

Simple Linear Regression

↳ y is continuous -

Relationship

Between $x \& y$.
is linear .

Hyperparams .

- We have to decide
before building the
model

$$y = \beta_0 + \beta_1 x$$

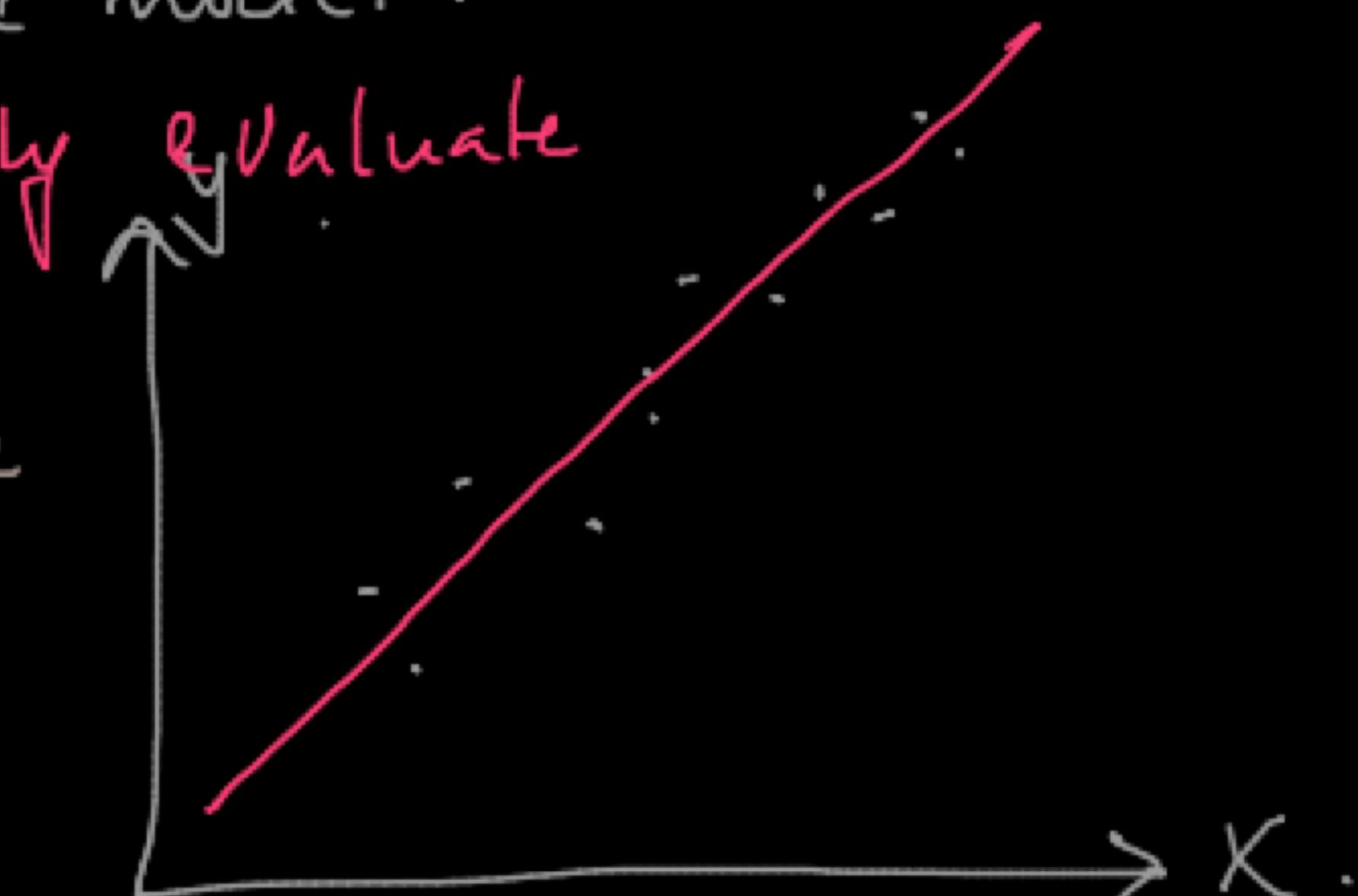
$\beta_0, \beta_1 \rightarrow$ Model parameters .

