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/var/folders/l/vws32q75dn59d0kxv7of3q3q40000g/T/ipykernel_47160/1359735096.py:14: UserWarning: To copy construct
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad(True), rather than torch.tensor(sourceTensor).
  x = torch.tensor(train_x).to(dtype=torch.float32)
/var/folders/l/vws32q75dn59d0kxv7of3q3q40000g/T/ipykernel_47160/1359735096.py:15: UserWarning: To copy constru
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad(True), rather than torch.tensor(sourceTensor).
  y = torch.tensor(train_y).to(dtype=torch.float32)
Epoch: 0 Loss: 1.2529636391148
Epoch: 100 Loss: 0.715587974807312
Epoch: 200 Loss: 0.67894240447998
Epoch: 300 Loss: 0.67933255719116
Epoch: 400 Loss: 0.678843140602118
Epoch: 500 Loss: 0.6786931753138589
Epoch: 600 Loss: 0.6788937411880493
Epoch: 700 Loss: 0.678494324208862
Epoch: 800 Loss: 0.678461925351587
Epoch: 900 Loss: 0.678347861671448
Epoch: 1000 Loss: 0.678208151276335
Epoch: 1100 Loss: 0.678224443711045
Epoch: 1200 Loss: 0.678168544481335
Epoch: 1300 Loss: 0.678121447563174
Epoch: 1400 Loss: 0.678077296124854
Epoch: 1500 Loss: 0.678037222465515
Epoch: 1600 Loss: 0.678000330294978
Epoch: 1700 Loss: 0.677947469252569
Epoch: 1800 Loss: 0.6779301166534424
Epoch: 1900 Loss: 0.677897393704607

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/var/folders/l/vws32q75dn59d0kxv7of3q3q40000g/T/ipykernel_47160/1359735096.py:43: UserWarning: To copy constru
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad(True), rather than torch.tensor(sourceTensor).
  t_x = torch.tensor(test_x).to(dtype=torch.float32)
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/var/folders/l/vws32q75dn59d0kxv7of3q3q40000g/T/ipykernel_47160/1359735096.py:15: UserWarning: To copy constru
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad(True), rather than torch.tensor(sourceTensor).
  y = torch.tensor(train_y).to(dtype=torch.float32)
Prediction: tensor([0.0949])
Expected: 0.1628191723823547
Test Loss: 0.7464152768641572
Epoch: 0 Loss: 1.188235878949439
Epoch: 100 Loss: 0.69733107673417684
Epoch: 200 Loss: 0.604076857952881
Epoch: 300 Loss: 0.604770584236145
Epoch: 400 Loss: 0.6044396758079529
Epoch: 500 Loss: 0.604286074638467
Epoch: 600 Loss: 0.6041932702048514
Epoch: 700 Loss: 0.604124724849597
Epoch: 800 Loss: 0.6040640738145007
Epoch: 900 Loss: 0.6040124297140209
Epoch: 1000 Loss: 0.6039613485338304
Epoch: 1100 Loss: 0.603912591942041
Epoch: 1200 Loss: 0.603863954540674
Epoch: 1300 Loss: 0.603816092043127
Epoch: 1400 Loss: 0.603766087173466
Epoch: 1500 Loss: 0.60371571792511
Epoch: 1600 Loss: 0.603667292163086
Epoch: 1700 Loss: 0.603621959686793
Epoch: 1800 Loss: 0.60357588259679
Epoch: 1900 Loss: 0.6035281419754028

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/var/folders/l/vws32q75dn59d0kxv7of3q3q40000g/T/ipykernel_47160/1359735096.py:43: UserWarning: To copy constru
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res_grad(True), rather than torch.tensor(sourceTensor).
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ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad(True), rather than torch.tensor(sourceTensor).
  y = torch.tensor(train_y).to(dtype=torch.float32)
Prediction: tensor([0.0272])
Expected: 0.2625302076397217
Test Loss: 0.621109560966492
Epoch: 0 Loss: 1.211025952928467
Epoch: 100 Loss: 0.64100807283088
Epoch: 200 Loss: 0.590543568134079
Epoch: 300 Loss: 0.589469015982971
Epoch: 400 Loss: 0.5891394633255005
Epoch: 500 Loss: 0.589056515468514
Epoch: 600 Loss: 0.588963237140855
Epoch: 700 Loss: 0.5888932677746893
Epoch: 800 Loss: 0.588827490805796
Epoch: 900 Loss: 0.58877032990224
Epoch: 1000 Loss: 0.5887168646388765
Epoch: 1100 Loss: 0.588667231934786
Epoch: 1200 Loss: 0.5886220932004836
Epoch: 1300 Loss: 0.588579477856453
Epoch: 1400 Loss: 0.5885380505615503
Epoch: 1500 Loss: 0.5884899500451774
Epoch: 1600 Loss: 0.588440564313423
Epoch: 1700 Loss: 0.588422650592651
Epoch: 1800 Loss: 0.588385435516357
Epoch: 1900 Loss: 0.588348686595085

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/var/folders/sl/wes3qg7d5n9dqkxvz7Of3q9400Qm/T/ipynkernel_47160/1359735096.py:43: UserWarning: To copy constur
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requir
res_grad=True), rather than torch.tensor(sourceTensor).
      t_x = torch.tensor(test_x).to(dtype=torch.float32)
/var/folders/sl/wes3qg7d5n9dqkxvz7Of3q9400Qm/T/ipynkernel_47160/1359735096.py:44: UserWarning: To copy construc
t from a tensor, it is recommended to use sourceTensor.clone().detach() or SourceTensor.clone().detach().requir
res_grad=True), rather than torch.tensor(sourceTensor).
      t_y = torch.tensor(test_y).to(dtype=torch.float32)
/var/folders/sl/wes3qg7d5n9dqkxvz7Of3q9400Qm/T/ipynkernel_47160/1359735096.py:114: UserWarning: To copy constru
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requir
res_grad=True), rather than torch.tensor(sourceTensor).
      x = torch.tensor(train_x).to(dtype=torch.float32)
/var/folders/sl/wes3qg7d5n9dqkxvz7Of3q9400Qm/T/ipynkernel_47160/1359735096.py:115: UserWarning: To copy constur
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requir
res_grad=True), rather than torch.tensor(sourceTensor).
      y = torch.tensor(train_y).to(dtype=torch.float32)
Prediction: tensor([0.1451])
Expected: 0.2331356704235077
Test Loss: 0.6280203771594193
Epoch: 0 Loss: 1.2351479613479614
Epoch: 100 Loss: 0.7165897713080554
Epoch: 200 Loss: 0.69087285249397
Epoch: 300 Loss: 0.6901394473007102
Epoch: 400 Loss: 0.6899202466010147
Epoch: 500 Loss: 0.6898622294044495
Epoch: 600 Loss: 0.689712346460011892
Epoch: 700 Loss: 0.689633846282959
Epoch: 800 Loss: 0.6895616024934912
Epoch: 900 Loss: 0.6894637153877168
Epoch: 1000 Loss: 0.6894286879596421
Epoch: 1100 Loss: 0.6893665790557661
Epoch: 1200 Loss: 0.6893067953970764
Epoch: 1300 Loss: 0.6892496347427368
Epoch: 1400 Loss: 0.6891950964927673
Epoch: 1500 Loss: 0.6891428682934461
Epoch: 1600 Loss: 0.6890920966669595
Epoch: 1700 Loss: 0.6890435814857483
Epoch: 1800 Loss: 0.6889983415603638
Epoch: 1900 Loss: 0.6889556646374046
    

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/var/folders/sl/wes3qg7d5n9dqkxvz7Of3q9400Qm/T/ipynkernel_47160/1359735096.py:43: UserWarning: To copy constur
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or SourceTensor.clone().detach().requir
res_grad=True), rather than torch.tensor(sourceTensor).
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/var/folders/sl/wes3qg7d5n9dqkxvz7Of3q9400Qm/T/ipynkernel_47160/1359735096.py:44: UserWarning: To copy constru
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      t_y = torch.tensor(test_y).to(dtype=torch.float32)
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ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requir
res_grad=True), rather than torch.tensor(sourceTensor).
      x = torch.tensor(train_x).to(dtype=torch.float32)
/var/folders/sl/wes3qg7d5n9dqkxvz7Of3q9400Qm/T/ipynkernel_47160/1359735096.py:115: UserWarning: To copy constru
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or SourceTensor.clone().detach().requir
res_grad=True), rather than torch.tensor(sourceTensor).
      y = torch.tensor(train_y).to(dtype=torch.float32)
Prediction: tensor([0.3991])
Expected: 0.95864297454834
Test Loss: 0.63984607066532
Epoch: 0 Loss: 1.3053832054138184
Epoch: 100 Loss: 0.7620270569892055
Epoch: 200 Loss: 0.704644918411775

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Epoch: 300 Loss: 0.7035305500030518
Epoch: 400 Loss: 0.7032220989663391
Epoch: 500 Loss: 0.7030153466336065
Epoch: 600 Loss: 0.702959287834167
Epoch: 700 Loss: 0.7029818998146057
Epoch: 800 Loss: 0.7028367518786662
Epoch: 900 Loss: 0.7027781009674072
Epoch: 1000 Loss: 0.7027227282524109
Epoch: 1100 Loss: 0.70267158784973356
Epoch: 1200 Loss: 0.7026217579841614
Epoch: 1300 Loss: 0.7025731203940247
Epoch: 1400 Loss: 0.7025274623161267
Epoch: 1500 Loss: 0.7024842500686664
Epoch: 1600 Loss: 0.7024430362291248
Epoch: 1700 Loss: 0.7024026531398967
Epoch: 1800 Loss: 0.7023637038258362
Epoch: 1900 Loss: 0.702325165271759



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/var/folders/al/wss32g75n9d0kxvz70f3q94000gn/T/ipykernel_47160/1359735096.py:43: UserWarning: To copy construct
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad_(True), rather than torch.tensor(sourceTensor).
 t_x = torch.tensor(test_x.t(), dtype=torch.float32)
/var/folders/al/wss32g75n9d0kxvz70f3q94000gn/T/ipykernel_47160/1359735096.py:44: UserWarning: To copy construct
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad_(True), rather than torch.tensor(sourceTensor).
 res_grad_train, rather than torch.tensor(sourceTensor).
t_y = torch.tensor(test_y.t(), dtype=torch.float32)
/var/folders/al/wss32g75n9d0kxvz70f3q94000gn/T/ipykernel_47160/1359735096.py:11: UserWarning: To copy construct
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad_(True), rather than torch.tensor(sourceTensor).
 x = torch.tensor(train_x.t(), dtype=torch.float32)
/var/folders/al/wss32g75n9d0kxvz70f3q94000gn/T/ipykernel_47160/1359735096.py:15: UserWarning: To copy construct
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad_(True), rather than torch.tensor(sourceTensor).
 y = torch.tensor(train_y.t(), dtype=torch.float32)
Prediction: tensor([0.1408])
Expected: tensor([0.7035760787010193])
Test Loss: 0.7336829304695129
Epoch: 0 Loss: 1.25625877532995
Epoch: 100 Loss: 0.703188061743124
Epoch: 200 Loss: 0.6702548265457153
Epoch: 300 Loss: 0.669442117214029
Epoch: 400 Loss: 0.6691703796386719
Epoch: 500 Loss: 0.669289974212646
Epoch: 600 Loss: 0.668935418289673
Epoch: 700 Loss: 0.6688162699508667
Epoch: 800 Loss: 0.6687558586323242
Epoch: 900 Loss: 0.668734716621399
Epoch: 1000 Loss: 0.668674111360372
Epoch: 1100 Loss: 0.668614629307861
Epoch: 1200 Loss: 0.6685563225881958
Epoch: 1300 Loss: 0.6685013473338515
Epoch: 1400 Loss: 0.6684504513134429
Epoch: 1500 Loss: 0.6684002876281738
Epoch: 1600 Loss: 0.668352723124643
Epoch: 1700 Loss: 0.6683073043822242
Epoch: 1800 Loss: 0.6682643890180859
Epoch: 1900 Loss: 0.668224453260864



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/var/folders/al/wss32g75n9d0kxvz70f3q94000gn/T/ipykernel_47160/1359735096.py:43: UserWarning: To copy construct
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  t_x = torch.tensor(test_x.t(), dtype=torch.float32)
/var/folders/al/wss32g75n9d0kxvz70f3q94000gn/T/ipykernel_47160/1359735096.py:44: UserWarning: To copy construct
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad_(True), rather than torch.tensor(sourceTensor).
  res_grad_train, rather than torch.tensor(sourceTensor).
t_y = torch.tensor(test_y.t(), dtype=torch.float32)
/var/folders/al/wss32g75n9d0kxvz70f3q94000gn/T/ipykernel_47160/1359735096.py:11: UserWarning: To copy construct
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad_(True), rather than torch.tensor(sourceTensor).
  x = torch.tensor(train_x.t(), dtype=torch.float32)
/var/folders/al/wss32g75n9d0kxvz70f3q94000gn/T/ipykernel_47160/1359735096.py:15: UserWarning: To copy construct
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad_(True), rather than torch.tensor(sourceTensor).
  y = torch.tensor(train_y.t(), dtype=torch.float32)
Prediction: tensor([0.1408])
Expected: tensor([0.7035760787010193])
Test Loss: 0.7336829304695129
Epoch: 0 Loss: 1.25625877532995
Epoch: 100 Loss: 0.703188061743124
Epoch: 200 Loss: 0.6702548265457153
Epoch: 300 Loss: 0.669442117214029
Epoch: 400 Loss: 0.6691703796386719
Epoch: 500 Loss: 0.669289974212646
Epoch: 600 Loss: 0.668935418289673
Epoch: 700 Loss: 0.6688162699508667
Epoch: 800 Loss: 0.6687558586323242
Epoch: 900 Loss: 0.668734716621399
Epoch: 1000 Loss: 0.668674111360372
Epoch: 1100 Loss: 0.668614629307861
Epoch: 1200 Loss: 0.6685563225881958
Epoch: 1300 Loss: 0.6685013473338515
Epoch: 1400 Loss: 0.6684504513134429
Epoch: 1500 Loss: 0.6684002876281738
Epoch: 1600 Loss: 0.668352723124643
Epoch: 1700 Loss: 0.6683073043822242
Epoch: 1800 Loss: 0.6682643890180859
Epoch: 1900 Loss: 0.668224453260864

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res_grad(True), rather than torch.tensor(sourceTensor).
    t_x = torch.tensor(test_x).to(dtype=torch.float32)
/var/folders/xj/wsl32g7d5n9dxxw70f3q94000m/T/ipykernel_47160/1359735096.py:44: UserWarning: To copy construct
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad(True), rather than torch.tensor(sourceTensor).
    t_y = torch.tensor(test_y).to(dtype=torch.float32)
/var/folders/xj/wsl32g7d5n9dxxw70f3q94000m/T/ipykernel_47160/1359735096.py:14: UserWarning: To copy constru
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
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    x = torch.tensor(train_x).to(dtype=torch.float32)
/var/folders/xj/wsl32g7d5n9dxxw70f3q94000m/T/ipykernel_47160/1359735096.py:15: UserWarning: To copy constru
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad(True), rather than torch.tensor(sourceTensor).
    y = torch.tensor(train_y).to(dtype=torch.float32)
Prediction: tensor([0.0353])
Expected: -0.193836954874802
Test Loss: 0.677802435403335
Epoch: 0 Loss: 1.202034141159505
Epoch: 100 Loss: 0.642698347568512
Epoch: 200 Loss: 0.617680847648059
Epoch: 300 Loss: 0.616966463725281
Epoch: 400 Loss: 0.6167298555374146
Epoch: 500 Loss: 0.616600566902161
Epoch: 600 Loss: 0.6165238618557108
Epoch: 700 Loss: 0.6164613962173462
Epoch: 800 Loss: 0.616408109664917
Epoch: 900 Loss: 0.616359531879425
Epoch: 1000 Loss: 0.6163142323493958
Epoch: 1100 Loss: 0.616271734276709
Epoch: 1200 Loss: 0.6162307858467102
Epoch: 1300 Loss: 0.6161919832229614
Epoch: 1400 Loss: 0.6161551475524902
Epoch: 1500 Loss: 0.6161200404167175
Epoch: 1600 Loss: 0.6160852593273926
Epoch: 1700 Loss: 0.6160517930984497
Epoch: 1800 Loss: 0.616018721255441
Epoch: 1900 Loss: 0.615985038963013

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/var/folders/xj/wsl32g7d5n9dxxw70f3q94000m/T/ipykernel_47160/1359735096.py:44: UserWarning: To copy constru
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad(True), rather than torch.tensor(sourceTensor).
    t_x = torch.tensor(test_x).to(dtype=torch.float32)
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    t_y = torch.tensor(test_y).to(dtype=torch.float32)
/var/folders/xj/wsl32g7d5n9dxxw70f3q94000m/T/ipykernel_47160/1359735096.py:14: UserWarning: To copy constru
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res_grad(True), rather than torch.tensor(sourceTensor).
    x = torch.tensor(train_x).to(dtype=torch.float32)
/var/folders/xj/wsl32g7d5n9dxxw70f3q94000m/T/ipykernel_47160/1359735096.py:15: UserWarning: To copy constru
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad(True), rather than torch.tensor(sourceTensor).
    y = torch.tensor(train_y).to(dtype=torch.float32)
Prediction: tensor([0.0077])
Expected: -0.01700027659535408
Test Loss: 0.607967617985856
Epoch: 0 Loss: 1.2429628372192383
Epoch: 100 Loss: 0.685939247436353
Epoch: 200 Loss: 0.670116126537323
Epoch: 300 Loss: 0.6694228649139404
Epoch: 400 Loss: 0.669174313545227
Epoch: 500 Loss: 0.669042289270496
Epoch: 600 Loss: 0.6689543724060059
Epoch: 700 Loss: 0.6688964827156607
Epoch: 800 Loss: 0.66889232812471
Epoch: 900 Loss: 0.6687790155410767
Epoch: 1000 Loss: 0.6687320470809537
Epoch: 1100 Loss: 0.6686875224111664
Epoch: 1200 Loss: 0.6686449646494768
Epoch: 1300 Loss: 0.668605029829773
Epoch: 1400 Loss: 0.668565989540494
Epoch: 1500 Loss: 0.6685284731444049
Epoch: 1600 Loss: 0.6684920787811279
Epoch: 1700 Loss: 0.6684564583003557

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Epoch: 1800 Loss: 0.6683621084945004
Epoch: 1800 Loss: 0.668366163273621

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| Epoch | Loss               |
|-------|--------------------|
| 1700  | 12.5               |
| 1750  | 0.67               |
| 1800  | 0.6683621084945004 |
| 1800  | 0.668366163273621  |



