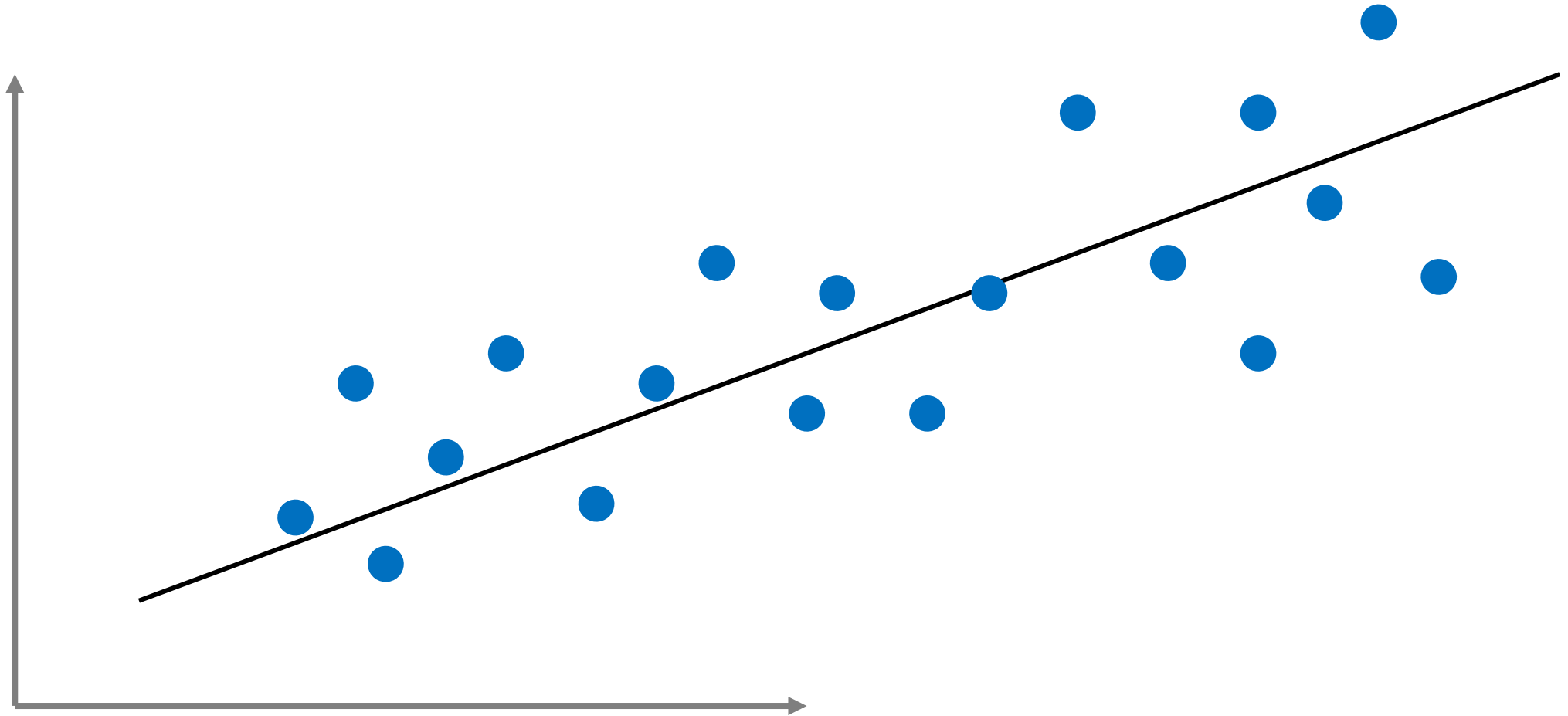


# Linear models

# Linear regression



# Error definition

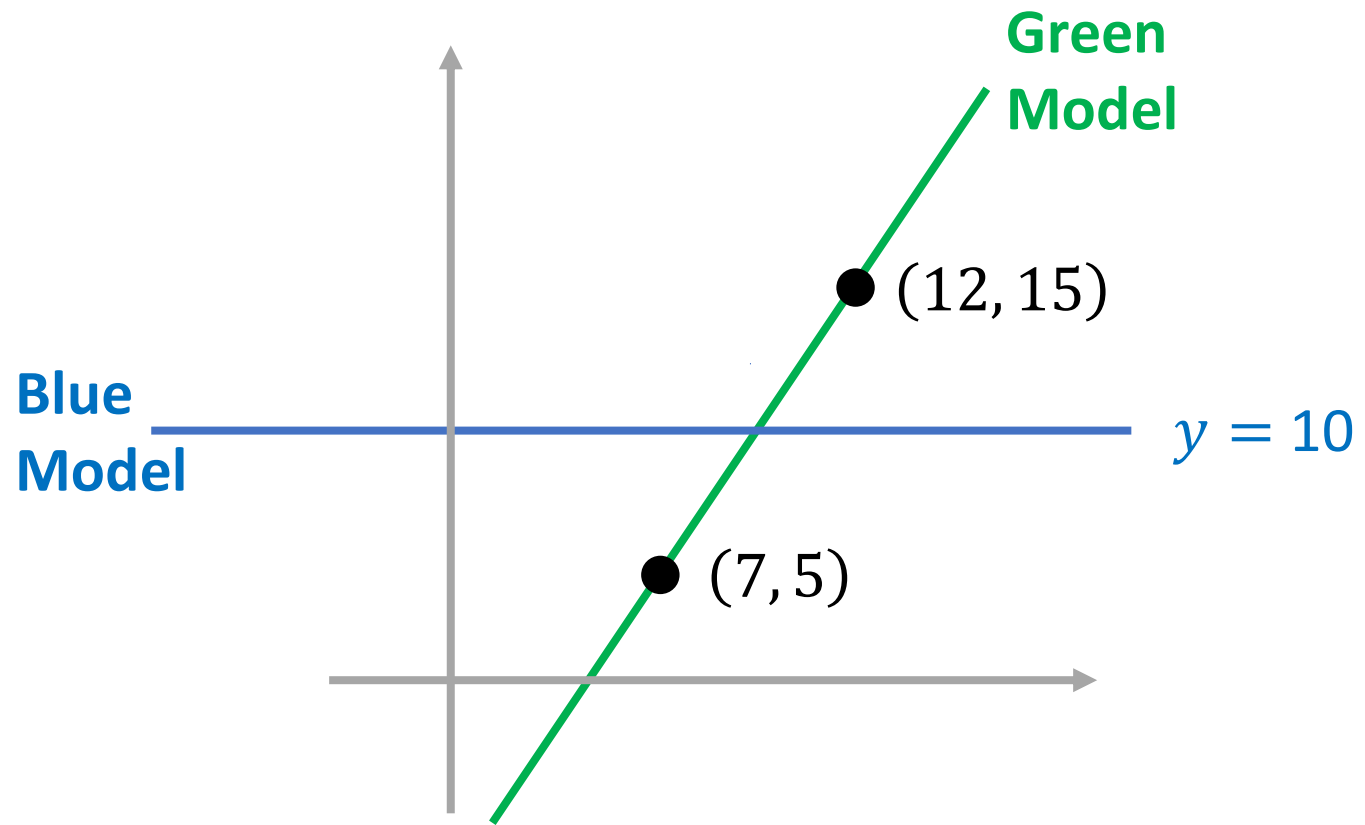
$y_i$  = Instance

$\hat{y}_i$  = Model

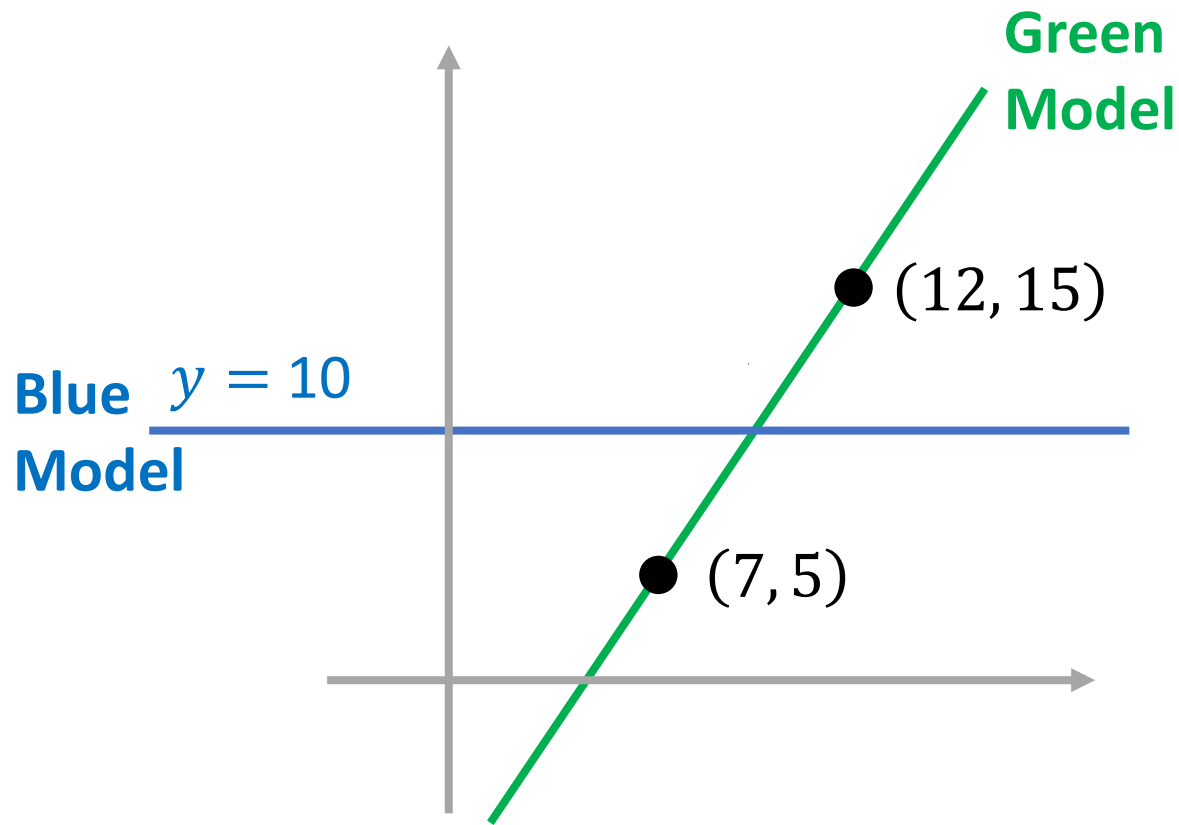
$$\varepsilon \propto \hat{y}_i - y_i$$

$$\varepsilon = 0$$

$$\varepsilon = 0$$



# Error definition



$$\varepsilon \propto \hat{y}_i - y_i$$

$$\varepsilon = 0$$

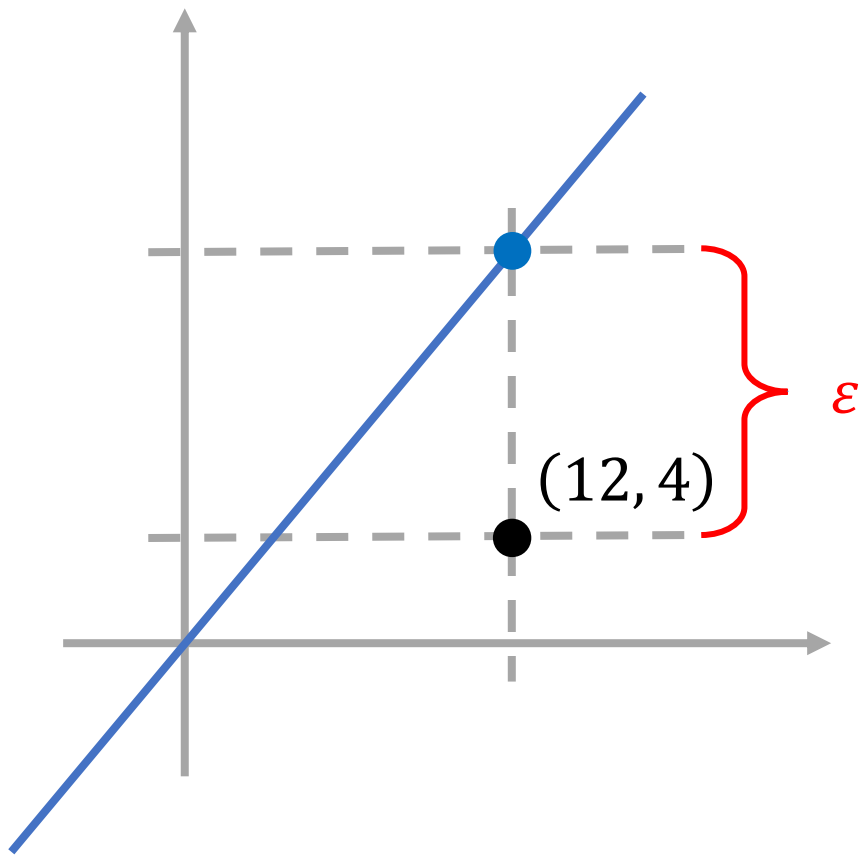
$$\varepsilon = 0$$

Solution:

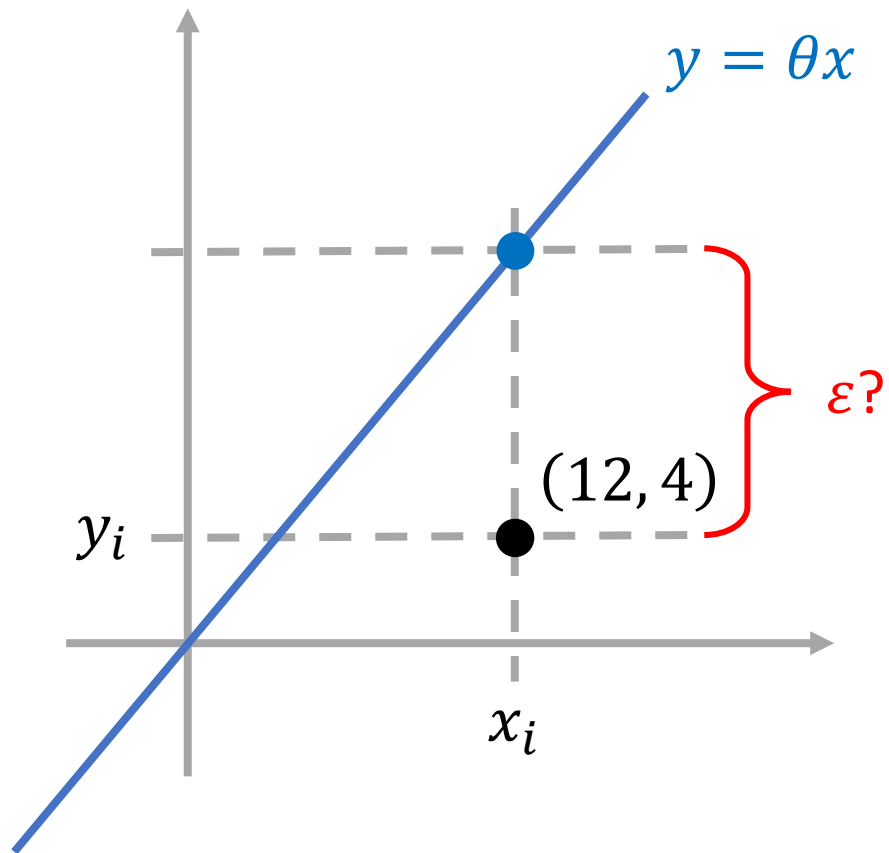
Residual sum  
of squares (RSS)

$$\varepsilon := RSS = \sum_{i=1}^m (\hat{y}_i - y_i)^2$$

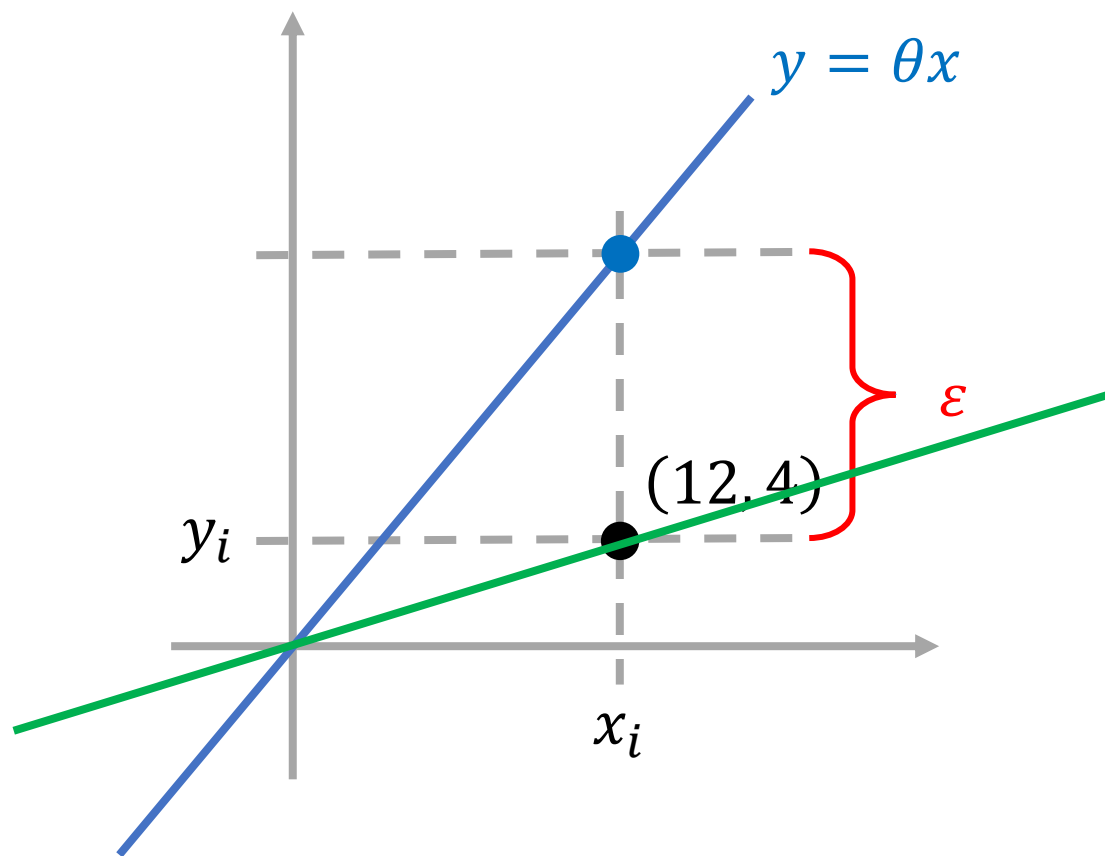
$$y = \theta x \quad m = 1$$



$$y = \theta x \quad m = 1$$



$$y = \theta x \quad m = 1$$



$$\begin{aligned} \varepsilon &= (y - 4)^2 \\ &= (12\theta - 4)^2 \\ &= (x_i\theta - y_i)^2 \end{aligned}$$

$$\frac{d\varepsilon}{d\theta} = 0 \quad \Rightarrow \quad \theta = 4/12 = y_i/x_i$$

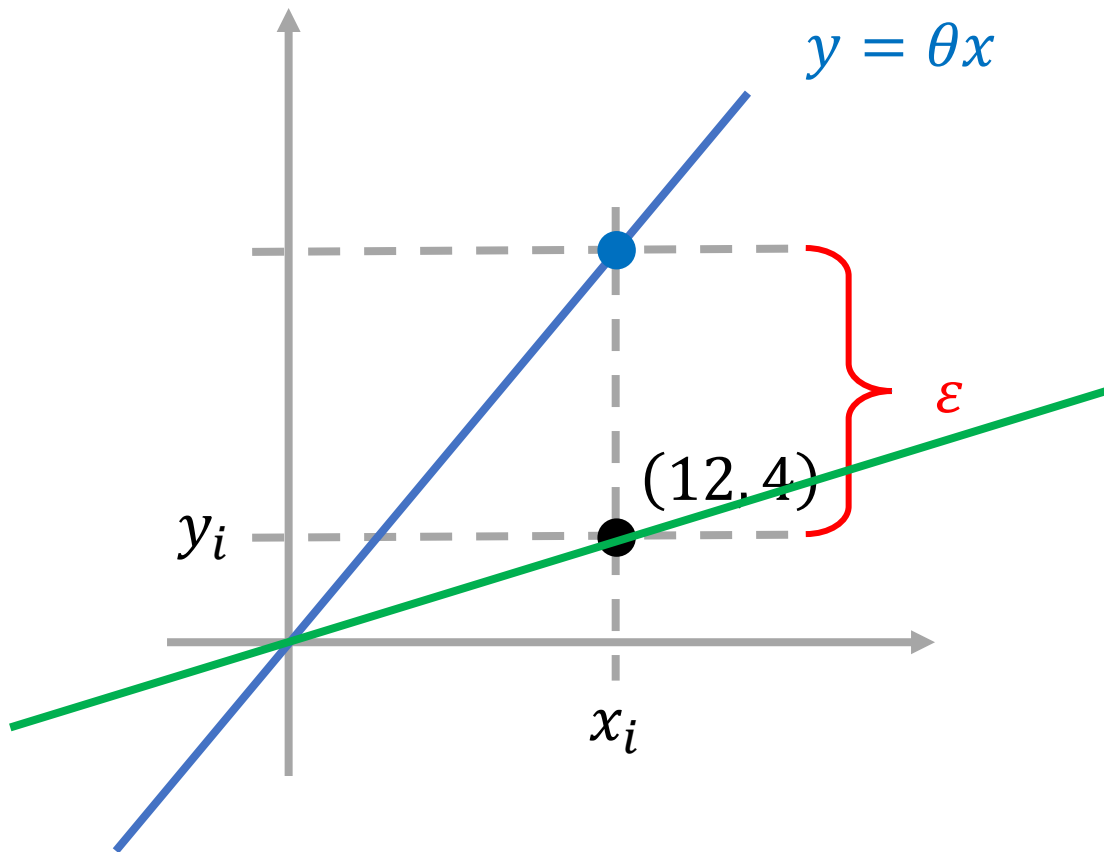
$$\therefore y = \frac{4}{12}x$$

$$\begin{aligned} y &= f(\theta) \\ \varepsilon &= g(y) \end{aligned} \quad \Rightarrow \quad \varepsilon = h(\theta)$$

$$y = \theta x \quad m = 1$$

>\_ Code

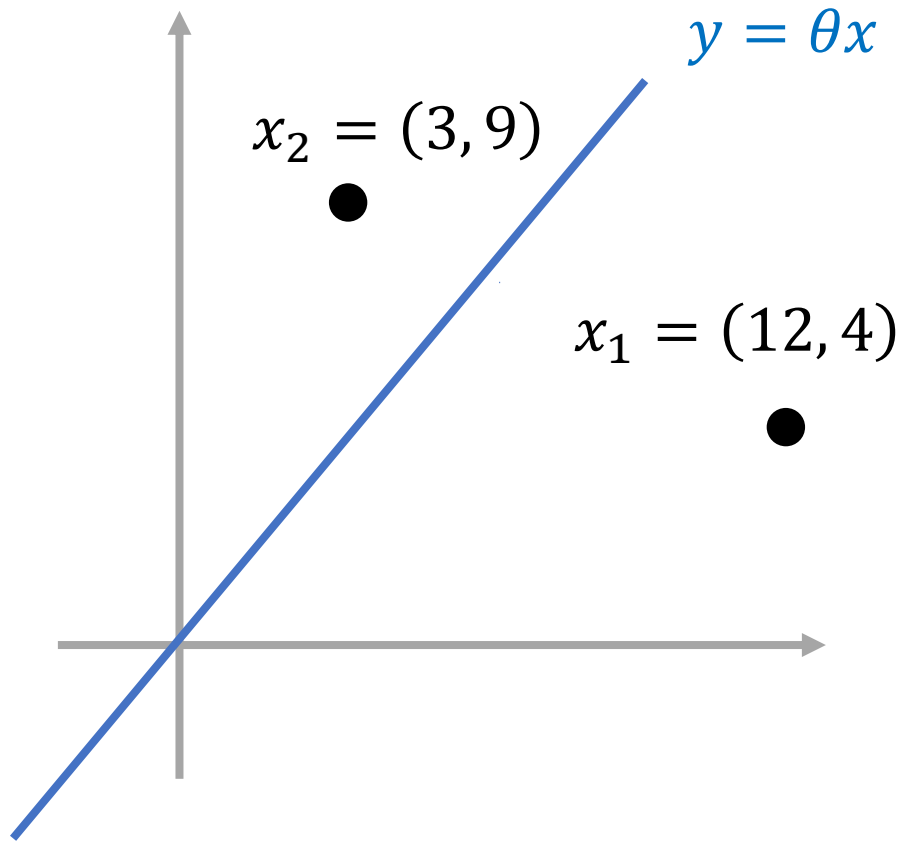
$$\therefore y = \frac{4}{12}x$$



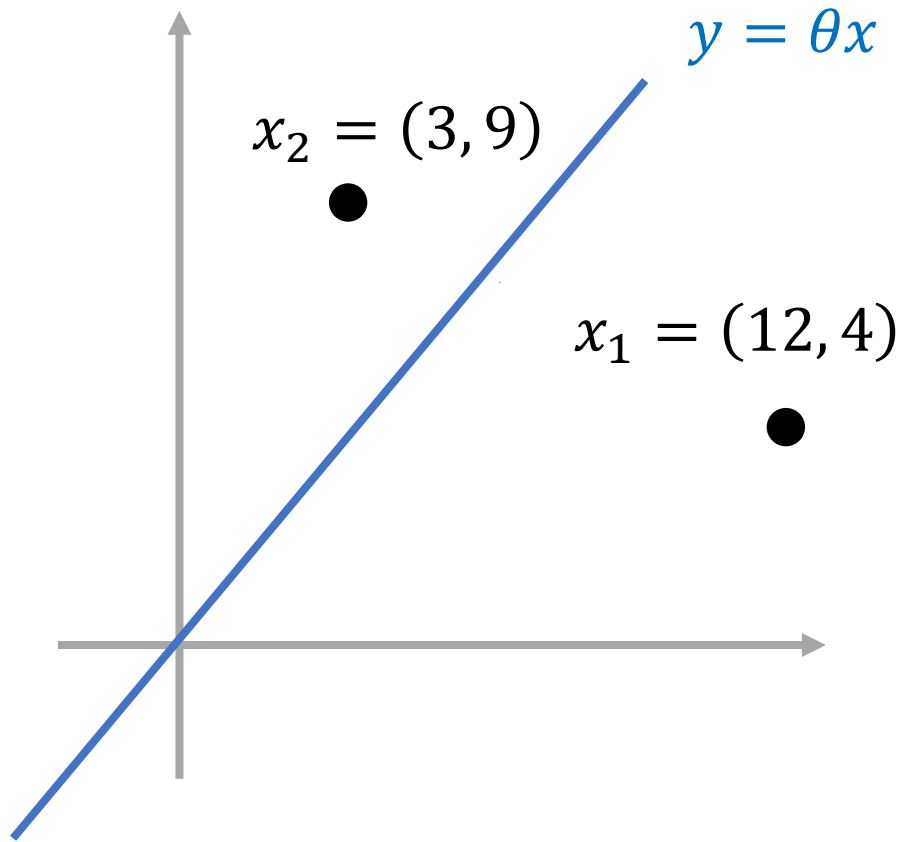
```
import matplotlib.pyplot as plt
xi = 12 # data points o o o o o
yi = 4
theta = yi/xi
plt.scatter(xi,yi)
# model
x = np.linspace(10, 14, num = 5)
y = theta * x
plt.plot(x, y)
plt.axis('equal')
plt.show()
```



