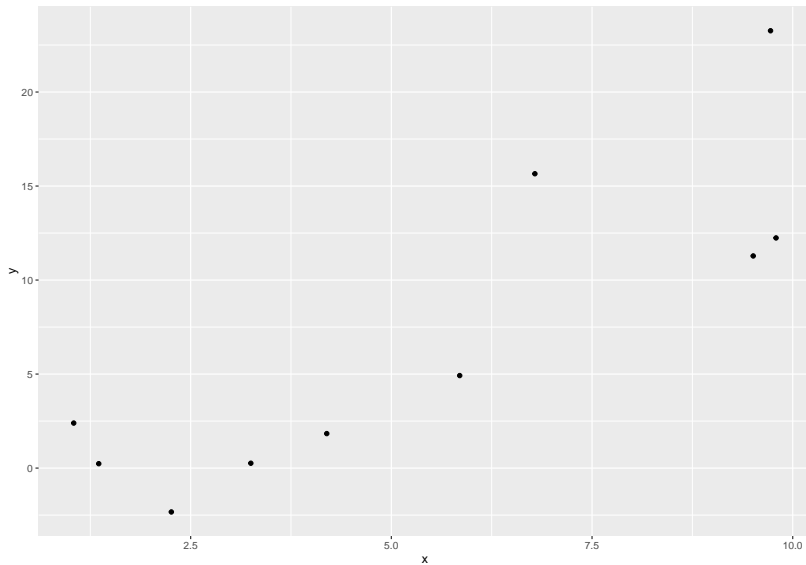


Principal Component Analysis

What it does?

How does it do it?

PCA in a view or coordinate rotation



Standard deviations (1, ..., p=2):

```
[1] 8.802072 1.716667
```

Another perspective of PCA

- ▶ Consider n points of data. We look for a direction where the projections of these points to it give the maximum variance.
- ▶ Projection of a point onto a direction (vector).
- ▶ A point is presented by a pair of number $(3, 4)$. A vector/direction is also presented by a pair of number: x-axis presented by $(1, 0)$ and y-axis presented by $(0, 1)$. A vector/direction of (a, b) could be a point connecting the origin $(0, 0)$ and the point (a, b) .
- ▶ A projection of a point (x_0, y_0) onto a vector (a, b) is a number (scalar), it is the dot product of the two pair or

$$ax_0 + by_0$$

- A vector also presents a subspace of one dimension. So we project a point of two dimension onto a subspace of one dimension, the projection should have only one number.

PCA as projections onto subspace

- ▶ If we have n points to a vector (one dimensional subspace), we will receive n numbers. Thus, a data of n points in two dimension (a pair), presented by a matrix, will turn into n numbers. So we can say that a matrix of $n \times 2$, projected onto a vector will be n numbers (n points in one dimensional subspace).
- ▶ So, n points projects onto a vector becomes n numbers. We want to find a vector/subspace that maximize the variance of this points. What is the variance of points. If the points have zero means, the variance is the length of the n points.
- ▶ Language of subspace and projection and the language of statistics. We should discuss this using one language only.

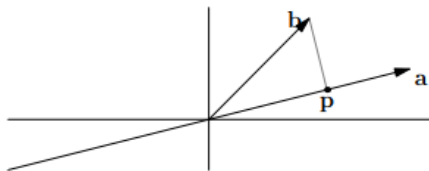
Projection of a point to a direction

- ▶ For simplicity, we first consider 2 dimension first
- ▶ Both a point A and a vector OA (O is the origin) is presented by a column vector.
- ▶ The projection of a point A, presented by a column vector $b = [b_1, b_2]^T$ onto a vector through the origin, also presented by a column vector, $a = [a_1, a_2]^T$ (or the span of this vector which is a 1-dimensional subspace) is

$$\frac{aa^T}{a^T a} b$$

Projection of a point to a direction

- $P = \frac{aa^T}{a^Ta}$ is called a projection matrix.



- For example, the projection of a point $x = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$ onto a direction of $v = [3, 2]^T$ (or onto $\text{span}(v)$) is

$$\frac{vv^T}{v^Tv}x = \begin{bmatrix} 2.076923 \\ 1.384615 \end{bmatrix}$$

- We usually consider the direction vector of length 1.

Checking

- ▶ Checking only.

What does the $v^T x$ present?

- ▶ Sometime, the projection of a point $x = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$ onto $\text{span}(v)$ where $\|v\| = 1$ can be presented by a dot product $x^T v$.
- ▶ This product is the length of the projected vector, which is also the coordinate of the projected point in a new axis v .
- ▶ This is because

$$u = \frac{vv^T}{v^T v} x = v \frac{v^T x}{v^T v} = vv^T x \implies \|u\| = \|v\| v^T x = v^T x$$

as $v^T v = \|v\|^2 = 1$.

Projections of n points to a direction

► The projection of vector x onto v is $x^T v$

► The projection n points $X = \begin{bmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_n^T \end{bmatrix}$ (X is a $n \times 2$ matrix) is

$$Xv = \begin{bmatrix} x_1^T v \\ x_2^T v \\ \vdots \\ x_n^T v \end{bmatrix}, \text{ which is a } n \times 1 \text{ matrix.}$$

► We can say that n points $x_1^T, x_2^T, \dots, x_n^T$ in R^2 are transformed to n points $x_1^T v, x_2^T v, \dots, x_n^T v$ in R^1 .

Variance and Total Variance

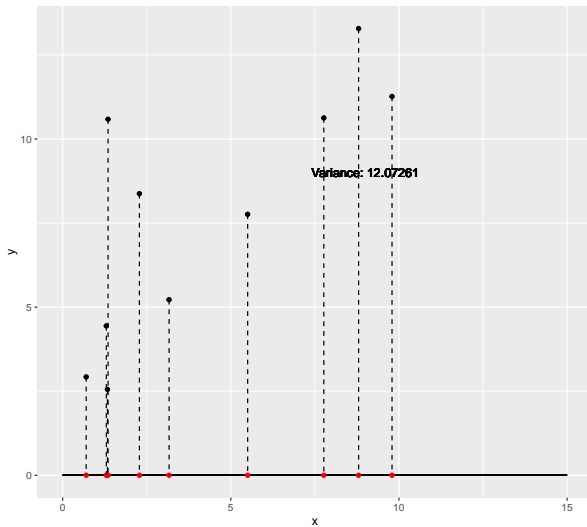
- ▶ In one dimension, the variance of n points/numbers a_1, a_2, \dots, a_n is $\frac{1}{n-1} \sum (a_i - \bar{a})^2$. If a is center, $\bar{a} = 0$, then the variance is $\frac{1}{n-1} \sum a_i^2 = \frac{1}{n-1} \|a\|^2 = \frac{1}{n-1} a^T a$.
- ▶ Let X be an $n \times 2$ data matrix. Let's X be centralized, which means both two columns have zero means. The projection of X onto v , Xv also has zero mean. Thus, the variance of the projection Xv is $\frac{1}{n-1} \|Xv\|^2$.
- ▶ The total variance of the data is the sum of the variance of the projection onto the x-axis ($\text{var}(x)$) and the variance of the projection onto y-axis ($\text{var}(y)$).
- ▶ If we rotate the xy axis into uv axis, the total variance does not change, $\text{var}(u) + \text{var}(v) = \text{var}(x) + \text{var}(y)$
- ▶ PC1 is the direction that has the maximum variance of the data.

Demonstration

[1] 26.21958

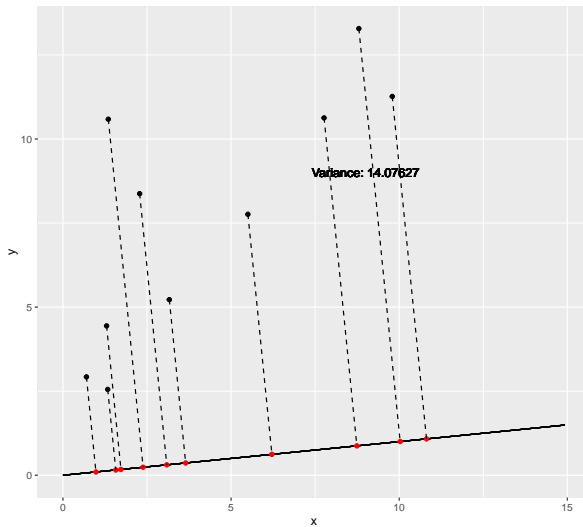
Variance: 12.07261

Direction vector: [1,0]

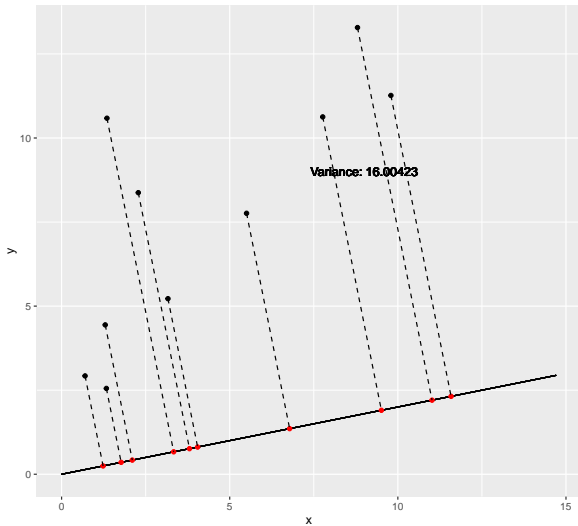


Variance: 14.07627

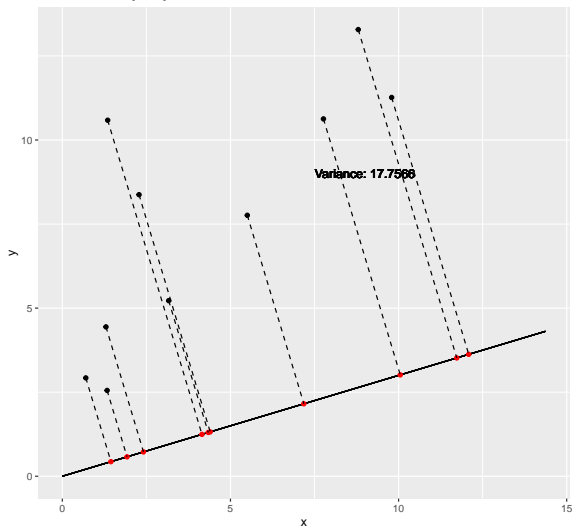
Direction vector: [1,0.1]



Variance: 16.00423
Direction vector: [1,0.2]

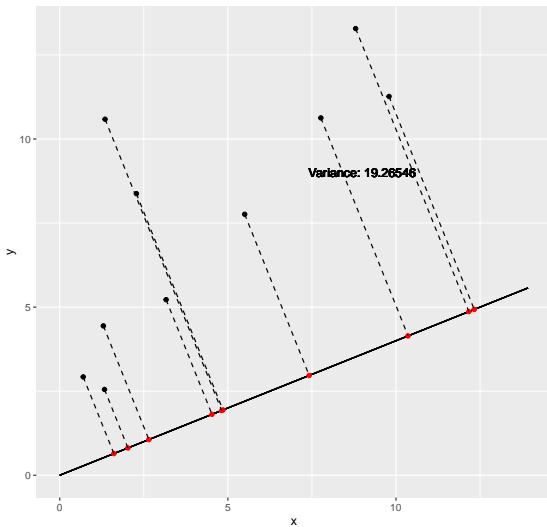


Variance: 17.7566
Direction vector: [1,0.3]



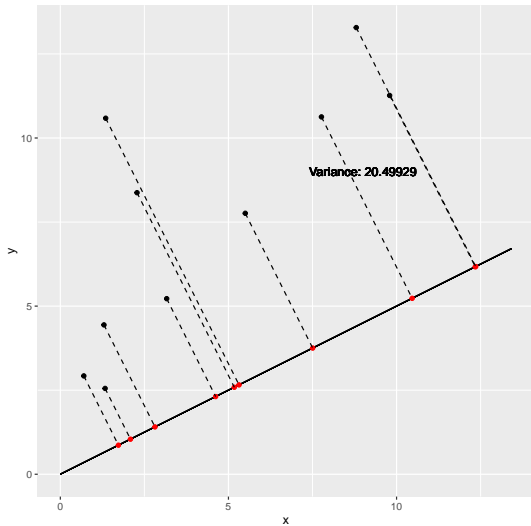
Variance: 19.26546

Direction vector: [1,0.4]



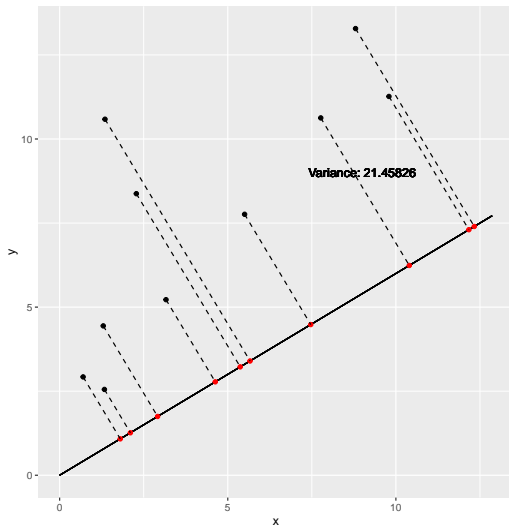
Variance: 20.49929

Direction vector: [1,0.5]



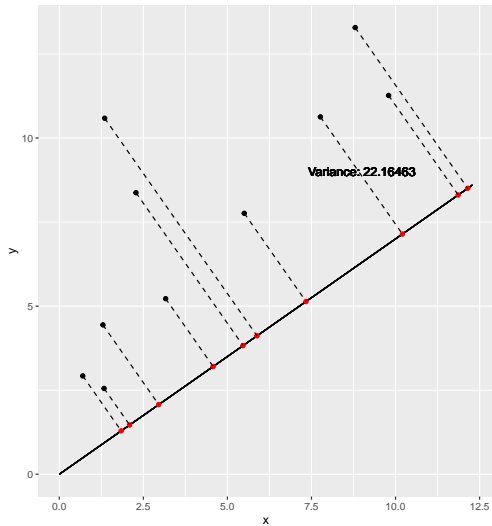
Variance: 21.45826

Direction vector: [1,0.6]



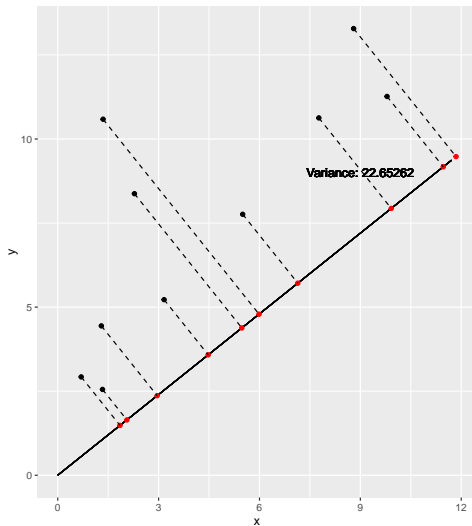
Variance: 22.16463

Direction vector: [1,0.7]

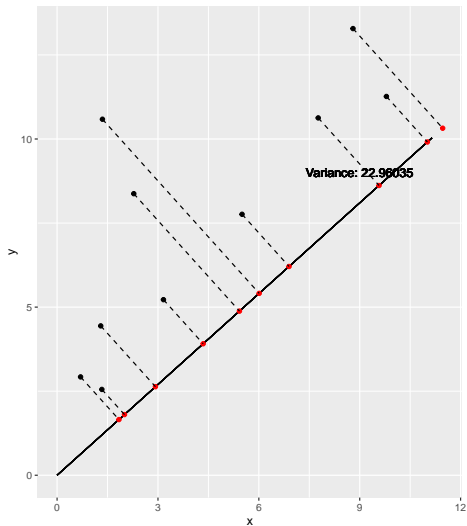


Variance: 22.65262

Direction vector: [1,0.8]

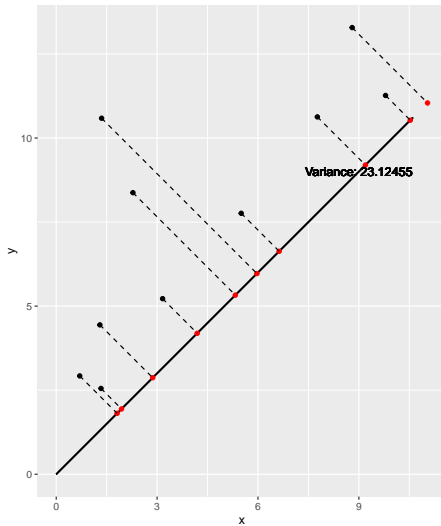


Variance: 22.96035
Direction vector: [1,0.9]



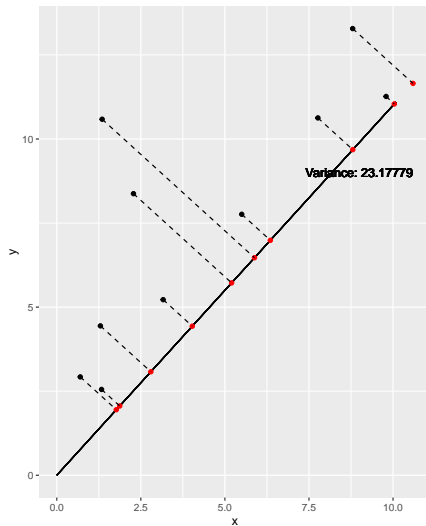
Variance: 23.12455

Direction vector: [1,1]



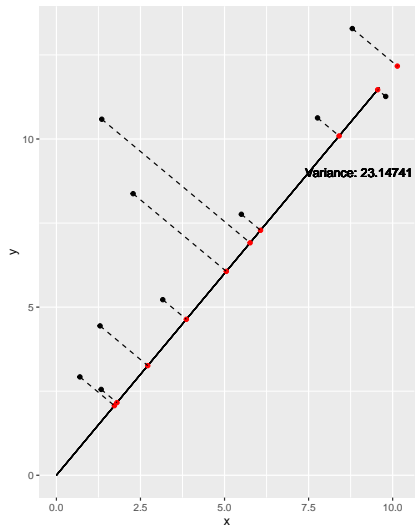
Variance: 23.17779

Direction vector: [1,1,1]



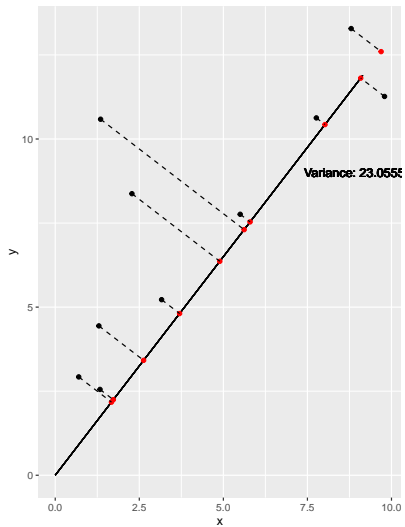
Variance: 23.14741

Direction vector: [1,1.2]

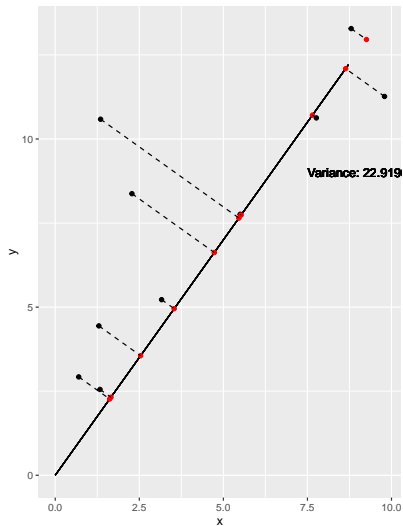


Variance: 23.05553

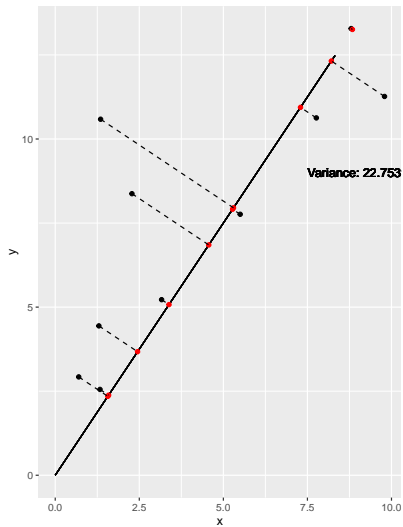
Direction vector: [1,1.3]



Variance: 22.9196
Direction vector: [1,1.4]

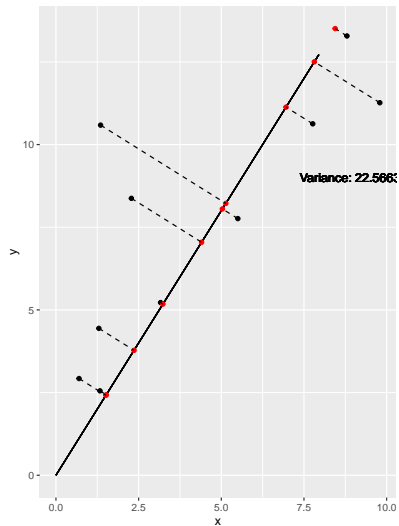


Variance: 22.7531
Direction vector: [1,1.5]



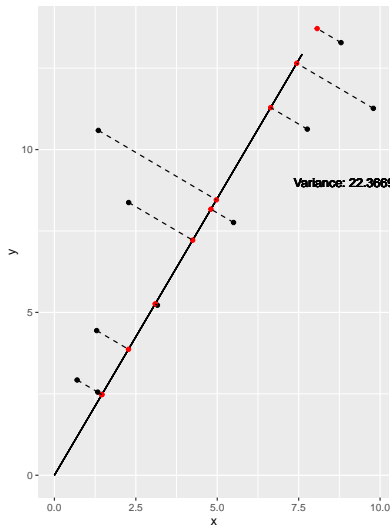
Variance: 22.56632

Direction vector: [1,1.6]



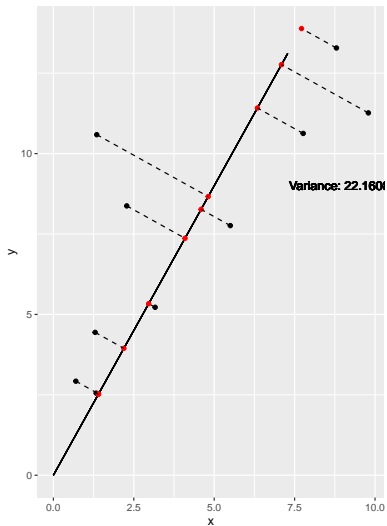
Variance: 22.36698

Direction vector: [1,1.7]



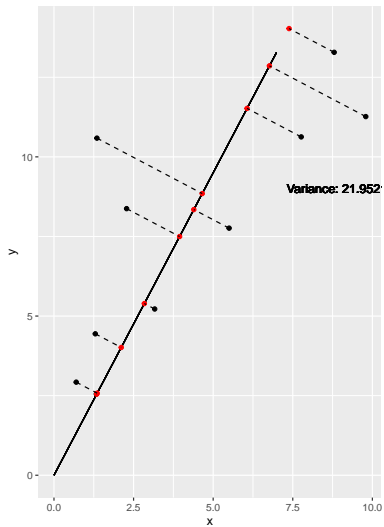
Variance: 22.16083

Direction vector: [1,1.8]



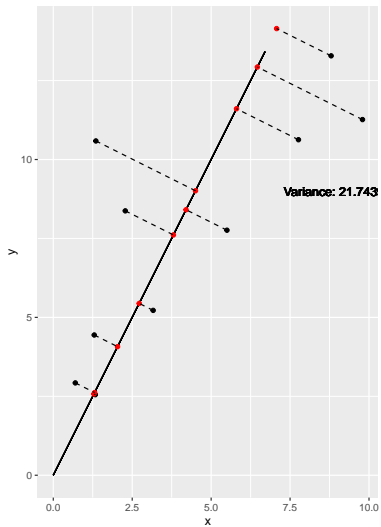
Variance: 21.95212

Direction vector: [1,1.9]



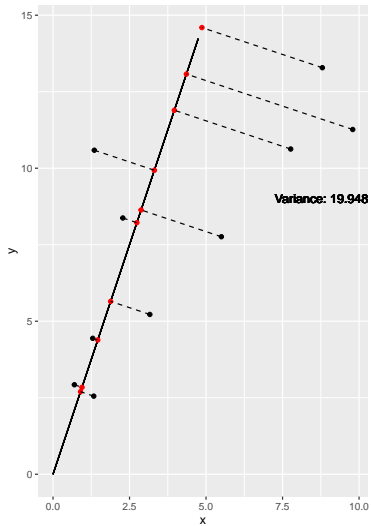
Variance: 21.74391

Direction vector: [1,2]



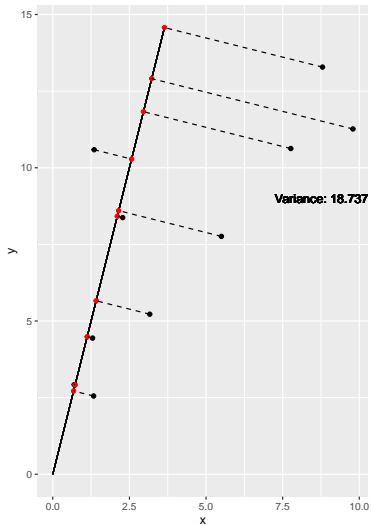
Variance: 19.94839

Direction vector: [1,3]



Variance: 18.73777

Direction vector: [1,4]



Variance: 23.17812

Direction vector: $[-0.669696257092749, -0.742635121197458]$