/var/folders/s1/wes3z7d5n9d0kxv70f3q94000m/T/ipykernel_47160/1359735096.py:43: UserWarning: To copy constu
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad=True), rather than torch.tensor(sourceTensor).
  t_x = torch.tensor(test_x).to(dtype=torch.float32)
/var/folders/s1/wes3z7d5n9d0kxv70f3q94000m/T/ipykernel_47160/1359735096.py:44: UserWarning: To copy constu
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad=True), rather than torch.tensor(sourceTensor).
  x = torch.tensor(train_x).to(dtype=torch.float32)
/var/folders/s1/wes3z7d5n9d0kxv70f3q94000m/T/ipykernel_47160/1359735096.py:45: UserWarning: To copy constu
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad=True), rather than torch.tensor(sourceTensor).
  y = torch.tensor(train_y).to(dtype=torch.float32)
Prediction: (5.4297e+03)
Expected: -0.760127028465271
Test Loss: 0.619696436843872
Epoch: 0 Loss: 1.2982003688812256
Epoch: 100 Loss: 0.7997296371459961
Epoch: 200 Loss: 0.6323673120981726
Epoch: 300 Loss: 0.6290260909179688
Epoch: 400 Loss: 0.628627589398708
Epoch: 500 Loss: 0.6282695571380615
Epoch: 600 Loss: 0.6281498962670898
Epoch: 700 Loss: 0.628075532756042
Epoch: 800 Loss: 0.628090808868408
Epoch: 900 Loss: 0.62795674620783997
Epoch: 1000 Loss: 0.6279124617535599
Epoch: 1100 Loss: 0.627817517852783
Epoch: 1200 Loss: 0.627833545207973
Epoch: 1300 Loss: 0.627798974514076
Epoch: 1400 Loss: 0.627766251546259
Epoch: 1500 Loss: 0.6277348391612292
Epoch: 1600 Loss: 0.6277046232634595
Epoch: 1700 Loss: 0.6276741623878479
Epoch: 1800 Loss: 0.62764477279736
Epoch: 1900 Loss: 0.627615479633968

13
12
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| Epoch | Loss              |
|-------|-------------------|
| 1700  | 12.5              |
| 1750  | 0.67              |
| 1800  | 0.62764477279736  |
| 1800  | 0.627615479633968 |



/var/folders/s1/wes3z7d5n9d0kxv70f3q94000m/T/ipykernel_47160/1359735096.py:43: UserWarning: To copy constu
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad=True), rather than torch.tensor(sourceTensor).
  t_x = torch.tensor(test_x).to(dtype=torch.float32)
/var/folders/s1/wes3z7d5n9d0kxv70f3q94000m/T/ipykernel_47160/1359735096.py:44: UserWarning: To copy constu
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad=True), rather than torch.tensor(sourceTensor).
  x = torch.tensor(train_x).to(dtype=torch.float32)
/var/folders/s1/wes3z7d5n9d0kxv70f3q94000m/T/ipykernel_47160/1359735096.py:45: UserWarning: To copy constu
ct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requi
res_grad=True), rather than torch.tensor(sourceTensor).
  y = torch.tensor(train_y).to(dtype=torch.float32)
Prediction: (5.4297e+03)
Expected: -0.760127028465271
Test Loss: 0.619696436843872
Epoch: 0 Loss: 1.2982003688812256
Epoch: 100 Loss: 0.7997296371459961
Epoch: 200 Loss: 0.6323673120981726
Epoch: 300 Loss: 0.6290260909179688
Epoch: 400 Loss: 0.628627589398708
Epoch: 500 Loss: 0.6282695571380615
Epoch: 600 Loss: 0.6281498962670898
Epoch: 700 Loss: 0.628075532756042
Epoch: 800 Loss: 0.628090808868408
Epoch: 900 Loss: 0.62795674620783997
Epoch: 1000 Loss: 0.6279124617535599
Epoch: 1100 Loss: 0.627817517852783
Epoch: 1200 Loss: 0.627833545207973
Epoch: 1300 Loss: 0.627798974514076
Epoch: 1400 Loss: 0.627766251546259
Epoch: 1500 Loss: 0.6277348391612292
Epoch: 1600 Loss: 0.6277046232634595
Epoch: 1700 Loss: 0.6276741623878479
Epoch: 1800 Loss: 0.62764477279736
Epoch: 1900 Loss: 0.627615479633968

```

```

Expected: 0.26450324058532715
Test Loss: 0.664580297470093
Epoch: 0 Loss: 1.234682440757315
Epoch: 100 Loss: 0.472641515731815
Epoch: 200 Loss: 0.66228524684906
Epoch: 300 Loss: 0.46136948855103
Epoch: 400 Loss: 0.861421120167786
Epoch: 500 Loss: 0.6613009572029114
Epoch: 600 Loss: 0.66121506690979
Epoch: 700 Loss: 0.661142587617432
Epoch: 800 Loss: 0.6610761880874634
Epoch: 900 Loss: 0.661021172659746
Epoch: 1000 Loss: 0.66094585878219604
Epoch: 1100 Loss: 0.660888526651104
Epoch: 1200 Loss: 0.660830080591878
Epoch: 1300 Loss: 0.660774407970566
Epoch: 1400 Loss: 0.660721696603394
Epoch: 1500 Loss: 0.6606723070144653
Epoch: 1600 Loss: 0.6606242504939555
Epoch: 1700 Loss: 0.6605780124646307
Epoch: 1800 Loss: 0.660533360574959
Epoch: 1900 Loss: 0.660488618782288

```

```

Prediction: tensor([0.7277])
Expected: 0.68389558721426
Test Loss: 0.6692646741867065
/usr/local/lib/python3.6/dist-packages/torch/nn/module.py:470: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  return torch._tensor_strides_and_metadata(self._tensor, self._storage, self._size, self._stride, self._requires_grad)
/usr/local/lib/python3.6/dist-packages/torch/nn/module.py:470: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  return torch._tensor_strides_and_metadata(self._tensor, self._storage, self._size, self._stride, self._requires_grad)

```

Question 3 (2 points)

We're now going to think about how easy it is to solve the general multiplication problem for real numbers: $y = x_1 * x_2$, when $x_1, x_2 \in \mathbb{R}$ are not bounded to the limited range $\{-1000, 1000\}$.

Define a "simple" feed-forward neural network as one where each layer l takes input from only the previous layer $l - 1$. Let's assume our simple feed-forward network only uses "standard" nodes, to which a weighted sum $z = \mathbf{w}^T \mathbf{x}$ of inputs, given weights \mathbf{w} , and then apply a differentiable activation function $f()$ to z . Example "standard" nodes include ReLU, Leaky ReLU, Sigmoid, TanH, and the linear/identity function.

Define "correctly" performing multiplication as estimating $y = x_1 * x_2$ to 2 decimal places of precision (i.e. $|\hat{y} - y| < 0.01$). Here, \hat{y} is the network's result and y is the true answer.

Is it possible to make a "simple" neural network that can correctly perform multiplication for any arbitrary pair $x_1, x_2 \in \mathbb{R}$? **Support your answer.**

Hint: Think about what a "standard" node calculates. Think about how you would implement multiplication with addition.

YOUR ANSWER HERE

No, it is not possible for a network to learn multiplication.

A standard node calculates a linear combination among the input variables, and we can rewrite multiplication as $\log(y) = \log(a) + \log(b)$. So essentially, after we apply log transformation on the dataset, we are actually making the algorithm to learn addition rather than multiplication. A neural network in the form $f(x) = \sigma(Ax + b)$ without log transformation on the data and labels would be insufficient because we could not represent multiplication with linear combination among the independent variables.

Question 4 (2 points)

Suppose you want to build a fully convolutional network, `YouNet`, which converts an image with cropped `imageNet` dimensions (256, 256), to MNIST dimensions (28, 28), and back to (256, 256). This network contains a convolutional layer that maps an image from (256, 256) \rightarrow (28, 28), and a transposed convolutional layer that maps an image from (28, 28) \rightarrow (256, 256).

```
import torch
import torch.nn as nn

class YouNet(nn.Module):
    def __init__(self,
                 kernel_1: tuple[int, int],
                 kernel_2: tuple[int, int],
                 stride_1: tuple[int, int] = (1, 1),
                 stride_2: tuple[int, int] = (1, 1)):
        super().__init__()
        self.conv1 = nn.Conv2d(1, kernel_1, stride=stride_1)
        self.conv2 = nn.ConvTranspose2d(1, kernel_2, stride=stride_2)

    def forward(self, x: torch.Tensor) -> tuple[torch.Tensor, torch.Tensor]:
        mnist = self.conv1(x)
        imagenet = self.conv2(mnist)
        return mnist, imagenet
```

- Find valid kernel sizes for the convolutional layers when `stride=(1, 1)`. By 'valid', we mean that using the kernel results in a `mnist.shape` and an `imagenet.shape` that pass the assert statement below.

```
kernel_1 = 229
kernel_2 = 229

network = YouNet(kernel_1, kernel_2)
mnist, imagenet = network(torch.zeros(1, 256, 256))
assert mnist.shape == (1, 1, 28, 28)
assert imagenet.shape == (1, 1, 256, 256)
```

- Find valid kernel sizes for when `stride=(8, 8)`.

```
kernel_1 = 40
kernel_2 = 40

network = YouNet(kernel_1, kernel_2, stride_1=(8, 8), stride_2=(8, 8))
mnist, imagenet = network(torch.zeros(1, 256, 256))

assert mnist.shape == (1, 1, 28, 28)
assert imagenet.shape == (1, 1, 256, 256)
```

- Suppose instead of processing an image of size (256, 256) with the `YouNet` you implemented in part 2, you want to process an input image of size (257, 257). What would the sizes of the two processed output images be? Why doesn't the `imagenet` output have dimensionality (257, 257)? (Hint: Does the strided convolution process all the rows and columns of the original image?)

YOUR ANSWER GOES HERE

The size of mnist would be (28, 28) and the imagenet output would be (256, 256). This is because the strided convolution does not process all the rows and columns of the original image, and therefore the last row and column would be strided.

- Suppose you are processing an image of size (264, 264) with the `YouNet` implemented in part 2. What would be the sizes of the two processed images output by the network? For an image of this size, does the `imagenet` output have the same size as the input?

The mnist output has dimension (28, 28) and the imagenet out has dimension (264, 264). Therefore, the `imagenet` output does have the same size as the input.

YOUR ANSWER GOES HERE

```
kernel_1 = 40
kernel_2 = 40

network = YouNet(kernel_1, kernel_2, stride_1=(8, 8), stride_2=(8, 8))
mnist, imagenet = network(torch.zeros(1, 1, 264, 264))

print(mnist.shape, imagenet.shape)

torch.Size([1, 1, 29, 29]) torch.Size([1, 1, 264, 264])
```

Question 5 (3 points)

The paper [Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift](#) is in our class readings list

Specifically, you are to reproduce the experiment in [section 4.1](#) of the paper, providing an output figure like [figure 1\(a\)](#).

This means making a network module that has [the architecture described in section 4.1](#) of the paper. You will need to create two alternative versions of your network module: one model that has at least one batch normalization layer, another module that has no batch normalization layer. Pytorch provides a handy [function](#) or [two](#) to help with this.

- Note, you don't have to duplicate their weight initializations. Using the default weight initializations is fine.

The famous [MNIST](#) dataset is available in [torchvision.datasets](#). You can download it just by declaring the dataset and specifying `download=True`. See the [torchvision.dataset](#) docs for more on that.

- Note, `torchvision.datasets` has both test and train datasets available for MNIST.
- Note, they never specify in the paper HOW BIG the testing (I think they mean VALIDATION, actually) set they use is. Yours could be just a couple of hundred examples.
- Note that you don't have to run the test after every training step. Every 20 training steps would be fine.

1. Put your graph similar to [figure 1\(a\)](#) from the paper below.

YOUR ANSWER GOES HERE

1. Put your analysis of the effectiveness of batch normalization for your network and dataset below. Did you duplicate their results?

YOUR ANSWER GOES HERE

Based on the graphs that I generated, it seems like Batch normalization does help making the distributions more stable and reducing the internal covariate shift. But in my case, it achieves a slightly higher test accuracy (96.94%) compared with the baseline model (96.06%) after 50 epochs.

1. Put all your code (including network modules, data loaders, testing and training code) below.

```
import time

class Net(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(28*28,100)
        self.fc2 = nn.Linear(100, 100)
        self.fc3 = nn.Linear(100, 100)
        self.fc4 = nn.Linear(100, 10)
        self.sigmoid = torch.nn.Sigmoid()
```

```
def forward(self, x):
    batch_size, channels, width, height = x.size()
    x = x.view(batch_size, -1)
    x = self.sigmoid(self.fc1(x))
    x = self.sigmoid(self.fc2(x))
    x = self.sigmoid(self.fc3(x))
    x = self.sigmoid(self.fc4(x))
    return x

net = Net()
net

]: Net(
  (fc1): Linear(in_features=784, out_features=100, bias=True)
  (fc2): Linear(in_features=100, out_features=100, bias=True)
  (fc3): Linear(in_features=100, out_features=100, bias=True)
  (fc4): Linear(in_features=100, out_features=10, bias=True)
  (sigmoid): Sigmoid()
)

class BNNet(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(28*28, 100)
        self.fc2 = nn.Linear(100, 100)
        self.fc3 = nn.Linear(100, 100)
        self.fc4 = nn.Linear(100, 10)
        self.sigmoid = torch.nn.Sigmoid()
        self.bn1 = torch.nn.BatchNorm1d(784)
        self.bn2 = torch.nn.BatchNorm1d(100)

    def forward(self, x):
        batch_size, channels, width, height = x.size()
        x = x.view(batch_size, -1)
        x = self.sigmoid(self.fc1(self.bn1(x)))
        x = self.sigmoid(self.fc2(self.bn2(x)))
        x = self.sigmoid(self.fc3(self.bn2(x)))
        x = self.sigmoid(self.fc4(self.bn2(x)))
        x = self.fc4(x)
        return x

bn = BNNet()
bn

]: BNNet(
  (fc1): Linear(in_features=784, out_features=100, bias=True)
  (fc2): Linear(in_features=100, out_features=100, bias=True)
  (fc3): Linear(in_features=100, out_features=100, bias=True)
  (fc4): Linear(in_features=100, out_features=10, bias=True)
  (sigmoid): Sigmoid()
  (bn1): BatchNorm1d(784, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (bn2): BatchNorm1d(100, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
```



