## ANIMAL BREEDING NOTES

## CHAPTER 6

## DISTRIBUTION FUNCTIONS OF RANDOM VARIABLES

Random variable: real value of a function of the outcome of an experiment. For instance, in animal breeding models, animals are assumed to be the product of random sampling because:
(1) Chromosomes segregate at random to produce gametes (within each parent), and
(2) Gametes unite at random to produce zygotes and, after growth and development, animals.

Thus, for a particular trait, e.g., birth weight (BW), we could have the following genetic values for 3 gametes from bull $B(X)$ and cow $C(Y)$ with frequencies $f(x)$ and $f(y)$ :

| Bull B |  | Cow C |  |
| :---: | :---: | :---: | :---: |
| x | $\mathrm{f}(\mathrm{x})$ | y | $\mathrm{f}(\mathrm{y})$ |
| 10 | 0.2 | 10 | 0.3 |
| 20 | 0.5 | 20 | 0.5 |
| 30 | 0.3 | 30 | 0.2 |

Here, X and Y are two random variables whose values are a function of the random segregation process in bull B and cow C .

Discrete random variables: random variables whose set of possible values is either finite or countable infinite. For a discrete random variable $X$, we can define the probability mass function $p(a)$ of $x$ as

$$
p(a)=P\{x=a\}
$$

where if X assumes any one of the values $\mathrm{x}_{1}, \mathrm{x}_{2}, \ldots, \mathrm{x}_{\infty}$, then

$$
\mathrm{p}\left(\mathrm{x}_{1}\right) \geq 0 \text { for } \mathrm{i}=1, \ldots, \infty
$$

and

$$
p(x)=0 \text { for all other values of } x
$$

Also, since X must take one of the values $\mathrm{X}_{\mathrm{i}}$,

$$
\sum_{\mathrm{i}=1}^{\infty} \mathrm{p}\left(\mathrm{x}_{\mathrm{i}}\right)=1
$$

Continuous random variables: random variables whose set of possible values is uncountable. A random variable $X$ is said to be continuous if there exists a non-negative function $f$, defined for all real $\mathrm{x} \in(-\infty, \infty)$, such that for any set B of real numbers,

$$
P\{X \in B\}=\int_{B} f(x) d x
$$

where $f(x)$ is the probability density function of random variable $X$.
Note: $\mathbf{f}(\mathbf{x}) \mathbf{d x} \approx \mathbf{P}(\mathbf{x} \leq \mathrm{X} \leq \mathrm{x}+\mathrm{dx})$ for dx small.
Since X must assume some value, $\mathrm{f}(\mathrm{x})$ must satisfy

$$
P\{X \in(-\infty, \infty)\}=\int_{-\infty}^{\infty} f(x) d x=1
$$

Note: If $\mathrm{B}=[\mathrm{a}, \mathrm{b}]$,

$$
\mathrm{P}\{\mathrm{X}=\mathrm{a}\}=\int_{a}^{a} \mathrm{f}(\mathrm{x}) \mathrm{dx}=0
$$

i.e., the probability that a continuous random variable will assume any fixed value is zero.

Thus, for a continuous random variable:

$$
P\{X<a\}=P\{X \leq a\}=\int_{-\infty}^{a} f(x) d x=F(a)
$$

where $\mathrm{F}(\mathrm{a})$ is the value of the cumulative distribution function (c.d.f.) of the random variable X at a.

## Cumulative distribution function (c.d.f.)

The c.d.f. of the random variable X is defined for all real numbers $\mathrm{b},-\infty<\mathrm{b}<\infty$, by

$$
F(b)=P\{X \leq b\}
$$

## Properties of the c.d.f.

(a) F is a non-decreasing function, i.e., if $a<b$, then $F(a) \leq F(b)$.
(b) $\lim \mathrm{F}(\mathrm{b})=1$
$b \rightarrow \infty$
(c) $\lim \mathrm{F}(\mathrm{b})=0$
$b \rightarrow-\infty$
(d) $\mathrm{F}(\mathrm{b})$ is right continuous, i.e.,

$$
\lim F(b)=F\left(b_{0}\right)
$$

$$
\mathrm{b} \rightarrow \mathrm{~b}_{0}^{+}
$$

where $\lim \Rightarrow$ as $b \rightarrow b_{0}$, each $b>b_{0}$.

$$
\mathrm{b} \rightarrow \mathrm{~b}_{0}^{+}
$$

The c.d.f. for:
(1) a discrete random variable is:

$$
\begin{aligned}
F(a) & =P\{X \leq a\} \\
& =\sum_{\text {all } x \leq a} p(x)
\end{aligned}
$$

(2) a continuous random variable is:

$$
\begin{aligned}
F(a) & =P\{X \in(-\infty, a]\} \\
& =P\{X \leq a\}
\end{aligned}
$$

$$
=\int_{-\infty}^{a} \mathrm{f}(\mathrm{x}) \mathrm{dx}
$$

Differentiating both sides yields:

$$
\frac{\mathrm{d}}{\mathrm{da}} \mathrm{~F}(\mathrm{a})=\mathrm{f}(\mathrm{a})
$$

i.e., the derivative of the c.d.f. is the probability density function.

## Animal breeding example (continued)

| Bull B |  |  | Cow C |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| x | $\mathrm{p}(\mathrm{x})$ | $\mathrm{F}(\mathrm{x})$ | y | $\mathrm{p}(\mathrm{y})$ | $\mathrm{F}(\mathrm{y})$ |
| 10 | 0.2 | 0.2 | 10 | 0.3 | 0.3 |
| 20 | 0.5 | 0.7 | 20 | 0.5 | 0.8 |
| 30 | 0.3 | 1.0 | 30 | 0.2 | 1.0 |

Joint distribution function: probability distribution function involving two or more random variables. For instance, if X and Y are two random variables, the joint cumulative distribution function of $X$ and $Y$ is given by:

$$
F(a, b)=P\{X \leq a, Y \leq b\}, \quad-\infty<a, b<\infty .
$$

## Marginal distributions

(a) Marginal distribution of X

$$
\begin{aligned}
& F_{X}(a)=P\{X \leq a\} \\
&=P\{X \leq a, Y<\infty\} \\
&=P \lim \{X \leq a, Y \leq b\} \\
& b \rightarrow \infty
\end{aligned}
$$

$$
\begin{aligned}
& =\lim _{b \rightarrow \infty} P\{X \leq a, Y \leq b\} \\
& =\lim _{b \rightarrow \infty} F(a, b) \\
& \equiv F(a, \infty)
\end{aligned}
$$

(b) Marginal distribution of Y

$$
\begin{aligned}
F_{Y}(b) & =P\{Y \leq b\} \\
& =\lim _{a \rightarrow \infty} F(a, b) \\
& \equiv F(\infty, b)
\end{aligned}
$$

## Discrete random variables

(a) Joint c.d.f. of X and Y

$$
\begin{aligned}
F(a, b) & =P\{X \leq a, Y \leq b\} \\
& =\sum_{\substack{\text { all } x \leq a \\
\text { all } y \leq b}} p(x, y)
\end{aligned}
$$

where

$$
\mathrm{p}(\mathrm{x}, \mathrm{y})=\mathrm{P}(\mathrm{X}=\mathrm{x}, \mathrm{Y}=\mathrm{y})=\text { joint probability mass function of } \mathrm{X} \text { and } \mathrm{Y} .
$$

Note: The marginal probability mass functions of $X$ and $Y$ can be obtained from $p(x, y)$, i.e.,

$$
p_{X}(x)=\sum_{y: p(x, y)>0} p(x, y)
$$

and

$$
p_{\mathrm{Y}}(\mathrm{y})=\sum_{\text {all } \mathrm{x}>0} \mathrm{p}(\mathrm{x}, \mathrm{y})
$$

(b) Marginal c.d.f. of X and Y .

$$
F_{X}(a)=\sum_{\text {all } x \leq a} p_{X}(x)
$$

and

$$
F_{Y}(b)=\sum_{\text {all } y \leq b} p_{Y}(y)
$$

## Continuous random variables

(a) Joint c.d.f. of X and Y

$$
\begin{aligned}
F(a, b) & =P\{X \leq a, Y \leq b\} \\
& =\int_{-\infty}^{a} \int_{-\infty}^{b} f(x, y) d x d y
\end{aligned}
$$

where

$$
\mathrm{f}(\mathrm{x}, \mathrm{y})=\frac{\partial^{2}}{\partial \mathrm{a} \partial \mathrm{~b}} \mathrm{~F}(\mathrm{a}, \mathrm{~b})
$$

The marginal probability density functions of X and Y are:

$$
\mathrm{f}_{\mathrm{X}}(\mathrm{x})=\int_{-\infty}^{\infty} \mathrm{f}(\mathrm{x}, \mathrm{y}) \mathrm{dy}
$$

and

$$
f_{Y}(y)=\int_{-\infty}^{\infty} f(x, y) d x
$$

(b) Marginal c.d.f. of X and Y

$$
F_{X}(a)=\int_{-\infty}^{a} f_{X}(x) d x
$$

and

$$
\mathrm{F}_{\mathrm{Y}}(\mathrm{~b})=\int_{-\infty}^{b} \mathrm{f}_{\mathrm{Y}}(\mathrm{y}) \mathrm{dy}
$$

## Conditional distributions

The conditional probability of event A given B is defined as the ratio of the joint probability of A and $B$ divided by the probability of $B$, assuming $P(B)>0$, i.e.,

$$
\mathrm{P}(\mathrm{~A} \mid \mathrm{B})=\frac{\mathrm{P}(\mathrm{~A}, \mathrm{~B})}{\mathrm{P}(\mathrm{~B})}
$$

## Discrete random variables

(a) Conditional probability mass function of $X$ given $Y=y$

$$
\begin{aligned}
p_{X \mid Y}(x \mid y) & =P\{X=x \mid Y=y\} \\
& =\frac{P\{X=x, Y=y\}}{P\{Y=y\}} \\
& =\frac{p(x, y)}{p_{Y}(y)} \quad \text { for all } y \text { such that } p_{Y}(y)>0
\end{aligned}
$$

(b) Conditional c.d.f. of X given $\mathrm{Y}=\mathrm{y}$

$$
\begin{aligned}
\mathrm{F}_{\mathrm{X} \mid \mathrm{Y}}(\mathrm{a} \mid \mathrm{y}) & =\mathrm{P}\{\mathrm{X} \leq \mathrm{a} \mid \mathrm{Y}=\mathrm{y}\} \\
& =\sum_{\mathrm{x} \leq \mathrm{a}} \mathrm{p}_{\mathrm{x} \mid \mathrm{Y}(\mathrm{x} \mid \mathrm{y})}
\end{aligned}
$$

If the random variables X and Y are independent, i.e., if

$$
\mathrm{P}\{\mathrm{X}=\mathrm{x}, \mathrm{Y}=\mathrm{y}\}=\mathrm{P}\{\mathrm{X}=\mathrm{x}\} \mathrm{P}\{\mathrm{Y}=\mathrm{y}\}
$$

then

$$
\begin{aligned}
\mathrm{p}_{\mathrm{X} \mid \mathrm{Y}}(\mathrm{x} \mid \mathrm{y}) & =\mathrm{p}_{\mathrm{X}}(\mathrm{x}) \\
& =\mathrm{P}\{\mathrm{X}=\mathrm{x}\}
\end{aligned}
$$

and

$$
\begin{aligned}
\mathrm{F}_{\mathrm{X} \mid \mathrm{Y}}(\mathrm{a} \mid \mathrm{y}) & =\mathrm{F}_{\mathrm{X}}(\mathrm{a}) \\
& =\mathrm{P}\{\mathrm{X} \leq \mathrm{a}\}
\end{aligned}
$$

## Continuous random variables

(a) Conditional probability density function of $X$ given $Y=y$

$$
\mathrm{f}_{\mathrm{X} \mid \mathrm{Y}}(\mathrm{x} \mid \mathrm{y})=\frac{\mathrm{f}(\mathrm{x}, \mathrm{y})}{\mathrm{f}_{\mathrm{Y}}(\mathrm{y})}
$$

Note:

$$
\begin{aligned}
f_{X \mid Y}(x \mid y) & =\frac{f(x, y) d x d y}{f_{Y}(y) d y} \\
& \approx \frac{P\{x \leq X \leq x+d x, y \leq Y \leq y+d y\}}{P(y \leq Y \leq y+d y)} \\
& \approx P\{x \leq X \leq x+d x \mid y \leq Y \leq y+d y\}
\end{aligned}
$$

where dx and dy are small values.
(b) Conditional c.d.f. of X given $\mathrm{Y}=\mathrm{y}$

$$
\begin{aligned}
\mathrm{F}_{\mathrm{X} \mid \mathrm{Y}}(\mathrm{a} \mid \mathrm{y}) & =\mathrm{P}\{X \leq a \mid Y=y\} \\
& =\int_{-\infty}^{a} f_{X \mid Y}(x \mid y) d x
\end{aligned}
$$

## Animal Breeding example (continued)

The joint probability mass function of $\mathbf{X}$ (i.e., Bull B) and $\mathbf{Y}$ (i.e., Cow C) is:

| Bull B (X) |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Cow C <br> (Y) |  |  | $\begin{gathered} \mathbf{x}=10 \\ \mathbf{p}(\mathbf{x}=\mathbf{1 0})=0.2 \end{gathered}$ | $\begin{gathered} \mathbf{x}=20 \\ \mathbf{p}(\mathbf{x}=\mathbf{2 0})=0.5 \end{gathered}$ | $\begin{gathered} \mathbf{x}=30 \\ \mathbf{p}(\mathbf{x}=\mathbf{3 0})=0.3 \end{gathered}$ | $\mathrm{p}_{\mathrm{Y}}(\mathrm{y})$ |
|  | $\mathbf{y}=10$ | $\begin{gathered} \mathbf{p}(\mathbf{y}=\mathbf{1 0}) \\ 0.3 \end{gathered}$ | 0.06 | 0.15 | 0.09 | 0.30 |
|  | $\mathbf{y}=20$ | $\begin{gathered} \mathbf{p}(\mathbf{y}=\mathbf{2 0}) \\ 0.5 \end{gathered}$ | 0.10 | 0.25 | 0.15 | 0.50 |
|  | $\mathbf{y}=30$ | $\begin{gathered} \mathbf{p}(\mathbf{y}=\mathbf{3 0}) \\ 0.2 \end{gathered}$ | 0.04 | 0.10 | 0.06 | 0.20 |
|  |  | $\mathbf{p}_{\mathrm{X}}(\mathbf{x})$ | 0.20 | 0.50 | 0.30 | 1.00 |

The joint c.d.f. of X and Y for $\mathrm{F}(20,10)$ is:

$$
\begin{aligned}
\mathrm{F}(20,10) & =\mathrm{P}\{\mathrm{X} \leq 20, \mathrm{Y} \leq 10\} \\
& =0.06+0.15 \\
& =0.21
\end{aligned}
$$

The marginal c.d.f. for $\mathrm{X}=10$ is:

$$
\begin{aligned}
\mathrm{F}_{\mathrm{X}}(10) & =\mathrm{p}_{\mathrm{X}}(10) \\
& =0.06+0.10+0.04 \\
& =0.20
\end{aligned}
$$

The conditional probability mass function of X given $\mathrm{Y}=30$ is:

$$
\begin{aligned}
\mathrm{p}_{\mathrm{X} \mid \mathrm{Y}}(\mathrm{x} \mid \mathrm{y}) & =\mathrm{P}\{\mathrm{X}=\mathrm{x} \mid \mathrm{Y}=30\} \\
& =\frac{\mathrm{P}\{\mathrm{X}=\mathrm{x}, \mathrm{Y}=30\}}{\mathrm{P}\{\mathrm{Y}=30\}}
\end{aligned}
$$

| x | $\mathrm{p}_{\mathrm{X} \mid \mathrm{Y}(\mathrm{x} \mid 30)}$ |
| :---: | :---: |
| 10 | $(0.04 / 0.20)=0.20=\mathbf{P}\{\mathbf{X}=\mathbf{1 0}\}$ |
| 20 | $(0.10 / 0.20)=0.50=\mathbf{P}\{\mathbf{X}=\mathbf{2 0}\}$ |
| 30 | $(0.06 / 0.20)=0.30=\mathbf{P}\{\mathbf{X}=\mathbf{3 0}\}$ |

In this example, $p_{x \mid y}(x \mid y)=p_{x}(x)$ because $X$ and $Y$ are independent, i.e.,

$$
P\{X=x, Y=y\}=P\{X=x\} P\{Y=y\}
$$

In fact, the $\mathrm{p}(\mathrm{x}, \mathrm{y})$ were computed as $\mathrm{p}_{\mathrm{X}}(\mathrm{x}) \mathrm{p}_{\mathrm{Y}}(\mathrm{y})$.
The conditional c.d.f. of $X$ given $Y=30$ is:

| x | $\mathrm{F}_{\mathrm{X} \mid \mathrm{Y}}$ |
| :---: | :---: |
| 10 | 0.20 |
| 20 | 0.70 |
| 30 | 1.00 |

which is the same as $\mathrm{F}_{\mathrm{X}}(\mathrm{x})$.

## References

Ross, S. 1976. A First Course in Probability Theory. Macmillan Publishing Co., Inc., NY.
Mood, A. M., F. A. Graybill, and D. C. Boes. 1974. Introduction to the Theory of Statistics. McGraw-Hill Series in Probability and Statistics, NY.