→ They are estimated by
the model .

Task of the algorithm: (OLS)

Ordinary Least Squares -

1. Visually evaluate
2. Quantify the strength of the relationship .



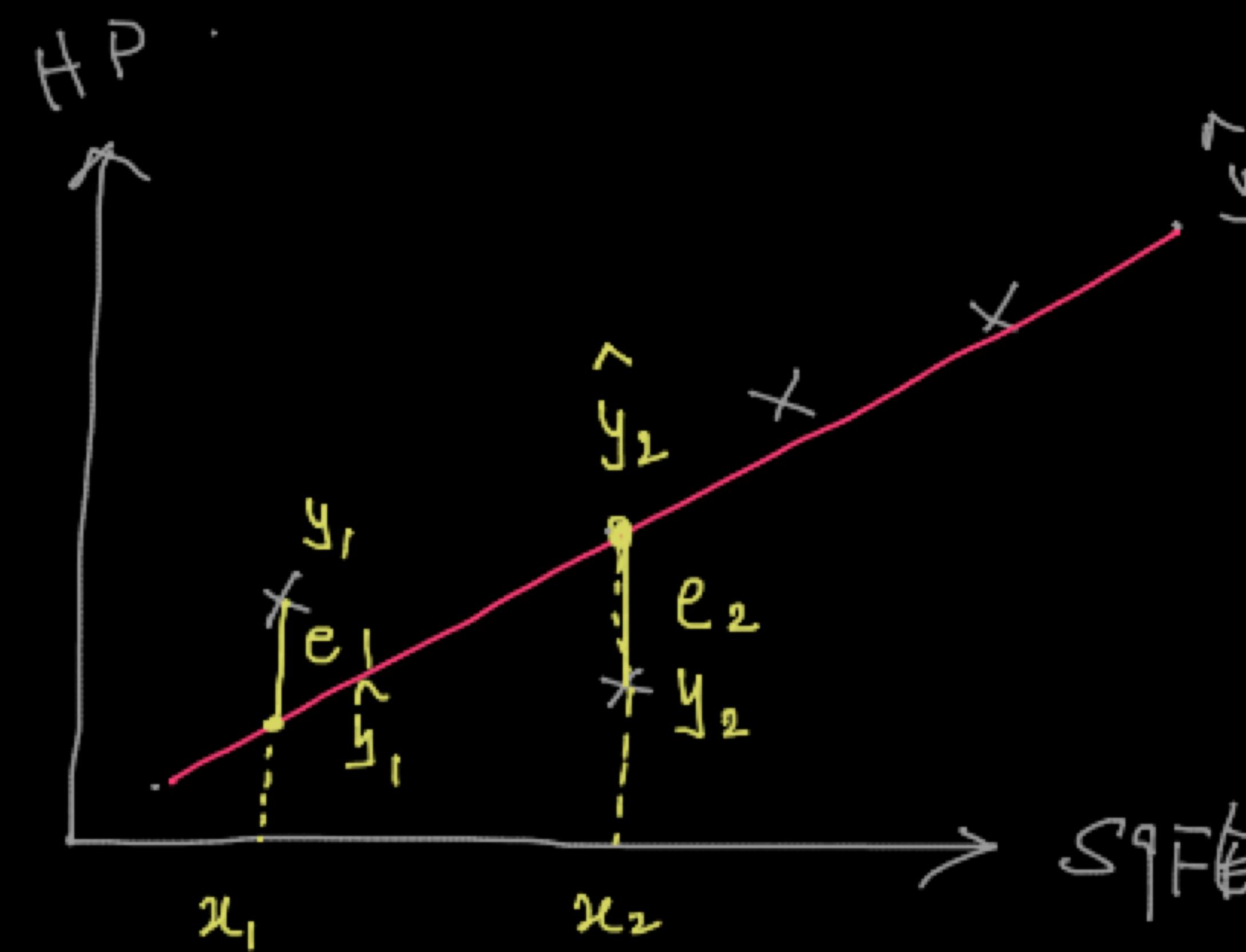
$r \Rightarrow$ Pearson's Correlation

Coefficient -

→ represents the Strength of the
LINEAR. Relationship b/w $x \& y$ -

$$SSE = \sum_{i=1}^n (\underline{y}_i - \hat{y}_i)^2$$

$$\hat{y} = \beta_0 + \beta_1 x$$



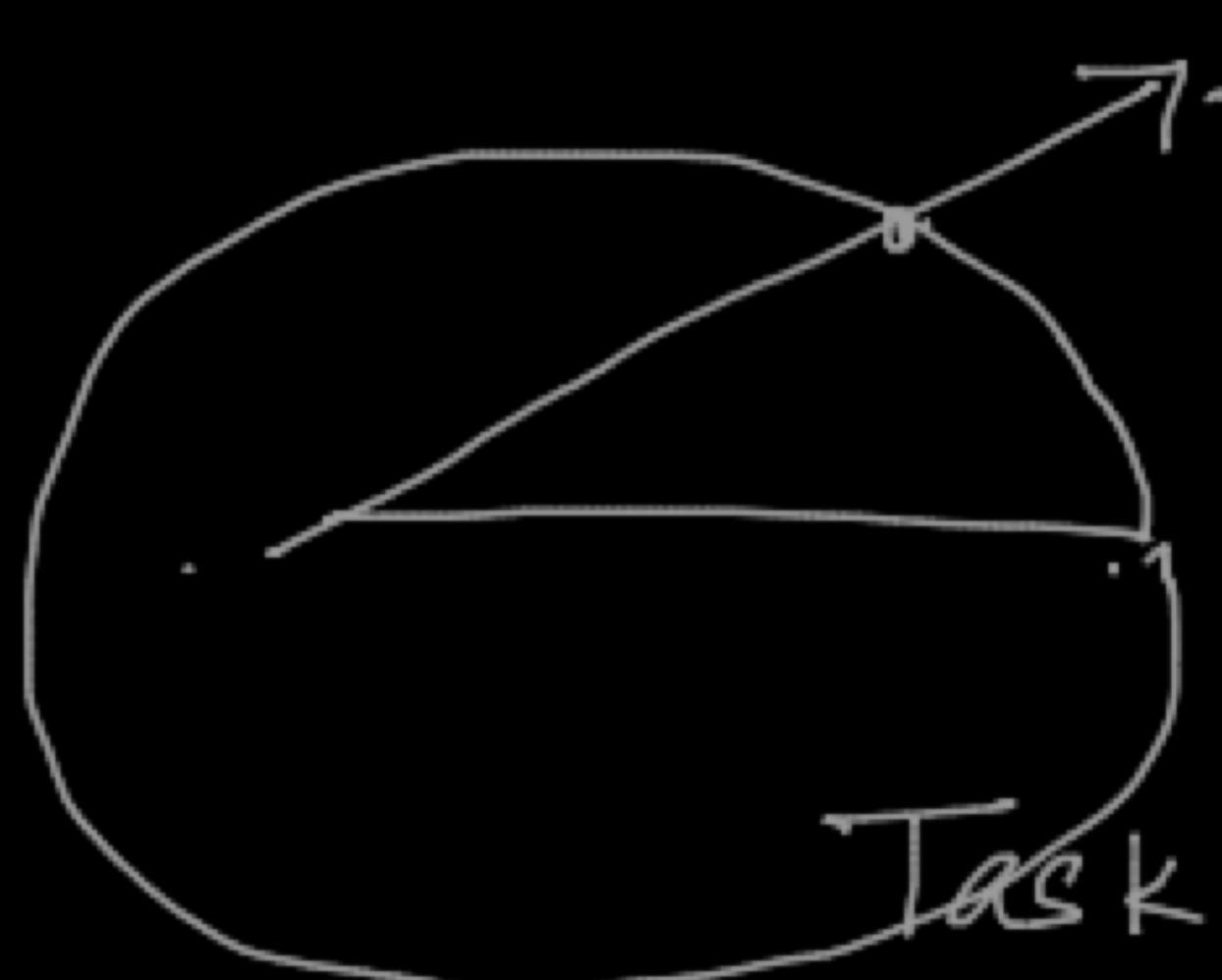
$y - \hat{y} \rightarrow$ Residual-
(Error)

Loss f_n \rightarrow Some f_n of the
Error or residual -

✓

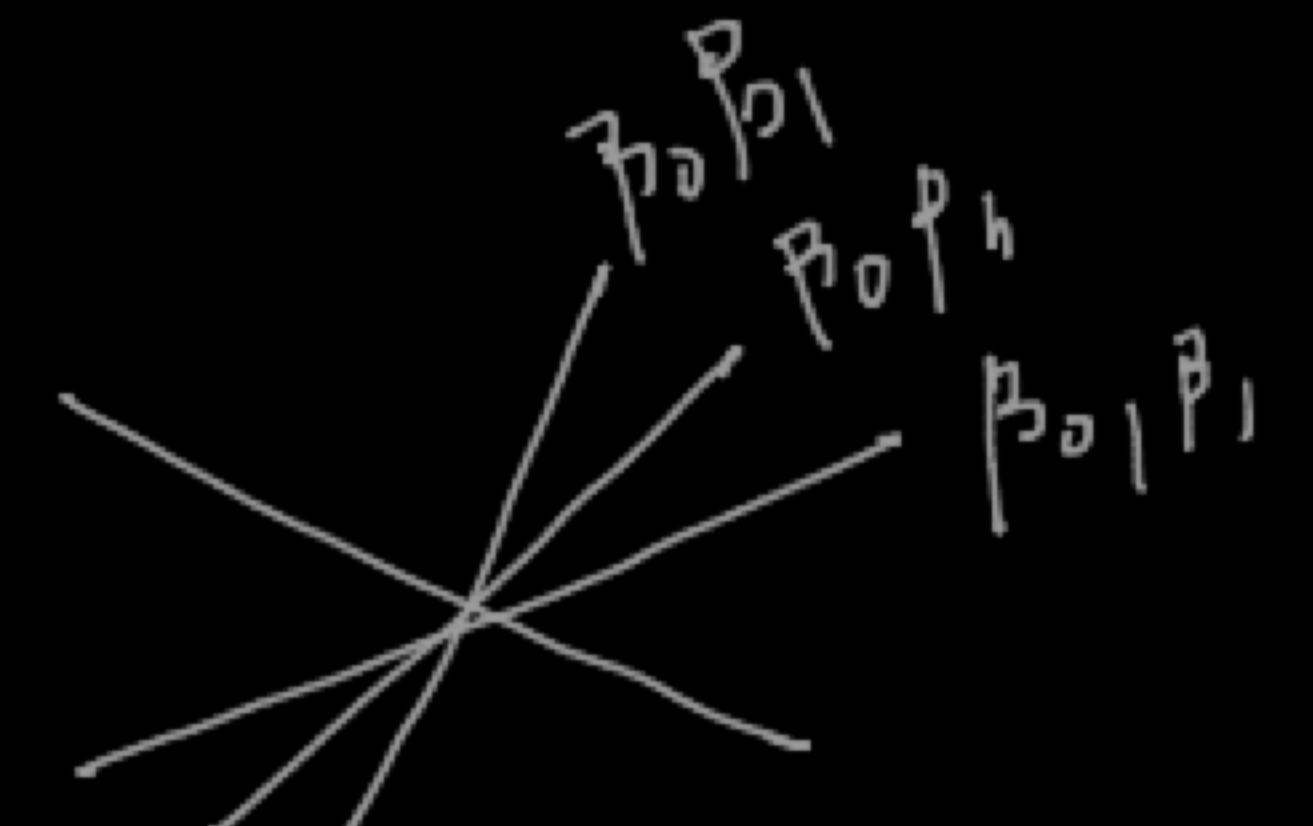
x	y	\hat{y}	$\sum (y - \hat{y})^2$
x_1	y_1	\hat{y}_1	$(y_1 - \hat{y}_1)^2$
x_2	y_2	\hat{y}_2	$(y_2 - \hat{y}_2)^2$
x_3	y_3	\hat{y}_3	$(y_3 - \hat{y}_3)^2$
x_4	y_4	\hat{y}_4	$(y_4 - \hat{y}_4)^2$
\vdots	\vdots	\vdots	\vdots
x_n	y_n	\hat{y}_n	$\sum (y_n - \hat{y}_n)^2$

