In [1]: import torch import torch.nn as nn import torch.nn.functional as F import numpy as np import matplotlib.pyplot as plt %matplotlib inline In [2]: X = torch.linspace(-1, 1, 200).reshape(-1, 1)In [3]: y=(np.sin(5*(np.pi*X)))/((5*(np.pi*X))) In [4]: plt.plot(X.numpy(), y.numpy()) plt.ylabel('y') plt.xlabel('x'); 1.0 0.8 0.6 0.4 0.2 0.0 -0.2 -1.00 -0.75 -0.50 -0.25 0.00 0.25 0.50 0.75 1.00 In [5]: In [6]: class Model0(nn.Module): def __init__(self, in_features=1, h2=5, h3=10, h4=10, h5=10, h6=10, h7=10, h8=5, out_features=1): super().__init__() self.fc1 = nn.Linear(in_features,h2) # input layer self.fc2 = nn.Linear(h2, h3)self.fc3 = nn.Linear(h3, h4)self.fc4 = nn.Linear(h4, h5)self.fc5 = nn.Linear(h5, h6)self.fc6 = nn.Linear(h6, h7)self.fc7 = nn.Linear(h7, h8)self.out = nn.Linear(h8, out_features) # output layer def forward(self, x): x = F.relu(self.fc1(x))x = F.relu(self.fc2(x))x = F.relu(self.fc3(x))x = F.relu(self.fc4(x))x = F.relu(self.fc5(x))x = F.relu(self.fc6(x))x = F.relu(self.fc7(x))x = self.out(x)return x model_zero = Model0() In [8]: criterion = nn.MSELoss() In [9]: optimizer = torch.optim.Adam(model_zero.parameters(), lr=0.001) In [10]: epochs = 2000 mod0_losses = [] for i in range(epochs): i+=1 # forward step y_pred = model_zero.forward(X) # compute loss (error) loss = criterion(y_pred, y) # append loss to a list for plotting and analysis mod0_losses.append(loss) # reset gadient at each epoch, because gradients are accumulating optimizer.zero_grad() # backprop the loss through the model and compute gradients loss.backward() # optimization step to upade weights and biases optimizer.step() In [11]: mod0_losses=torch.tensor(mod0_losses) In []: In [12]: In []: In [13]: class Model1(nn.Module): def __init__(self, in_features=1, h2=10, h3=18, h4=15, h5=4, out_features=1): super().__init__() self.fc1 = nn.Linear(in_features,h2) # input layer self.fc2 = nn.Linear(h2, h3)self.fc3 = nn.Linear(h3, h4)self.fc4 = nn.Linear(h4, h5)self.out = nn.Linear(h5, out_features) # output layer def forward(self, x): x = F.relu(self.fc1(x))x = F.relu(self.fc2(x))x = F.relu(self.fc3(x))x = F.relu(self.fc4(x))x = self.out(x)return x In [14]: model_one=Model1() In [15]: model_one Model1(Out[15]: (fc1): Linear(in_features=1, out_features=10, bias=True) (fc2): Linear(in_features=10, out_features=18, bias=True) (fc3): Linear(in_features=18, out_features=15, bias=True) (fc4): Linear(in_features=15, out_features=4, bias=True) (out): Linear(in_features=4, out_features=1, bias=True) criterion = nn.MSELoss() optimizer = torch.optim.Adam(model_one.parameters(), lr=0.001) In [18]: epochs = 2000mod1_losses = [] for i in range(epochs): i+=1 # forward step y_pred_mod1 = model_one.forward(X) # compute loss (error) loss = criterion(y_pred_mod1, y) # append loss to a list for plotting and analysis mod1_losses.append(loss) # reset gadient at each epoch, because gradients are accumulating optimizer.zero_grad() # backprop the loss through the model and compute gradients loss.backward() # optimization step to upade weights and biases optimizer.step() In [19]: mod1_losses=torch.tensor(mod1_losses) In []: In [20]: In []: In [21]: class Model2(nn.Module): def __init__(self, in_features=1, h2=190, out_features=1): super().__init__() self.fc1 = nn.Linear(in_features,h2) # input layer self.out = nn.Linear(h2, out_features) # output layer def forward(self, x): x = F.relu(self.fc1(x))x = self.out(x)return x In [22]: model_two=Model2() In [23]: criterion = nn.MSELoss() In [24]: optimizer = torch.optim.Adam(model_two.parameters(), lr=0.001) In [25]: epochs = 2000 mod2_losses = [] for i in range(epochs): i+=1 # forward step $y_pred_mod2 = model_two.forward(X)$ # compute loss (error) loss = criterion(y_pred_mod2, y) # append loss to a list for plotting and analysis mod2_losses.append(loss) # reset gadient at each epoch, because gradients are accumulating optimizer.zero_grad() # backprop the loss through the model and compute gradients loss.backward() # optimization step to upade weights and biases optimizer.step() In [26]: mod2_losses=torch.tensor(mod2_losses) In [27]: plt.plot(range(epochs), mod0_losses.numpy(), 'r') plt.plot(range(epochs), mod1_losses.numpy(), 'g') plt.plot(range(epochs), mod2_losses.numpy(), 'b') plt.legend(['model0', 'model1', 'model2']) plt.ylabel('Loss') plt.xlabel('Epochs') plt.show() - model0 0.20 model1 model2 0.15 S 0.10 0.05 0.00 1000 1250 1500 1750 2000 500 250 750 0 Epochs In [28]: **#Plotting all Models** plt.plot(X.numpy(), y_pred.detach().numpy(), 'r') plt.plot(X.numpy(), y_pred_mod1.detach().numpy(),'g') plt.plot(X.numpy(), y_pred_mod2.detach().numpy(), 'b') plt.legend(['model0', 'model1', 'model2']) plt.ylabel('y') plt.xlabel('x'); 1.0 model0 model1 0.8 model2 0.6 0.4 0.2 0.0 -0.2 -1.00 -0.75 -0.50 -0.25 0.00 0.25 0.50 0.75 1.00 In []: In []: In []: In []: In [29]: In []: In []: In []: In []: In [30]: import torch import torch.nn as nn import torch.nn.functional as F import numpy as np import matplotlib.pyplot as plt **%matplotlib** inline In [31]: X1 = torch.linspace(-1, 1, 150).reshape(-1, 1)In [32]: y1=np.sign(np.sin(5*np.pi*X1)) In [33]: plt.plot(X1.numpy(), y1.numpy()) plt.ylabel('y') plt.xlabel('x'); 1.00 0.75 0.50 0.25 > 0.00 -0.25-0.50-0.75-1.00-1.00 -0.75 -0.50 -0.25 0.00 0.25 0.50 0.75 1.00 In [36]: class Modelzf2(nn.Module): def __init__(self, in_features=1, h2=5, h3=10, h4=10, h5=10, h6=10, h7=10, h8=5, out_features=1): super().__init__() self.fc1 = nn.Linear(in_features, h2) # input layer self.fc2 = nn.Linear(h2, h3)self.fc3 = nn.Linear(h3, h4)self.fc4 = nn.Linear(h4, h5)self.fc5 = nn.Linear(h5, h6)self.fc6 = nn.Linear(h6, h7)self.fc7 = nn.Linear(h7, h8)self.out = nn.Linear(h8, out_features) # output layer def forward(self, x): x = F.relu(self.fc1(x))x = F.relu(self.fc2(x))x = F.relu(self.fc3(x))x = F.relu(self.fc4(x))x = F.relu(self.fc5(x))x = F.relu(self.fc6(x))x = F.relu(self.fc7(x))x = self.out(x)return x In [37]: model_zero_f2=Modelzf2() In [38]: for param in model_zero_f2.parameters(): sum=sum+param.numel() print("No of parameters in model =", sum) No of parameters in model = 571 In [39]: criterion = nn.MSELoss() In [40]: optimizer = torch.optim.Adam(model_zero_f2.parameters(), lr=0.001) In [41]: epochs = 2000 $mod0_losses_f2 = []$ for i in range(epochs): i+=1 # forward step y_pred_mod0_f2 = model_zero_f2.forward(X1) # compute loss (error) loss = criterion(y_pred_mod0_f2, y1) # append loss to a list for plotting and analysis mod0_losses_f2.append(loss) # reset gadient at each epoch, because gradients are accumulating optimizer.zero_grad() # backprop the loss through the model and compute gradients loss.backward() # optimization step to upate weights and biases optimizer.step() In [42]: mod0_losses_f2=torch.tensor(mod0_losses_f2) In []: In [45]: In []: In [46]: class Modelof2(nn.Module): def __init__(self, in_features=1, h2=10, h3=18, h4=15, h5=4, out_features=1): super().__init__() self.fc1 = nn.Linear(in_features,h2) # input layer self.fc2 = nn.Linear(h2, h3)self.fc3 = nn.Linear(h3, h4)self.fc4 = nn.Linear(h4, h5)self.out = nn.Linear(h5, out_features) # output layer def forward(self, x): x = F.relu(self.fc1(x))x = F.relu(self.fc2(x))x = F.relu(self.fc3(x))x = F.relu(self.fc4(x))x = self.out(x)return x In [47]: model_one_f2 = Modelof2() In [48]: sum=0 for param in model_one_f2.parameters(): sum=sum+param.numel() print("parameters =", sum) parameters = 572In [49]: criterion = nn.MSELoss() In [50]: optimizer = torch.optim.Adam(model_one_f2.parameters(), lr=0.001) In [51]: epochs = 2000 $mod1_losses_f2 = []$ for i in range(epochs): i+=1 # forward step y_pred_mod1_f2 = model_one_f2.forward(X1) # compute loss (error) loss = criterion(y_pred_mod1_f2, y1) # append loss to a list for plotting and analysis mod1_losses_f2.append(loss) # reset gadient at each epoch, because gradients are accumulating optimizer.zero_grad() # backprop the loss through the model and compute gradients loss.backward() # optimization step to upate weights and biases optimizer.step() mod1_losses_f2=torch.tensor(mod1_losses_f2) In []: In [55]: In [60]: class Model2f2(nn.Module): def __init__(self, in_features=1, h2=190, out_features=1): super().__init__() self.fc1 = nn.Linear(in_features,h2) self.out = nn.Linear(h2, out_features) def forward(self, x): x = F.relu(self.fc1(x))x = self.out(x)return x In [61]: model_two_f2 = Model2f2() In [62]: model_two_f2 Model2f2(Out[62]: (fc1): Linear(in_features=1, out_features=190, bias=True) (out): Linear(in_features=190, out_features=1, bias=True) In [63]: for param in model_two_f2.parameters(): sum=sum+param.numel() print("parameters =", sum) parameters = 571In [64]: criterion = nn.MSELoss() In [65]: optimizer = torch.optim.Adam(model_two_f2.parameters(), lr=0.001) In [66]: epochs = 2000 $mod2_losses_f2 = []$ for i in range(epochs): i+=1 # forward step $y_pred_mod2_f2 = model_two_f2.forward(X1)$ # compute loss (error) loss = criterion(y_pred_mod2_f2, y1) # append loss to a list for plotting and analysis mod2_losses_f2.append(loss) # reset gadient at each epoch, because gradients are accumulating optimizer.zero_grad() # backprop the loss through the model and compute gradients loss.backward() # optimization step to upate weights and biases optimizer.step() In [67]: mod2_losses_f2=torch.tensor(mod2_losses_f2) In [70]: #x vs y_pred for all models using F2 plt.plot(range(epochs), mod0_losses_f2.numpy(), 'r') plt.plot(range(epochs), mod1_losses_f2.numpy(), 'g') plt.plot(range(epochs), mod2_losses_f2.numpy(), 'b') plt.legend(['model0', 'model1', 'model2']) plt.ylabel('Loss') plt.xlabel('Epochs') plt.show() 1.2 model0 model1 1.0 model2 0.8 SS 0.6 0.4 0.2 0.0 0 250 500 750 1000 1250 1500 1750 2000 Epochs In [71]: #Plotting all Models predicted values plt.plot(X1.numpy(), y_pred_mod0_f2.detach().numpy(),'r') plt.plot(X1.numpy(), y_pred_mod1_f2.detach().numpy(),'y') plt.plot(X1.numpy(), y_pred_mod2_f2.detach().numpy(),'b') plt.legend(['model0', 'model1', 'model2']) plt.ylabel('y') plt.xlabel('x'); 1.5 1.0 0.5 > 0.0 model1 model2 -0.5-1.0-1.5-1.00 -0.75 -0.50 -0.25 0.00 0.25 0.50 0.75 1.00 In []: In []: In []: In []: