EG2080 Monte Carlo Methods in Engineering



RANDOM VARIABLES AND RANDOM NUMBERS



BASIC DEFINITIONS

- An experiment (or trial) is an observation of a phenomenon, the result of which is random.
- The result of an experiment is called its outcome.
- The set of possible outcomes for an experiment is called its sample space.

Examples:

- Throwing a die: Integer between 1 and 6.
- Sum of throwing two dice: Integer between 2 and 12.
- The weight of a person: Real number larger than 0.

NOTATION

Random variables

Upper-case Latin letter, for example X, Y, Z.

Sometimes more than one letter is used (for example NI in the Ice-cream Company).

Observation (outcome) of a random variable

Lower-case counterpart of the symbol of the corresponding random variable, for example x, y, z.

Can sometimes be indexed to differentiate observations, for example x_i , y_i , z_i .

NOTATION

Probability distribution

Latin f in lower or upper case (depending on interpretation) and an index showing the corresponding symbol of the random variable.

- Density function: $f_{X'} f_{Y'} f_{Z'}$
- Distribution function: $F_{X'}$, $F_{Y'}$, F_{Z} .

 The index makes it easier to differentiate the probability distributions when one is dealing with more than one random variable.





.

NOTATION

Statistical properties of a probability distribution

Lower-case greek letter and an index showing the corresponding symbol of the random variable:

- Expectation value (mean): $\mu_{X'}$ $\mu_{Y'}$ $\mu_{Z'}$
- Standard deviation: $\sigma_{\!X'}$ $\sigma_{\!Y'}$ $\sigma_{\!Z'}$

NOTATION

Estimates



Latin counterpart of the greek symbol that is estimated. Can be upper-case or lower-case depending on interpretation.

- Estimated expectation value: $m_{X'}$, $m_{Y'}$, $m_{Z'}$
- Estimated standard deviation: $s_{X'}$, $s_{Y'}$, $s_{Z'}$.

RANDOM VARIABLES - Concept

- A random variable is a way to represent a sample space by assigning one or more numerical values to each outcome.
- If each outcome produces one value, the probability distribution is univariate.
- If each outcome produces more than one value, the probability distribution is multivariate.
- If the sample space is finite or countable infinite, the random variable is discrete otherwise, it is continuous.



RANDOM VARIABLES

- Probability Distributions
- A probability distribution describes the sample space of a random variable.
- A probability distribution can be described in several different ways.
 - Frequency function/density function.
 - Distribution function.
 - Population (set of units).



RANDOM VARIABLES - Frequency function



Definition 1: The probability of the outcome x for a univariate discrete random variable X is given by the frequency function $f_X(x)$, i.e.,

$$P(X=x) = f_X(x).$$

RANDOM VARIABLES - Density Function



The probability that the outcome is exactly \mathcal{X} is infinitesimal for a continuous random variable. Therefore, we use a density function to represent the probability that the outcome is approximately equal to x.

Definition 2: The probability of the outcomes X for a univariate continuous random variable X is given by the density function $f_X(x)$, i.e.,

$$P(X \in X) = \int_{X} f_X(x) dx.$$

10

RANDOM VARIABLES

Frequency and Density Functions



Lemma: Frequency functions and density functions have the following property:

$$\sum_{x=-\infty}^{\infty} f_X(x) = 1 \text{ or } \int_{-\infty}^{\infty} f_X(x) dx = 1.$$

RANDOM VARIABLES

- Distribution Function



Definition 3: The probability that the outcome of a univariate random variable X is less than or equal to some arbitrary level x is given by the distribution function $F_X(x)$, i.e.,

$$P(X \le x) = F_X(x).$$

RANDOM VARIABLES

- Distribution Function



Lemma: A distribution function has the following properties:

$$\lim_{x \to -\infty} F_X(x) = 0.$$

$$\lim_{x \to +\infty} F_X(x) = 1.$$

•
$$x_1 < x_2 \Rightarrow F_X(x_1) < F_X(x_2)$$
. (Increasing)

•
$$\lim_{h \to 0^+} F_X(x+h) = F_X(x)$$
. (Right-continuous)

RANDOM VARIABLES - Density, frequency and distribution functions



Lemma: The relation between distribution functions and frequency/density functions can be written as

$$F_X(x) = \sum_{\xi = -\infty}^{x} f_X(\xi) \text{ or } F_X(x) = \int_{-\infty}^{x} f_X(\xi) d\xi.$$

RANDOM VARIABLES

- Multivariate Distributions



The definitions 1–3 can easily be extended to the multivariate case.

