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Welcome to WOA7015 Advance Machine Learning Lab - Week 4

This code is generated for the purpose of WOA7015 module. The code is available in github https://github.com/shiernee/Advanced_ML

1.0 Effect of weight and bias to sigmoid function

This is the code to generate the figure in slide 6

1.1 Effect of weight on sigmoid function

```
import matplotlib.pyplot as plt
import numpy as np
import imageio

# create sigmoid function
f = lambda x, w, b: 1/(1 + np.exp(-(w*x + b)))

x = np.arange(-10, 10, 0.01).reshape([-1, 1])

# effect of weight on sigmoid function
filenames = []
for i in np.arange(1, 5, 0.1):
    w = np.ones([1, 1]) * i * 0.5
    b = np.ones([1, 1]) * 0

    plt.plot(x, f(x, w, b))
    plt.title('w = %0.1f' % i)
    plt.grid()
    plt.savefig('w %0.1f.png' % i)
    plt.close()
    filenames.append('w %0.1f.png' % i)

# Build GIF
with imageio.get_writer('w_mygif.gif', mode='I') as writer:
        for filename in filenames:
                image = imageio.imread(filename)
                writer.append_data(image)
```

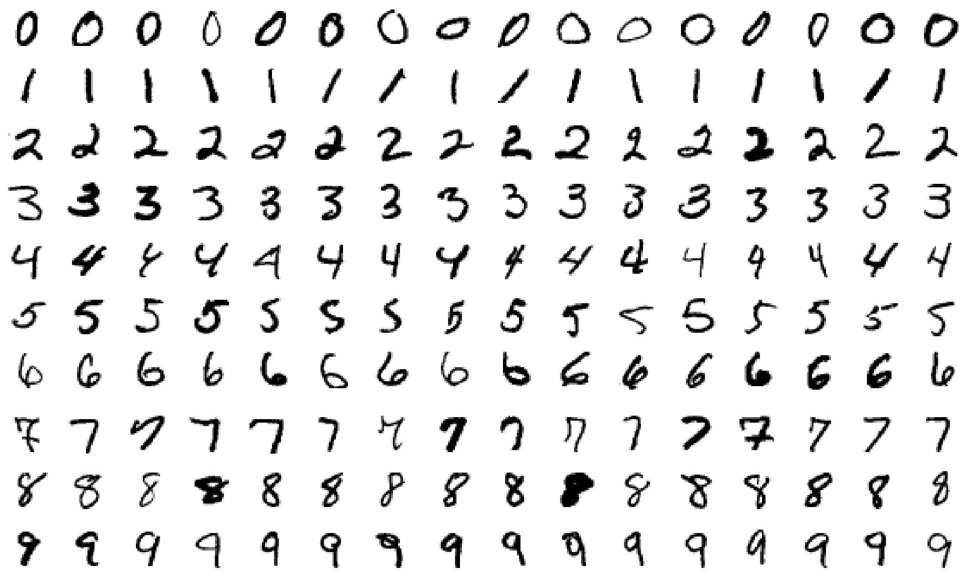
1.1 Effect of bias on sigmoid function

```
import matplotlib.pyplot as plt
import numpy as np
import imageio

# create sigmoid function
f = lambda x, w, b: 1/(1 + np.exp(-(w*x + b)))

x = np.arange(-10, 10, 0.01).reshape([-1, 1])

# effect of bias on sigmoid function
filenames = []
for i in np.arange(1, 5, 0.1):
    w = np.ones([1, 1])
    b = np.ones([1, 1])* i

    plt.plot(x, f(x, w, b))
    plt.title('b = %0.1f' % i)
    plt.grid()
    plt.savefig('b %0.1f.png' % i)
    plt.close()
    filenames.append('b %0.1f.png' % i)

# Build GIF
with imageio.get_writer('b_mygif.gif', mode='I') as writer:
        for filename in filenames:
                image = imageio.imread(filename)
                writer.append_data(image)
```

2.0 Logistic Regression

In this section, we will learn how to create train a Logistic Regression Model using pytorch. We will use MNIST image, as shown below.

PyTorch (https://pytorch.org/) is an open source machine learning library based on the Torch library, used for applications such as computer vision and natural language processing, primarily developed by Facebook's AI Research lab.



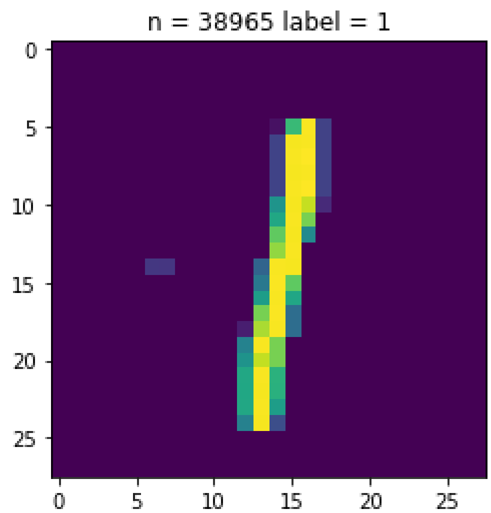
```
# 2.1 import library
import torch
import torch.nn as nn
import torchvision
import torchvision.transforms as transforms
```

```
#2.2 Set the Hyper-parameter
input_size = 28 * 28  # 784
num_classes = 10
num_epochs = 5
batch_size = 100
learning_rate = 0.001
```

```
#2.3 Data loader
# MNIST dataset (images and labels)
train_dataset = torchvision.datasets.MNIST(root='../../data', train=True, transform=transforms.ToT

test_dataset = torchvision.datasets.MNIST(root='../../data', train=False, transform=transforms.ToT

# Data loader (input pipeline)
train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=batch_
                                           shuffle=True)

test_loader = torch.utils.data.DataLoader(dataset=test_dataset,
                                          batch_size=batch_s
                                          shuffle=False)
```

```
# 2.3.1 Check data
print(train_dataset)
print('----------------')
print(test_dataset)
print()

import matplotlib.pyplot as plt
print('training data shape: ', train_dataset.data.shape)
n = np.random.randint(0, 60000)
plt.imshow(train_dataset.data[n])
plt.title(f'n = %d label = %d' % (n, train_dataset.train_labels[n].numpy()))
```

```
Dataset MNIST
    Number of datapoints: 60000
    Root location: ../../data
    Split: Train
    StandardTransform
Transform: ToTensor()
----------------
Dataset MNIST
    Number of datapoints: 10000
    Root location: ../../data
    Split: Test
    StandardTransform
Transform: ToTensor()

training data shape:  torch.Size([60000, 28, 28])
/usr/local/lib/python3.7/dist-packages/torchvision/datasets/mnist.py:52: UserWarning: tr
  warnings.warn("train_labels has been renamed targets")
Text(0.5, 1.0, 'n = 38965 label = 1')
```




```
#2.4 Logistic regression model
model = nn.Linear(input_size, num_classes)
```

```
#2.5 Cross Entropy Loss
# nn.CrossEntropyLoss() computes softmax internally
criterion = nn.CrossEntropyLoss()
```

```
#2.6 Optimizer Stochastic Gradient Descent
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
```

```
#2.7 Train the model
total_step = len(train_loader)
for epoch in range(num_epochs):
        for i, (images, labels) in enumerate(train_loader):
                # Reshape images to (batch_size, input_size)
                images = images.reshape(-1, input_size)

                # Forward pass
                outputs = model(images)
                loss = criterion(outputs, labels)

                # Backward and optimize
                optimizer.zero_grad()
                loss.backward()
                optimizer.step()

                if (i+1) % 100 == 0:
                        print ('Epoch [{}/{}], Step [{}/{}], Loss: {:.4f}'
                                      .format(epoch+1, num_epochs, i+1, total_step, loss.item()))
```

```
Epoch [1/5], Step [100/600], Loss: 2.2188
Epoch [1/5], Step [200/600], Loss: 2.1407
Epoch [1/5], Step [300/600], Loss: 2.0685
Epoch [1/5], Step [400/600], Loss: 1.9928
Epoch [1/5], Step [500/600], Loss: 1.8859
Epoch [1/5], Step [600/600], Loss: 1.8397
Epoch [2/5], Step [100/600], Loss: 1.7071
Epoch [2/5], Step [200/600], Loss: 1.7180
Epoch [2/5], Step [300/600], Loss: 1.5984
Epoch [2/5], Step [400/600], Loss: 1.5472
Epoch [2/5], Step [500/600], Loss: 1.5466
Epoch [2/5], Step [600/600], Loss: 1.4119
Epoch [3/5], Step [100/600], Loss: 1.4913
Epoch [3/5], Step [200/600], Loss: 1.4807
Epoch [3/5], Step [300/600], Loss: 1.3060
Epoch [3/5], Step [400/600], Loss: 1.3812
Epoch [3/5], Step [500/600], Loss: 1.3186
Epoch [3/5], Step [600/600], Loss: 1.3270
Epoch [4/5], Step [100/600], Loss: 1.3312
Epoch [4/5], Step [200/600], Loss: 1.1570
Epoch [4/5], Step [300/600], Loss: 1.2126
Epoch [4/5], Step [400/600], Loss: 1.1013
```

```
Epoch [4/5], Step [500/600], Loss: 1.1696
Epoch [4/5], Step [600/600], Loss: 1.0363
Epoch [5/5], Step [100/600], Loss: 1.0819
Epoch [5/5], Step [200/600], Loss: 1.1336
Epoch [5/5], Step [300/600], Loss: 1.0116
Epoch [5/5], Step [400/600], Loss: 0.9087
Epoch [5/5], Step [500/600], Loss: 0.9763
Epoch [5/5], Step [600/600], Loss: 1.0733
```

```
#2.8 Test the model
# In test phase, we don't need to compute gradients (for memory efficiency)
with torch.no_grad():
    correct = 0
    total = 0
    for images, labels in test_loader:
        images = images.reshape(-1, input_size)
        outputs = model(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum()

    print('Accuracy of the model on the 10000 test images: {} %'.format(100 * correct
```

```
Accuracy of the model on the 10000 test images: 82.30000305175781 %
```

```
#2.9 Save the model checkpoint
torch.save(model.state_dict(), 'model.ckpt')
```

Exercise 1 (10%): Create custom loss function

In this section, you will need to create our own Cross Entropy loss function and compare with Pytorch's Cross Entropy loss. The objective of this exercise is to enable you to design your own loss in the future.

Follow the steps below:

1. Import libraries - copy section 2.1
2. Set hyperparameter - copy section 2.2
3. Data loader - copy section 2.3
4. Initialize Logistic Regression - copy section 2.4
5. Create custom_CrossEntropyLoss class - copy the following code. Your task is to ***code the log_softmax equation in the log_softmax function.***

```
#  Custom Loss - Cross Entropy Loss
class custom_CrossEntropyLoss(nn.Module):
```

```
    def __init__(self, weight=None, size_average=True):
        super(custom_CrossEntropyLoss, self).__init__()

    def forward(self, inputs, targets, smooth=1):
        num_examples = targets.shape[0]
        batch_size = inputs.shape[0]
        softmax_outputs = self.log_softmax(inputs)
        outputs = softmax_outputs[range(batch_size), targets]
        return -torch.sum(outputs)/num_examples

    @staticmethod
    def log_softmax(x):
      return ### put the log_softmax function here ###
```

6. Initialize custom_CrossEntropyLoss loss as criterion - copy section 2.5. Replace *nn.CrossEntropyLoss* with *custom_CrossEntropyLoss*
7. Train the model, evaluate it on your testing data. Save your model.
8. Compare the loss computed from torch and our custom loss.