$$SSE = e_1^2 + e_2^2 + e_3^2 + \dots + e_n^2$$



Task of the algorithm:

'Those β 's which will minimize the squared loss'



Gradient Descent

↗
OLS

How well is the model doing.

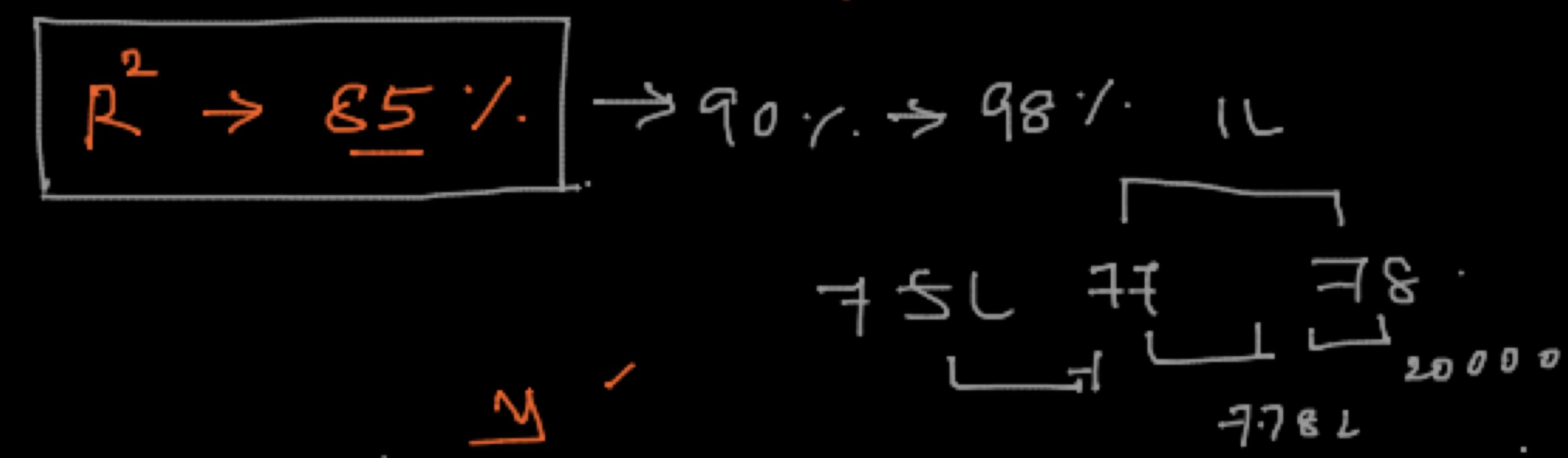
1. $R^2 \leftarrow$ What is the percentage of Variation explained by the features in the model.

2. Metrics — MSE

→ RMSE

→ MAE

→ MAPE



	Feature	Metric
Wc	# Bed	$\frac{\sum(y_i - \bar{y})^2}{n}$
800	30	
100	47	
700	23	
2500	65	$\bar{y} =$
3000	97	
3000	100	
		$\bar{y} = 50 \text{ Lakh}$

$$R^2 = \frac{\text{Explained Variation} - (\hat{y} - \bar{y})}{\text{total Variation}} = \frac{\sum(\hat{y}_i - \bar{y})^2}{\sum(y_i - \bar{y})^2}$$

Explained Variation: $\sum(\hat{y}_i - \bar{y})^2$

Total Variation: $\sum(y_i - \bar{y})^2$

Unexplained Variation: $\sum(y_i - \hat{y}_i)^2$

Sq Ft
x y

$\bar{y} \Rightarrow$ Avg Value

absolute-

$$\begin{array}{ccccccc} x & y & \hat{y} & (y - \hat{y}) & (y - \hat{y})^2 & |(y - \hat{y})| \\ & & & \text{Residual} & & & \\ \rightarrow & x_1 & y_1 & \hat{y}_1 & (y_1 - \hat{y}_1) & (y_1 - \hat{y}_1)^2 & +ve \quad |(y_1 - \hat{y}_1)|/y_1 \\ & x_2 & y_2 & \hat{y}_2 & & & +ve \quad |(y_2 - \hat{y}_2)|/y_2 \\ & x_3 & y_3 & \hat{y}_3 & & & +ve \\ & \vdots & & & & & \vdots \\ x_n & y_n & \hat{y}_n & & & & \sum \frac{|(y_i - \hat{y}_i)|}{n} = MAE \quad \overbrace{\text{MAPE}}^{\frac{\sum |(y_i - \hat{y}_i)|}{\sum y_i}} \\ & & & & (y_n - \hat{y}_n)^2 & & \\ & & & & \sum \frac{(y_i - \hat{y}_i)^2}{n} & & \end{array}$$

$$\checkmark \quad MSE = \frac{SSE}{n} \Rightarrow \underline{w}(\underline{Lack})^2$$

$$\checkmark \quad RMSE = \sqrt{MSE} \rightarrow (\underline{Q} \underline{Lack}) \pm 2L$$

=

Machine Learning
(supervised)

Regression

$\rightarrow y$ is Continuous

Classification

$- y$ is Categorical

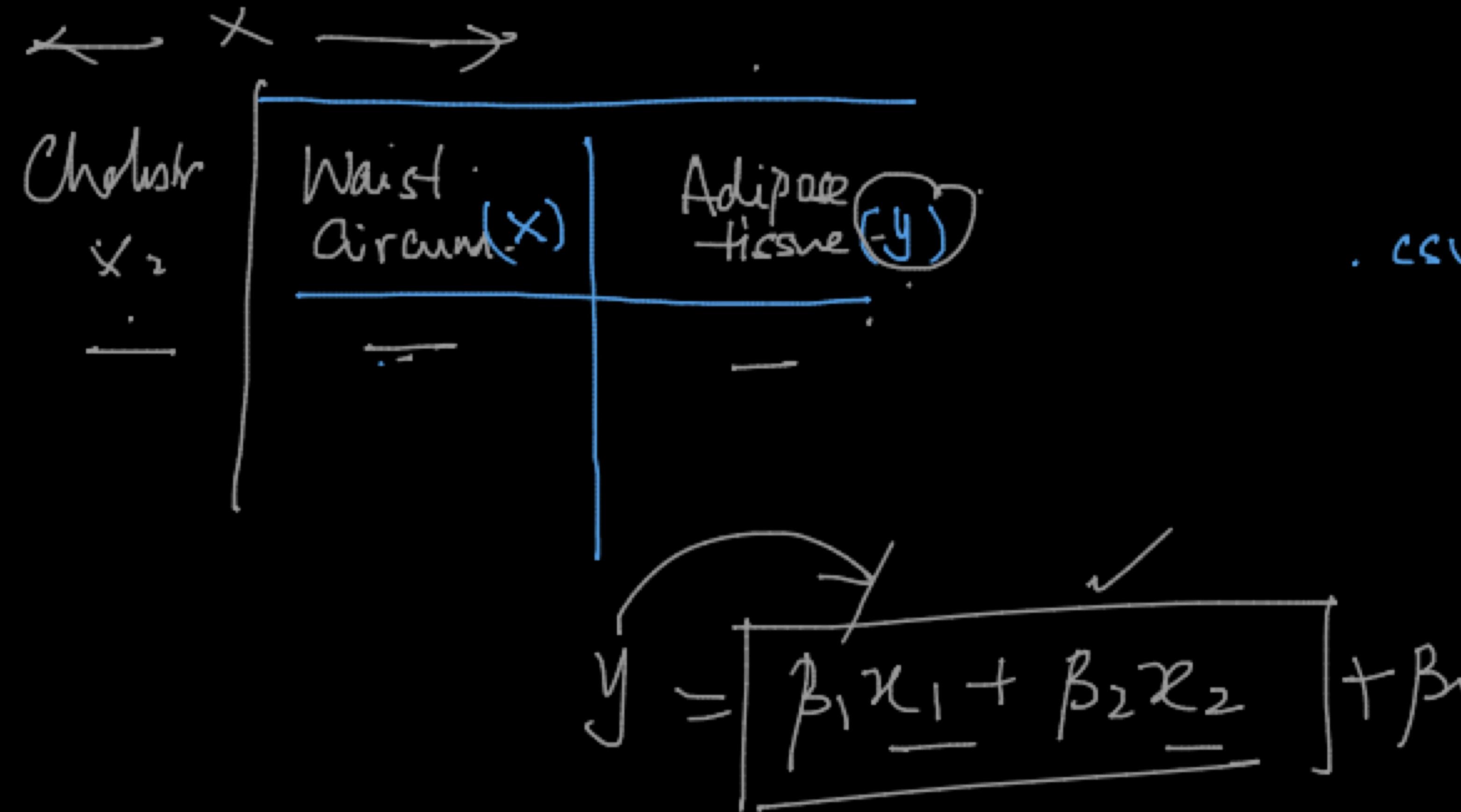
x	y	\hat{y}	$E = (y - \hat{y})$	$(y - \hat{y})^2$	$ y - \hat{y} $
x_1	y_1	\hat{y}_1	$(y_1 - \hat{y}_1) = +ve \pm 2L$	4	2
x_2	y_2	\hat{y}_2	$(y_2 - \hat{y}_2) = -ve \pm 1L$	1	1
x_3	y_3	\hat{y}_3	$(y_3 - \hat{y}_3) = -ve \pm 2L$	4	2
:	:	:	:	:	
x_n	y_n	\hat{y}_n	$(y_n - \hat{y}_n) = +ve \pm 1L$	1	1
$\times o$				$\frac{1}{10} L = SSE$	$\frac{6/4}{10} = MAE$

$$\checkmark MSE = \left(\frac{104}{4} \right) = (2.5)L^2$$

$$RMSE = \sqrt{MSE} = \boxed{1.58} L = \frac{36.58}{33.42} L$$

1. Defined a loss function ✓
 $\text{SSE} \Rightarrow \text{Squared loss}$

2. We will find those model params which will minimize the loss. ✓



Break
 $(10, 10 \text{ am})$

$\beta_1 = 0$

$\hat{y} = \beta_0 + \beta_1 x_1 \uparrow \text{unit}$

... in \hat{y} .

x_1	x_2	x_3	y
1	1	1	y_1
2	1	1	y_2

β_1

$$\check{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$

$y = f(x)$
 \hookrightarrow linear eqn

$$\beta_2 = 0 \quad \beta_1 = 0$$

$$H_0: \beta_1 = 0; H_a: \beta_1 \neq 0$$

$P < 0.0 \rightarrow x_1$ is a good predictor.

$$H_0: \beta_2 = 0; H_a: \beta_2 \neq 0$$

$P = 0.43 > 0.05 \rightarrow \beta_2 = 0;$
 x_2 is not a good predictor.