Examples:

- Discrete, three-dimensional distribution: $P((X,Y,Z)=(x,y,z))=f_{X,Y,Z}(x,y,z).$
- Continuous, two-dimensional distribution:

$$P(X \le x, Y \le y) = F_{X, Y}(x, y) = \int_{-\infty}^{x} \int_{-\infty}^{y} f_{X, Y}(\xi, \psi) d\xi d\psi.$$

POPULATIONS



For analysis of Monte Carlo simulation it can be convenient to consider observations of random variables as equivalent to selecting an individual from a population.

- The random variable X can be represented by the population X.
- An individual in the population X is referred to as a unit.
- Unit i is associated to the value x_i . The values of the units do not have to be unique, i.e, it is possible that $x_i = x_j$ for two units i and j.

POPULATIONS



- The population X has the units $\chi_1,...,\chi_{N'}$ i.e., X is a set with N elements.
- It is possible that *N* is infinite.
- A random observation of X is equivalent to randomly selecting a unit from the population X.
- The probability of selecting a particular unit is 1/N. Hence,

$$F_X(x) = \frac{N_{\{x_i \in X: x_i \le x\}}}{N}. \tag{1}$$

EXAMPLE 2 - Discrete r.v.

Let *X* be the result of throwing a fair six-sided die once.

- a) State the frequency function $f_X(x)$.
- b) State the distribution function $F_{\mathbf{Y}}(x)$.
- c) Enumerate the population X.

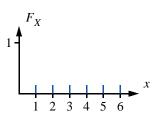
18

EXAMPLE 2 - Discrete r.v.

Solution:







$$f_X(x) = \begin{cases} \frac{1}{6} & x = 1, 2, 3, 4, 5, 6, \\ 0 & \text{all other } x. \end{cases}$$

EXAMPLE 2 - Discrete r.v.

Solution (cont.)



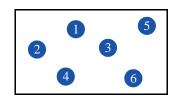
$$F_X(x) = \begin{cases} 0 & x < 1, & 1 \\ 1/6 & 1 \le x < 2, \\ 2/6 & 2 \le x < 3, \\ 3/6 & 3 \le x < 4, \\ 4/6 & 4 \le x < 5, \\ 5/6 & 5 \le x < 6, \\ 1 & 6 \le x. \end{cases}$$

EXAMPLE 2 - Discrete r.v.

Solution (cont.)

c) $X = \{1, 2, 3, 4, 5, 6\}.$





EXAMPLE 3 - Continuous r.v.

Let X be a random variable which is uniformly distributed between 10 and 20.

- a) State the frequency function $f_X(x)$.
- b) State the distribution function $F_{\mathbf{X}}(x)$.
- c) Enumerate the population X.

21

22

EXAMPLE 3 - Continuous r.v.

Solution:

a)



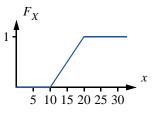
5 10 15 20 25 30

$$f_X(x) = \begin{cases} 0.1 & 10 \le x \le 20, \\ 0 & \text{all other } x. \end{cases}$$

EXAMPLE 3 - Continuous r.v.

Solution (cont.)

b)



$$F_X(x) = \begin{cases} 0 & x \le 10, \\ 0.1x - 1 & 10 \le x \le 20, \\ 1 & 20 \le x. \end{cases}$$

EXAMPLE 3 - Continuous r.v.

Solution (cont.)

c) The population has one unit for each real number between 10 and 20.



EXPECTATION VALUE

The expectation value of a random variable is the mean of the all possible outcomes weighted according to their probability:

Definition 4: The expectation value of the random variable *X* is given by

$$E[X] = \sum_{x = -\infty}^{\infty} x f_X(x) \text{ (discrete)},$$

2

24

EXPECTATION VALUE

Definition 4 (cont.)

$$E[X] = \int_{-\infty}^{\infty} x f_X(x) dx \text{ (continuous),}$$

or

KTH Electrical Engineering

$$E[X] = \frac{1}{N} \sum_{i=1}^{N} \chi_i$$
 (population).



EXPECTATION VALUE

Not all random variables have an expectation value!

Example (St. Petersburg paradox): A player tosses a coin until a tail appears. If a tail is obtained for the first time in the j: th trial, the player wins $2^{j-1} \in$.

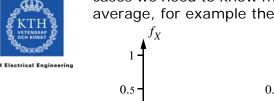
Let X be the payout when playing this game. The probability that trial j is the first trial where the tail appears is 2^{-j} , $j=1,2,3,\ldots$ Hence we get

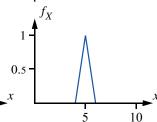
$$E[X] = \sum_{j=1}^{\infty} 2^{-j} \cdot 2^{j-1} = \sum_{j=1}^{\infty} \frac{1}{2}.$$

VARIANCE

The expectation value provided important information about a random variable, but in many cases we need to know more than the expected average, for example the spread.

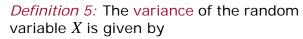
10





VARIANCE

A common measure of the spread is the variance, i.e., the expected quadratic deviation from the expectation value.



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

= $E[X^{2}] - (E[X])^{2}$ (general),

$$Var[X] = \sum_{x = -\infty} (x - E[X])^{2} f_{X}(x)$$
(discrete),

29

30

VARIANCE

Definition 5 (cont.)

$$Var[X] = \int_{-\infty}^{\infty} (x - E[X])^{2} f_{X}(x) dx$$
(continuous),

or

KTH Electrical Engineering

$$Var[X] = \frac{1}{N} \sum_{i=1}^{N} (\chi_i - E[X])^2$$
 (population).



STANDARD DEVIATION

It is in many cases convenient to have a measure of the spread which has the same unit as the expectation value. Therefore, the notion standard deviation has been introduced:

Definition 6: The standard deviation of the random variable *X* is given by

$$\sigma_X = \sqrt{Var[X]}$$
.

COVARIANCE

For multivariate distributions it is sometimes necessary to describe how the random variables interact:



Definition 7: The covariance of two random variables *X* and *Y* is given by

$$Cov[X, Y] = E[(X - E[X])(Y - E[Y])] =$$

= $E[XY] - E[X]E[Y].$

Lemma:
$$Cov[X, Y] = Cov[Y, X],$$

 $Cov[X, X] = Var[X].$

COVARIANCE

A covariance matrix, Σ_{X} , states the covariance between all random variables in a multivariate distribution:



$$\begin{split} & \boldsymbol{\Sigma_{X}} = \\ & = \begin{bmatrix} Var[\boldsymbol{X}_{1}] & Cov[\boldsymbol{X}_{1}, \boldsymbol{X}_{2}] \cdots Cov[\boldsymbol{X}_{1}, \boldsymbol{X}_{k}] \\ Cov[\boldsymbol{X}_{2}, \boldsymbol{X}_{1}] & Var[\boldsymbol{X}_{2}] \\ \vdots & \ddots & \\ Cov[\boldsymbol{X}_{k}, \boldsymbol{X}_{1}] & Var[\boldsymbol{X}_{k}] \end{bmatrix} \end{split}$$

33

34

CORRELATION COEFFICIENT

The covariance is an absolute measure of the interaction between two random variables. Sometimes it is preferable to use a relative measure:



Definition 8: The correlation coefficient of two random variables *X* and *Y* is given by

$$\rho_{X, Y} = \frac{Cov[X, Y]}{\sqrt{Var[X]Var[Y]}}.$$



We can conclude from definition 8 that the correlation coefficient always is in the interval [-1, 1].



- $\rho_{X, Y} > 0 \Rightarrow X$ and Y positively correlated If the outcome of X is low then it is likely that the outcome of Y is also low and vice versa.
- $\rho_{X, Y} < 0 \Rightarrow X$ and Y are negatively correlated. If the outcome of X is low then it is likely that the outcome of Y is high and vice versa.
- $\rho_{X, Y} = 0 \Leftrightarrow Cov(X, Y) = 0 \Rightarrow X$ and Y uncorrelated

INDEPENDENT RANDOM VARIABLES



KTH Electrical Engineering

A very important special case when studying multivariate distributions is when the random variables are independent.

Definition 9: X and Y are independent random variables if it holds for each x and y that

$$f_{X,Y}(x,y) = f_X(x)f_Y(y) \Leftrightarrow F_{X,Y}(x,y) = F_X(x)F_Y(y).$$

INDEPENDENT RANDOM VARIABLES



Theorem 1: If X and Y are independent then

$$E[XY] = E[X]E[Y].$$

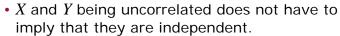
Theorem 2: If X and Y are independent then they are also uncorrelated.

Warning! Correlations are easily misunderstood!

37

35

CORRELATIONS



Example: Y uniformly distributed between -1 and 1, $X = Y^2 \Rightarrow \rho_{XY} = 0$, although X is dependent of Y.

• A correlation only indicates that *there is* a relation, but does not say anything about the *cause* of the relation.

Example: X=1 if a driver wears pants, otherwise 0, Y=1 if driver involved in an accident, otherwise 0. The conclusion if $\rho_{X,Y}>0$ should not be that wearing pants increases the risk of traffic accidents. In reality such a correlation would probably be due to a more indirect relation.





i) E[aX] = aE[X]



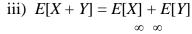
ii)
$$E[g(X)] = \int g(x)f_X(x)dx$$
 (continuous),

$$E[g(X)] = \sum_{x}^{-\infty} g(x) f_X(x)$$
 (discrete),

$$E[g(X)] = \frac{1}{N} \sum_{i=1}^{N} g(\chi_i)$$
 (population).

ARITHMETICAL OPERATIONS

Theorem 3 (cont.)



iv)
$$E[g(X, Y)] = \int_{-\infty - \infty}^{\infty} \int_{-\infty - \infty}^{\infty} g(x, y) f_{XY}(x, y) dx dy$$
 (continuous),

$$E[g(X, Y)] = \sum_{x} \sum_{y} g(x, y) f_{XY}(x, y)$$
 (discrete).

ARITHMETICAL OPERATIONS

Theorem 3 (cont.)



$$E[g(X, Y)] = \frac{1}{N} \sum_{i=1}^{N} g(x_i, y_i)$$
(population)

Theorem 4:

i)
$$Var[aX] = a^2 Var[X]$$

ii)
$$Var[X + Y] =$$

= $Var[X] + Var[Y] + 2Cov[X, Y]$

41

42

ARITHMETICAL OPERATIONS

Theorem 4 (cont.)

iii)
$$Var[X - Y] =$$

= $Var[X] + Var[Y] - 2Cov[X, Y]$

iv)
$$Var\begin{bmatrix} k \\ \sum_{i=1}^{k} X_i \end{bmatrix} = \sum_{i=1}^{k} \sum_{j=1}^{k} Cov[X_i, X_j]$$



ARITHMETICAL OPERATIONS

Theorem 5: If X and Y are independent random variables and Z = X + Y then the probability distribution of Z can be calculated using a convolution formula, i.e.,

$$f_{Z}(x) = \int_{-\infty}^{\infty} f_{X}(t) f_{Y}(x-t) dt$$

or

$$f_{Z}(x) = \sum_{t} f_{X}(t) f_{Y}(x-t).$$



PROBABILITY DISTRIBUTIONS



- Probability distributions can be defined arbitrarily, but there are also general probability distributions which appear in many practical applications.
- Density function, distribution functions, expectation values and variances for many general probability distributions can be found in mathematical handbooks. The English version of Wikipedia also provides a lot of information.

RANDOM NUMBERS



- A random number generator is necessary to create random samples for a computer simulation.
- A random number generator is a mathematical function that generate a sequence of numbers.

45

RANDOM NUMBERS



- Modern programming languages have built-in functions for generating random numbers from U(0, 1)-distributions and some other distributions.
- The underlying formula behind the most common random number generators is the following:

$$X_{i+1} = aX_i \pmod{m}.*$$
 (2)

* The operator mod *m* denotes the remainder when dividing by *m*.

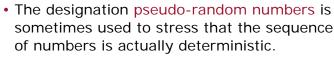
RANDOM NUMBERS

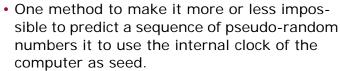


- Starting with a certain seed, X₀, the equation
 (2) will generate a deterministic sequence of numbers, {X_i}.
- The sequence will eventually repeat itself (at least after *m* numbers).
- The sequence $U_i = X_i/m$ will imitate a real sequence of U(0, 1)-distributed random numbers if the constants a and m are chosen appropriately.

Example: $a = 7^5 = 16807$ and $m = 2^{31} - 1$.

RANDOM NUMBERS

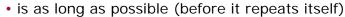


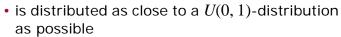


· An advantage of pseudo-random numbers is that a simulation can be recreated by using the same seed again.



A good random number generator will generate a sequence of random numbers which





· has a negligible correlation between the numbers in the sequence.



RANDOM NUMBERS

How do we generate the inputs Y to a computer simulation?

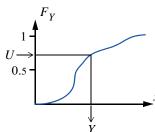
- A pseudo-random number generator provides U(0, 1)-distributed random numbers.
- Y generally has some other distribution.

There are several methods to transform U(0, 1)distributed random numbers to an arbitrary distribution.

In this course we will use the inverse transform method.



Theorem 6: If a random variable U is U(0, 1)-distributed then $Y = F_V^{-1}(U)$ has the distribution function $F_{\nu}(x)$.







EXAMPLE 4 - Inverse transform method



A pseudo-random number generator providing U(0, 1)-distributed random numbers has generated the value U=0.40.

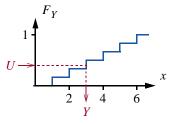
- a) Transform \boldsymbol{U} to a result of throwing a fair six-sided die.
- b) Transform U to a result from a U(10, 20)-distribution.

EXAMPLE 4 - Inverse transform method



Solution:

a) Graphic solution:



In the general case, a discrete inverse distribution function can be calculated using a search algorithm.

53

EXAMPLE 4 - Inverse transform method



Solution (cont.)

b) The inverse distribution function is given by

$$F_{Y}^{-1}(x) = \begin{cases} 10 & x \le 0, \\ 10x + 10 & 0 \le x \le 1, \\ 20 & 1 \le x. \end{cases}$$

$$\Rightarrow Y = F_V^{-1}(0.4) = 14.$$

NORMALLY DISTRIBUTED RANDOM NUMBERS



The normal distribution does not have an inverse distribution function! However, it is possible to use an approximation: *

Theorem 7: If a random variable U is U(0, 1)-distributed then Y is N(0, 1)-distributed if Y is calculated as follows:

* This method is therefore referred to as the "approximative inverse transform method".

NORMALLY DISTRIBUTED RANDOM NUMBERS



Theorem 7 (cont.)

$$Q = \begin{cases} U & \text{if } 0 \le U \le 0.5, \\ 1 - U & \text{if } 0.5 < U \le 1, \end{cases}$$
$$t = \sqrt{-2 \ln Q},$$

NORMALLY DISTRIBUTED RANDOM NUMBERS



Theorem 7 (cont.)

$$z = t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}$$

$$c_0 = 2.515517, \qquad d_1 = 1.432788,$$

$$c_1 = 0.802853, \qquad d_2 = 0.189269,$$

$$c_2 = 0.010328, \qquad d_3 = 0.001308,$$

5

58

NORMALLY DISTRIBUTED RANDOM NUMBERS



Theorem 7 (cont.)

$$Y = \begin{cases} -z & \text{if } 0 \le U < 0.5, \\ 0 & \text{if } U = 0.5, \\ z & \text{if } 0.5 < U \le 1. \end{cases}$$



CORRELATED RANDOM NUMBERS

- It is convenient if the inputs Y in a computer simulation are independent, because then the random variables can be generated separately.
- However, it is also possible to generate correlated random numbers.
 - Correlated normally distributed numbers.
 - General method.

CORRELATED RANDOM NUMBERS - Normal distribution



Theorem 8: Let $X = [X_1, ..., X_K]^T$ be a vector of independent N(0, 1)-distributed components. Let $\mathbf{B} = \Sigma^{1/2}$, i.e., let λ_i and g_i be the i: th eigenvalue and the i: th eigenvector of Σ and define the following matrices:

$$\mathbf{P} = [g_1, ..., g_K],$$

$$\Lambda = \operatorname{diag}(\lambda_1, ..., \lambda_K),$$

CORRELATED RANDOM NUMBERS - Normal distribution



Theorem 8 (cont.)

$$\boldsymbol{B} = \boldsymbol{P} \Lambda^{1/2} \boldsymbol{P}^T.$$

Then $Y = \mu + BX$ is a random vector where the elements are normally distributed with the mean μ and the covariance matrix Σ .

