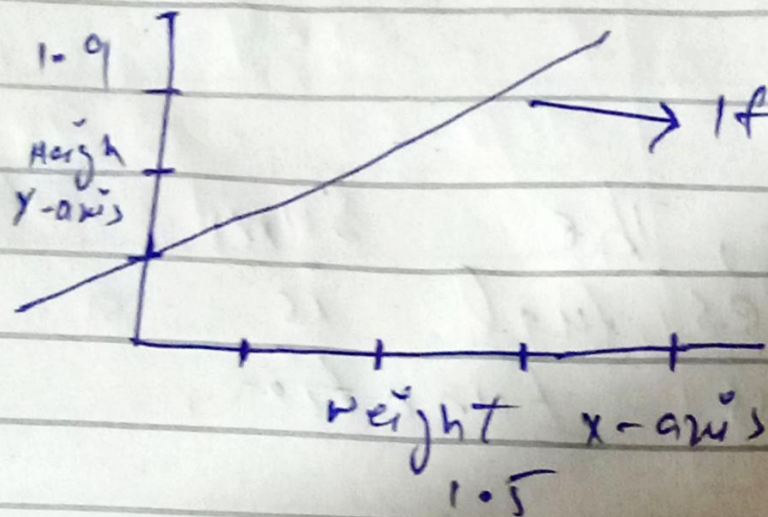


# Gradient Descent



→ If we fit a line to the data.

$$\text{Predicted} = \text{intercept} + \text{slope} \times \text{Weight}$$

learn how Gradient Descent  
can fit a line to data  
by finding the optimal value  
for the intercept and the  
slope.

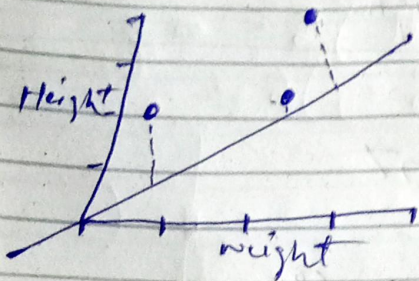


the Least Squares estimate  
for the slope, 0.64

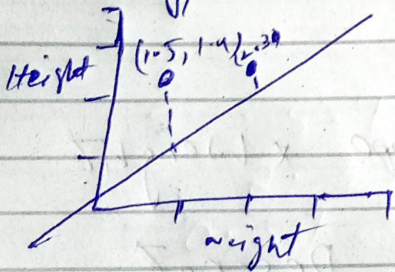
pick a random value for the intercept

we can use 0, but any  
no will do

$$0 + 0.64 \times \text{weight}$$



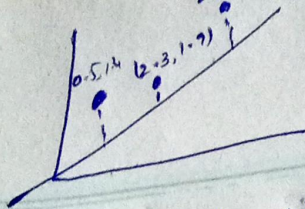
In M2 Pingo, The sum of  
the squared residual is a  
type of Loss Function.



$$\begin{aligned} \text{Predict Height} &= 0 + 0.64 \times 0.5 \\ &= 0.32 \end{aligned}$$

we calculate the difference  
between 1.4 & the observed Height



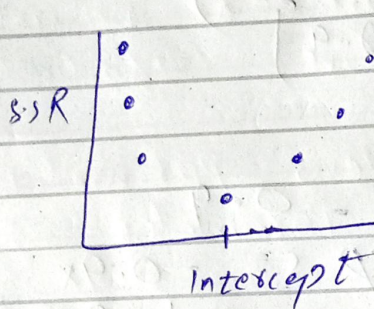


$$\text{Residual} = 1.4 - 0.32 = 1.1$$

The sum of the squared Residual.

$$(1.1)^2 + (0.4)^2 + (1.3)^2 = 3.1$$

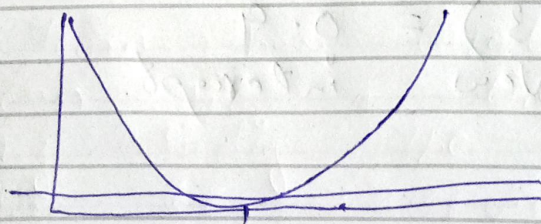
3.1 is the sum of the squared Residuals.



Finding optimal values.

$$\text{Predicted Height} = \text{Intercept} + 0.84 \times w$$

$$S.S.R = (1.4 - (\text{inte} + 0.84 \times 0.5))^2 + (1.4 - (\text{inte} + 0.84 \times 2.3))^2 + (3.2 - (\text{inte} + 0.84 \times 2.9))^2$$





$$\frac{d}{d \text{ inte}} \text{ sum of SR} = \frac{d}{d \text{ inte}} (1.4 - (\text{inte} + 0.64 \times 0.5))^2$$

$$+ \frac{d}{d \text{ inte}} (1.9 - (\text{inte} + 0.64 \times 2.3))^2$$

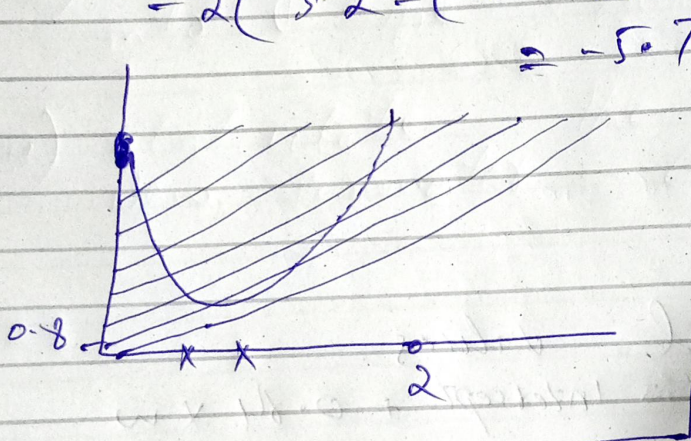
$$+ \frac{d}{d \text{ inte}} (3.2 - (\text{inte} + 0.64 \times 2.9))^2$$

$$= -2(1.4 - (\text{inte} + 0.64 \times 0.5))$$

$$- 2(1.9 - (\text{inte} + 0.64 \times 2.3))$$

$$- 2(3.2 - (\text{inte} + 0.64 \times 2.9))$$

$$= -5.7$$



$$\text{step } s = -0.9 \times 0.1 = -0.09$$

$$= -5.7 \times 0.1 = -0.57$$

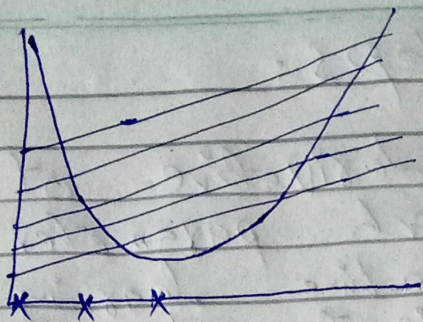
$$= 2.3 \times 0.1 = -0.23$$

$$= 0.57 - (-0.23) = 0.8$$

New intercept

$$0.89$$



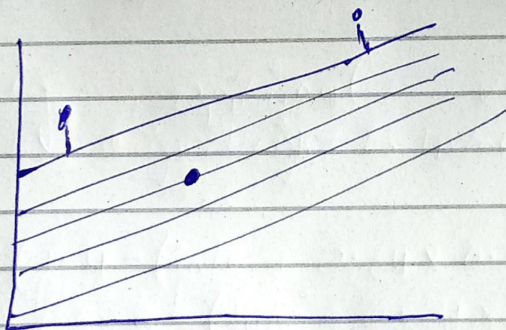


0 ← 0.7 0.8 0.9

The least step = 0.9  
very close to 0

$$\text{step} = 0.0009 \times 0.9 = 0.0009$$

Maximum step of gradient  
more than 1000  
gradient will stop



Repeat until all step closed  
to + 0 and each  
Maximum No. of step.



## All steps:

- 1) Take the derivative of loss -  $f$  for each parameter in it fancy Machine learning Lingo Gradient of the loss function.
- 2) Pick random value for the parameters.
- 3) Plug the parameter value into the derivative Gradient.
- 4) Calculate the New parameters  
$$\text{New Parameter} = \text{Old Parameter} - \text{step}$$