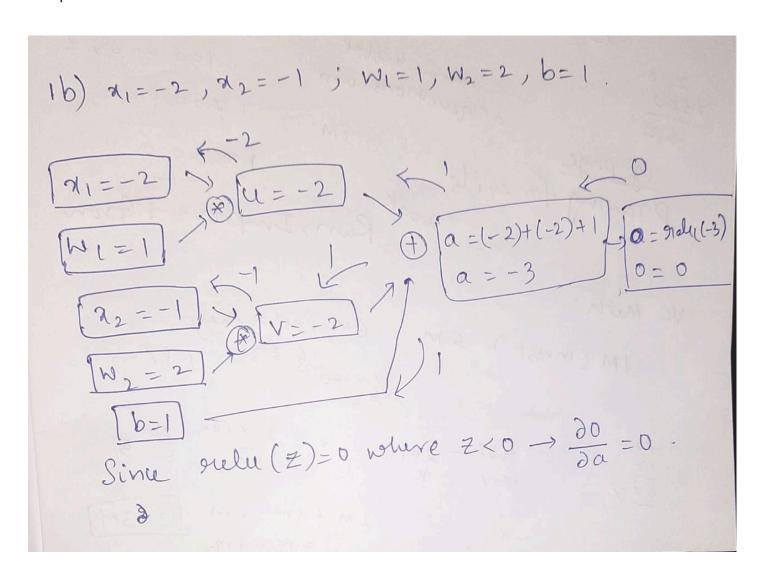
## Lecture 09 Submission Pranav

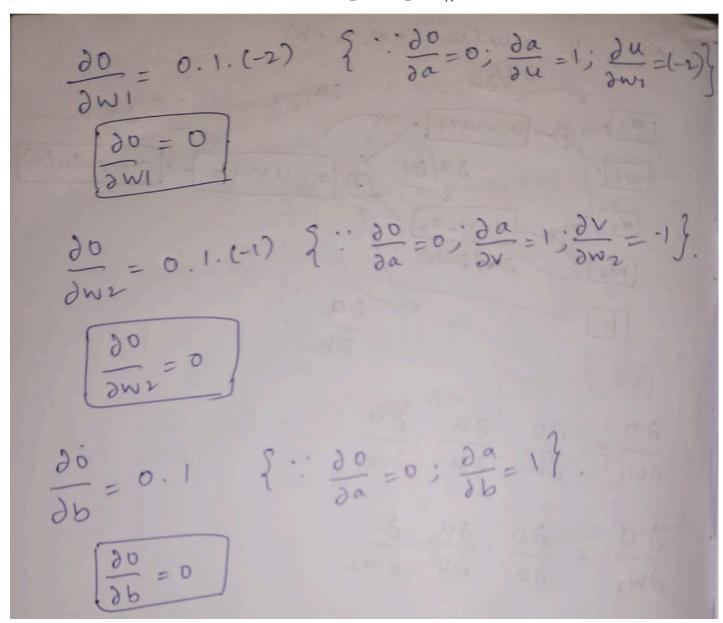
#### 1 Answer

Drawing the computation graph for the given equation and writing the derivatives for each

Ja) 
$$y = \operatorname{nelu}(w_1x_1 + w_2x_2 + b)$$
 $\partial u/\partial w_1$ 
 $\partial u/\partial w_1$ 
 $\partial u/\partial w_2$ 
 $\partial u/\partial w_2$ 

1b - Substituting the given values into the graph and then using the above derivied gradients to compute values





