

Special Topics: Deep Learning: Sheet 1| COMP 499/691

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Assignment 01 Answer

```
In [ ]: import numpy as np
import math
import matplotlib.pyplot as plt
import torch
import torchvision
import torchvision.transforms as transforms
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import timeit
```

```
In [5]: def imshow(img):
img = img / 2 + 0.5      # unnormalize
npimg = img.numpy()
plt.imshow(np.transpose(npimg, (1, 2, 0)))
```

1.B

```
In [43]: param_dict={
    "W1": torch.randn((13, 20), requires_grad=True),
    "W2": torch.randn((20, 10), requires_grad=True),
    "W3": torch.randn((10, 1), requires_grad=True),
    "B1": torch.randn((20), requires_grad=True),
    "B2": torch.randn((10), requires_grad=True),
    "B3": torch.randn((1), requires_grad=True)
}
```

```
In [47]: ## Define the network
def my_nn(input,param_dict):
    W1=param_dict["W1"]
    W2=param_dict["W2"]
    W3=param_dict["W3"]
    B1=param_dict["B1"]
    B2=param_dict["B2"]
    B3=param_dict["B3"]
    h1 = torch.tanh((input @ W1) + B1)
    h2 = torch.tanh((h1 @ W2) + B2)
    output = h2 @ W3 + B3
    # output=torch.flatten(output.reshape(-1,1))
    return output/1000
```

1.E

```
In [48]: example_data = torch.randn(( 20,13))
# example_data
```

1.D

```
In [53]: from sklearn.datasets import load_boston
X, y = load_boston(return_X_y=True)
y= torch.as_tensor(y).float()
# print(X)

loss_fn = torch.nn.MSELoss(size_average=False)
train_losses = []
train_counter = []
parameter_list = param_dict.values()
optimizer = optim.SGD(parameter_list, lr=0.001,momentum=0.01)
start = timeit.default_timer()
y_pred=[]
for i in range(15):
    optimizer.zero_grad()
    y_pred=my_nn(torch.as_tensor(X).float(),param_dict)
#     print(y)
#     print(y_pred)
#     print(y_pred[0].size())
#     print(y_pred)
#     print(y)
    loss = loss_fn(y_pred, y)
    print("MSE=",loss.item())
    loss.backward()
    optimizer.step()
    train_losses.append(loss.item())
    train_counter.append(i)
```

```
MSE= 96401352.0
MSE= 95561328.0
MSE= 94722312.0
MSE= 93892960.0
MSE= 93072504.0
MSE= 92261576.0
MSE= 91459680.0
MSE= 90667224.0
MSE= 89883904.0
MSE= 89109376.0
MSE= 88342960.0
MSE= 87585816.0
MSE= 86837600.0
MSE= 86097416.0
MSE= 85365352.0
```

Boston dataset requires feature engineering at frist

2.A

```
In [73]: def exp_reducer(w,x):
          return torch.tanh_(w.mm(x))
import torch
Tensors={"W1": torch.rand(30, 2, requires_grad=True),
"W2" : torch.rand(30, 30, requires_grad=True),
"W3" : torch.rand(10, 30, requires_grad=True),
"X": torch.rand(2, 1, requires_grad=True)
}
y=torch.autograd.functional.jacobian(exp_reducer,(Tensors["W1"], Tensors["X"]),create_graph=True)
y=torch.autograd.functional.jacobian(exp_reducer,(Tensors["W2"], y[0][0][0]),create_graph=True)
y=torch.autograd.functional.jacobian(exp_reducer,(Tensors["W3"], y[0][0][0]),create_graph=True)
print(y[1].shape)
```

```
torch.Size([10, 30, 30, 30])
```

2.B

```
In [75]: ### import torch
Tensors={"W1": torch.rand(30, 2, requires_grad=True),
"W2" : torch.rand(30, 30, requires_grad=True),
"W3" : torch.rand(10, 30, requires_grad=True),
"X": torch.rand(2, 1, requires_grad=True)
}
# Tensors["X"].zero_grad()
y=torch.tanh_(Tensors["W1"].mm(Tensors["X"]))
# print(y)
y.sum().backward(retain_graph=True)
y=torch.tanh_(Tensors["W2"].mm(y))
y.sum().backward(retain_graph=True)
y=torch.tanh_(Tensors["W3"].mm(y))
y.sum().backward(retain_graph=True)
print("inp.grad")
print(Tensors["X"].grad)
```

```
inp.grad
tensor([[6.1222],
        [6.7758]])
```

2.e

Forward Mode AutoDif: $M^3 + M^2 \text{ Ops} = O(M^3)$

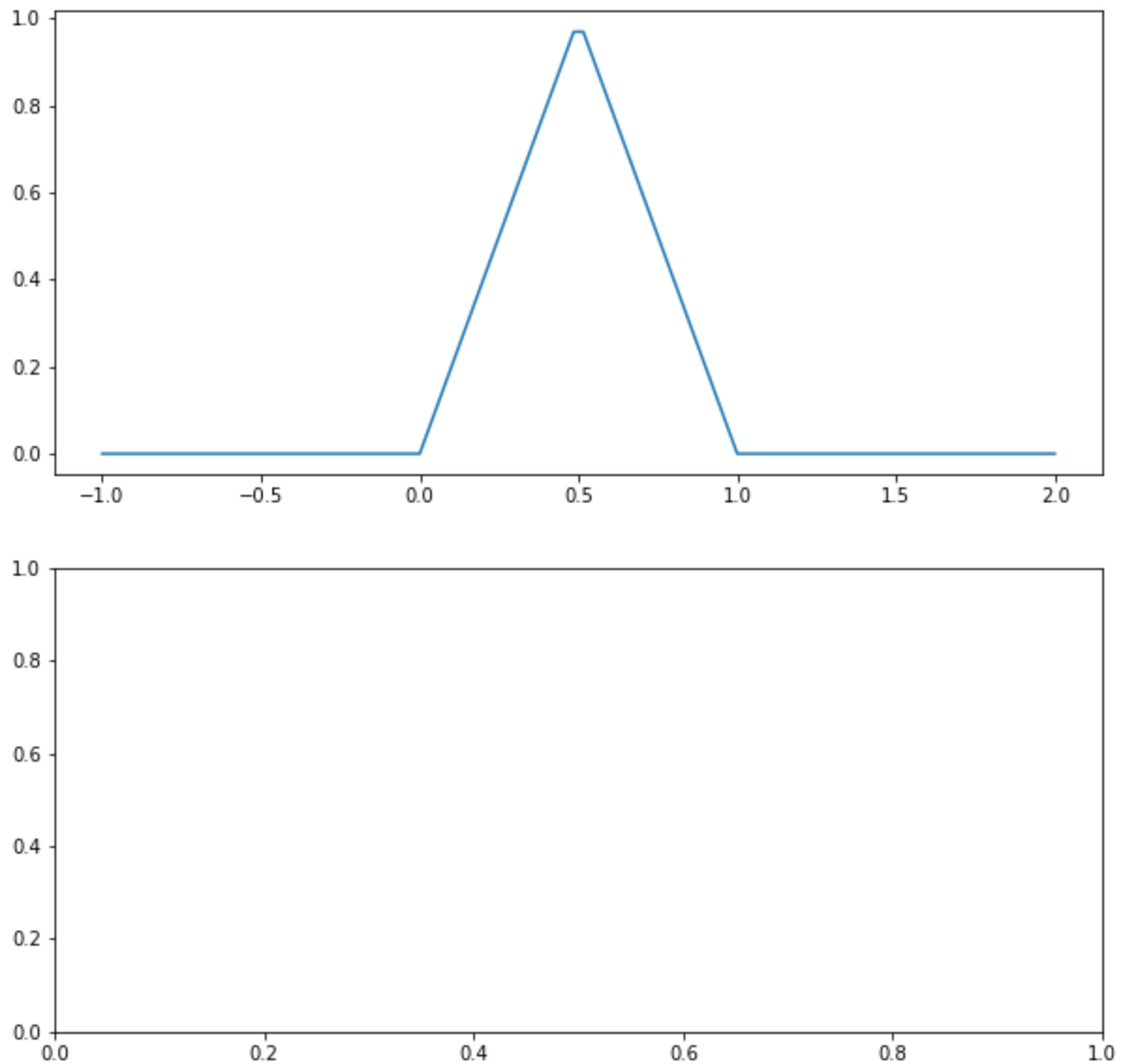
Reverse Mode AutoDiff (Backprop): $M^2 + M^2 \text{ Ops} = O(M^2)$

- Finite difference requires $2 \cdot D$ forward passes, with D parameters
- Reverse Mode AD, often $\sim 2x$ forward pass
- Forward Mode AD speed / forward pass would increase with width

3.b

```
In [255]: def my_fun(x):  
    if x>0 and x<=0.5:  
        return 2*x  
    elif x>=0.5 and x<=1:  
        return 2*(1-x)  
    else:  
        return 0  
  
fig, axs = plt.subplots(2,figsize=(10,10))  
x=np.linspace(-1,2,100)  
y=[]  
for i in x:  
    y.append(my_fun(i))  
axs[0].plot(x, y)
```

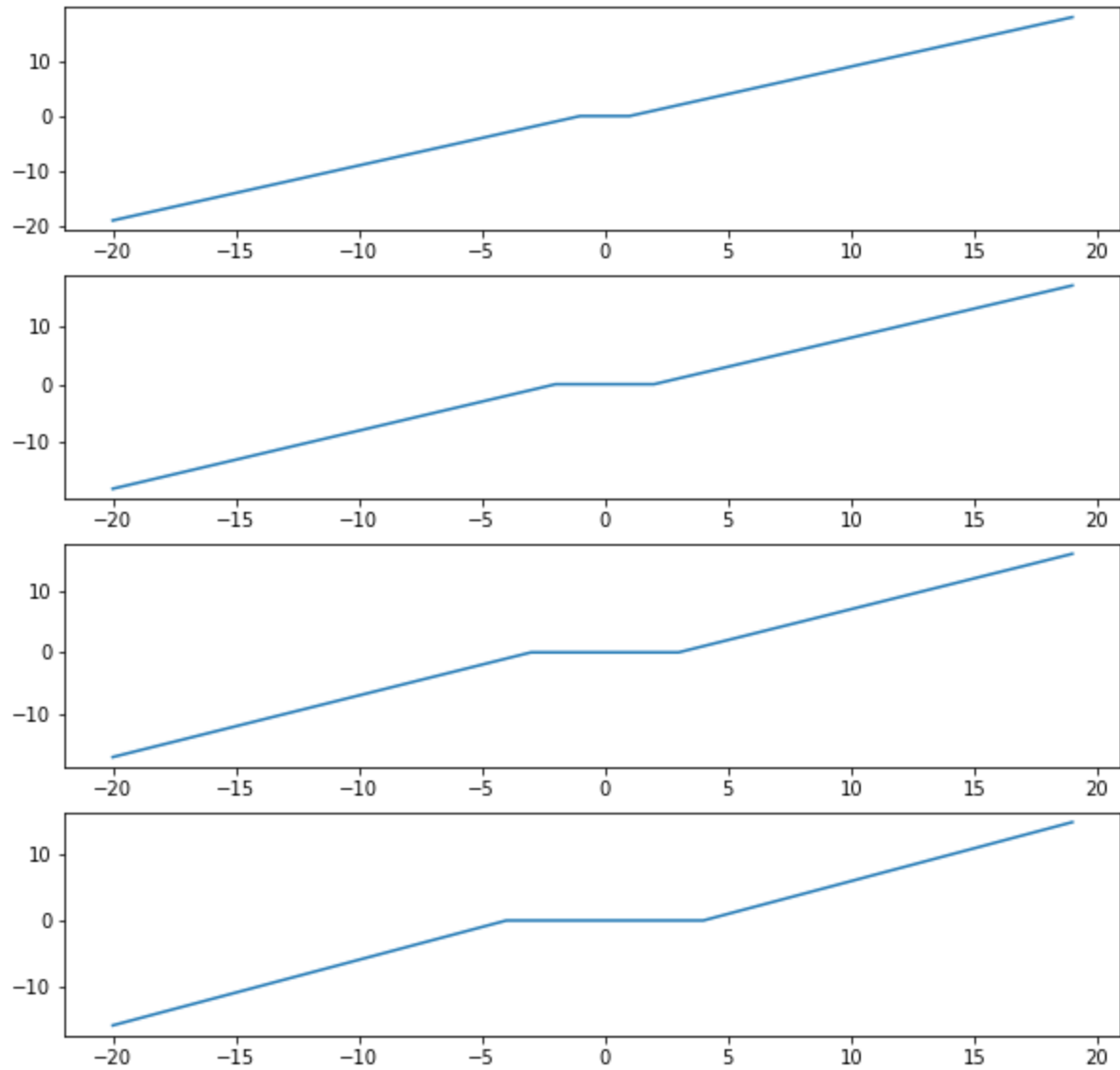
Out[255]: [<matplotlib.lines.Line2D at 0x812ede4a08>]



```
In [240]: def my_fun(x,s):
            return max(abs(x)-s,0)*math.copysign(1, x)

start=20
x=range(-1*start,start)

s=[1,2,3,4]
fig, axs = plt.subplots(4,figsize=(10,10))
for z in s:
    y=[]
    for i in x:
        y.append(my_fun(i,z))
    axs[z-1].plot(x, y,label="s="+str(z)+",x=["+str(start)+", "+str(start)+"]")
```



```
In [55]: import torch.nn as nn
import torch.nn.functional as F

class my_model(nn.Module):
    def __init__(self, depth):
        super(my_model, self).__init__()
        self.depth=depth
        self.post_activation=np.zeros(self.depth)
        self.linears = nn.ModuleList([nn.Linear(28*28, 50)])
        self.linears.extend([nn.Linear(50, 50) for i in range(1, self.depth-1)])
        self.linears.append(nn.Linear(50, 10))

    def forward(self, x):
        x= x.view(-1, 28*28)
        x.requires_grad_(True)
        for i in range(len(self.linears)):
            x =F.tanh(self.linears[i](x))
#             x =F.sigmoid(self.linears[i](x))
            self.post_activation[i]=(self.post_activation[i]+ F.log_softmax(x).mean())/2
        return F.softmax(x)
```

4.B

```
In [ ]: def xavier(ni,no):
    return np.random.randn(ni,no)*np.math.sqrt(6/(ni+no))
xavier(100,100)

def weights_init_uniform(m,d):
    classname = m.__class__.__name__
    # for every Linear layer in a model..
    for layer in m.linears:
        # apply a uniform distribution to the weights and a bias=0
        layer.weight.data.uniform_(-1*d, d)
        layer.bias.data.fill_(0)
    return m
```

```
In [ ]: batch_size_train=32
batch_size_test=32
train_loader = torch.utils.data.DataLoader(
    torchvision.datasets.MNIST('/files/', train=True, download=True,
                               transform=torchvision.transforms.Compose([
                                   torchvision.transforms.ToTensor(),
                                   torchvision.transforms.Normalize(
                                       (0.1307,), (0.3081,))
                               ])),
    batch_size=batch_size_train, shuffle=True)

test_loader = torch.utils.data.DataLoader(
    torchvision.datasets.MNIST('/files/', train=False, download=True,
                               transform=torchvision.transforms.Compose([
                                   torchvision.transforms.ToTensor(),
                                   torchvision.transforms.Normalize(
                                       (0.1307,), (0.3081,))
                               ])),
    batch_size=batch_size_test, shuffle=True)

examples = enumerate(test_loader)
batch_idx, (example_data, example_targets) = next(examples)
print(example_data.shape)
```

4.C

```
In [160]: ds=[0.01,0.1,2]
loss=torch.nn.CrossEntropyLoss()
models=[]
for d in ds:
    model = my_model(8)
    model=weights_init_uniform(model,d)
    models.append(model)

for model in models:
    model.train()
    # print(model)
    # print(model.linears[1].weight.data)
    # print(model.linears[1].bias.data)
    for batch_idx, (data, target) in enumerate(train_loader):
        # optimizer.zero_grad()
        output = model(data)
        # print( output.shape)
        output.retain_grad()
        # print(target.shape)
        loss = F.nll_loss(output, target)
        loss.backward()
```

c:\program files\python37\lib\site-packages\ipykernel_launcher.py:18: UserWarning: Implicit dimension choice for log_softmax has been deprecated. Change the call to include d

im=X as an argument.
c:\program files\python37\lib\site-packages\ipykernel_launcher.py:19: UserWarning: Implicit dimension choice for log_softmax has been deprecated. Change the call to include d

```

In [171]: a=range(1,len(model.linears)+1)
          idx=0

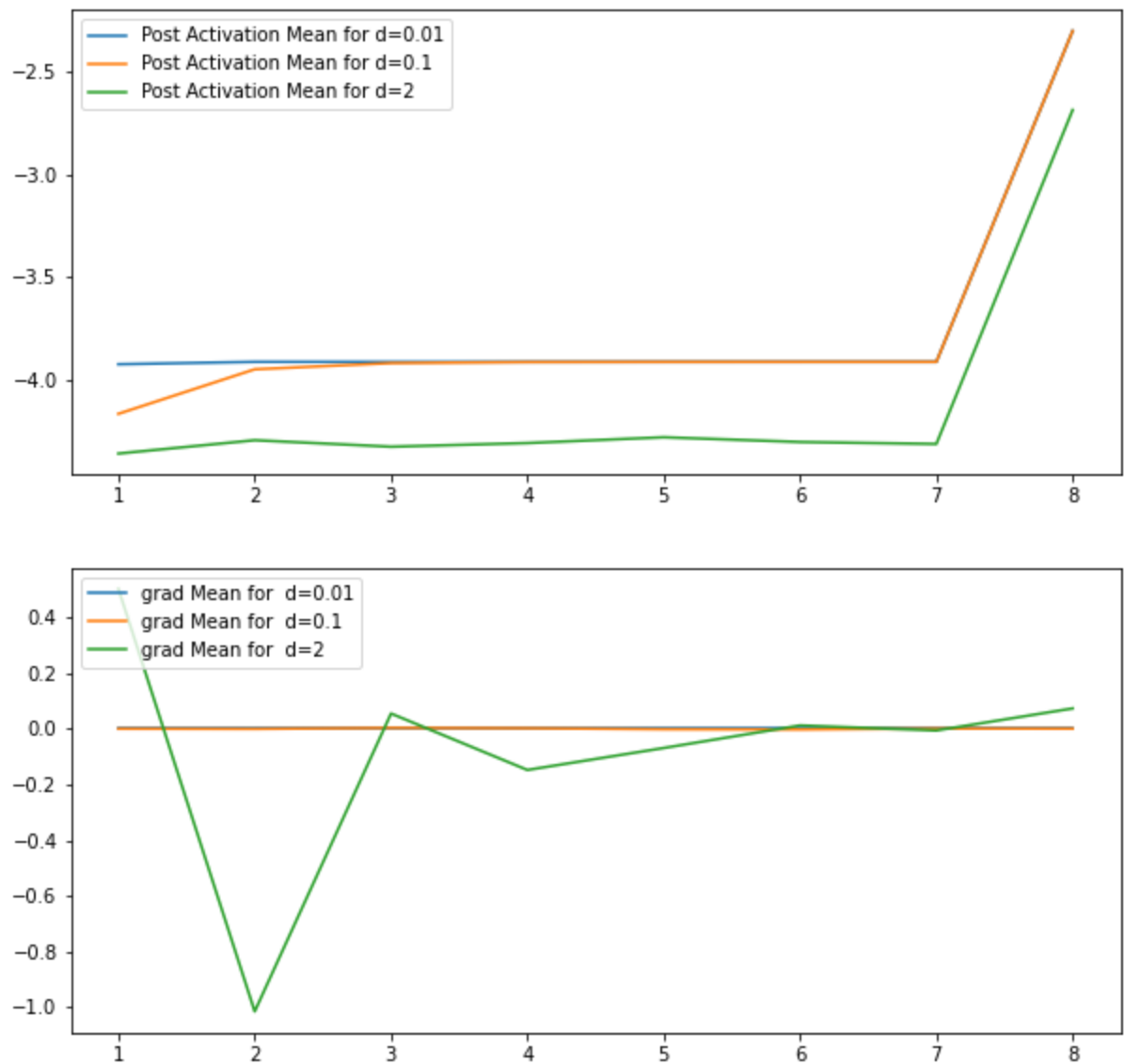
          fig, axs = plt.subplots(2,figsize=(10,10))

          for model in models:
              c=[]
              for l in model.linears:
                  c.append(l.weight.grad.mean())
              axs[0].plot(a, model.post_activation, label="Post Activation Mean for d="+str(ds[idx]
              ))
              axs[1].plot(a, c, label="grad Mean for d="+str(ds[idx]))
              idx=idx+1

          axs[1].legend(loc="upper left")
          axs[0].legend(loc="upper left")

```

Out[171]: <matplotlib.legend.Legend at 0x812c3d9b08>




```
In [188]: class Net(nn.Module):
def __init__(self):
    super(Net, self).__init__()
    self.conv1 = nn.Conv2d(1, 10, kernel_size=5)
    self.conv2 = nn.Conv2d(10, 20, kernel_size=5)
    self.conv2_drop = nn.Dropout2d()
    self.fc1 = nn.Linear(320, 50)
    self.fc2 = nn.Linear(50, 10)

def forward(self, x):
    x = F.relu(F.max_pool2d(self.conv1(x), 2))
    x = F.relu(F.max_pool2d(self.conv2_drop(self.conv2(x)), 2))
    x = x.view(-1, 320)
    x = F.relu(self.fc1(x))
    x = F.dropout(x, training=self.training)
    x = self.fc2(x)
    return F.log_softmax(x)
```

```

In [189]: criterion=torch.nn.CrossEntropyLoss()
model = Net()
train_losses = []
train_counter = []
optimizer = optim.SGD(model.parameters(), lr=0.001,momentum=0.01)
for epoch in range(5):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        optimizer.zero_grad()
        output = model(data)
        # print( output.shape)
        output.retain_grad()
        # print(target.shape)
        loss = criterion(output, target)
        loss.backward()
        optimizer.step()
        train_losses.append(loss.item())
        train_counter.append((batch_idx*32) + (epoch*len(train_loader.dataset)))
    print('Train Epoch: {} [{} / {}] ({:.0f}%) \tLoss: {:.6f}'.format(
        epoch, batch_idx * len(data), len(train_loader.dataset),
        100. * batch_idx / len(train_loader), loss.item()))

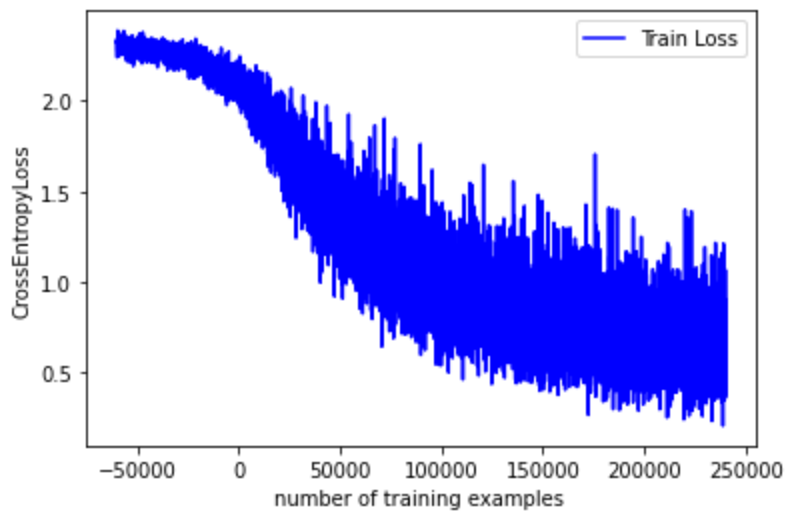
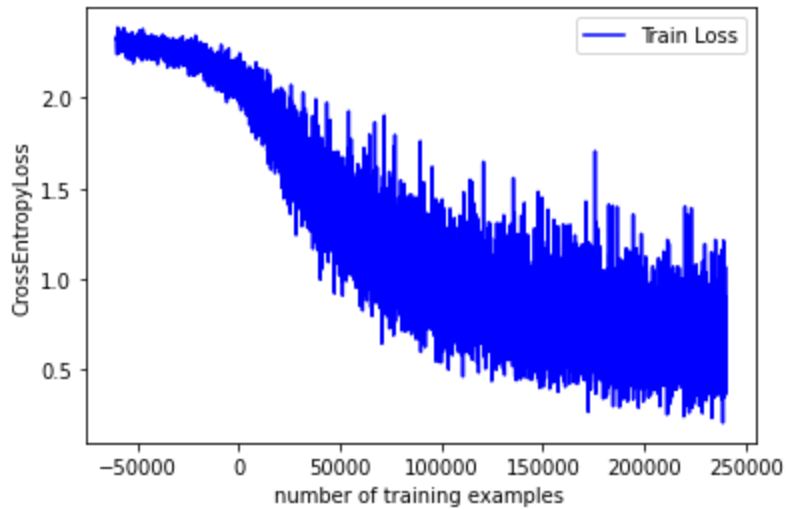
fig = plt.figure()
plt.plot(train_counter, train_losses, color='blue')
plt.legend(['Train Loss'], loc='upper right')
plt.xlabel('number of training examples ')
plt.ylabel('CrossEntropyLoss')
fig

```

c:\program files\python37\lib\site-packages\ipykernel_launcher.py:17: UserWarning: Implicit dimension choice for log_softmax has been deprecated. Change the call to include dim=X as an argument.

Train Epoch: 0	[59968/60000 (100%)]	Loss: 2.115380
Train Epoch: 1	[59968/60000 (100%)]	Loss: 1.042703
Train Epoch: 2	[59968/60000 (100%)]	Loss: 0.677108
Train Epoch: 3	[59968/60000 (100%)]	Loss: 0.645059
Train Epoch: 4	[59968/60000 (100%)]	Loss: 0.653246

Out[189]:



```

In [203]: ds=[0.01,0.1,2]
criterion=torch.nn.CrossEntropyLoss()
models=[]

for d in ds:
    model = my_model(8)
    model=weights_init_uniform(model,d)
    train_losses = []
    train_counter = []
    optimizer = optim.SGD(model.parameters(), lr=0.001,momentum=0.01)
    print("for d=",d)
    for epoch in range(2):
        model.train()
        for batch_idx, (data, target) in enumerate(train_loader):
            # print(batch_idx)
            if batch_idx<50 :
                optimizer.zero_grad()
                output = model(data)
                # print( output.shape)
                output.retain_grad()
                # print(target.shape)
                loss = criterion(output, target)
                loss.backward()
                optimizer.step()
                train_losses.append(loss.item())
                train_counter.append(batch_idx)
            print('Train Epoch: {} [{}/{}] ({:.0f}%) \tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.item()))

fig = plt.figure()
plt.plot(train_counter, train_losses, color='blue')
plt.legend(['Train Loss'], loc='upper right')
plt.xlabel('number of training examples ')
plt.ylabel('CrossEntropyLoss')
fig

```

for d= 0.01

c:\program files\python37\lib\site-packages\ipykernel_launcher.py:19: UserWarning: Implicit dimension choice for log_softmax has been deprecated. Change the call to include dim=X as an argument.

c:\program files\python37\lib\site-packages\ipykernel_launcher.py:20: UserWarning: Implicit dimension choice for softmax has been deprecated. Change the call to include dim=X as an argument.

Train Epoch: 0 [59968/60000 (100%)] Loss: 2.302585

Train Epoch: 1 [59968/60000 (100%)] Loss: 2.302586

for d= 0.1

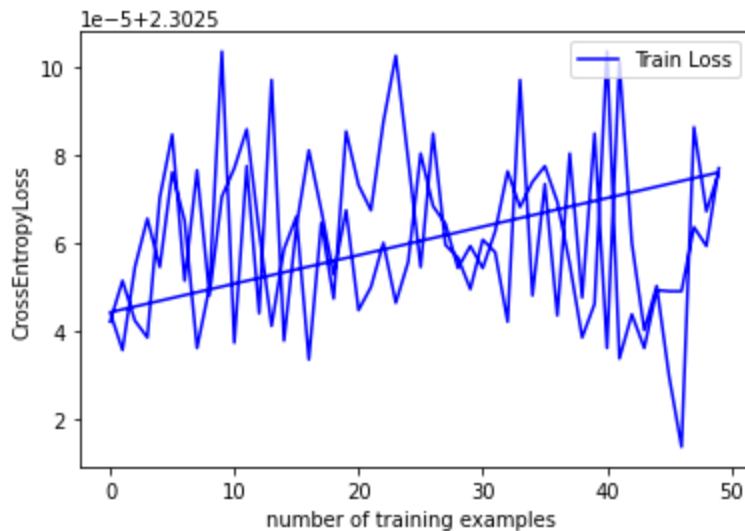
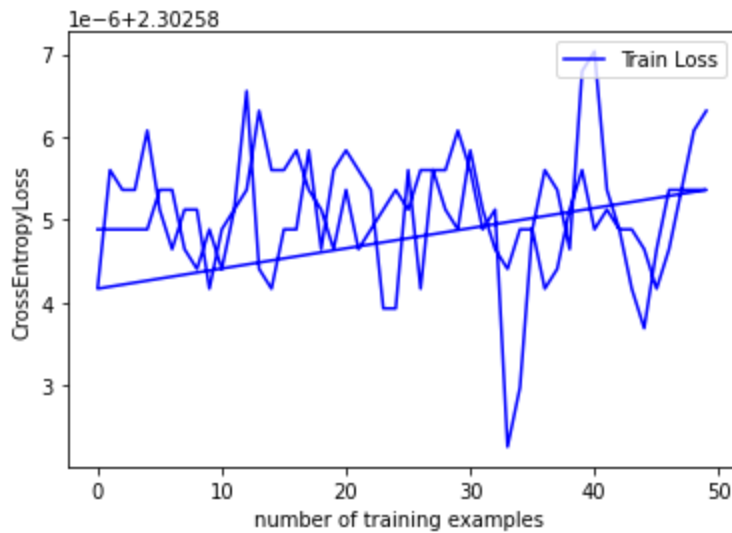
Train Epoch: 0 [59968/60000 (100%)] Loss: 2.302576

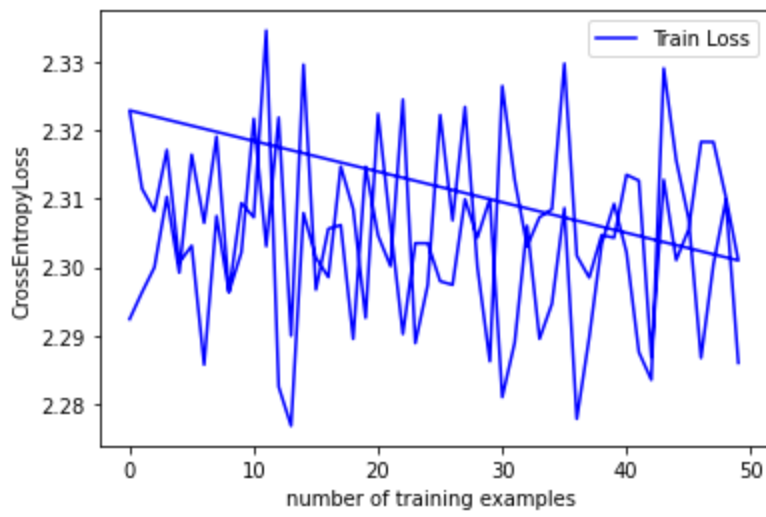
Train Epoch: 1 [59968/60000 (100%)] Loss: 2.302577

for d= 2

Train Epoch: 0 [59968/60000 (100%)] Loss: 2.301005

Train Epoch: 1 [59968/60000 (100%)] Loss: 2.286055





4.E

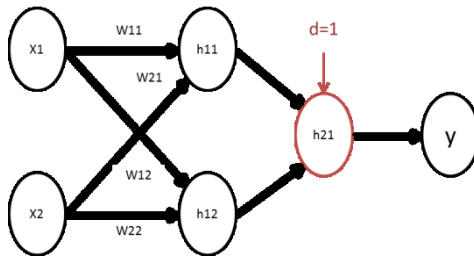
- Model does not generalize well regardless of depth
- Model Train loss still fluctuate with more epochs
- different Weight Initializations do not help
- CNN can capture more complex features so generalize well with less depth and epochs

In []:

3.

3.1 XNOR function:

Activation Function: **RELU**

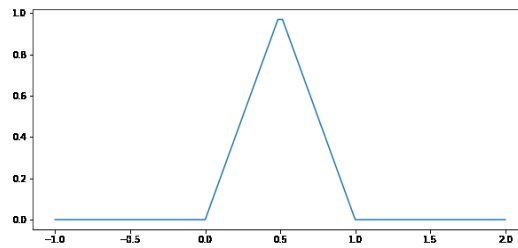


$$f(x;W, c,w, b,d) = \max\{0,(w^T * \max\{0,W^T * x + c\} + b)+d\}$$

$$W = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} \quad c = \begin{pmatrix} 0 \\ -1 \end{pmatrix} \quad b = 0 \quad w = \begin{pmatrix} -2 \\ 4 \end{pmatrix} \quad d = 1$$

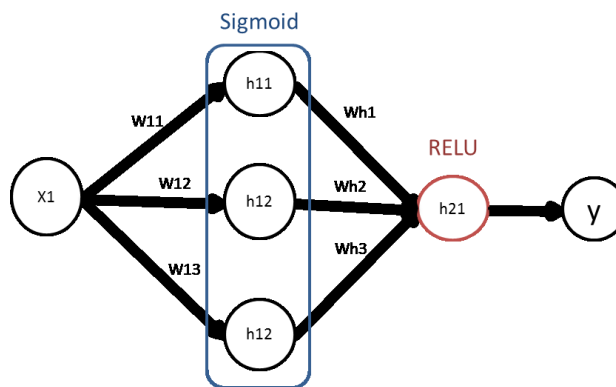
$$\begin{pmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{pmatrix} * \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 1 & 1 \\ 1 & 1 \\ 2 & 2 \end{pmatrix} + \begin{pmatrix} 0 & -1 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{pmatrix} \rightarrow \text{RELU} \begin{pmatrix} 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{pmatrix} * \begin{pmatrix} -2 \\ 4 \end{pmatrix} \rightarrow \begin{pmatrix} -2 \\ -2 \\ -2 \\ 0 \end{pmatrix} + 1 \rightarrow \text{RELU} \begin{pmatrix} -1 \\ -1 \\ -1 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}$$

3.2 Function graph:

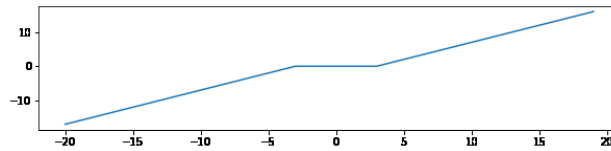


$$f(x;W, c,w, b) = \max\{0,w^T * \text{Sig}(W^T * x + c) + b\}$$

$$W = \begin{pmatrix} 1 \\ 2 \\ -2 \end{pmatrix} \quad c = \begin{pmatrix} 0 \\ 2 \end{pmatrix} \quad b = 0 \quad w = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

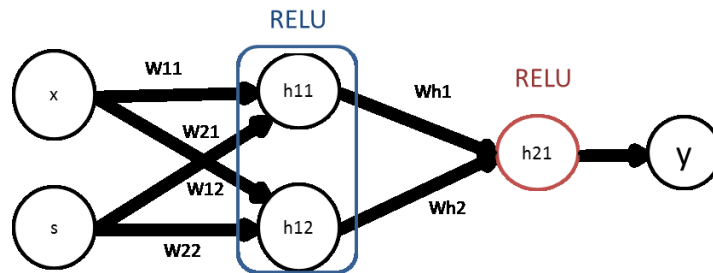


3.3 Function graph



$$f(x; W, c, w, b) = \max\{0, w^T * \max\{W^T * x + c, 0\} + b\}$$

$$W = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \quad c = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad b = 0 \quad w = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$



5.

A. $L(X; w; y) = \frac{1}{2} \|Xw - y\|^2 = \frac{1}{2} (Xw - y)^T (Xw - y) = \frac{1}{2} w^T X^T X w + \frac{1}{2} y^T y - w^T X^T y.$

$$\nabla L(X; w; y) = X^T X w - X^T y = 0 \Rightarrow X^T X w = X^T y.$$

$$\arg \min_w L(X; w; y) = \arg \min_w \frac{1}{2} \sum_{i=1}^N (w^T x(i) - y(i))^2 = \frac{1}{2} (X^T X)^{-1} X^T y$$