```
def training_loop(input_model, save_path, epochs, batch_size, device="cpu"):\n    # initialize model\n    model = input_model\n    model.to(device) # we'll cover this in the next section!\n\n    # initialize an optimizer to update our model's parameters during training\n    optimizer = torch.optim.Adam(model.parameters())\n\n    # make a new directory in which to download the MNIST dataset\n    data_dir = "./data/"\n\n    # initialize a Transform object to prepare our data\n    transform = torchvision.transforms.Compose([\n        torchvision.transforms.ToTensor(),\n        lambda x: x/255,\n        lambda x: x.float(),\n    ])\n\n    # load MNIST "test" dataset from disk\n    mnist_test = torchvision.datasets.MNIST(data_dir, train=False, download=False, transform=transform)\n\n    # load MNIST "train" dataset from disk and set aside a portion for validation\n    mnist_train_full = datasets.MNIST(data_dir, train=True, download=False, transform=transform)\n    mnist_train, mnist_val = torch.utils.data.random_split(mnist_train_full, [55000, 5000])\n\n    # initialize a DataLoader object for each dataset\n    train_dataloader = torch.utils.data.DataLoader(mnist_train, batch_size=batch_size, shuffle=True)\n    val_dataloader = torch.utils.data.DataLoader(mnist_val, batch_size=batch_size, shuffle=False)\n    test_dataloader = torch.utils.data.DataLoader(mnist_test, batch_size=batch_size, shuffle=False)\n\n    # a PyTorch categorical cross-entropy loss object\n    loss_fn = torch.nn.CrossEntropyLoss()\n\n    # time training process\n    st = time.time()\n\n    val_stat = []\n    epoch_stat = []\n\n    # time to start training!\n    for epoch_idx, epoch in enumerate(range(epochs)):\n\n        best_acc = 0.0\n\n        train_loss = 0.0\n        train_acc = 0.0\n        train_total = 0\n        model.train()\n        for batch_idx, batch in enumerate(train_dataloader):\n\n            optimizer.zero_grad()\n\n            x, y = batch\n            x = x.to(device)\n            y = y.to(device)\n\n            # generate predictions and compute loss\n            output = model(x)\n            loss = loss_fn(output, y)\n\n            # compute accuracy\n            preds = output.argmax(dim=1)\n            acc = preds.eq(y).sum().item()/len(y)\n\n            # compute gradients and update model parameters\n            loss.backward()\n            optimizer.step()\n\n            # update statistics\n            train_loss += (loss * len(x))\n            train_acc += (acc * len(x))\n            train_total += len(x)\n\n        #print every 20 steps\n        if batch_idx > 0 and (batch_idx + 1) % 20 == 0:\n\n            train_loss /= train_total\n            train_acc /= train_total\n\n            # perform validation once per 20 steps\n            val_loss = 0.0\n            val_acc = 0.0\n            val_total = 0\n            model.eval()\n            for vbatch_idx, vbatch in enumerate(val_dataloader):\n\n                # don't compute gradients during validation\n                with torch.no_grad():\n\n                    # unpack data and labels\n                    vx, vy = vbatch\n                    vx = vx.to(device) # we'll cover this in the next section!\n                    vy = vy.to(device) # we'll cover this in the next section!\n\n                    # generate predictions and compute loss\n                    output = model(vx)\n                    loss = loss_fn(output, vy)\n\n                    # compute accuracy\n                    preds = output.argmax(dim=1)\n                    acc = preds.eq(vy).sum().item()/len(vy)\n\n                    # update statistics\n                    val_loss += (loss * len(vx))\n                    val_acc += (acc * len(vx))\n                    val_total += len(vx)\n\n            val_loss /= val_total\n            val_acc /= val_total\n\n            val_stat.append(val_acc)\n            epoch_stat.append(batch_idx + 1 + (epoch_idx) * len(train_dataloader))\n\n        if val_acc > best_acc:\n\n            best_acc = val_acc\n            torch.save(model.state_dict(), save_path)\n\n    return model, save_path, val_stat, epoch_stat\n\nIn [290]:\nbatch_size = 60\nepochs = 50\nmodel, save_path, val_stat, epoch_stat = training_loop(Net(), "hw2_baseline.pt", epochs, batch_size, "cpu")\n\nIn [296]:\nbn_model, bn_save_path, bn_val_stat, bn_epoch_stat = training_loop(BNNet(), "hw2_bn.pt", epochs, batch_size, "cpu")\n\nIn [302]:\n# Display activations\n\nplt.plot(epoch_stat, val_stat, 'k--', label = f"Train (baseline) score {val_stat[-1]:.4f}")\nplt.plot(bn_epoch_stat, bn_val_stat, 'b-', label = f"Train (BatchNorm) score {bn_val_stat[-1]:.4f}")\nplt.legend()\nplt.show()\n\n10\n0.9\n0.8\n0.7\n0.6\n0.5\n0.4\n0.3\n0.2\n0\n010000200003000040000\n--- Train (baseline) score 0.9606\n— Train (BatchNorm) score 0.9694
```

In []:

In []: