# Stochastic Processes

# **Basic Terminology**

#### **OUTCOME**

Each thing that can occur in an expiriment is called an outcome. In the example of tossing a coin we have two outcomes 'heads' or 'tails' which we can denote by the letters H and T respectively.

#### SAMPLE SPACE

The set of all possible outcomes of an experiment is known as the sample space. By convention we label it  $\Omega$ . In our simple coin tossing scenario we would have  $\Omega = \{H, T\}$  If we toss two coins our sample space would become  $\Omega = \{HH, HT, TH, TT\}$ 

#### **EVENT**

A subset of the probability space is called an event. We define an event using the following notation.

 $A = \{ \varpi \in \Omega; \varpi = H \}$  "This means the set of all outcomes  $\varpi$  such that  $\varpi$  is a head".

#### PROBABILITY MEASURE

A probability measure P is a function that assigns to each element  $\varpi$  in  $\Omega$  a probability such that

$$\sum_{\omega\in\square}P(\varpi)=1$$

Since an event A is a subset of  $\Omega$  then the probability of an event is given by

$$P(A) = \sum_{\omega \in A} P(\varpi)$$

#### PROBABILITY SPACE

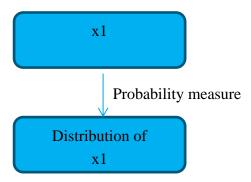
A probability space  $P(\Omega, P)$  consists of a sample space and a probability measure. The sample space is the set of outcomes and the probability measure is a function that assigns to each element  $\varpi$  in  $\Omega$  a value in [0,1] such that

#### **RANDOM VARIABLE**

A random variable x is a real valued function defined on  $\Omega$ . Put another way a random variable maps each outcome from the sample space  $\Omega$  to a real number.

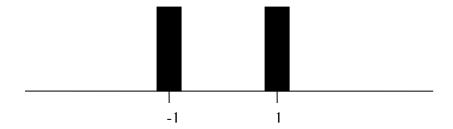
#### **PROBABILITY DISTRIBUTION**

We now introduce one more important concept, that of a probability distribution. A random variable is a function defined on  $\Omega$  whereas its distribution is a tabulation of the probabilities that the random variable takes its various values. A random variable is **not** a distribution.



Under the probability measure P defined on  $\Omega$  either a head or tail are equally likely so our distribution becomes

$$P(x_1 = 1) = 0.5, P(x_1 = -1) = 0.5$$



#### **EXPECTATION**

We can define the expectation or expected value of any random variable X under a probability measure P as.

$$E(X) = \sum_{\omega \in} X(\omega) P(\omega)$$

- Weighted average of the values the random variable X can take
- Weighting by the probability of each value
- Measure of centrality

#### EXPECTATION OF VARIABLE SQUARED

We are often interested in expectation of the square of the variable which we call the mean squared.

$$E(x_1^2) = [x_1(H)]^2 P(H) + [x_1(T)]^2 P(T) = 0.5 + 0.5 = 1.0$$

$$\tilde{E}(x_1^2) = [x_1(H)]^2 \tilde{P}(H) + [x_1(T)]^2 \tilde{P}(T) = 0.75 + 0.25 = 1.0$$

#### VARIATION FROM EXPECTED VALUE

For any actual value of a random variable X we can calculate the difference between that value and the expectation  $X(\omega) - E(X)$ . We might ask the question "on average how much does a given value differ from the expected value?" We could calculate the average difference as  $\sum_{\omega \in \square} [X(\omega) - E(X)]P(\omega)$  however where the distribution is symmetric around the mean this value will be zero. A more instructive measure is given by calculating the average of the difference squared

$$\sum_{\omega\in\Omega}[X(\omega)-E(X)]^2P(\omega)$$

Under our two probability measures we get

$$[x_1(H) - E(x_1)]^2 P(H) + [x_1(T) - E(x_1)]^2 P(H) = 0.5 + 0.5 = 1.0$$
$$[x_1(H) - E(x_1)]^2 \tilde{P}(H) + [x_1(T) - E(x_1)]^2 \tilde{P}(H) = 0.5 + 0.5 = 1.5$$
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#### EXPECTATION OF A CONSTANT MULTIPLE OF A RANDOM VARIABLE

$$E[aX + b] = aE[X] + b$$

$$E[aX + b] = \sum_{\omega \in \Omega} (aX(\omega) + b)P(\omega)$$

From definition 1

$$= \sum_{\omega \in \Omega} (aX(\omega)) P(\omega) + \sum_{\omega \in \Omega} bP(\omega)$$

By multiplying out the brackets

$$= a \sum_{\omega \in \Omega} (X(\omega)) P(\omega) + \sum_{\omega \in \Omega} b P(\omega)$$

From the properties of summation

$$= aE[X] + b\sum_{\omega \in \Omega} P(\omega)$$

From definition 1

$$= aE[X] + b.1$$

From axioms of probability

$$= aE[X] + b$$

#### **EXPECTATION OF A FUNCTION OF RANDOM VARIABLE**

$$E[g(X)] = \sum_{\omega \in \Omega} g(X(\omega))P(\omega)$$

• The expectation of a function of a random variable is **not equal** to the function of the expectation  $E[g(X)] \neq g[E(X)]$ 

#### **VARIANCE**

$$Var[X] = E[(X - \mu)^2] = E[X^2] - (E[X])^2$$
Let  $\mu = E[X]$ 

$$E[(X - \mu)^2] = \sum_{\omega \in \Omega} (X(\omega) - \mu)^2 \ P(\omega)$$
 From definition
$$= \sum_{\omega \in \Omega} ((X(\omega))^2 - 2\mu X(\omega) + \mu^2) P(\omega)$$
 Multiplying out
$$= \sum_{\omega \in \Omega} (X(\omega))^2 P(\omega) + \sum_{\omega \in \Omega} -2\mu X(\omega) P(\omega) + \sum_{\omega \in \Omega} \mu^2 P(\omega)$$

$$= E[X^2] + \sum_{\omega \in \Omega} -2\mu X(\omega) P(\omega) + \sum_{\omega \in \Omega} \mu^2 P(\omega)$$
 From definition 3
$$= E[X^2] + -2\mu \sum_{\omega \in \Omega} X(\omega) P(\omega) + \mu^2 \sum_{\omega \in \Omega} P(\omega)$$
 Properties of summations
$$= E[X^2] - 2\mu \mu + \mu^2 \sum_{\omega \in \Omega} P(\omega)$$

$$= E[X^2] - 2\mu \mu + \mu^2$$
 Axioms of probability
$$= E[X^2] - \mu^2$$

$$= E[X^2] - (E[X])^2$$

#### VARIANCE OF A CONSTANT PROPERTY

$$Var[a] = 0$$

#### VARIANCE OF A CONSTANT MULTIPLE

$$Var[aX] = aVar[X]$$

$$Var[aX] = E[(aX - E[aX])^{2}]$$

$$= E[(aX - aE[X])^{2}]$$
From definition 2
$$= E[(aX - a\mu)^{2}]$$
Letting  $\mu = E[X]$ 

$$= \sum_{\omega \in \Omega} (aX(\omega) - a\mu)^{2} P(\omega)$$
From definition
$$= \sum_{\omega \in \Omega} a^{2}(X(\omega) - \mu)^{2} P(\omega)$$

$$= a^{2} \sum_{\omega \in \Omega} (X(\omega) - \mu)^{2} P(\omega)$$
From definition 4

# Adding Random variables

#### Expectation of the sum of two finite countable variables

If X is a random variable with sample space  $\{x_1, x_2, \ldots, x_m\}$  and Y is an independent random variable with sample space  $\{y_1, y_2, \ldots, y_n\}$  then the sample space of the joint distribution will be given by a set of pairs

$$\{x_1, y_1\}, \{x_1, y_2\}, \dots, \{x_1, y_n\}$$

$$\{x_2, y_1\}, \{x_2, y_2\}, \dots, \{x_2, y_n\}$$

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$$\{x_m, y_1\}, \{x_m, y_2\}, \dots, \{x_m, y_n\}$$

The expectation of the sum of the two variables in then given by

$$\sum_{i=1}^{m} \sum_{j=1}^{n} (x_i + y_j) p(x_i, y_j)$$

Multiplying out we get

$$\sum_{i=1}^{m} \sum_{j=1}^{n} x_i p(x_i, y_j) + \sum_{i=1}^{m} \sum_{j=1}^{n} y_j p(x_i, y_j)$$

Noting that  $\sum_{j=1}^{n} p(x_i, y_j) = p(x_i)$  and  $\sum_{i=1}^{m} p(x_i, y_j) = p(y_j)$ 

$$\sum_{i=1}^{m} x_{i} p(x_{i}) + \sum_{j=1}^{n} x_{j} p(y_{j})$$

Therefore we can note that

$$E[X + Y] = E[X] + E[Y]$$

# Expectation of the sum of n identically distributed random variables

We can calculate the expectation of the sum of n identically distributed random variables denoted by  $X_1, X_2, ...., X_n$  as  $E[X_1] + E[X_2] + .... + E[X_n]$  which is equal to

$$n. E[X_n]$$

# Worked example

Imagine a random event that involves the tossing of a single coin. We have two outcomes, heads or tails in our *sample space*  $\Omega$ 

$$\Omega = \{H, T\}.$$

Furthermore, let us define a *random variable*  $x_1$  that takes the value of plus one dollar if we obtain a head and minus one dollar if we obtain a tail.

$$x_1(H) = 1, x_1(T) = -1$$

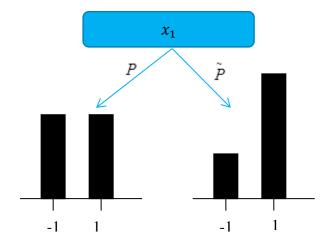
Notice that our random variable does not say anything about the probability of a head or tail. It just tells us what value we assign to the outcomes of the sample space. A probability measure is a real valued function that maps each outcome of the sample space to a probability. If our coin is fair we could have a measure P such that

$$P(H) = 0.5, P(T) = 0.5$$

We might however have a different measure for a loaded coin

$$\tilde{P}(H) = 0.75, \tilde{P}(T) = 0.25$$

Applying a probability measure to a random variable gives us a distribution. The distribution shows the probability of each value of the random variable. Different measures give different distributions.



## TABLE 1 SUMMARY

Outcome	Н	Each outcome is a thing that can occur in an experiment
Sample Space	$\Omega = \{H, T\}$	The set of all possible outcomes that can occur in an experiment is called the sample space
Event	$A = \{ \varpi \in \Omega; \varpi = H \}$	A subset of the sample space is called an event
Probability Measure	P(H) = P(T) = 0.5	A probability measure P is a function that assigns to each element $\varpi$ in $\Omega$ a probability such that $\sum_{\omega \in \square} P(\varpi) = 1$
Probability Space	$({H,T}, P(H) = P(T)) = 0.5)$	A probability space consists of a sample space and a probability measure
Random Variable	$x_1(H) = 1, x_1(T) = -1$	A random variable is a real valued function defined on the sample space.
Probability Distribution	$P(x_1 = 1) = 0.5, P(x_1 = -1) = 0.5$	Tabulation of the probabilities that the random variable takes its various values.
Expectation	$(X) = x_1(H)P(H) + x_1(T)P(T) = 0$	We define the expected value of our random variable under the probability measure P
Variation	$[x_1(H) - E(x_1)]^2 \tilde{P}(H) + [x_1(T) - E(x_1)]^2 \tilde{P}(H) = 1.5$	

# Summing Identical Independent random variables

We can create a new game by playing the original games twice. We define  $x_1$  as the profit/loss from the first coin toss and  $x_2$  as the profit/loss from the second toss. We can then define the random variable  $X = x_1 + x_2$  as the total profit or loss at the end of the two tosses. The sample space becomes

$$\Omega = \{\omega_1 \omega_2\} = \{HH, HT, TH, TT\}$$

The measure becomes

$$P(HH) = P(HT) = P(TH) = P(TT) = 0.25$$

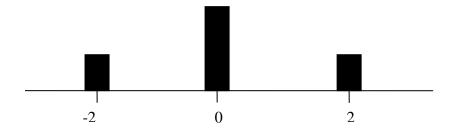
Giving us the random variable

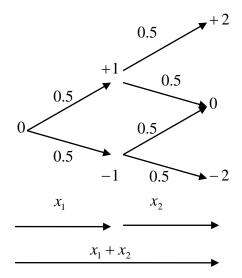
$$X(HH) = 2, X(HT) = (TH) = 0, X(TT) - 2$$

Applying our measure to the random variable we get our probability distribution

$$P(X = 2) = 0.25, P(X = 0) = 0.5, P(X = -2) = 0.25$$

Which is visualizedd as flollows

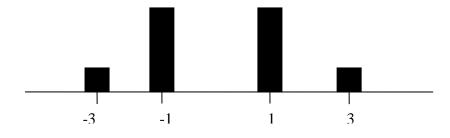


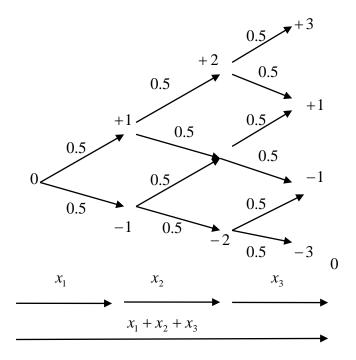


- $\mu = 0$
- $\sigma^2 = 0.25(2-0)^2 + 0.25(-2-0)^2 = 2.0$

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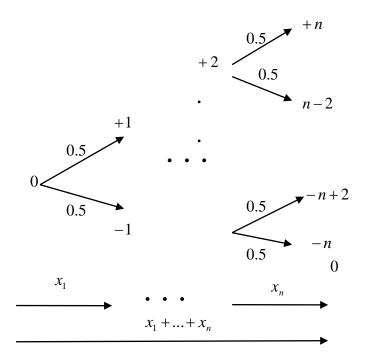
Let us go one-step further and look at summing three toin tosses.  $X_3 = x_1 + x_2 + x_3$ We get the following distribution, whose mean is zero and whose variance is three.





- $\bullet$   $\mu = 0$
- $\sigma^2 = 0.125(3-0)^2 + 0.125(-3-0)^2 + 0.375(1-0)^2 + 0.375(-1-0)^2 = 3.0$

Taking this process to its logical conclusion by summing n of our independent, identically distributed random variables we obtain the random variable  $X_n = x_1 + ... + x_n$  which is distributed with mean zero and variance n.



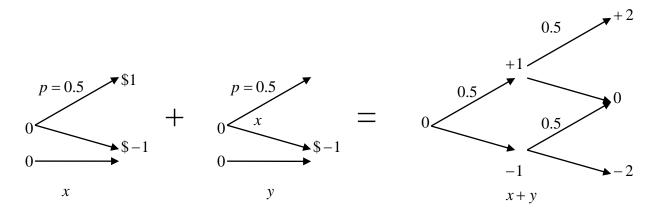
From a proof of why the sum of n independent, identically distributed random variables with mean  $\mu$  and variance  $\sigma^2$  is a random variable with mean  $n\mu$  and variance  $n\sigma^2$  see below

#### **Proofs**

#### Expectation of sum of N I.I.D random variables

$$E[X + X + X + X + X + \dots + X] = NE[X]$$

The following figure shows the general approach



We have random variable x with sample space  $\{x_1, x_2\} = \{1,0\}$  and a second identically distributed random variable y with sample space  $\{y_1, y_2\} = \{1,0\}$ . The sample space of the joint distribution x + y is given by the set of pairs

$$\{x_1, y_1\}, \{x_1, y_2\}$$

$$\{x_2, y_1\}, \{x_2, y_2\}$$

The expectation of the sum of the variables is then given by

$$\sum_{i=1}^{2} \sum_{j=1}^{2} (x_i + y_j) p(x_i, y_j)$$

Multiplying out

$$\sum_{i=1}^{2} \sum_{j=1}^{2} x_i p(x_i, y_j) + \sum_{i=1}^{2} \sum_{j=1}^{2} y_j p(x_i, y_j)$$

Noting that  $\sum_{j=1}^{n} p(x_i, y_j) = p(x_i)$  and  $\sum_{i=1}^{m} p(x_i, y_j) = p(y_j)$ 

$$\sum_{i=1}^{m} x_{i} p(x_{i}) + \sum_{j=1}^{n} x_{j} p(y_{j})$$

Therefore we can note that

$$E[X+Y] = E[X] + E[Y]$$

#### **GENERALISING**

If x is a random variable with sample space  $\{x_1, x_2, \ldots, x_m\}$  and y is an independent random variable with sample space  $\{y_1, y_2, \ldots, y_n\}$  then the sample space of the joint distribution will be given by a set of pairs

$$\{x_1, y_1\}, \{x_1, y_2\}, \dots, \{x_1, y_n\}$$

$$\{x_2, y_1\}, \{x_2, y_2\}, \dots, \{x_2, y_n\}$$

.

$$\{x_m, y_1\}, \{x_m, y_2\}, \dots, \{x_m, y_n\}$$

The expectation of the sum of the two variables in then given by

$$\sum_{i=1}^{m} \sum_{j=1}^{n} (x_i + y_j) p(x_i, y_j)$$

Multiplying out we get

$$\sum_{i=1}^{m} \sum_{j=1}^{n} x_i p(x_i, y_j) + \sum_{i=1}^{m} \sum_{j=1}^{n} y_j p(x_i, y_j)$$

Noting that  $\sum_{j=1}^{n} p(x_i, y_j) = p(x_i)$  and  $\sum_{i=1}^{m} p(x_i, y_j) = p(y_j)$ 

$$\sum_{i=1}^{m} x_{i} p(x_{i}) + \sum_{i=1}^{n} x_{j} p(y_{j})$$

Therefore we can note that

$$E[X + Y] = E[X] + E[Y]$$

**Furthermore** 

$$E[X + X] = E[X] + E[X] = 2E[X]$$

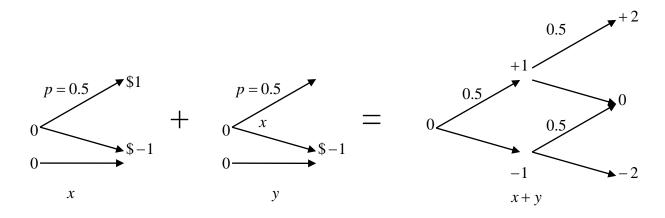
And

$$E[X + X + X + X + \dots + X] = NE[X]$$

#### Variance of sum of I.I.D random variables

$$Var[x + y] = Var[x] + Var[y]$$

The following diagram shows the general approach.



We have random variable x with sample space  $\{x_1, x_2\} = \{1,0\}$  and another identically distributed random variable y with sample space  $\{y_1, y_2\} = \{1,0\}$ . The sample space of the joint distribution x + y is given by the set of pairs

$$\{x_1, y_1\}, \{x_1, y_2\}$$

$$\{x_2, y_1\}, \{x_2, y_2\}$$

#### **PROOF**

$$Var[x + y] = E[(x + y)^{2}] - \{E[x + y]\}^{2}$$

$$Var[x + y] = E[(x^2 + 2xy + y^2)] - \{E[x] + E[Y]\}^2$$

$$Var[x + y] = E[x^2] + E[y^2] + E[2xy] - \{E[x] + E[Y]\}^2$$

$$Var[x + y] = E[x^2] + E[y^2] + E[2xy] - E[x]^2 - E[y]^2 - 2E[x][y]$$

$$Var[x + y] = E[x^2] + E[y^2] + 2E[x][y] - E[x]^2 - E[y]^2 - 2E[x][y]$$

$$Var[x + y] = E[x^2] - E[x]^2 + E[y^2] - E[y]^2$$

$$Var[x + y] = Var[x] + E[y]$$