Inicializando con pesos identicos **Objetivos** Definir una red neuronal con los pesos inicializados con el mismo valor y ver que pasa Tabla de contenido Veremos el problema de inicializar los pesos con el mismo valor. • Módulo red neuronal y función de entrenamiento • Crear algunos datos • Definir la red neuronal, inicializar los pesos con el mismo valor, definir costo, optimizador y entrenar el • Definir la red neuronal, inicializar los pesos con el método por defecto, definir costo, optimizador y entrenar el modelo Preparación In [1]: import os os.environ['KMP\_DUPLICATE\_LIB\_OK']='True' # Import the libraries we need for this lab In [2]: import torch import torch.nn as nn from torch import sigmoid import matplotlib.pylab as plt import numpy as np torch.manual seed(0) Out[2]: <torch.\_C.Generator at 0x248ce2a7250> Para graficar el modelo: In [3]: # The function for plotting the model def PlotStuff(X, Y, model, epoch, leg=True): plt.plot(X.numpy(), model(X).detach().numpy(), label=('epoch ' + str(epoch))) plt.plot(X.numpy(), Y.numpy(), 'r') plt.xlabel('x') if leg == True: plt.legend() else: pass Módulo red neuronal y función de entrenamiento Definimos las activaciones y la salida de la primera capa lineal como un atributo; esto NO es una buena práctica. In [4]: # Define the class Net class Net(nn.Module): # Constructor def \_\_init\_\_(self, D\_in, H, D out): super(Net, self).\_\_init\_\_() # hidden layer self.linear1 = nn.Linear(D\_in, H) self.linear2 = nn.Linear(H, D out) # Define the first linear layer as an attribute, this is not good practice self.a1 = None self.11 = None self.12=None # Prediction def forward(self, x): self.l1 = self.linear1(x)self.a1 = sigmoid(self.l1) self.l2=self.linear2(self.a1) yhat = sigmoid(self.linear2(self.al)) return yhat Definimos la función de entrenamiento: # Define the training function def train(Y, X, model, optimizer, criterion, epochs=1000): cost = []total=0 for epoch in range(epochs): total=0 for y, x in zip(Y, X): yhat = model(x)loss = criterion(yhat, y) loss.backward() optimizer.step() optimizer.zero\_grad() #cumulative loss total+=loss.item() cost.append(total) **if** epoch % 300 == 0: PlotStuff(X, Y, model, epoch, leg=True) plt.show() plt.scatter(model.al.detach().numpy()[:, 0], model.al.detach().numpy()[:, plt.title('activations') plt.show() return cost Creamos algunos datos In [6]: # Make some data X = torch.arange(-20, 20, 1).view(-1, 1).type(torch.FloatTensor)Y = torch.zeros(X.shape[0]) Y[(X[:, 0] > -4) & (X[:, 0] < 4)] = 1.0Definir la red neuronal, inicializar los pesos con el mismo valor, definir costo, optimizador y entrenar el modelo Creamos la función de pérdida de entropía cruzada In [7]: # The loss function def criterion cross(outputs, labels): out = -1 \* torch.mean(labels \* torch.log(outputs) + (1 - labels) \* torch.log(1 - < return out Definimos la red neuronal: In [8]: # Train the model # size of input D\_in = 1 # size of hidden layer # number of outputs D out = 1 # learning rate learning\_rate = 0.1 # create the model model = Net(D\_in, H, D\_out) La siguiente es la inicialización por defecto de PyTorch: In [9]: model.state\_dict() Out[9]: OrderedDict([('linear1.weight', tensor([-0.0075], [0.5364]])),('linear1.bias', tensor([-0.8230, -0.7359])), ('linear2.weight', tensor([[-0.2723, 0.1896]])),('linear2.bias', tensor([-0.0140]))]) Inicializamos todos los pesos en 1 y los sesgos en 0: model.state dict()['linear1.weight'][0]=1.0 In [10]: model.state dict()['linear1.weight'][1]=1.0 model.state dict()['linear1.bias'][0]=0.0 model.state dict()['linear1.bias'][1]=0.0 model.state dict()['linear2.weight'][0]=1.0 model.state dict()['linear2.bias'][0]=0.0 model.state dict() Out[10]: OrderedDict([('linear1.weight', tensor([[1.], [1.]])), ('linear1.bias', tensor([0., 0.])), ('linear2.weight', tensor([[1., 1.]])),
('linear2.bias', tensor([0.]))]) Optimizador y entrenamiento del modelo: In [11]: #optimizer optimizer = torch.optim.SGD(model.parameters(), lr=learning rate) #train the model usein cost cross = train(Y, X, model, optimizer, criterion cross, epochs=1000) #plot the loss plt.plot(cost cross) plt.xlabel('epoch') plt.title('cross entropy loss') 1.0 epoch 0 0.8 0.6 0.4 0.2 0.0 -10 -15 -5 10 15 -20 0 20 activations 1.0 0.8 0.6 0.4 0.2 0.0 0.0 0.2 0.4 0.6 0.8 1.0 1.0 epoch 300 0.8 0.6 0.4 0.2 0.0 -15 -i0 -5 10 15 -20 Ó activations 1.0 0.8 0.6 0.4 0.2 0.0 0.0 0.2 0.4 0.6 0.8 1.0 1.0 epoch 600 0.8 0.6 0.4 0.2 0.0 -15 -10 10 20 activations 1.0 0.8 0.6 0.4 0.2 0.0 0.2 0.4 0.6 0.0 0.8 1.0 1.0 epoch 900 0.8 0.6 0.4 0.2 0.0 -io -5 10 15 -20 -15 0 20 activations 1.0 0.8 0.6 0.4 0.2 0.0 0.0 0.2 0.4 0.6 0.8 1.0 Out[11]: Text(0.5, 1.0, 'cross entropy loss') cross entropy loss 28 26 24 22 20 18 16 200 400 600 800 1000 epoch Examinando la salida vemos que todos los parámetros cambiaron de la misma forma: In [12]: model.state\_dict() Out[12]: OrderedDict([('linear1.weight', tensor([[1.9340], [1.9340]])), ('linear1.bias', tensor([-9.0725, -9.0725])), ('linear2.weight', tensor([[-3.3976, -3.3976]])), ('linear2.bias', tensor([-0.6546]))]) yhat=model(torch.tensor([[-2.0],[0.0],[2.0]])) In [13]: yhat Out[13]: tensor([[0.3420], [0.3418],[0.3337]], grad\_fn=<SigmoidBackward>) Definimos la red neuronal, costo, optimizador y entrenamos el modelo In [14]: Train the model # size of input # size of hidden layer # number of outputs D out = 1 # learning rate learning\_rate = 0.1 # create the model model = Net(D\_in, H, D\_out) Repetimos los pasos previos pero ahora usando MSE: In [15]: #optimizer optimizer = torch.optim.SGD(model.parameters(), lr=learning rate) #train the model usein cost\_cross = train(Y, X, model, optimizer, criterion\_cross, epochs=1000) #plot the loss plt.plot(cost\_cross) plt.xlabel('epoch') plt.title('cross entropy loss') 1.0 epoch 0 0.8 0.6 0.4 0.2 0.0 10 -15 -10 -20 -5 0 15 20 activations 0.8 0.6 0.4 0.2 0.0 0.2 0.6 0.8 1.0 1.0 epoch 300 0.8 0.6 0.4 0.2 0.0 -10 <del>-</del>20 -15 -5 Ó activations 1.0 0.8 0.6 0.2 0.0 0.6 0.2 0.4 0.0 0.8 1.0 1.0 epoch 600 0.8 0.6 0.4 0.2 0.0 -10 10 -15 -20 15 activations 1.0 0.8 0.6 0.4 0.2 0.0 0.4 0.6 0.8 1.0 epoch 900 0.8 0.6 0.4 0.2 -10 ò activations 1.0 0.8 0.6 0.4 0.2 0.0 0.6 cross entropy loss 20.0 17.5 15.0 12.5 10.0 7.5 5.0 2.5 0.0 200 400 800 600 1000

epoch