

Principal Component Analysis

Data:

x_1	x_2	...	x_{1000}

dimension = 1000

dimension
→
reduction

x_1	x_2	...	x_{20}

dim = 20

Dimension
Reduction

remove some "less important" variables :

(LASSO, Decision tree, Forest, Gradient boosting ...)

Variable selection | Feature selection techniques

create a set of fewer variables from the
original variables : PCA ...

Variable extraction | Feature extraction techniques.

Data

x_1	x_2	x_3	x_4	x_5	y

→

u_1	u_2	y

"Truth" $y = \underbrace{(x_1 + 2x_2 - x_3)^2}_{u_1} + \cos(\underbrace{x_1 + 6x_5}_{u_2}) + \varepsilon$

$$E(y | x_1, x_2 \dots x_5) = E(y | u_1, u_2)$$

$$u_1 = x_1 + 2x_2 - x_3$$

$$u_2 = x_1 + 6x_5$$

* Dimension Reduction

Data 1

x_1	x_2	x_3	x_4	x_5

Five variables or the dimension is 5
 $d = 5$

variable
extraction

(PCA)

variable selection

x_1	x_3

($d = 2$)

Data 2

$u_1 =$

$u_2 =$

$2x_1 + x_3$	$x_4 + 6x_5$

Example :

$$y = (2x_1 + x_3)^3 + \log(x_4 + 6x_5)^2$$

PCA in a view or coordinate rotation

Variance of the Projection

Data :

x	y	<u>z</u>
1	1	2024
2	2	2024
3	5	2024
4	7	2024

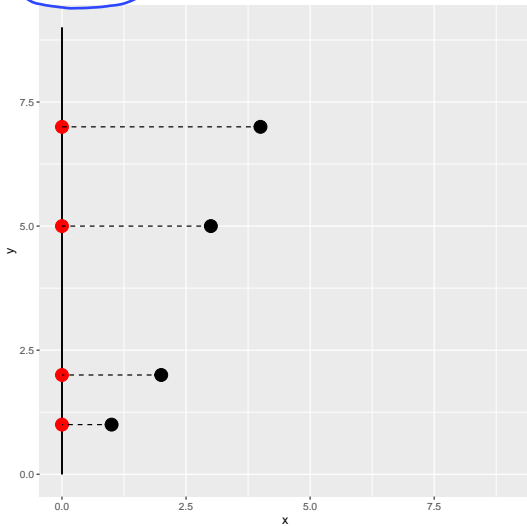
→ $v(z) = 0$

► $V(x) = 1.67$

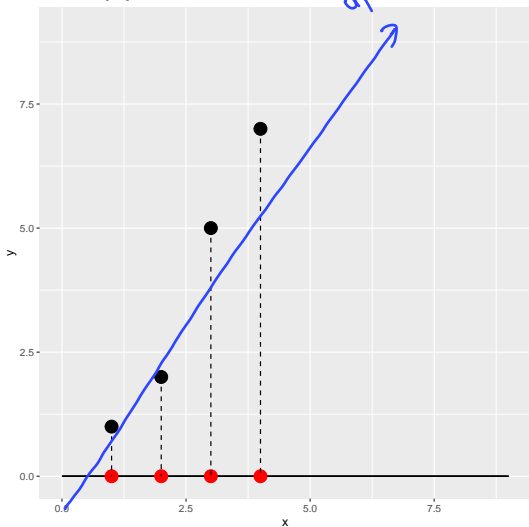
► $V(y) = 7.58$

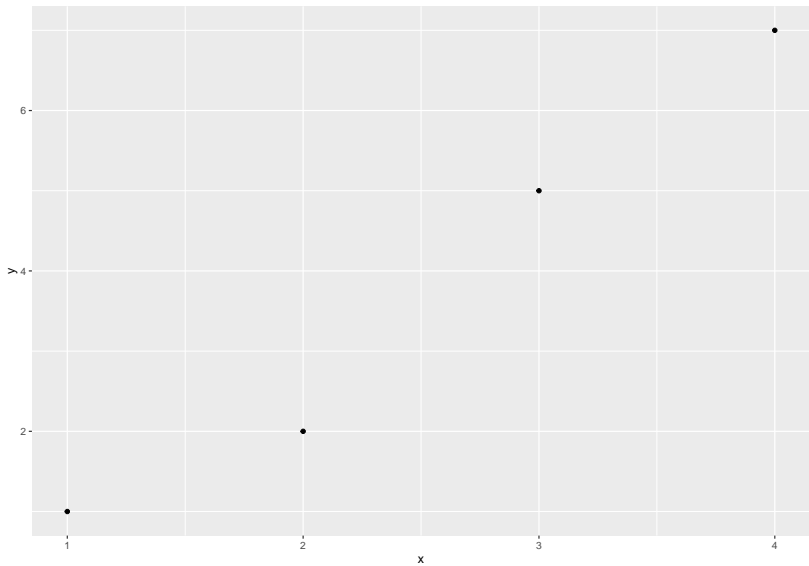
► Total variance: $V(x) + V(y) = 9.25$

Variance: 7.58
Direction z : $[0, 1]$



Variance: 1.67
Direction $z: [1, 0]$

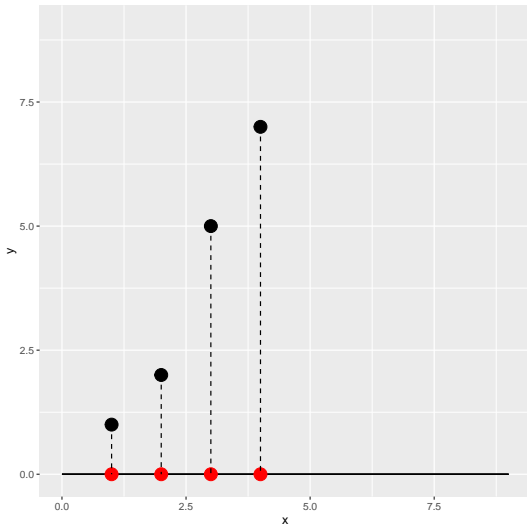




[1] 9.25

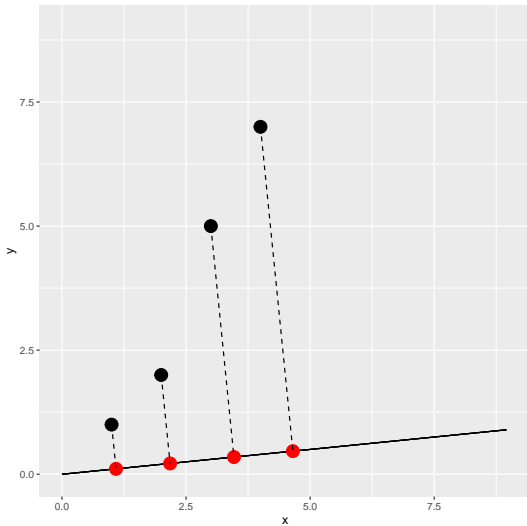
Variance 1.67

Direction $z: [1, 0]$

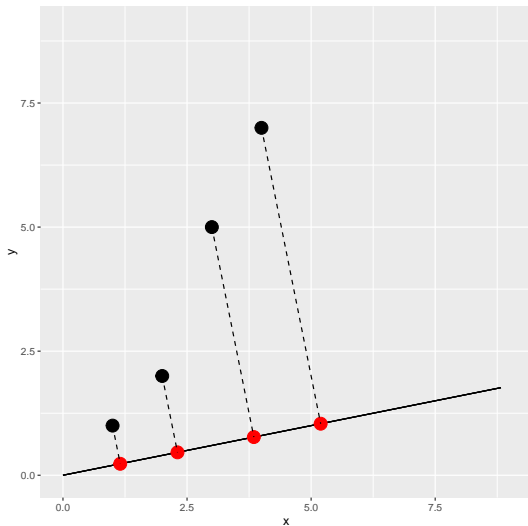


Variance: 2.42

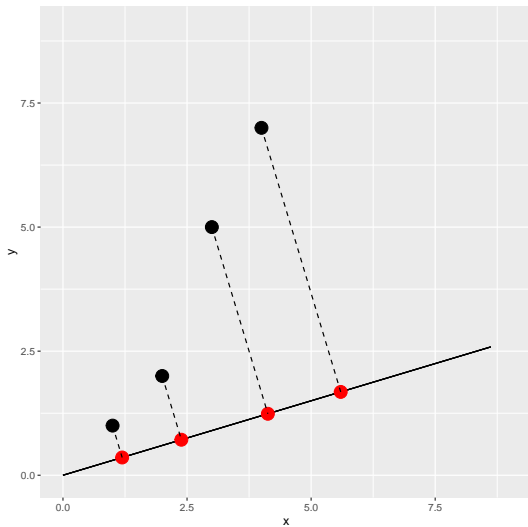
Direction z : [1,0.1]



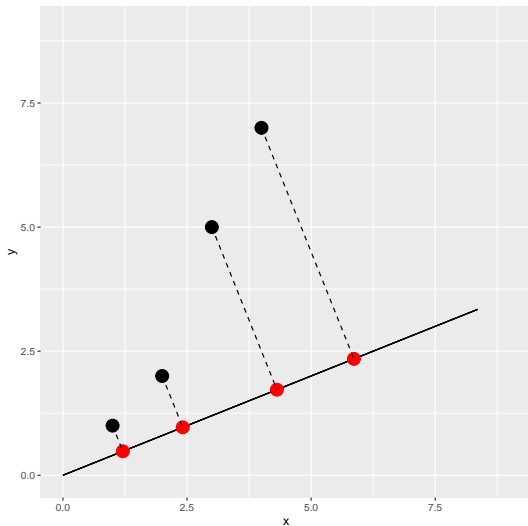
Variance: 3.24
Direction z : [1,0.2]



Variance: 4.08
Direction z: [1,0.3]

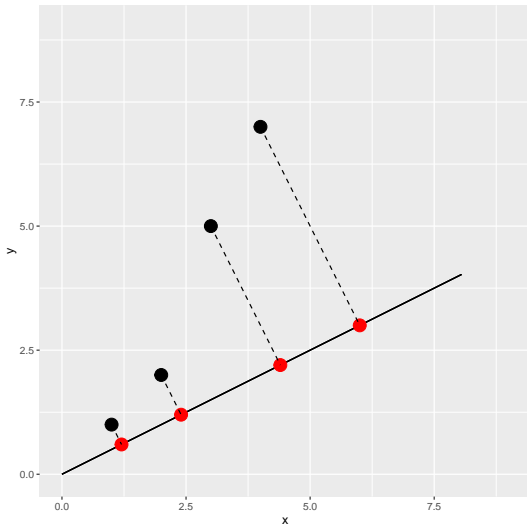


Variance: 4.9
Direction z : [1,0.4]

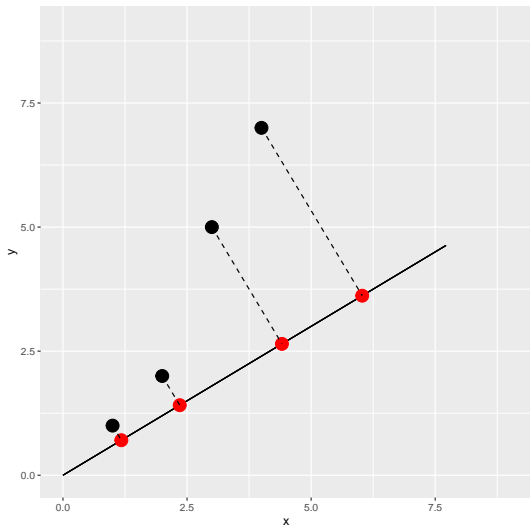


Variance: 5,65

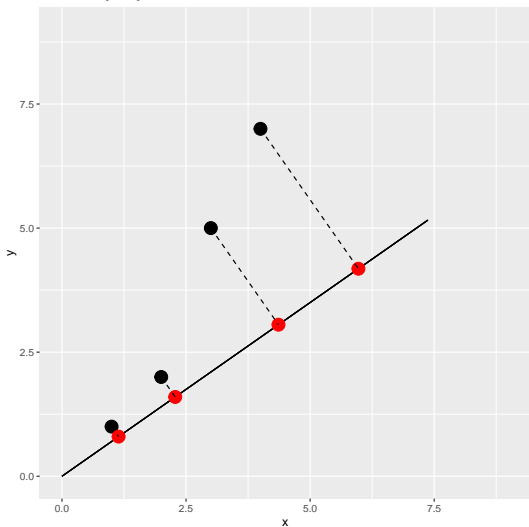
Direction z : [1,0.5]



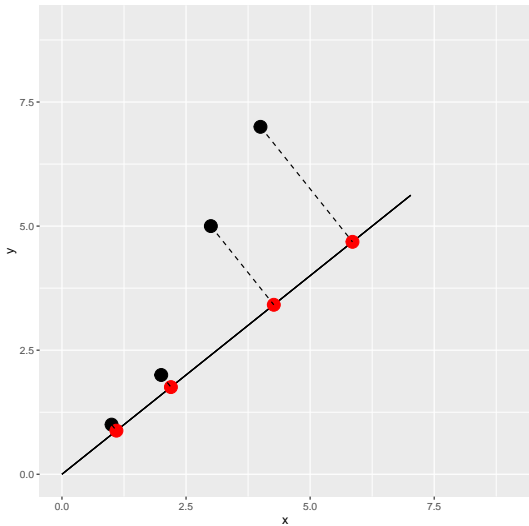
Variance: 6.32
Direction z : [1,0.6]



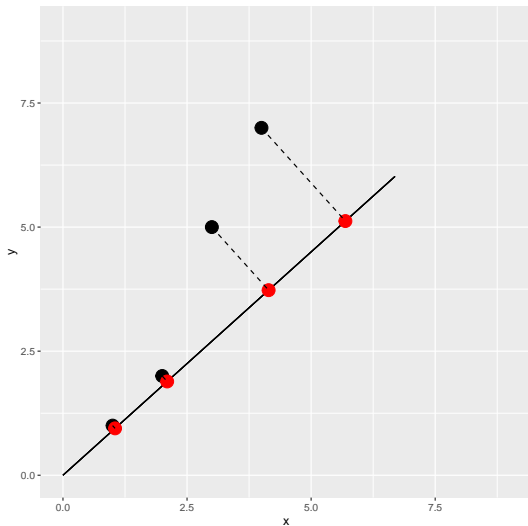
Variance: 6.9
Direction z : $[1, 0.7]$



Variance: 7.39
Direction z : [1,0.8]

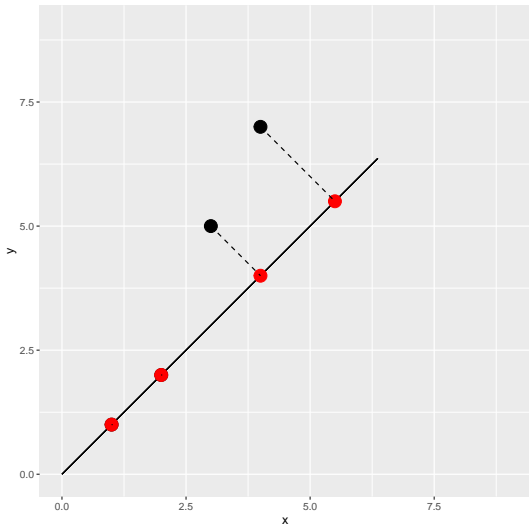


Variance: 7.8
Direction z : [1,0.9]

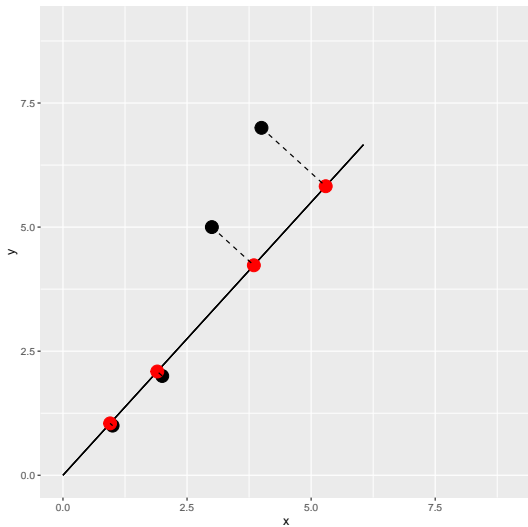


Variance: 8.13

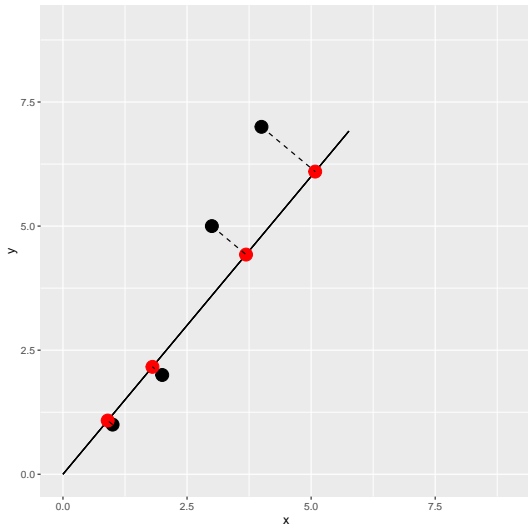
Direction z : [1, 1]



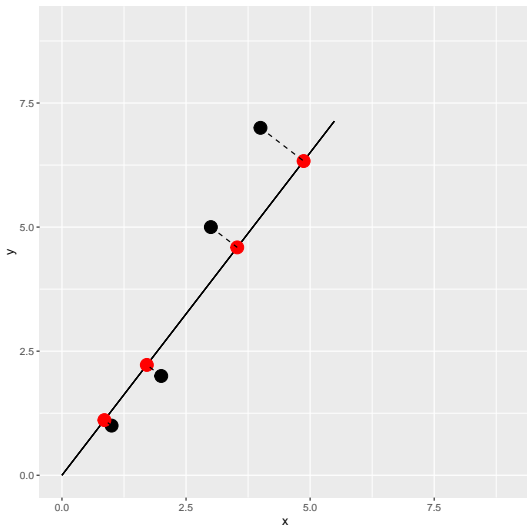
Variance: 8.39
Direction z : $[1, 1, 1]$



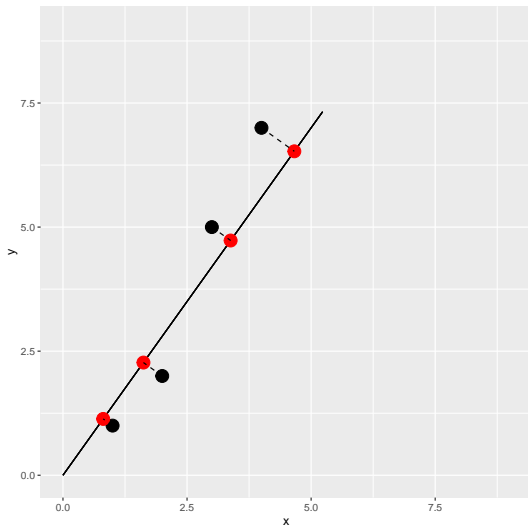
Variance: 8.6
Direction z : [1, 1.2]



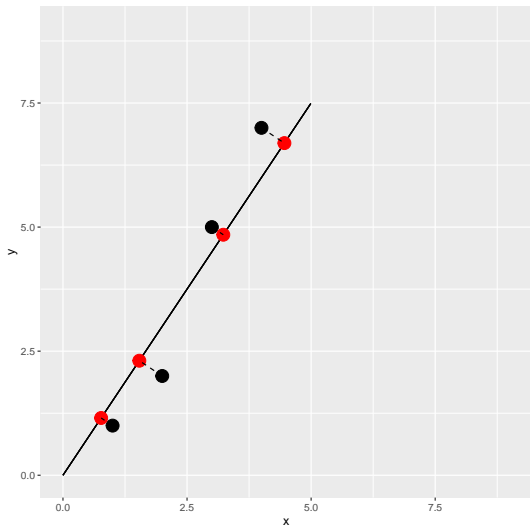
Variance: 8.77
Direction z : [1, 1.3]



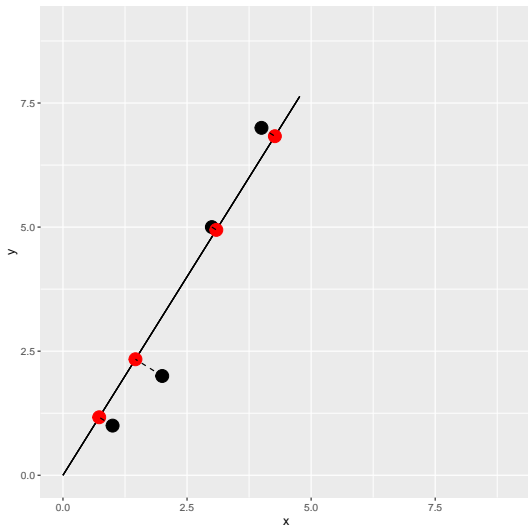
Variance: 8.9
Direction z : [1, 1.4]



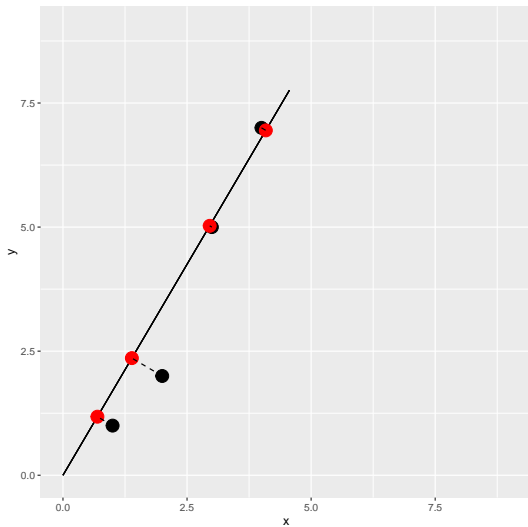
Variance: 8.99
Direction z : [1, 1.5]



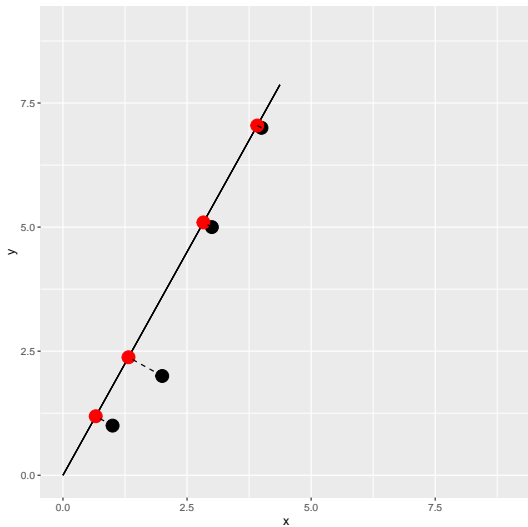
Variance: 9.07
Direction z : [1, 1.6]



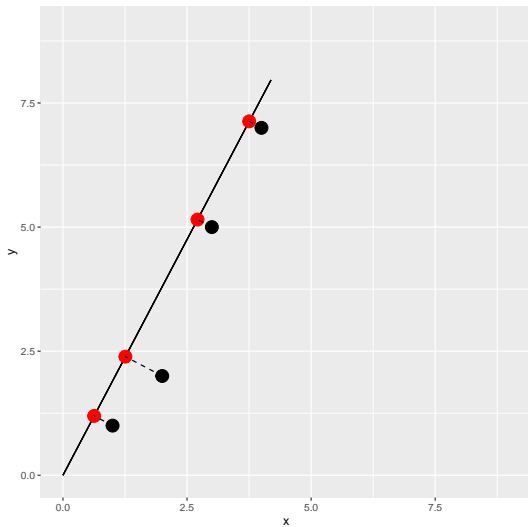
Variance: 9.12
Direction z : [1, 1.7]



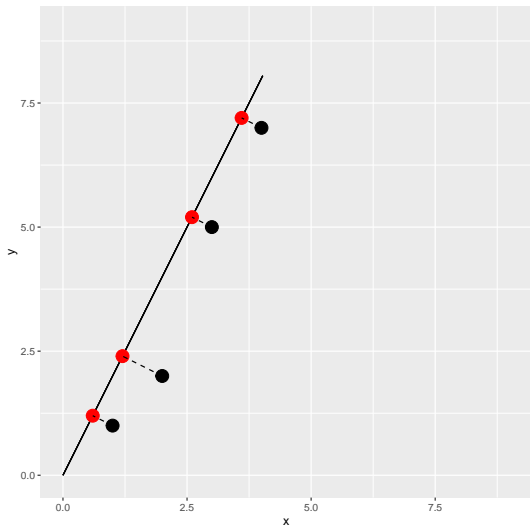
Variance: 9.16
Direction z : $[1, 1.8]$



Variance: 9.18
Direction z : [1, 1.9]

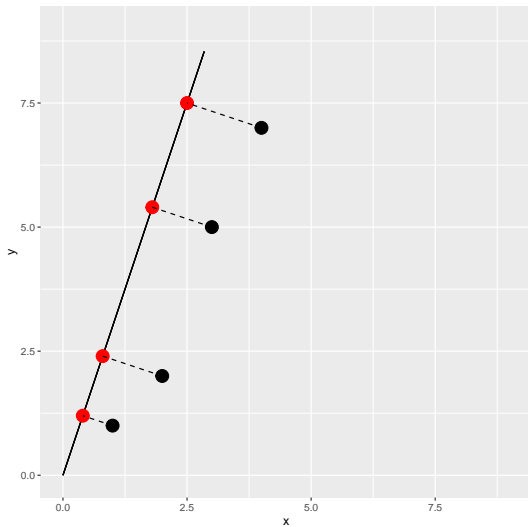


Variance: 9.2
Direction z : [1,2]



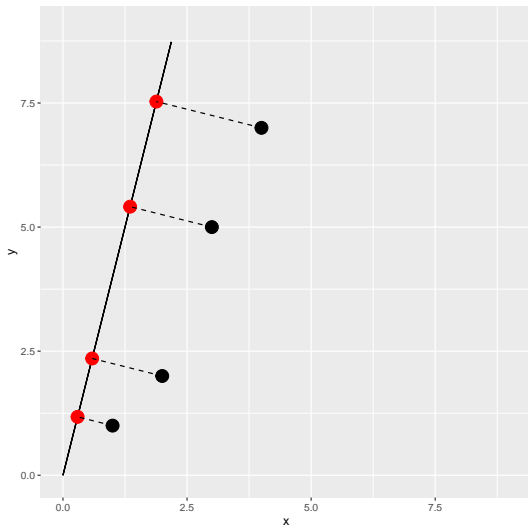
Variance: 9.09

Direction z : [1,3]



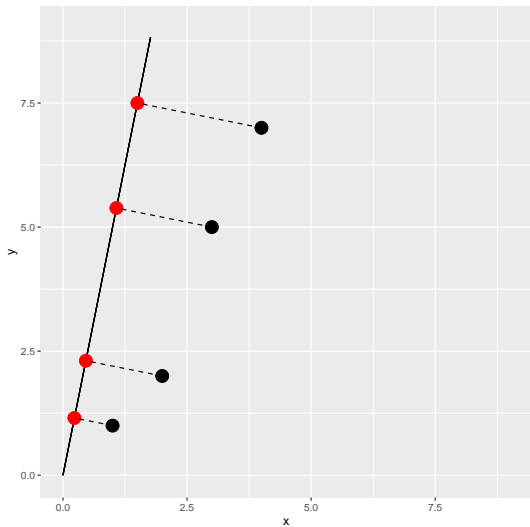
Variance: 8.88

Direction z : [1,4]



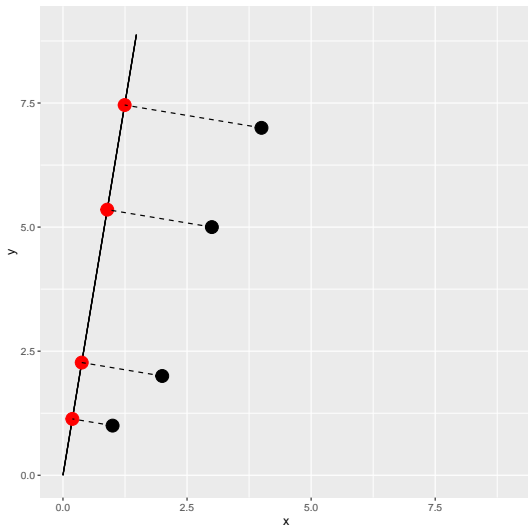
Variance: 8.7

Direction z : [1,5]



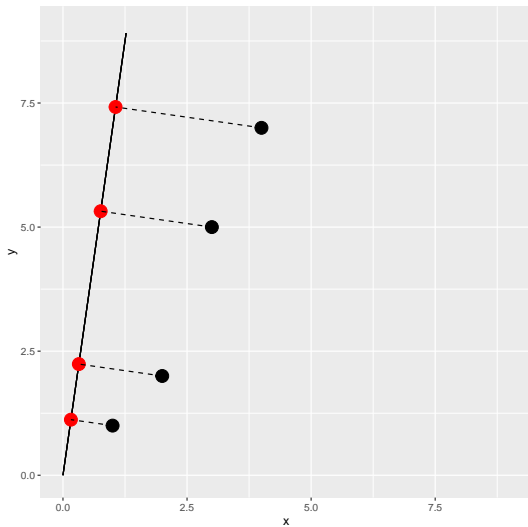
Variance: 8.56

Direction z : [1,6]



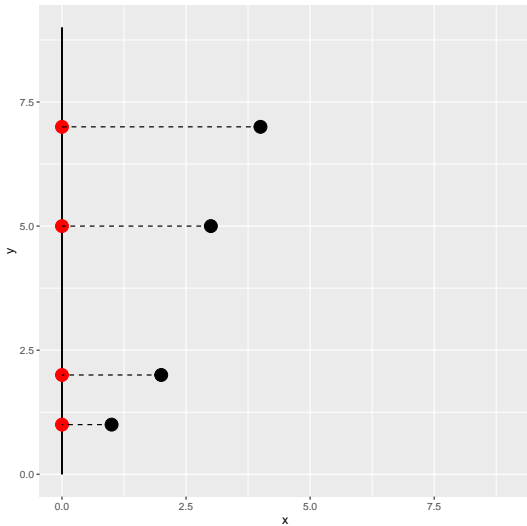
Variance: 8.45

Direction z : [1,7]



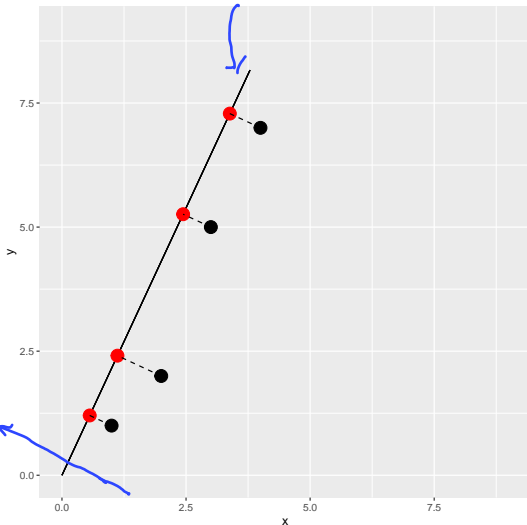
Variance: 7.58

Direction z : $[0, 1]$



Variance: 9.21
Direction z: [0.42, 0.91]

$$PC1 = \underbrace{.42x} + \underbrace{.91y}$$



9.21 out
of

9.25 variation

information

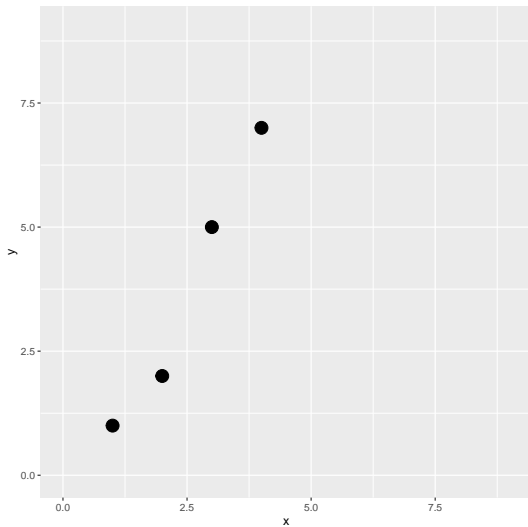
what about

.05 variation

left

Variance: 0.04

Direction z : $[-0.91, 0.42]$



Rotation Matrix or PC Loading

► $\Phi =$

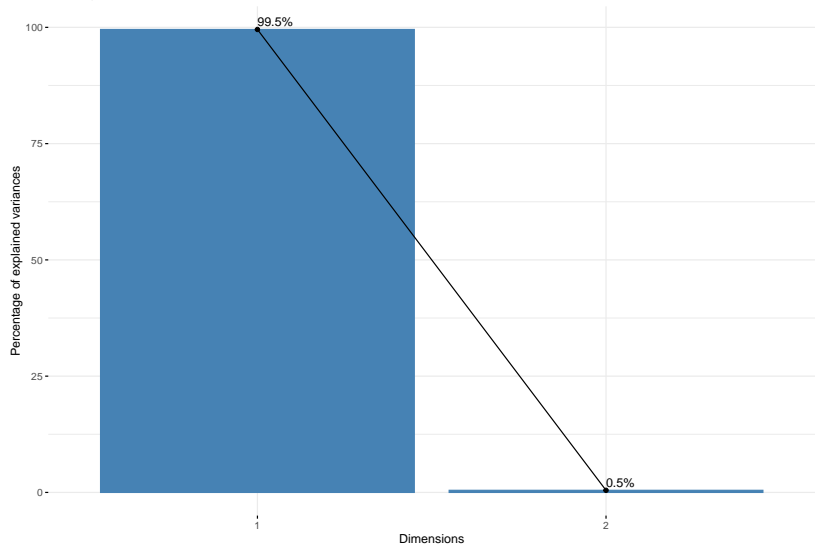
	PC1	PC2
x	0.42	-0.91
y	0.91	0.42

PC Scores

► $Z = X \cdot \Phi =$

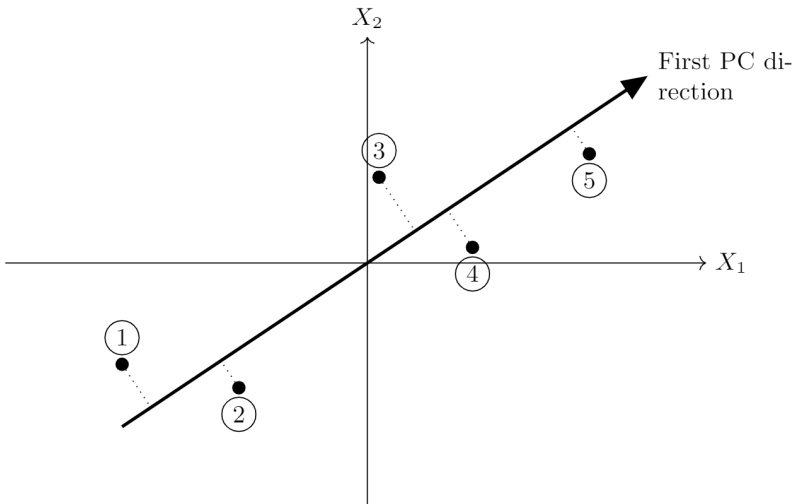
	PC1	PC2
[1,]	1.33	-0.49
[2,]	2.66	-0.97
[3,]	5.80	-0.62
[4,]	8.03	-0.68

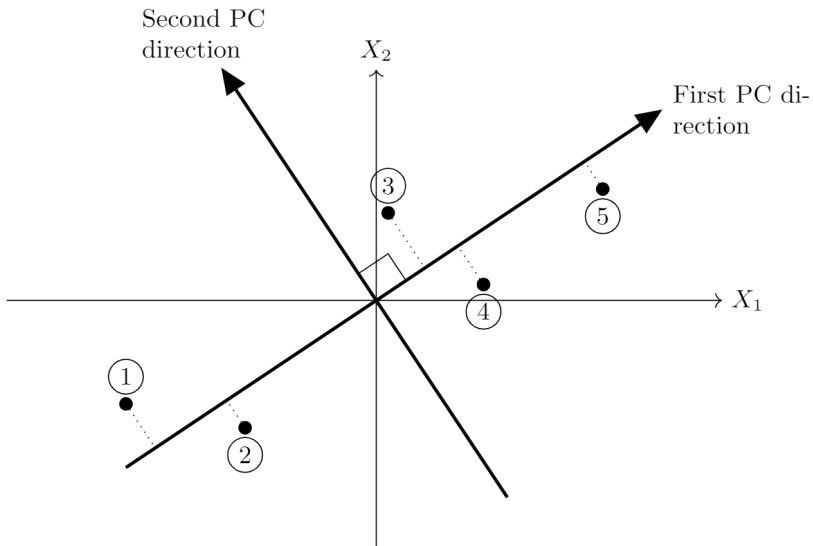
Scree plot



► What direction maximizes the variance?

- ▶ What direction maximizes the variance?
- ▶ The first principal component





Formula

- ▶ Write down matrix form of the example

$$X \rightarrow X \cdot \phi = Z$$

- ▶ ϕ is PC loading
- ▶ z is PC scores

In general

Original data matrix
(fat matrix!)

$$\begin{array}{ccccc} \underline{X_1} & \underline{X_2} & \cdots & \cdots & \underline{X_p} \\ \left(\begin{array}{ccccc} x_{11} & x_{12} & \cdots & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & \cdots & x_{np} \end{array} \right) \end{array}$$

\mathbf{X}

New data matrix
(thin matrix!)

$$\begin{array}{ccc} \underline{Z_1} & \cdots & \underline{Z_M} \\ \left(\begin{array}{ccc} z_{11} & \cdots & z_{1M} \\ z_{21} & \cdots & z_{2M} \\ \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{nM} \end{array} \right) \end{array}$$

$\mathbf{X}\phi_1 \quad \cdots \quad \mathbf{X}\phi_M$

compressed
 \longrightarrow

Example

	Independent variables	
Observation	X_1	X_2
1	-2	2
2	2	-2

- The data set consists of only these two observations.
- The first principal component loading for X_1 , ϕ_{11} , is 0.7071.
- The first principal component loading for X_2 , ϕ_{21} , is negative.

Calculate the first principal component score for Observation 1.

PC Loadings

	First PC	Second PC
Murder	0.5359	-0.4182
Assault	0.5832	-0.1880
UrbanPop	0.2782	0.8728
Rape	0.5434	0.1673

How many PC should we use?

► Performance during two sporting events

X100m	Long.jump	Shot.put	High.jump	X400m	X110m.hurdle	Discus
11.04	7.58	14.83	2.07	49.81	14.69	43.75
10.76	7.40	14.26	1.86	49.37	14.05	50.72
11.02	7.23	14.25	1.92	48.93	14.99	40.87
11.34	7.09	15.19	2.10	50.42	15.31	46.26
11.13	7.30	13.48	2.01	48.62	14.17	45.67
10.83	7.31	13.76	2.13	49.91	14.38	44.41

Scree Plot