### 2 Answer

import torch
from torch.autograd import grad
import torch.nn.functional as F
from torch.nn import ReLU

import matplotlib.pyplot as plt
%matplotlib inline

```
import pandas as pd
import matplotlib.pyplot as plt
import torch
%matplotlib inline
df = pd.read_csv('./linreg-data.csv', index_col=0)
df.tail()
\rightarrow
                x1
                          x2
                                     У
     995 -0.942094 -0.835856 -22.324428
     996 1.222445 -0.403177 -52.121493
     997 -0.112466 -1.688230 -57.043196
     998 -0.403459 -0.412272 -27.701833
     999 0.021351 -0.499017
                              -9.804714
# Assign features and target
X = torch.tensor(df[['x1', 'x2']].values, dtype=torch.float)
y = torch.tensor(df['y'].values, dtype=torch.float) + 144
# Shuffling & train/test split
torch.manual_seed(123)
shuffle idx = torch.randperm(y.size(0), dtype=torch.long)
X, y = X[shuffle_idx], y[shuffle_idx]
percent70 = int(shuffle_idx.size(0)*0.7)
X_train, X_test = X[shuffle_idx[:percent70]], X[shuffle_idx[percent70:]]
y_train, y_test = y[shuffle_idx[:percent70]], y[shuffle_idx[percent70:]]
# Normalize (mean zero, unit variance)
mu, sigma = X_train.mean(dim=0), X_train.std(dim=0)
X_{train} = (X_{train} - mu) / sigma
X \text{ test} = (X \text{ test} - mu) / sigma
```

### Computing gradients manually

Here I've taken X as an n x 2 matrix and initialised the weights and biases accordingly as well, I've added an extra relu function to simulate the model.

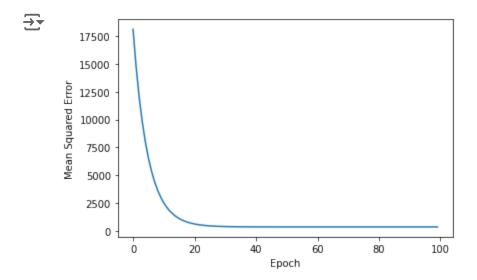
However since we added 144 to y tensor and all values are positive as well as the derivative of relu for positive values is 1, I just calculated the loss and the derivatives accordingly

```
class LinearRegression():
    def init (self, num features):
        self.num features = num features
        self.weights = torch.rand(num_features, 1,
                                   dtype=torch.float)
        self.bias = torch.rand(1, dtype=torch.float)
    def forward(self, x):
        netinputs = torch.add(torch.mm(x, self.weights), self.bias)
        activations = netinputs
        relu = ReLU()
        return relu(activations).view(-1)
    def backward(self, x, yhat, y):
        grad loss yhat = 2*(yhat - y)
        grad_yhat_weights = x
        grad_yhat_bias = 1.
        grad_loss_weights = torch.mm(grad_yhat_weights.t(),
                                         grad loss yhat.view(-1, 1)) / y.size(0)
        grad loss bias = torch.sum(grad yhat bias*grad loss yhat) / y.size(0)
        return (-1)*grad loss weights, (-1)*grad loss bias
def loss(yhat, y):
    return torch.mean((yhat - y)**2)
def train(model, x, y, num_epochs, learning_rate=0.01):
    cost = []
    for e in range(num_epochs):
        #### Compute outputs ####
        yhat = model.forward(x)
        #### Compute gradients ####
        negative_grad_w, negative_grad_b = model.backward(x, yhat, y)
        #### Update weights ####
        model.weights += learning_rate * negative_grad_w
        model.bias += learning_rate * negative_grad_b
        #### Logging ####
```

 $\overline{2}$ 

```
באחרוו: הפס | גוסב: ס/דים האח
                 MSE: 371.61084
    Epoch: 084
    Epoch: 085
               | MSE: 371.61069
    Epoch: 086 | MSE: 371.61066
    Epoch: 087 | MSE: 371.61057
    Epoch: 088
                 MSE: 371.61050
    Epoch: 089 | MSE: 371.61050
    Epoch: 090
                 MSE: 371.61050
    Epoch: 091 | MSE: 371.61047
    Epoch: 092 | MSE: 371.61041
    Epoch: 093 |
                 MSE: 371.61044
    Epoch: 094 | MSE: 371.61041
    Epoch: 095
                 MSE: 371.61038
    Epoch: 096 | MSE: 371.61038
                 MSE: 371,61038
    Epoch: 097
    Epoch: 098 | MSE: 371.61038
                 MSE: 371.61032
    Epoch: 099 |
    Epoch: 100 | MSE: 371.61038
plt.plot(range(len(cost)), cost)
plt.ylabel('Mean Squared Error')
```

```
plt.xlabel('Epoch')
plt.show()
```



```
train_pred = model.forward(X_train)
test_pred = model.forward(X_test)
print('Train MSE: %.5f' % loss(train_pred, y_train))
print('Test MSE: %.5f' % loss(test_pred, y_test))
    Train MSE: 371.61038
    Test MSE: 406.87973
print('Weights', model.weights)
print('Bias', model.bias)
```

# 2 Linear Regression Semi Manual

### Computing the gradients semi manually

Here, I've defined the loss function and used the grad function from pytorch and used required\_grad to calculate the gradients

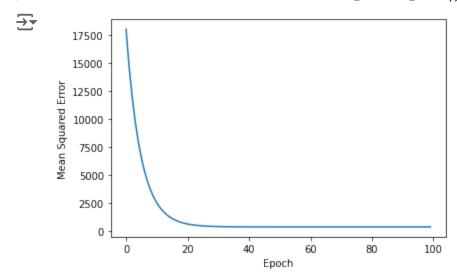
I used the retain\_graph=True as well to retain the graph while calculating derivatives of weights and then using that graph for biases

```
class LinearRegression2():
    def __init__(self, num_features):
        self.num features = num features
        self.weights = torch.rand(num features, 1,
                                   dtype=torch.float,
                                  requires grad=True)
        self.bias = torch.rand(1, dtype=torch.float, requires_grad=True)
    def forward(self, x):
        netinputs = torch.add(torch.mm(x, self.weights), self.bias)
        activations = netinputs
        return F.relu(activations).view(-1)
    def backward(self, x, yhat, y):
        grad loss yhat = 2*(yhat - y)
        grad_yhat_weights = x
        grad_yhat_bias = 1.
        # Chain rule: inner times outer
        grad_loss_weights = torch.mm(grad_yhat_weights.t(),
                                         grad_loss_yhat.view(-1, 1)) / y.size(0)
        grad_loss_bias = torch.sum(grad_yhat_bias*grad_loss_yhat) / y.size(0)
        # return negative gradient
        return (-1)*grad_loss_weights, (-1)*grad_loss_bias
def loss_func(yhat, y):
    return torch.mean((yhat - y)**2)
```

```
def train(model, x, y, num_epochs, learning_rate=0.01):
    cost = []
    for e in range(num_epochs):
        yhat = model.forward(x)
        loss = loss func(yhat, y)
        #### Compute gradients using the grad function of pytorch ####
        negative_grad_w = grad(loss, model.weights, retain_graph=True)[0] * (-1)
        negative\_grad\_b = grad(loss, model.bias)[0] * (-1)
        model.weights = model.weights + learning_rate * negative_grad_w
        model.bias = model.bias + learning rate * negative grad b
        #### Logging ####
        with torch.no grad():
          yhat = model.forward(x)
          curr loss = loss func(yhat, y)
          print('Epoch: %03d' % (e+1), end="")
          print(' | MSE: %.5f' % curr_loss)
          cost.append(curr loss)
    return cost
model = LinearRegression2(num_features=X_train.size(1))
cost = train(model,
             X_train, y_train,
             num epochs=100,
             learning rate=0.05)
```

 $\rightarrow$ 

```
בטטכוו: בטט
                | MSE: 3/1.04///
                 MSE: 371.64066
    Epoch: 064
    Epoch: 065
                 MSE: 371.63489
    Epoch: 066 |
                 MSE: 371.63028
    Epoch: 067 | MSE: 371.62646
    Epoch: 068
                 MSE: 371.62338
    Epoch: 069 | MSE: 371.62091
    Epoch: 070 |
                 MSE: 371.61890
    Epoch: 071 |
                 MSE: 371.61728
    Epoch: 072 | MSE: 371.61600
    Epoch: 073 |
                 MSE: 371.61490
    Epoch: 074 | MSE: 371.61404
    Epoch: 075
                 MSE: 371.61334
    Epoch: 076 | MSE: 371.61279
                 MSE: 371,61234
    Epoch: 077
    Epoch: 078 | MSE: 371.61197
    Epoch: 079
                 MSE: 371.61163
    Epoch: 080 | MSE: 371.61136
    Epoch: 081 |
                 MSE: 371.61121
    Epoch: 082 |
                 MSE: 371.61105
    Epoch: 083 |
                 MSE: 371.61090
    Epoch: 084 |
                 MSE: 371.61081
    Epoch: 085
                 MSE: 371.61069
    Epoch: 086 | MSE: 371.61063
    Epoch: 087 | MSE: 371.61057
    Epoch: 088
                 MSE: 371.61053
    Epoch: 089 | MSE: 371.61050
    Epoch: 090 |
                 MSE: 371.61044
    Epoch: 091 | MSE: 371.61044
    Epoch: 092
                 MSE: 371.61044
    Epoch: 093 |
                 MSE: 371.61041
    Epoch: 094 |
                 MSE: 371.61044
    Epoch: 095 |
                 MSE: 371.61041
    Epoch: 096
                 MSE: 371.61038
    Epoch: 097 | MSE: 371.61038
    Epoch: 098 |
                 MSE: 371.61038
    Epoch: 099 | MSE: 371.61041
    Epoch: 100 | MSE: 371.61032
plt.plot(range(len(cost)), cost)
plt.ylabel('Mean Squared Error')
plt.xlabel('Epoch')
plt.show()
```



### 2 Linear Regression Automatic

Here I've removed backward function completely and used the optimiser function from pytorch and then just used to step and compute the gradients as well.

```
class LinearRegression3(torch.nn.Module):
    def __init__(self, num_features):
        super(LinearRegression3, self).__init__()
        self.linear = torch.nn.Linear(num_features, 1)

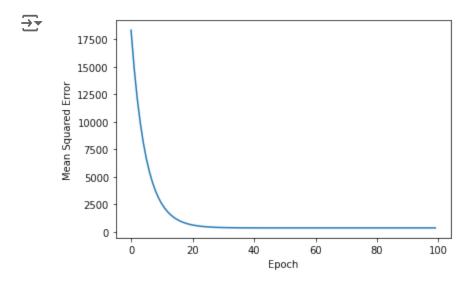
def forward(self, x):
    netinputs = self.linear(x)
    activations = netinputs
    return F.relu(activations).view(-1)
```

```
def train(model, x, y, num_epochs, learning_rate=0.01):
    cost = []
    optimizer = torch.optim.SGD(model.parameters(), lr =learning rate)
    for e in range(num epochs):
        yhat = model.forward(x)
        loss = F.mse loss(yhat, y)
        optimizer.zero grad()
        loss.backward()
        optimizer.step()
        #### Logging ####
        with torch.no grad():
            yhat = model.forward(x)
            curr_loss = F.mse_loss(yhat, y)
            print('Epoch: %03d' % (e+1), end="")
            print(' | MSE: %.5f' % curr_loss)
            cost.append(curr loss)
    return cost
model = LinearRegression3(num_features=X_train.size(1))
cost = train(model,
             X_train, y_train,
             num_epochs=100,
             learning rate=0.05)
Free Epoch: 001 | MSE: 18315.29297
    Epoch: 002 | MSE: 14911.81543
    Epoch: 003 | MSE: 12149.74121
    Epoch: 004 | MSE: 9912.19141
    Epoch: 005 | MSE: 8099.72217
    Epoch: 006 | MSE: 6631.58008
    Epoch: 007 | MSE: 5442.34912
    Epoch: 008 | MSE: 4479.04297
    Epoch: 009 | MSE: 3698.74146
    Epoch: 010 | MSE: 3066.67676
    Epoch: 011 | MSE: 2554.68774
    Epoch: 012 | MSE: 2139.96460
    Epoch: 013 | MSE: 1804.02747
    Epoch: 014 | MSE: 1531.90967
    Epoch: 015 | MSE: 1311.48657
    Epoch: 016 | MSE: 1132.93799
    Epoch: 017 | MSE: 988.30878
    Epoch: 018 | MSE: 871.15466
    Epoch: 019 | MSE: 776.25659
    Epoch: 020 | MSE: 699.38641
```

```
Epoch: 021 | MSE: 637.11926
    Epoch: 022 |
                 MSE: 586.68115
    Epoch: 023 | MSE: 545.82477
    Epoch: 024 | MSE: 512.72974
    Epoch: 025 | MSE: 485.92166
    Epoch: 026 | MSE: 464.20621
    Epoch: 027 | MSE: 446.61624
    Epoch: 028 | MSE: 432.36777
    Epoch: 029 | MSE: 420.82593
    Epoch: 030 | MSE: 411.47665
    Epoch: 031 | MSE: 403.90338
    Epoch: 032 | MSE: 397.76883
    Epoch: 033 | MSE: 392.79965
    Epoch: 034 | MSE: 388.77441
    Epoch: 035
                 MSE: 385.51382
    Epoch: 036 | MSE: 382.87262
    Epoch: 037 | MSE: 380.73331
    Epoch: 038 | MSE: 379.00027
    Epoch: 039 | MSE: 377.59653
    Epoch: 040 | MSE: 376.45938
    Epoch: 041 | MSE: 375.53821
    Epoch: 042 | MSE: 374.79208
    Epoch: 043 |
                 MSE: 374.18768
    Epoch: 044 | MSE: 373.69809
    Epoch: 045 | MSE: 373.30151
                 MSE: 372.98029
    Epoch: 046 |
    Epoch: 047 | MSE: 372.72003
               | MSE: 372.50925
    Epoch: 048
    Epoch: 049 | MSE: 372.33850
    Epoch: 050 | MSE: 372.20020
    Epoch: 051 | MSE: 372.08813
    Epoch: 052 | MSE: 371.99738
    Epoch: 053 | MSE: 371.92383
    Epoch: 054 | MSE: 371.86432
    Epoch: 055 | MSE: 371.81610
    Epoch: 056 |
                 MSE: 371.77701
    Epoch: 057
                | MSE: 371.74533
    Epoch: 058 | MSE: 371.71970
Start coding or generate with AI.
plt.plot(range(len(cost)), cost)
plt.ylabel('Mean Squared Error')
```

```
https://colab.research.google.com/drive/1Es7DZB5J6GHBYHJRScG5PbdCZfmRmeJr#printMode=true
```

```
plt.xlabel('Epoch')
plt.show()
```



```
Start coding or generate with AI.

Start coding or generate with AI.

train_pred = model.forward(X_train)
test_pred = model.forward(X_test)

print('Train MSE: %.5f' % F.mse_loss(train_pred, y_train))
print('Test MSE: %.5f' % F.mse_loss(test_pred, y_test))

Train MSE: 371.61035
Test MSE: 406.88037

list(model.parameters())

[Parameter containing:
tensor([[ 0.3622, 37.8791]], requires_grad=True), Parameter containing:
tensor([143.4497], requires_grad=True)]
```

#### 3 Answer

Writing the automatic version using the sequential class and computing the loss and showing it is no different

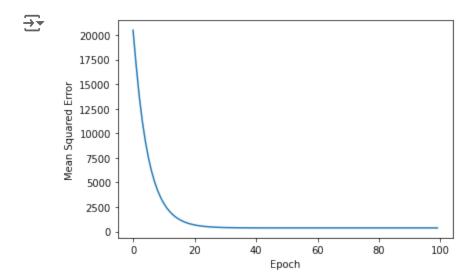
```
class LinearRegressionSequential(torch.nn.Module):
    def __init__(self, num_features):
```

```
super(LinearRegressionSequential, self).__init__()
        self.my_network = torch.nn.Sequential(
            torch.nn.Linear(num_features, 1),
            torch.nn.ReLU()
        )
    def forward(self, x):
        netinputs = self.my network(x)
        activations = netinputs
        return activations.view(-1)
def train(model, x, y, num_epochs, learning_rate=0.01):
    cost = []
    optimizer = torch.optim.SGD(model.parameters(), lr =learning rate)
    for e in range(num epochs):
        yhat = model.forward(x)
        loss = F.mse loss(yhat, y)
        optimizer.zero grad()
        loss.backward()
        optimizer.step()
        #### Logging ####
        with torch.no grad():
            yhat = model.forward(x)
            curr_loss = F.mse_loss(yhat, y)
            print('Epoch: %03d' % (e+1), end="")
            print(' | MSE: %.5f' % curr_loss)
            cost.append(curr loss)
    return cost
model = LinearRegressionSequential(num_features=X_train.size(1))
cost = train(model,
             X_train, y_train,
             num epochs=100,
             learning_rate=0.05)
Free Epoch: 001 | MSE: 20488.75781
    Epoch: 002 | MSE: 16986.41211
    Epoch: 003 | MSE: 13830.63574
    Epoch: 004 | MSE: 11274.26953
```

```
Epoch: 005 | MSE: 9203.45898
Epoch: 006
             MSE: 7525.97559
Epoch: 007
            MSE: 6167.10986
Epoch: 008
            MSE: 5066.34521
Epoch: 009 | MSE: 4174.65527
Epoch: 010
            MSE: 3452.33032
Epoch: 011 |
            MSE: 2867.20117
Epoch: 012
            MSE: 2393.20850
Epoch: 013
            MSE: 2009.24353
Epoch: 014 |
            MSE: 1698.20642
Epoch: 015
            MSE: 1446.24585
Epoch: 016
            MSE: 1242.14075
Epoch: 017
            MSE: 1076.80212
Epoch: 018
            MSE: 942.86633
Epoch: 019
             MSE: 834.36884
Epoch: 020 |
            MSE: 746.47845
Epoch: 021 |
            MSE: 675.28107
Epoch: 022
            MSE: 617.60626
Epoch: 023
            MSE: 570.88525
Epoch: 024 |
            MSE: 533.03815
Epoch: 025
            MSE: 502.37915
Epoch: 026 |
            MSE: 477.54321
Epoch: 027
            MSE: 457.42416
Epoch: 028
            MSE: 441.12634
Epoch: 029
            MSE: 427.92389
Epoch: 030
            MSE: 417.22876
Epoch: 031
            MSE: 408.56479
Epoch: 032
             MSE: 401.54648
Epoch: 033
             MSE: 395.86099
Epoch: 034
            MSE: 391.25531
Epoch: 035
            MSE: 387.52438
Epoch: 036
            MSE: 384.50195
Epoch: 037
            MSE: 382.05365
Epoch: 038
             MSE: 380.07031
Epoch: 039
            MSE: 378.46365
Epoch: 040
            MSE: 377.16205
Epoch: 041 |
            MSE: 376.10776
Epoch: 042 |
            MSE: 375.25366
Epoch: 043 |
            MSE: 374.56174
Epoch: 044
            MSE: 374.00125
Epoch: 045
            MSE: 373.54718
Epoch: 046 |
            MSE: 373.17935
Epoch: 047
             MSE: 372.88138
Epoch: 048 |
            MSE: 372.64001
             MSE: 372,44443
Epoch: 049
Epoch: 050 |
            MSE: 372.28604
Epoch: 051 |
            MSE: 372.15771
Epoch: 052
            MSE: 372.05380
Epoch: 053
            MSE: 371.96954
Epoch: 054
            MSE: 371.90137
Epoch: 055
             MSE: 371.84607
Epoch: 056 |
            MSE: 371.80133
Epoch: 057
             MSE: 371.76508
Enach. AEO
             MCE. 271 72560
```

Start coding or generate with AI.

```
plt.plot(range(len(cost)), cost)
plt.ylabel('Mean Squared Error')
plt.xlabel('Epoch')
plt.show()
```



Start coding or generate with AI.

Start coding or generate with AI.

```
train_pred = model.forward(X_train)
test_pred = model.forward(X_test)
```

print('Train MSE: %.5f' % F.mse\_loss(train\_pred, y\_train))
print('Test MSE: %.5f' % F.mse\_loss(test\_pred, y\_test))