\sum_{y'} p(x, y')} = \frac{p(x, y)}{p_X(x)}.$$ (4)

This is a function of $x$, known as the conditional pmf of $Y$ given $X = x$ and it defines the conditional distribution of $Y$ given $X = x$.

12.7.1 Example (Pitman [5, Exercise 6.1.5, p. 399]) Let $X$ and $Y$ be independent Poisson random variables with parameters $\mu$ and $\lambda$. What is the distribution of $X$ given $X + Y = n$?

You may or may not recall what the distribution of $X + Y$ is, so let’s just roll out the old convolution formula (recalling that $X$ and $Y$ are always nonnegative):

$$P(X + Y = n) = \sum_{k=0}^{n} P(k, n - k)$$

$$= \sum_{k=0}^{n} \frac{e^{-\mu} \mu^k}{k!} e^{-\lambda} \frac{\lambda^{n-k}}{(n-k)!}$$

$$= \frac{e^{-(\mu+\lambda)}}{n!} \sum_{k=0}^{n} \frac{n!}{k!(n-k)!} \mu^k \lambda^{n-k}$$

$$= \frac{e^{-(\mu+\lambda)}}{n!} (\mu + \lambda)^n$$

which is a Poisson($\mu + \lambda$) distribution.

So

$$P(X = k \mid X + Y = n) = \frac{P(X = k, X + Y = n)}{P(X + Y = n)}$$

$$= \frac{P(X = k, Y = n - k)}{P(X + Y = n)}$$

$$= \frac{P(X = k) P(Y = n - k)}{P(X + Y = n)}$$

$$= \frac{(e^{-\mu} \frac{\mu^k}{k!}) (e^{-\lambda} \frac{\lambda^{n-k}}{(n-k)!})}{e^{-(\mu+\lambda)} (\mu + \lambda)^n}$$

$$= \frac{(n)}{k!} (\mu + \lambda)^n$$

$$= \frac{(n)}{k!} \frac{\mu^k \lambda^{n-k}}{(\mu + \lambda)^n}$$

$$= \frac{(n) \mu^k \lambda^{n-k}}{(\mu + \lambda)^n}.$$
This is just the probability that a Binomial\((n, p)\) random variable is equal to \(k\), when \(p = \mu/(\mu + \lambda)\).

\[
P(N_s = k \mid N_t = n) = \binom{n}{k} \left(\frac{\lambda s}{\lambda s + \lambda(t - s)}\right)^k \left(\frac{\lambda(t - s)}{\lambda s + \lambda(t - s)}\right)^{n-k}
\]

\[
= \binom{n}{k} \left(\frac{s}{t}\right)^k \left(\frac{t-s}{t}\right)^{n-k}
\]

When you think about it, one interpretation of the Poisson process, that arrivals are uniformly scattered in an interval, so the probability of hitting \([0, s]\) given that \([0, t]\) has been hit is just \(s/t\). (Remember \(s < t\).) So the probability of getting \(k\) hits on \([0, s]\) given \(n\) hits on \([0, t]\) is given by the Binomial with probability of success \(s/t\).

### 12.8 Conditional Expectation

In one way, conditional expectation is quite simple. It is the expectation of a random variable with respect to a conditional distribution.

For instance,

\[
E(Y \mid X = x) = \sum_y y P(Y = y \mid X = x) = \sum_y y \frac{p(y)}{p_X(x)}.
\]

#### 12.8.1 Example

Continuing with the previous example: Let \(X\) and \(Y\) be independent Poisson random variables with parameters \(\mu\) and \(\lambda\). Then we saw that the distribution of \(X\) given \(Y = y\) was a Binomial\((n, \mu/(\mu + \lambda))\) distribution:

\[
P(X = k \mid X + Y = n) = \binom{n}{k} \left(\frac{\mu}{\mu + \lambda}\right)^k \left(\frac{\lambda}{\mu + \lambda}\right)^{n-k}.
\]

Now a Binomial\((n, \mu/(\mu + \lambda))\) has expectation \(n\mu/(\mu + \lambda)\), so

\[
E(X \mid X + Y = n) = \frac{n\mu}{\mu + \lambda}
\]

Similarly

\[
E(Y \mid X + Y = n) = \frac{n\lambda}{\mu + \lambda}
\]

which implies the comforting conclusion that

\[
E(X \mid X + Y = n) + E(Y \mid X + Y = n) = n.
\]
12.9 Conditional Expectation, Part 2

So far we have defined $E(Y \mid X = x)$ for discrete random variables. This quantity depends on $x$, so we can write it as a function of $x$. Let’s use the name $v$ for this function, because $y$ is the Latin equivalent of the Greek $v$.

$$v(x) = E(Y \mid X = x).$$

The random variable $v(X)$ is known as the **conditional expectation of $Y$ given $X$**, which is written

$$E(Y \mid X) = v(X).$$

The thing to see is that this is a random variable since it is a function of the random variable $X$. By Theorem 12.6.1 $E(Y \mid X)$ is $\sigma(X)$-measurable. Another way to say this is that

$$E(Y \mid X) \text{ is a random variable that equals } E(Y \mid X = x) \text{ when } X = x.$$

12.9.1 Example Let $S$ be the six-point sample space consisting of $(x, y)$ pairs

$$S = \{(0, 0), (0, 1), (0, 2), (1, 0), (1, 1), (1, 2)\}$$

with probability measure given in the following diagram where the numbers in each box represent the probability of the sample point:

\[
\begin{array}{c|cc}
| & y = 2 & y = 1 & y = 0 \\
\hline
x = 0 & \frac{3}{24} & \frac{1}{24} & \frac{1}{24} \\
x = 1 & \frac{5}{24} & \frac{3}{24} & \frac{3}{24} \\
\end{array}
\]

Let $X$ and $Y$ be random variables on $S$ defined by $X(x, y) = x$ and $Y(x, y) = y$. Then

$$p_X(0) = p_X(1) = \frac{1}{2},$$

so

$$E X = 1p_X(1) + 0p_X(0) = \frac{1}{2},$$

and

$$p_Y(0) = \frac{1}{2}, \quad p_Y(1) = \frac{1}{3}, \quad p_Y(2) = \frac{1}{6}$$

so

$$E Y = 2p_Y(2) + 1p_Y(1) + 0p_Y(0) = \frac{2}{3}.$$

The event $X = 0$ is highlighted below.

\[
\begin{array}{c|cc}
| & 2 & 1 \\
\hline
0 & \frac{3}{24} & \frac{1}{24} \\
1 & \frac{5}{24} & \frac{3}{24} \\
\end{array}
\]
So

\[ \mathbf{E}(Y \mid X = 0) = 2P(Y = 2 \mid X = 0) + 1P(Y = 1 \mid X = 0) + 0P(Y = 0 \mid X = 0) \]

\[ = 2 \frac{P(Y = 2, X = 0)}{P(X = 0)} + 1 \frac{P(Y = 1, X = 0)}{P(X = 0)} + 0 \frac{P(Y = 0, X = 0)}{P(X = 0)} \]

\[ = \frac{3}{2} + \frac{5}{2} + 0 \frac{4}{2} \]

\[ = \frac{11}{12}. \]

Similarly

\[ \mathbf{E}(Y \mid X = 1) = \frac{5}{12}. \]

Thus the random variable \( \mathbf{E}(Y \mid X) \) is defined on \( S \) by

\[ \mathbf{E}(Y \mid X)(x, y) = \begin{cases} \frac{11}{12} & x = 0, \\ \frac{5}{12} & x = 1, \end{cases} \]

which can be represented in the diagram, where now the numbers in each box represent the value of the random variable \( \mathbf{E}(Y \mid X) \):

\[
\begin{array}{ccc}
2 & \frac{14}{12} & \frac{5}{12} \\
1 & \frac{11}{12} & \frac{5}{12} \\
0 & \frac{11}{12} & \frac{5}{12} \\
0 & 1 & & \end{array}
\]

The expectation of the random variable \( \mathbf{E}(Y \mid X) \) is

\[ \mathbf{E}\left( \mathbf{E}(Y \mid X) \right) = \frac{11}{12} \cdot \frac{1}{2} + \frac{5}{12} \cdot \frac{1}{2} = \frac{2}{3}. \]

From the calculation above,

\[ \mathbf{E}\left( \mathbf{E}(Y \mid X) \right) = \frac{2}{3} = \mathbf{E}Y. \]

\[ \square \]

12.10 Conditional Expectation is a Positive Linear Operator Too

Ordinary expectation is a positive linear operator that assigns random variables a real number. Conditional expectation assigns random variables another random variable, but it is also linear and positive:

\[ \mathbf{E}(aY + bZ \mid X) = a \mathbf{E}(Y \mid X) + b \mathbf{E}(Z \mid X) \]

\[ Y \geq 0 \implies \mathbf{E}(Y \mid X) \geq 0. \]
12.11 Iterated Conditional Expectation

Since $E(Y \mid X)$ is a random variable, we can take its expectation.

\[ E(E(Y \mid X)) = EY. \]

More remarkable is the following generalization.

12.11.1 Theorem For a (Borel) function $\varphi$,

\[ E(\varphi(X)E(Y \mid X)) = E(\varphi(X)Y). \]

Proof: Let $v(x) = E(Y \mid X = x)$. Then

\[ v(x) = \sum_y \frac{yp(x,y)}{p(x)}, \]

and so

\[
E(\varphi(X)E(Y \mid X)) = E(\varphi(X)v(X)) \\
= \sum_x \varphi(x)v(x)p(x) \\
= \sum_x \varphi(x) \left( \sum_y \frac{yp(x,y)}{p(x)} \right) p(x) \\
= \sum_x \varphi(x) \left( \sum_y yp(x,y) \right) \\
= \sum_{(x,y)} \varphi(x)yp(x,y) \\
= E(\varphi(X)Y).
\]

In light of Theorem 12.6.1 we have the following corollary.

12.11.2 Corollary If $Z$ is $\sigma(X)$-measurable, then

\[ E(ZE(Y \mid X)) = E(ZY). \]

12.12 * Conditional Expectation is an Orthogonal Projection

Recall Corollary 12.6.2, which states that the space of $\sigma(X)$-measurable random variables is a vector subspace. If we further restrict attention to $L_2$, the space of square-integrable random variables, we have the inner product defined by

\[ (X, Y) = E(XY). \]

See Section 9.12 *.

Recall from your linear algebra class that in an inner product space, the orthogonal projection of a vector $y$ on a subspace $M$ is the unique vector $y_M$ such that $y_M \in M$, and $(y - y_M) \perp M$. It turns out that conditional expectation with respect to $X$ is the orthogonal projection on to the subspace of $\sigma(X)$-measurable random variables.
12.12.1 Theorem Let $X, Y,$ and $Z$ have finite variances, and assume that $Z$ is $\sigma(X)$-measurable. Then
\[ E((Y - E(Y \mid X))Z) = 0. \]

Proof: Expand $(Y - E(Y \mid X))Z$ to get
\[ E((YZ - E(Y \mid X))Z) = E(YZ) - E(E(Y \mid X)Z), \]
since expectation is a linear operator. By Corollary 12.11.2,
\[ E(E(Y \mid X)Z) = E(YZ). \]
Substituting this in the previous equation proves the theorem.

What this says is that the random variable $Y - E(Y \mid X)$ is orthogonal to $Z$ for every $\sigma(X)$-measurable random variable $Z$. Since $E(Y \mid X)$ is itself $\sigma(X)$-measurable, we have
\[ E(Y \mid X) \text{ is the orthogonal projection of } Y \text{ onto the vector space of } \sigma(X)-\text{measurable, where} \]
the inner product $(X, Y)$ is given by $E(XY)$.

12.13 Conditional Expectation and Densities

When $X$ and $Y$ have a joint density the definition of $P(Y = y \mid X = x)$ seems ill-defined: Since when $X$ has a density, $P(X = x) = 0$ for every $x$, we cannot define $P(Y = y \mid X = x)$ as $P(Y = y, X = x)/P(X = x)$, since that would entail division by zero.

It is beyond the scope of this course to prove it, but the following approach works. Given an interval $B$, a real number $x$, and $\varepsilon > 0$, consider
\[ P(Y \in B \mid X \in (x - \varepsilon, x + \varepsilon)) = \frac{P(Y \in B, X \in (x - \varepsilon, x + \varepsilon))}{P(X \in (x - \varepsilon, x + \varepsilon)).} \]

If the marginal density $f_X$ of $X$ is positive and continuous at $x$, then the denominator is positive, so we are no longer dividing by zero. What we want is for this to tend to a limit as $\varepsilon$ tends to zero, and in fact it does, a result known as the Radon–Nikodym Theorem.

Define
\[ f_Y(y \mid X = x) = \frac{f(x, y)}{f_X(x)} \]
so
\[ f(x, y) = f_Y(y \mid X = x) f_X(x). \]

For a function $h: \mathbb{R} \to \mathbb{R}$,
\[ E(h(Y) \mid X = x) = \int h(y) f_Y(y \mid X = x) \, dy \]
\[ = \int h(y) \frac{f(x, y)}{f_X(x)} \, dy. \]
12.14 Conditioning with Several Variables

Let $Y$, $X_1$, $\ldots$, $X_n$ have joint density $f(y, x_1, \ldots, x_n)$. The conditional density of $Y$ given $X_1 = x_1, \ldots, X_n = x_n$ is then

$$f_Y(y \mid x_1, \ldots, x_n) = \frac{f(y, x_1, \ldots, x_n)}{f_{X_1, \ldots, X_n}(x_1, \ldots, x_n)},$$

and we may speak of $E(Y \mid X_1, \ldots, X_n)$, etc.

Similarly,

$$f_{X_1, \ldots, X_n}(x_1, \ldots, x_n \mid Y = y) = \frac{f(y, x_1, \ldots, x_n)}{f_Y(y)},$$

and we may speak of $E(X_1, \ldots, X_n \mid Y)$, etc.

If

$$f_{(X,Y)}(x, y \mid Z = z) = f_X(x \mid Z = z)f_Y(y \mid Z = z),$$

we say that $X$ and $Y$ are conditionally independent given $Z = z$.

Bibliography