$$y = \theta x \quad m = 2$$

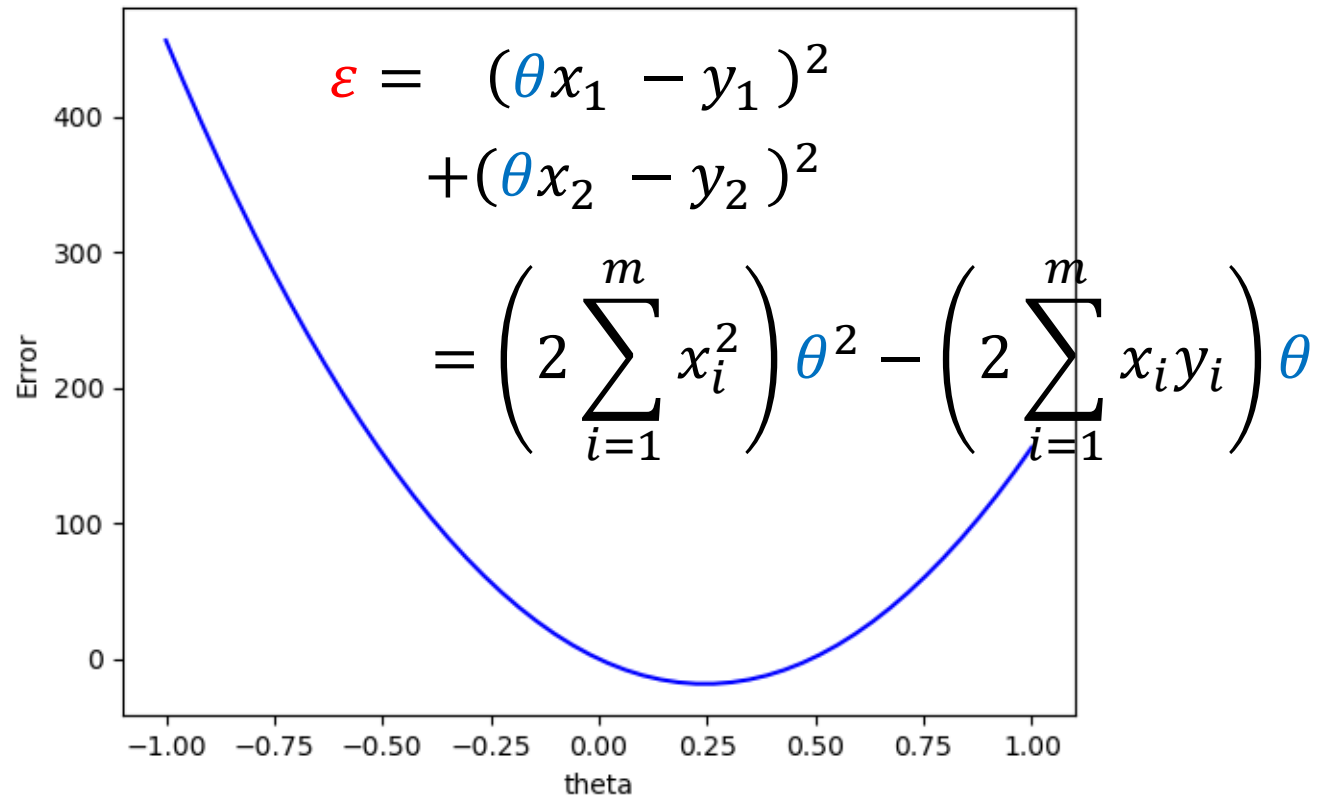
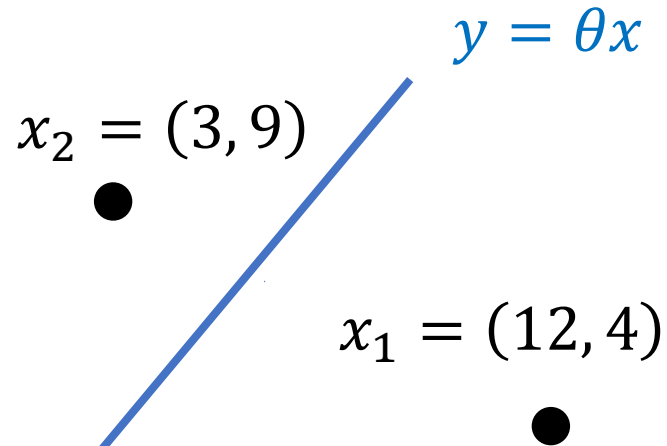


$$y = \theta x \quad m = 2$$



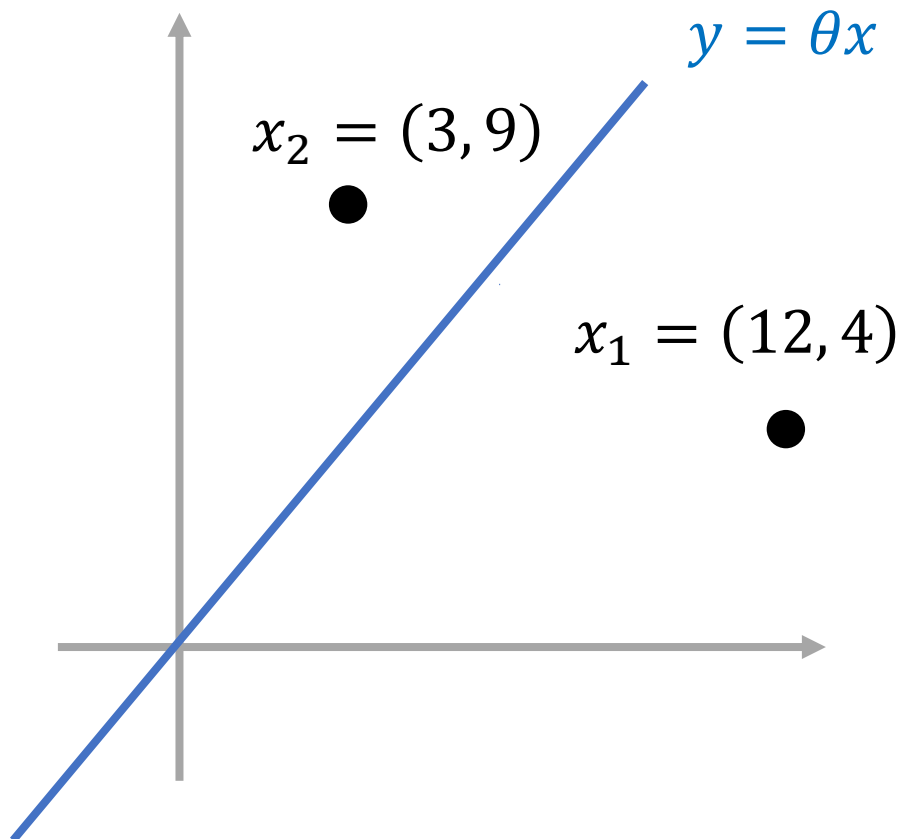
$$\varepsilon = (\theta x_1 - y_1)^2 + (\theta x_2 - y_2)^2$$

$$y = \theta x \quad m = 2$$



```
x=np.array([12,3])
y=np.array([4,9])
theta=np.linspace(-1, 1)
error=2*np.sum(x**2)*theta**2-2*np.sum(x*y)*theta
plt.plot(theta,cost,'b-')
plt.show()
```

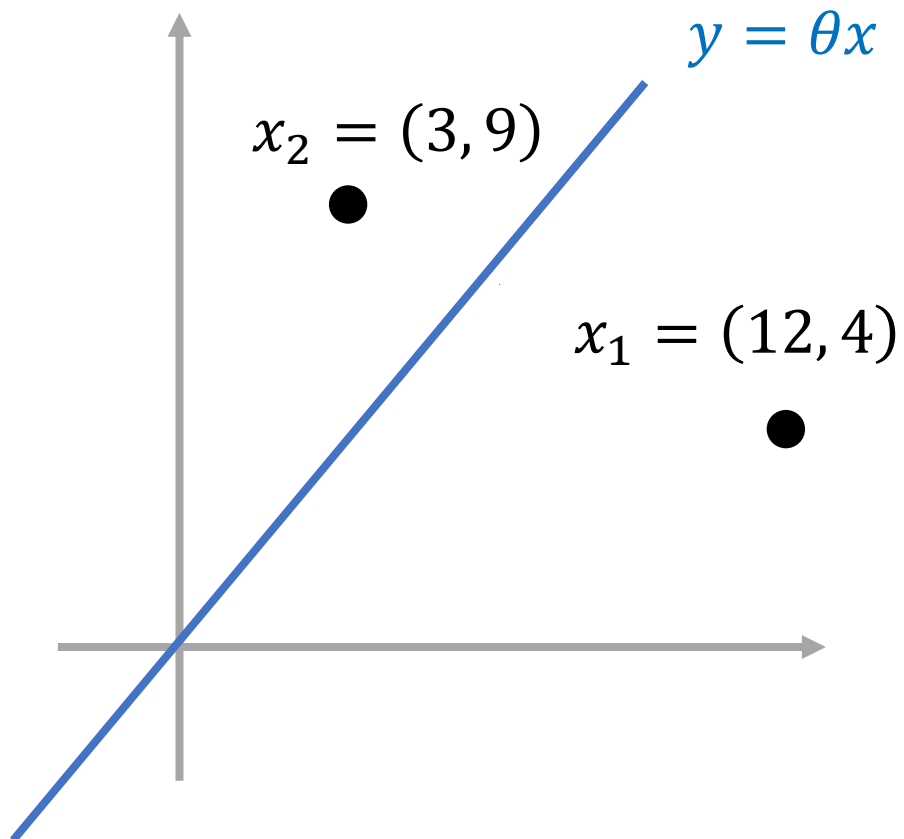
$$y = \theta x \quad m = 2$$



$$\varepsilon = (\theta x_1 - y_1)^2 + (\theta x_2 - y_2)^2$$

$$\frac{d\varepsilon}{d\theta} = 0 \quad \Rightarrow \quad \theta = \frac{x_1 y_1 + x_2 y_2}{x_1^2 + x_2^2}$$

$$y = \theta x \quad m = 2$$



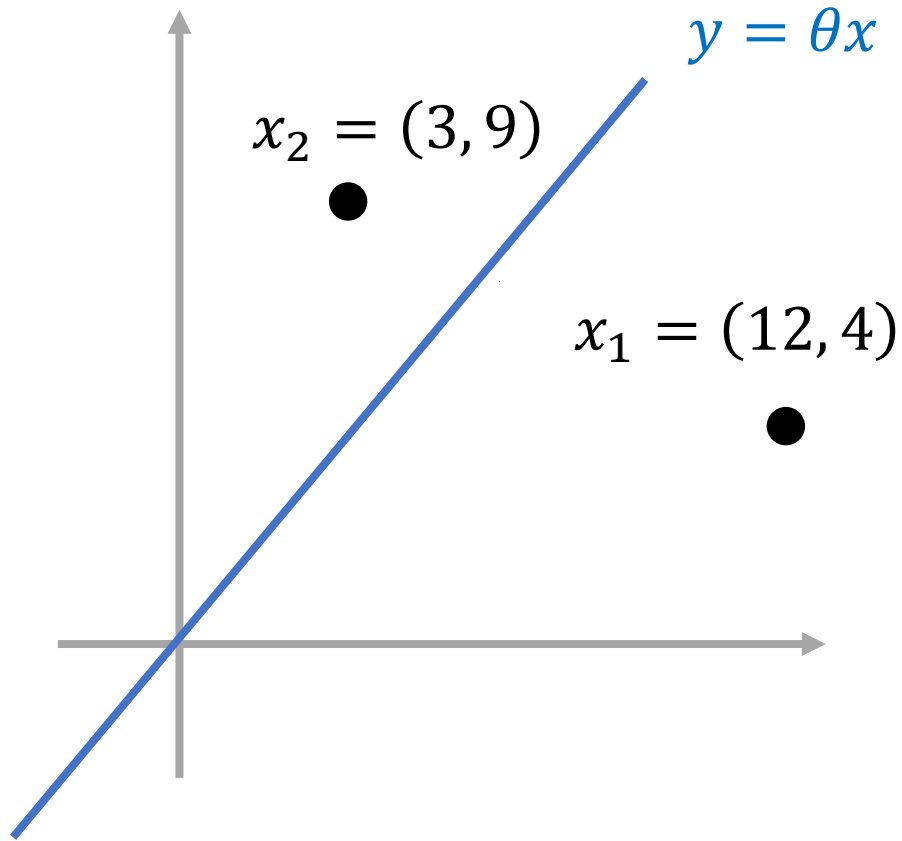
$$\varepsilon = (\theta x_1 - y_1)^2 + (\theta x_2 - y_2)^2$$

$$\frac{d\varepsilon}{d\theta} = 0 \Rightarrow \theta = \frac{x_1 y_1 + x_2 y_2}{x_1^2 + x_2^2}$$

Matrix form for fast vectorized computations

$$\begin{pmatrix} \boxed{\phantom{0}} & \boxed{\phantom{0}} \\ \boxed{\phantom{0}} & \boxed{\phantom{0}} \end{pmatrix}$$

$$y = \theta x \quad m = 2$$



$$\varepsilon = (\theta x_1 - y_1)^2 + (\theta x_2 - y_2)^2$$

$$\frac{d\varepsilon}{d\theta} = 0 \quad \Rightarrow \quad \theta = \frac{x_1 y_1 + x_2 y_2}{x_1^2 + x_2^2}$$

Matrix form for fast vectorized computations

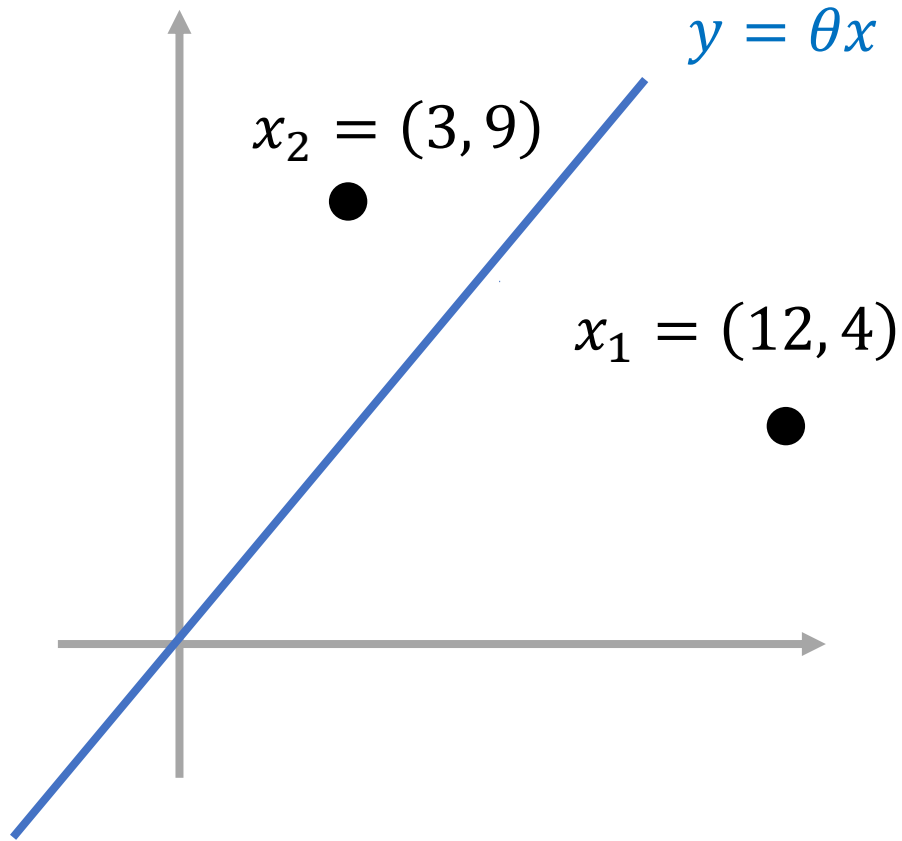
$$\begin{pmatrix} \square & \square \\ \square & \square \end{pmatrix} \quad \mathbf{x} := \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \quad \mathbf{y} := \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}$$

$$\Rightarrow \theta = \frac{(x_1, x_2)^T \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}}{(x_1, x_2)^T \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}} = \mathbf{x}^T \mathbf{y} / \mathbf{x}^T \mathbf{x}$$

$$y = \theta x \quad m = 2$$

$$\theta = \frac{(x_1, x_2)^T \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}}{(x_1, x_2)^T \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}} = \mathbf{x}^T \mathbf{y} / \mathbf{x}^T \mathbf{x}$$

>\_ Code



```
import numpy as np
import matplotlib.pyplot as plt
xi=np.array([3, 12]) # data points o o o
yi=np.array([9, 4])
theta=sum(xi*yi)/sum(xi**2)
plt.scatter(xi,yi)
# model
x=np.linspace(min(xi),max(xi),num=5)
y=theta*x
plt.plot(x, y)
plt.axis('equal')
plt.show()
```

# Model Evaluation. Pearson correlation coefficient

## Pearson Correlation Coefficient



$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

$$\rho_{X,Y} = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} \quad (\text{Eq.1})$$

where:

- $\text{cov}$  is the **covariance**
- $\sigma_X$  is the **standard deviation** of  $X$
- $\sigma_Y$  is the standard deviation of  $Y$

Pearson

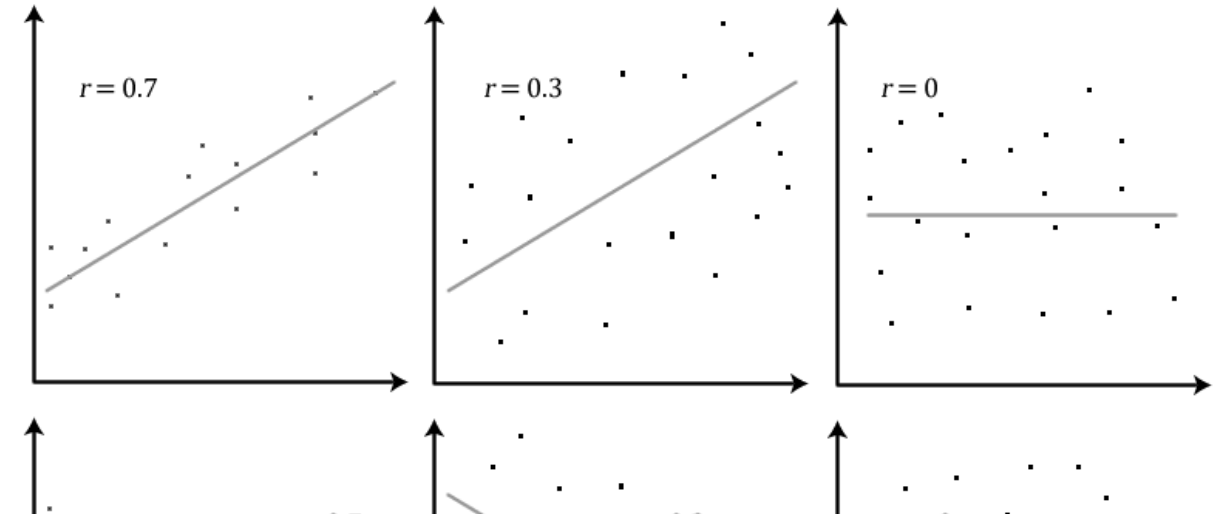
We need to calculate

$$\sum_{i=1}^n x_i$$

Age
Height (cm)

$$\sum (x_i^2)$$

$$\sum (y_i^2)$$



The formula for  $\rho$  can be expressed in terms of mean and expectation. Since

$$\text{cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)],^{[7]}$$

the formula for  $\rho$  can also be written as

$$\rho_{X,Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \quad (\text{Eq.2})$$

where:

- $\sigma_Y$  and  $\sigma_X$  are defined as above
- $\mu_X$  is the **mean** of  $X$



# Model Evaluation. $R^2$ Statistic

## Pearson Correlation Coefficient



$$r = \sqrt{\quad}$$

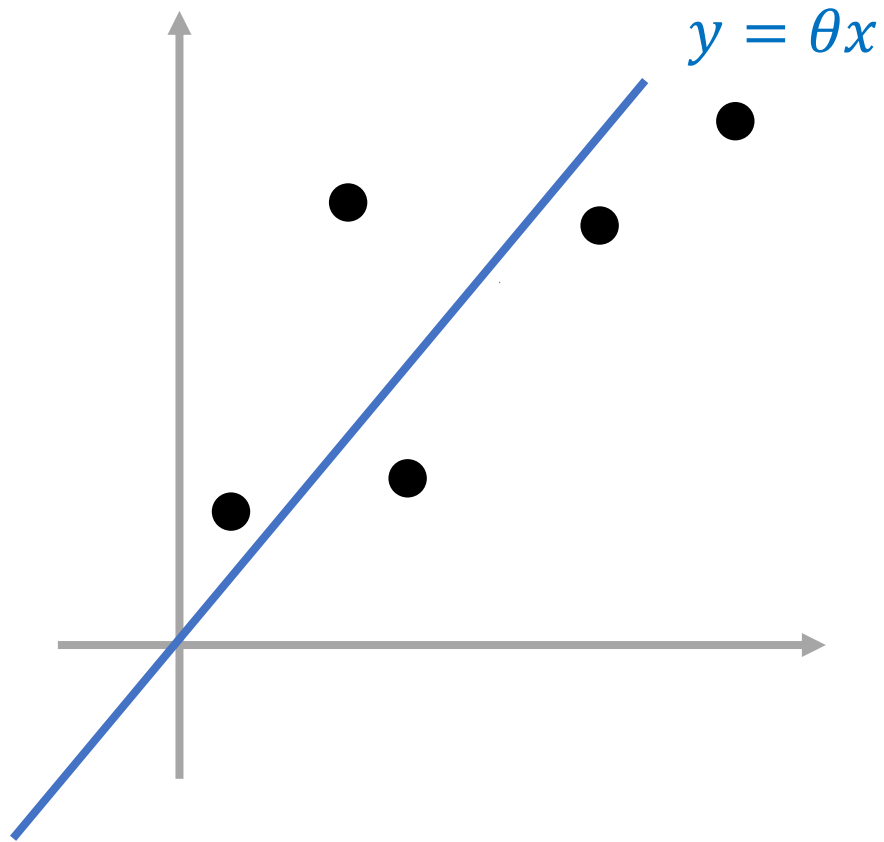
To calculate  $R^2$ , we use the formula

$$R^2 = \frac{\text{TSS} - \text{RSS}}{\text{TSS}} = 1 - \frac{\text{RSS}}{\text{TSS}} \quad (3.17)$$

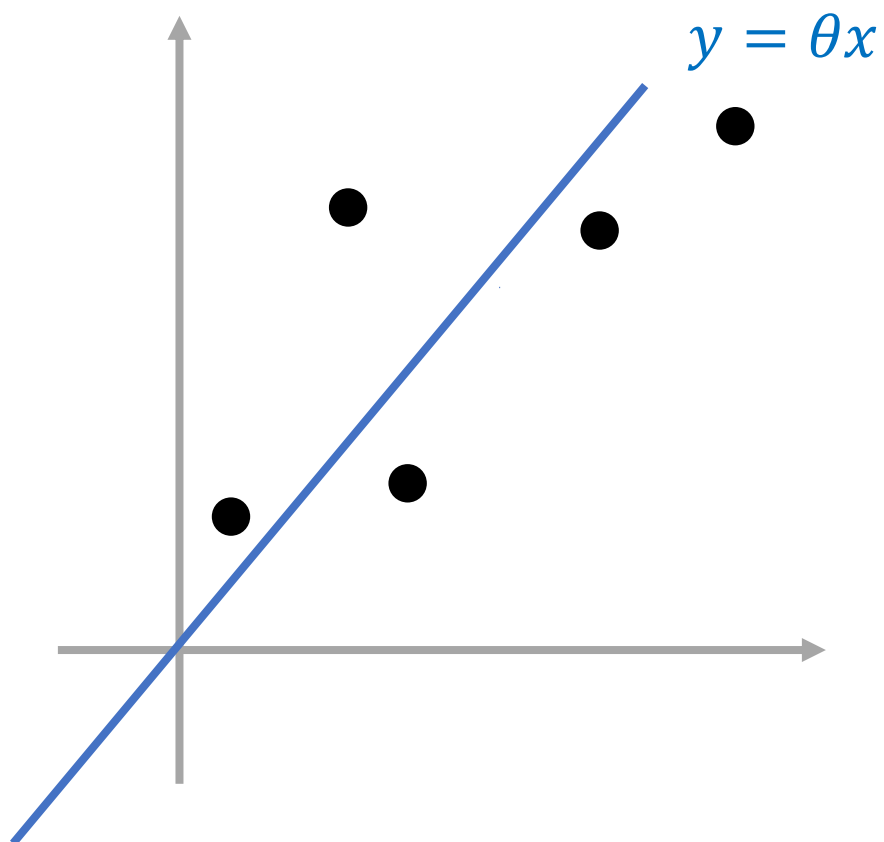
where  $\text{TSS} = \sum (y_i - \bar{y})^2$  is the *total sum of squares*, and RSS is defined in (3.16). TSS measures the total variance in the response  $Y$ , and can be thought of as the amount of variability inherent in the response before the

total sum of  
squares

$$y = \theta x \quad m$$

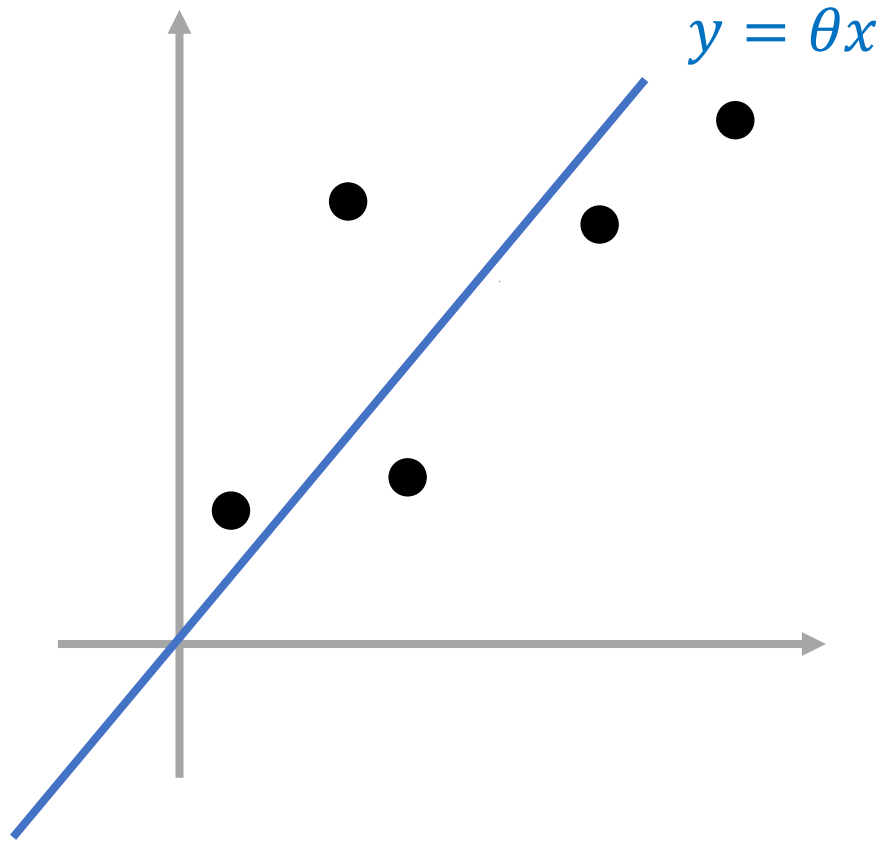


$$y = \theta x \quad m$$



$$\begin{aligned} \varepsilon = & (\theta x_1 - y_1)^2 \\ & + (\theta x_2 - y_2)^2 \\ & \vdots \\ & + (\theta x_m - y_m)^2 \end{aligned}$$

$$y = \theta x \quad m$$



$$\begin{aligned} \varepsilon = & (\theta x_1 - y_1)^2 \\ & + (\theta x_2 - y_2)^2 \\ & \vdots \\ & + (\theta x_m - y_m)^2 \end{aligned}$$

$$\frac{d\varepsilon}{d\theta} = 0 \quad \Rightarrow \quad \theta = \frac{\sum_{i=1}^m x_i y_i}{\sum_{i=1}^m x_i^2}$$

Matrix form for fast vectorized computations

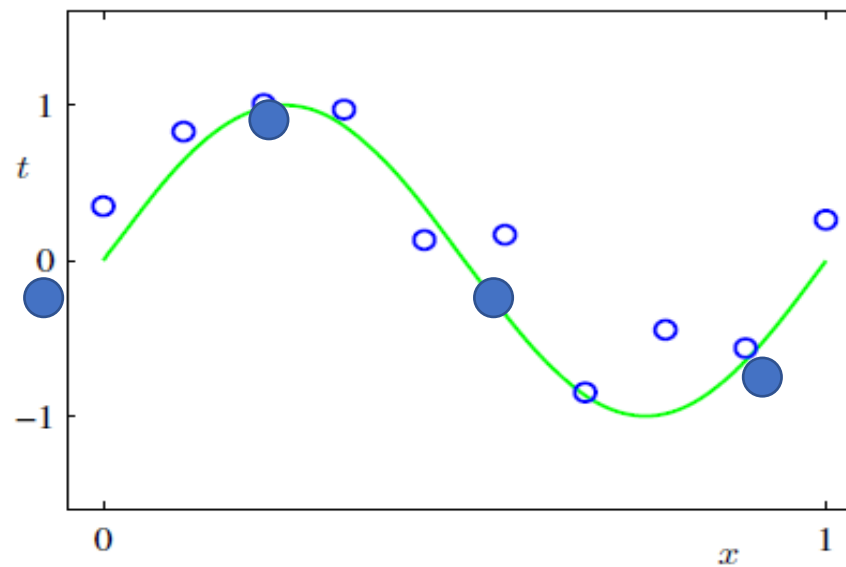
$$\begin{pmatrix} \boxed{\phantom{0}} & \boxed{\phantom{0}} \\ \boxed{\phantom{0}} & \boxed{\phantom{0}} \end{pmatrix} \quad \mathbf{x} := \begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix} \quad \mathbf{y} := \begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix}$$

$$\Rightarrow \quad \theta = \mathbf{x}^T \mathbf{y} / \mathbf{x}^T \mathbf{x}$$

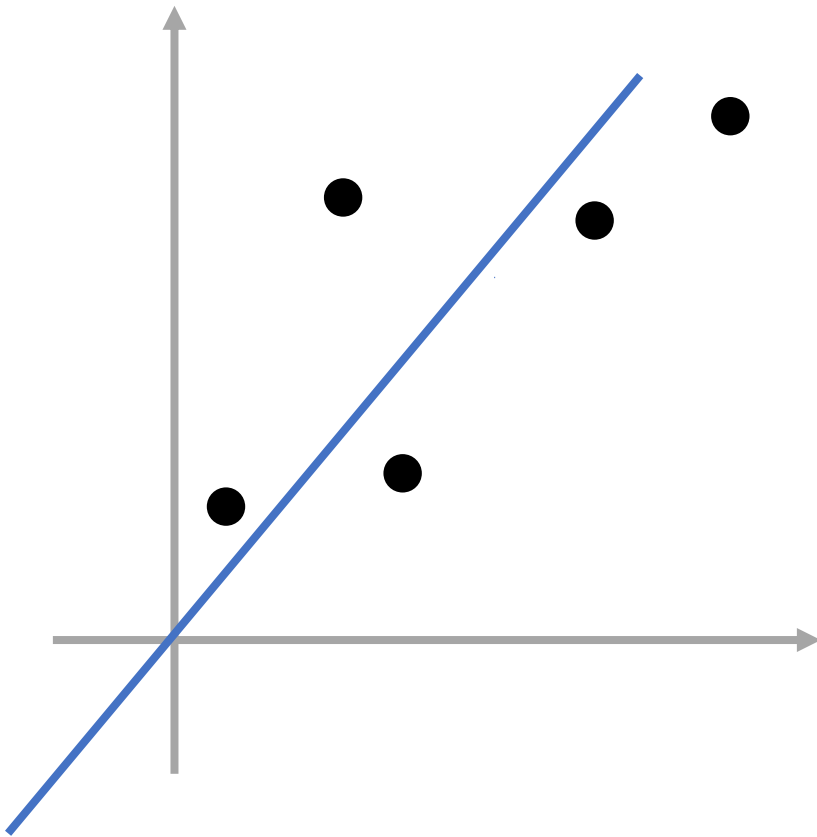
# Your turn

1.  $y = \theta x + 5$

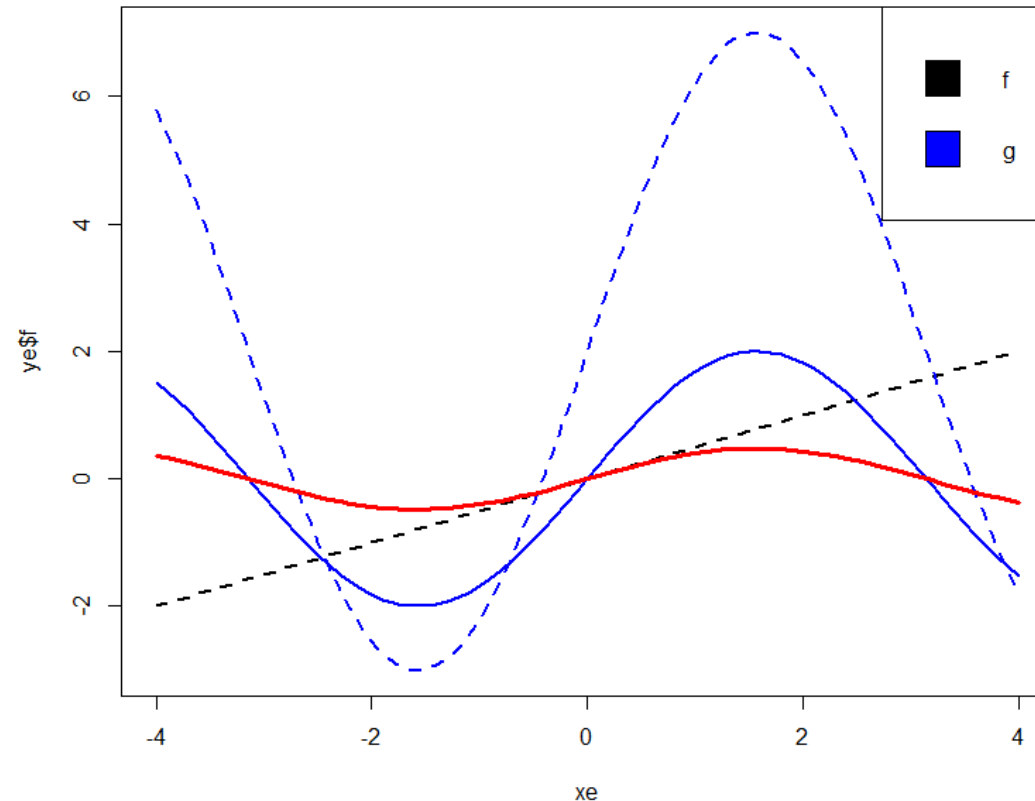
2.  $y = A \sin(x)$



$$y = \theta x + b$$



Aplicacion (reescalamiento de datos). Las dos curvas punteadas son los datos originales (regularmente muestreados). La curva azul punteada (g) es la curva a reescalar verticalmente (dilatación/contracción) y a trasladar de tal manera que se parezca lo más posible a la curva punteada negra (f). La solución mediante regresión es la curva roja continua. Encuentren la formula matematica para obtener la curva continua. Esto fue aplicado en el caso de well logs para hacer el match y en recibos de CFE con datos de sensores.



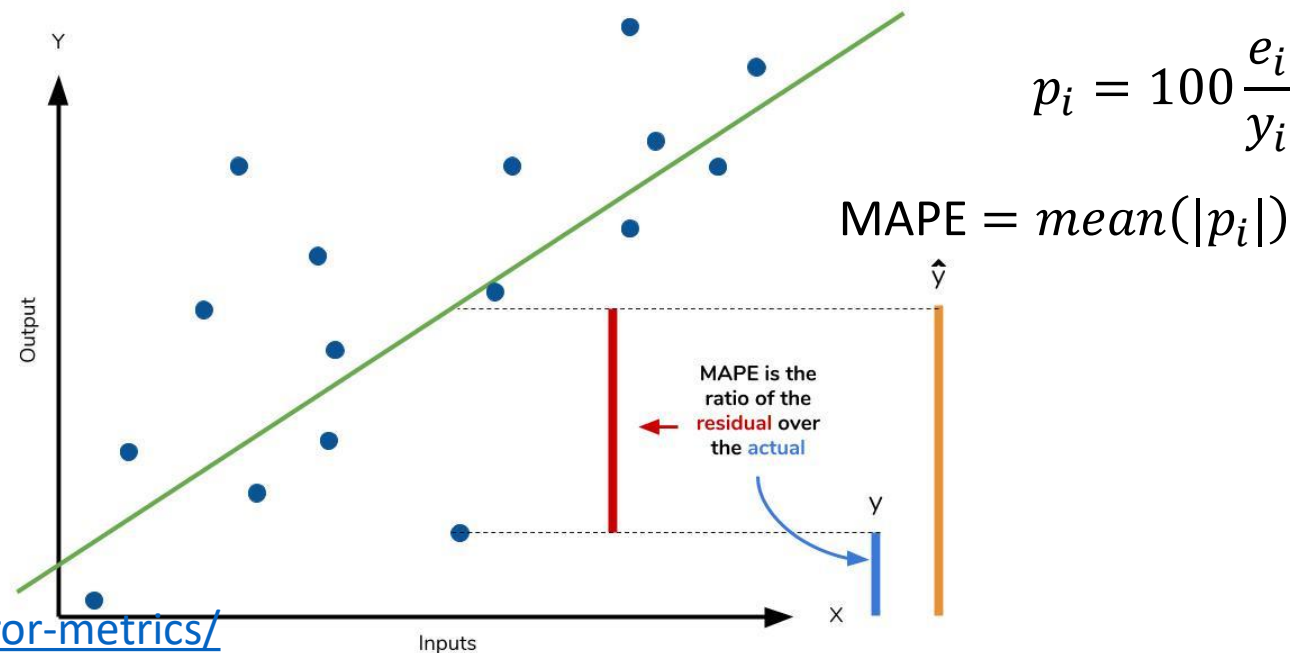
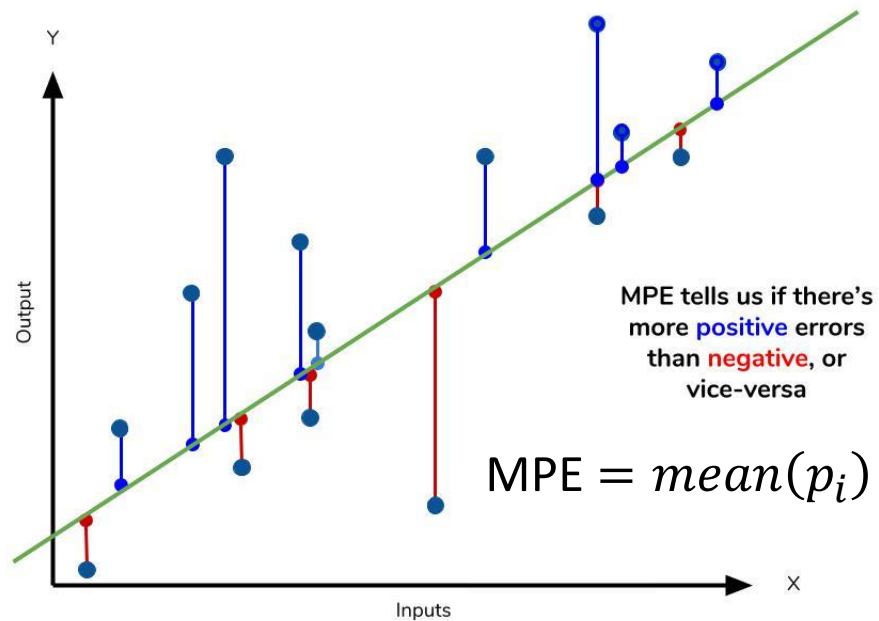
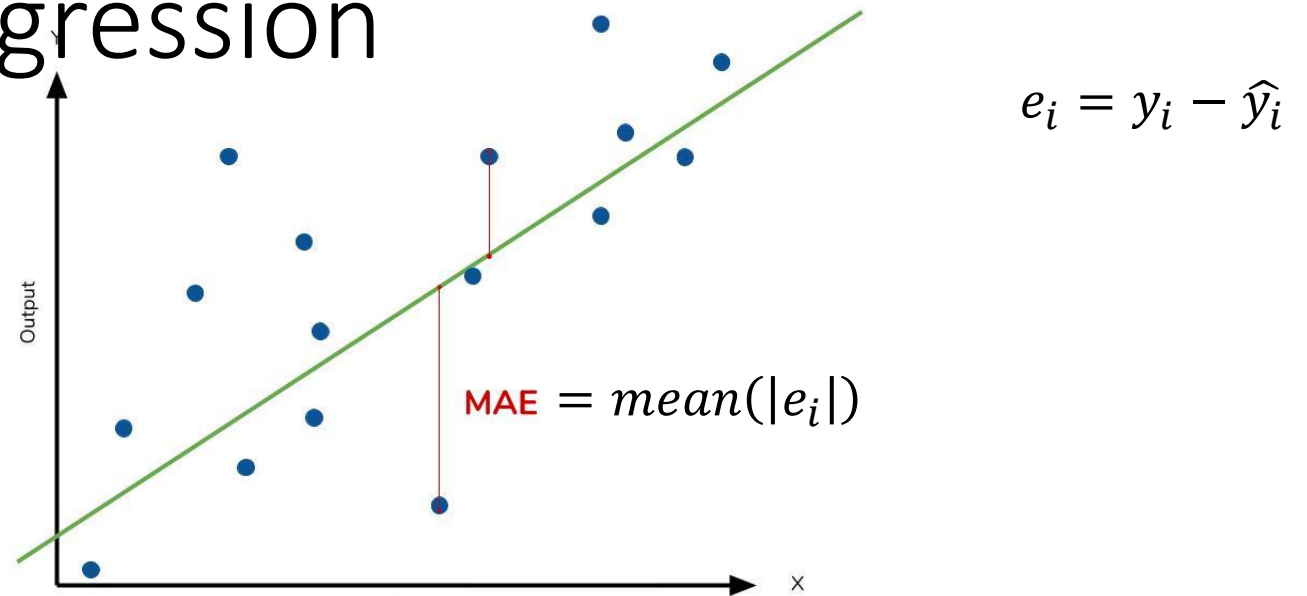
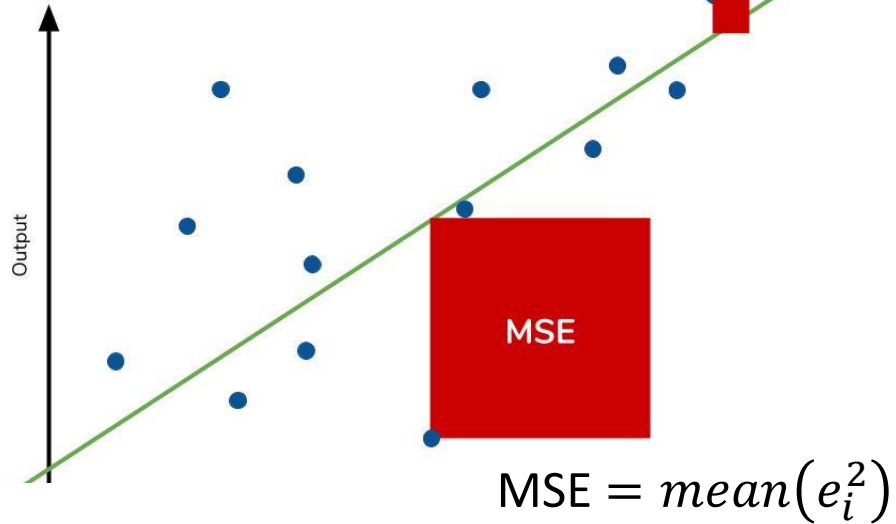
# Evaluation metrics for regression

<a href="#"><code>metrics.explained_variance_score</code></a> (y_true, ...)	Explained variance regression score function
<a href="#"><code>metrics.max_error</code></a> (y_true, y_pred)	max_error metric calculates the maximum residual error.
<a href="#"><code>metrics.mean_absolute_error</code></a> (y_true, y_pred, \*)	Mean absolute error regression loss
<a href="#"><code>metrics.mean_squared_error</code></a> (y_true, y_pred, \*)	Mean squared error regression loss
<a href="#"><code>metrics.mean_squared_log_error</code></a> (y_true, ...)	Mean squared logarithmic error regression loss
<a href="#"><code>metrics.median_absolute_error</code></a> (y_true, y_pred, \*)	Median absolute error regression loss
<a href="#"><code>metrics.r2_score</code></a> (y_true, y_pred, \*[, ...])	R <sup>2</sup> (coefficient of determination) regression score function.
<a href="#"><code>metrics.mean_poisson_deviance</code></a> (y_true, y_pred, \*)	Mean Poisson deviance regression loss.
<a href="#"><code>metrics.mean_gamma_deviance</code></a> (y_true, y_pred, \*)	Mean Gamma deviance regression loss.
<a href="#"><code>metrics.mean_tweedie_deviance</code></a> (y_true, y_pred, \*)	Mean Tweedie deviance regression loss.

<https://scikit-learn.org/stable/modules/classes.html#module-sklearn.metrics>

<https://www.dataquest.io/blog/understanding-regression-error-metrics/>

# Evaluation metrics for regression





# Evaluation metrics for regression (Accuracy)

Mean absolute error:  $MAE = \text{mean}(|e_t|)$ ,

Root mean squared error:  $RMSE = \sqrt{\text{mean}(e_t^2)}$ .

Mean absolute percentage error:  $MAPE = \text{mean}(|p_t|)$ .

$sMAPE = \text{mean} (200|y_t - \hat{y}_t|/(y_t + \hat{y}_t))$ .

For time series:

[2013 A Survey of forecast error measures](https://otexts.com/fpp2/accuracy.html)

<https://otexts.com/fpp2/accuracy.html>

Rob J Hyndman, Anne B Koehler (2006). Another look at measures of forecast accuracy

2009 Elena Deza, Michel Marie Deza\_Encyclopedia of Distances, metric dissimilarity error

# Multiple linear Regression

