

## \* Linear Regression prediction (in dimension)

It is a method to help us understand the relationship between 2 variables :- The prediction (Independent) variable  $x$  sometimes called a feature.

The target dependent variable  $y$

The relationship between the variables.

$$\text{Right side} \quad Y = b + wx$$

This is sometimes called a linear mapping but in the one dimensional case, it just the equation of a line.

The Parameters:-

- $b$  :- bias

- $w$  :- The slope or weight

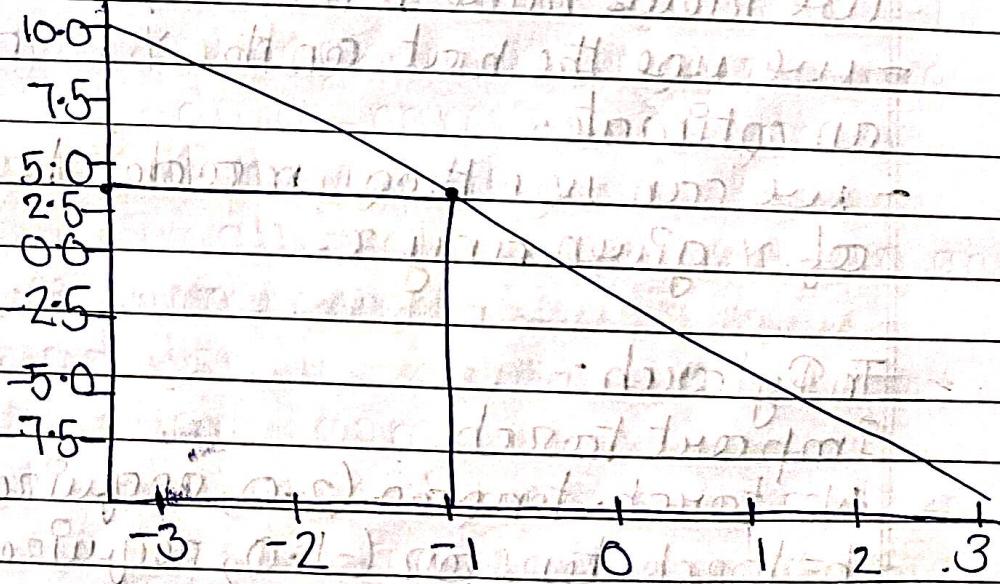
## Simple Linear Regression :- Forward

$$\hat{y} = 1 - 3x$$

$$= 1 - 3(-1) = 10.0$$

$$= \cancel{-} 4 = 7.5$$

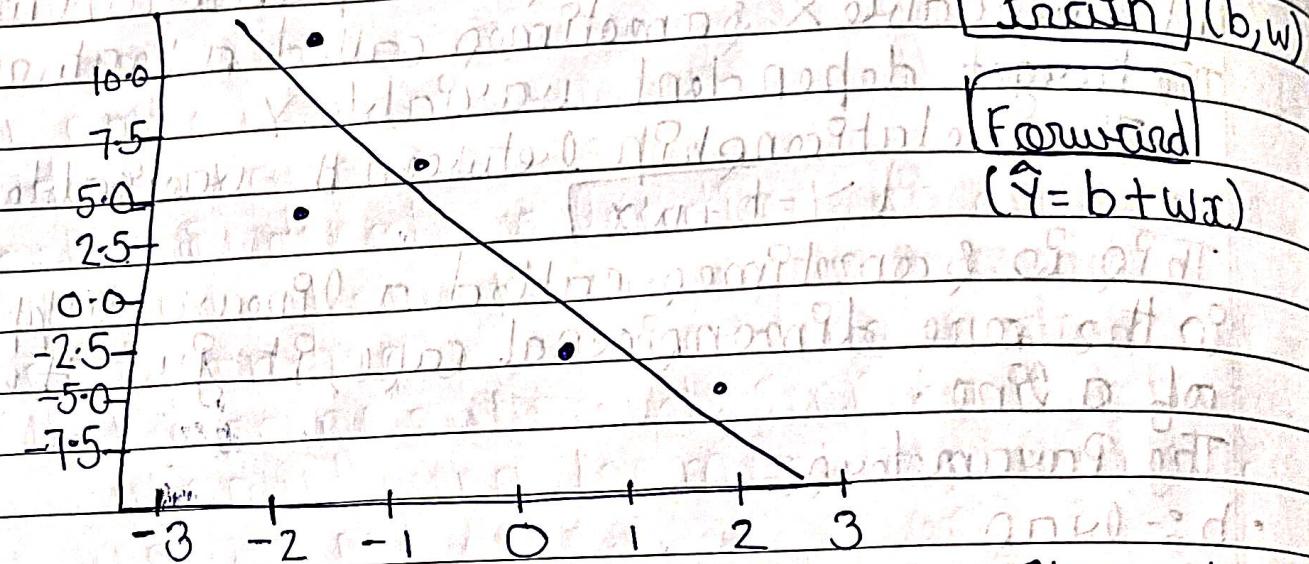
10.0	5.0	0.0	-2.5	-5.0	-7.5



The line will map the dependent variable  $x$ , to the estimated value of  $y$ , the hat on the  $y$  indicates it's an estimate.

In Pytorch, we call the prediction step the forward step

In linear regression we have 2 steps:- we have a set of training Points



- we use these training points to fit or train the model & get parameters.
- we then use these parameters in the model & then we now have a model;
- we use the hat on the y to denote these model as an estimate.
- we can use this model to predict any value of y given any x.

In Pytorch:-

Import torch

w = torch.tensor(5.0, requires\_grad=True)

b = torch.tensor(-1.0, requires\_grad=True)

def forward(x):

$$y = w * x + b$$

return y

- we will use object in the
- we will use from the model:

$$y = \text{model}(x)$$

- The Parameter "in-features" is the size of each input sample or the no of columns.
- The Parameter "out-features" is the size of each output sample.

an to produce an  
make a prediction:

, out\_features=1)

- To get the same results everytime we run the code we use the random seed.

From torch.nn import Linear

torch.manual\_seed(1)

model = Linear(in\_features=1, out\_features=1)

Print(list(model.Parameters()))

### • Custom modules:-

- In Pytorch it is customary to make a custom module to create a model, using the package nn.module.

- Take just python object.

- A custom module allows us to wrap multiple objects to make more complex modules.

### Custom modules for linear regression:-

Import torch.nn as nn

class LR(nn.Module):

```
def __init__(self, in_size, output_size):
```

```
    Super().__init__()
```

```
    self.linear = nn.Linear(in_size, output_size)
```

```
def forward(self, x):
```

```
    out = self.linear(x)
```

```
    return out
```

- we will use the constructor Linear to produce an object in this case called model.  
we will use the object model to make a prediction.

```
From torch.nn import Linear  
model = Linear(in_features=1, out_features=1)  
y = model(x)
```

To get the same results everytime we run the code we use the random seed.

```
From torch.nn import Linear  
torch.manual_seed(1)
```

```
model = Linear(in_features=1, out_features=1)
```

```
Print(list(model.parameters()))
```

Custom modules:-

In Pytorch it is customary to make a custom module to create a model, using the package nn.module.

It's just python object.  
Custom module allows us to wrap multiple objects to make more complex modules.

Custom modules for linear regression:

```
import torch.nn as nn
```

class LR(nn.Module):

```
def __init__(self, in_size, output_size):  
    super(LR, self).__init__()  
    self.linear = nn.Linear(in_size, output_size)
```

## \* Linear Regression training:-

Illustration of a dataset using mathematical notation:-

$$D = \{(x_1, y_1), \dots, (x_n, y_n)\}$$

- Imagine this set with many thousands of ordered pairs.
- Each pair denotes a location, or data point, within a cartesian plane. Corresponding x, y coordinates are marked with the same subscript, linking them together. Subscript range from  $n=1$  to  $N$  with  $N$  defining the set size.
- Commonly we will encounter datasets organized as tensors.

## \* (Simple) Linear Regression

- Regression is a method to predict a continuous value.
- Predicting housing price ( $y$ ) giving the size of the house ( $x$ )
- Predicting stock ( $y$ ) price using interest rate ( $x$ )
- Fuel economy of car ( $y$ ) given horsepower ( $x$ )

## \* Loss:-

- Loss is a precursor to cost.
- The loss tells you how bad your model's prediction is compared to the actual value.

## In simple:-

It's just the average of the squared differences between what you predicted and what it really is.

- If predictions are close  $\rightarrow$  loss is small  $\rightarrow$  good!
- If predictions are far  $\rightarrow$  loss is big  $\rightarrow$  bad!

In Pytorch we calculate this automatically for you

`import torch.nn as nn`

`loss_fn = nn.MSELoss`

`loss = loss_fn(y_pred, y_true)`

### \* Gradient Descent :-

It is an optimization algorithm used to update model parameters (like weights and biases) to minimize the loss (error).

In Pytorch GID works like this :-

- Define a model (some weights you want to learn).
- Compute the loss from the output.
- Compute the gradients (how to change weights to reduce loss).
- Update the weights using the gradients.

Eg :-

`import torch`

`x = torch.tensor([1.0, 2.0, 3.0])`

`y_true = torch.tensor([2.0, 4.0, 6.0])`

`w = torch.tensor([0.0], requires_grad=True)`

`lx = 0.01`

for epoch in range(100):

`y_pred = w * x`

`loss = ((y_true - y_pred) ** 2).mean()`

`loss.backward()`

The difference between cost & loss:-

cost :- The average loss over the entire training dataset.

loss :- The error for one data point (or one batch).

with torch  
 $w = 0$   
 $w \cdot \text{grad} \cdot z$   
Print(f'Epoch  
{E})

### \* Cost function:-

It is just a measure of how wrong our model

- It compares:-

The model's prediction

The actual true value (what it should be)

And gives you one number  $\rightarrow$  The error

Goal is to :- make this number as small as possible

### \* Mean Squared Error (MSE)

It is one of the most common cost fn, especially for regression (Predicting numbers).

How it works (MSE):-

- For each data point :-

Find the error  $\rightarrow$  (True value - Predicted value)

- Square that error:-

(Squaring makes it positive and penalizes bigger mistakes more)

- Add up all the squared errors.

- Divide by the number of data points  $\rightarrow$  Take the mean

MSE Formula:-

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_{\text{true}} - y_{\text{pred}})^2$$

with torch.no\_grad():

$$w = l_x * w \cdot \text{grad}$$

$w \cdot \text{grad} \cdot \text{zero}_()$

Point(f'Epoch {epoch + 1}): w = {w - Item() \* 4F}  
{loss \* Item() \* 4F})

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