6

62

CORRELATED RANDOM NUMBERS - General method



Consider a multivariate distribution $Y = [Y_1, ..., Y_K]$ with the density function f_Y .

- \bullet Step 1. Calculate the density function of the first element, $f_{Y\!1}.$
- Step 2. Randomise the value of the first element according to f_{V1} .
- Step 3. Calculate the conditional density function of the next element, i.e.,

$$f_{Yk|[Y_1, ..., Y_{k-1}] = [\psi_1, ..., \psi_{k-1}]}$$

CORRELATED RANDOM NUMBERS - General method



 Step 4. Randomise the value of the k:th element according to the conditional probability distribution obtained from

$$f_{Yk|[Y_1, ..., Y_{k-1}] = [\psi_1, ..., \psi_{k-1}]}$$

 Step 5. Repeat step 3–4 until all elements have been randomised.

CORRELATED RANDOM NUMBERS - Alternative method



 This method is only applicable to discrete probability distributions.

However, a continuous probability distribution can of course be approximated by a discrete distribution.

 The idea is to use a modified distribution function for the inverse transform method.

CORRELATED RANDOM NUMBERS - Alternative method



Original distribution function: $F_{Y1, Y2}(y_1, y_2)$ is the probability that $Y_1 \le y_1$ and $Y_2 \le y_2$.

Modified distribution function: Arrange all units in the population in an ordered list; $F_{Y1, Y2}(n)$ is now the probability to select one of the n first units in the list.

The order of the list might influence the efficiency of some variance reduction techniques!

6

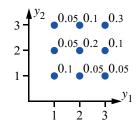
66

EXAMPLE 5 - Correlated discrete random numbers



Consider the multivariate probability distribution $f_{Y1, Y2}$ to the right.

According to the definition, we have $\rho_{Y1-Y2} \approx 0.4$.





EXAMPLE 5 - Correlated discrete random numbers

- a) Apply the general method to randomise values of Y_1 and Y_2 using the two independent random numbers $\tilde{U}_1=0.15$ and $U_2=0.62$ from a U(0,1)-distribution.
- b) Apply the alternative method to randomise values of Y_1 and Y_2 using the random number $U_1=0.12$ from a $U(0,\,1)$ -distribution.

EXAMPLE 5 - Correlated discrete random numbers



Solution: a) The probability distribution of the first element is given by

element is given by
$$f_{Y1}(y_1) = \sum_{\psi_2} f_{Y1, Y2}(y_1, \psi_2) = \begin{cases} 0.05 & 0.2 & 0.1 \\ 0.05 & 0.2 & 0.1 \\ 0.05 & 0.05 & 0.05 \end{cases}$$

$$= \begin{cases} 0.2 & y_1 = 1, \\ 0.35 & y_1 = 2, \Rightarrow Y_1 = F_{Y1}^{-1}(0.15) = 1. \\ 0.45 & y_1 = 3. \end{cases}$$

EXAMPLE 5 - Correlated discrete random numbers



$$= \begin{cases} 0.5 & y_2 = 1, \\ 0.25 & y_2 = 2, \implies Y_2 = F_{Y2|Y_1 = 1}^{-1}(0.62) = 2. \\ 0.25 & y_2 = 3. \end{cases}$$

6

EXAMPLE 5 - Correlated discrete random numbers



Solution: b) Assume that units are listed as follows:

Number	1	2	3	4	5	6	7	8	9
Unit	1	1	2	1	2	2	2	2	2
Y_{1}	l I	I	2	I	2	3	2	3	3
Y_2	1	2	1	3	2	1	3	2	3

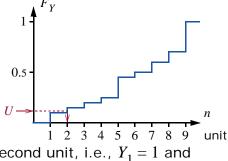
EXAMPLE 5 - Correlated discrete random numbers



Solution(cont.)

The modified distribution function is shown to the right.

The value U = 0.12 corre-



sponds to the second unit, i.e., $Y_1 = 1$ and $Y_2 = 2$.