5% will be given if step 1 - 4 are done correctly

3% will be given if step 5-7 is done correctly

2% will be given if your custom loss and pytorch loss is near zero.

```
# your code here
# 2.1 import library
import torch
import torch.nn as nn
import torchvision
import torchvision.transforms as transforms

# 2.2 Set the Hyper-parameters
input_size = 28 * 28  # 784
num_classes = 10
num_epochs = 5
batch_size = 100
learning_rate = 0.001

# 2.3 Data loader
# MNIST dataset (images and labels)
train_dataset = torchvision.datasets.MNIST(root='../../data', train=True, transform=transforms.ToTe

test_dataset = torchvision.datasets.MNIST(root='../../data', train=False, transform=transforms.ToTe

# Data loader (input pipeline)
train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=batch_
```

```
                                                                                           shuffle=True)

test_loader = torch.utils.data.DataLoader(dataset=test_dataset,
                                                                                         batch_size=batch_s
                                                                                         shuffle=False)

# 2.4 Logistic regression model
model = nn.Linear(input_size, num_classes)

#  Custom Loss - Cross Entropy Loss
class custom_CrossEntropyLoss(nn.Module):
        def __init__(self, weight=None, size_average=True):
                super(custom_CrossEntropyLoss, self).__init__()

        def forward(self, inputs, targets, smooth=1):
                num_examples = targets.shape[0]
                batch_size = inputs.shape[0]
                #print(inputs)
                #print('-------------------------')
                softmax_outputs = self.log_softmax(inputs)
                outputs = softmax_outputs[range(batch_size), targets]
                return -torch.sum(outputs)/num_examples

        @staticmethod
        def log_softmax(x):
            for i in range(x.shape[0]):
                x[i] = (x[i].exp() / x[i].exp().sum()).log()
            return x

# 2.5 Cross Entropy Loss
# nn.CrossEntropyLoss() computes softmax internally
criterion = custom_CrossEntropyLoss()


# 2.6 Optimizer Stochastic Gradient Descent
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

# 2.7 Train the model
total_step = len(train_loader)
for epoch in range(num_epochs):
        for i, (images, labels) in enumerate(train_loader):
                # Reshape images to (batch_size, input_size)
                images = images.reshape(-1, input_size)

                # Forward pass
                outputs = model(images)
                loss = criterion(outputs, labels)

                # Backward and optimize
                optimizer.zero_grad()
                loss.backward()
```

```
            optimizer.step()

            if (i+1) % 100 == 0:
                print ('Epoch [{}/{}], Step [{}/{}], Loss: {:.4f}'
                       .format(epoch+1, num_epochs, i+1, total_step, loss.item()))
```

```
Epoch [1/5], Step [100/600], Loss: 2.2002
Epoch [1/5], Step [200/600], Loss: 2.0756
Epoch [1/5], Step [300/600], Loss: 1.9939
Epoch [1/5], Step [400/600], Loss: 1.9161
Epoch [1/5], Step [500/600], Loss: 1.8536
Epoch [1/5], Step [600/600], Loss: 1.7779
Epoch [2/5], Step [100/600], Loss: 1.7538
Epoch [2/5], Step [200/600], Loss: 1.6609
Epoch [2/5], Step [300/600], Loss: 1.6373
Epoch [2/5], Step [400/600], Loss: 1.5971
Epoch [2/5], Step [500/600], Loss: 1.4709
Epoch [2/5], Step [600/600], Loss: 1.4243
Epoch [3/5], Step [100/600], Loss: 1.4395
Epoch [3/5], Step [200/600], Loss: 1.4104
Epoch [3/5], Step [300/600], Loss: 1.3765
Epoch [3/5], Step [400/600], Loss: 1.2895
Epoch [3/5], Step [500/600], Loss: 1.3429
Epoch [3/5], Step [600/600], Loss: 1.2583
Epoch [4/5], Step [100/600], Loss: 1.1188
Epoch [4/5], Step [200/600], Loss: 1.2182
Epoch [4/5], Step [300/600], Loss: 1.1161
Epoch [4/5], Step [400/600], Loss: 1.1710
Epoch [4/5], Step [500/600], Loss: 1.1147
Epoch [4/5], Step [600/600], Loss: 1.0738
Epoch [5/5], Step [100/600], Loss: 1.2371
Epoch [5/5], Step [200/600], Loss: 1.1170
Epoch [5/5], Step [300/600], Loss: 1.0849
Epoch [5/5], Step [400/600], Loss: 1.0532
Epoch [5/5], Step [500/600], Loss: 1.0697
Epoch [5/5], Step [600/600], Loss: 0.9447
```

```
# 2.8 Test the model
# In test phase, we don't need to compute gradients (for memory efficiency)
with torch.no_grad():
    correct = 0
    total = 0
    for images, labels in test_loader:
        images = images.reshape(-1, input_size)
        outputs = model(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum()

    print('Accuracy of the model on the 10000 test images: {:.4f} %'.format(100 * corr
```

```
Accuracy of the model on the 10000 test images: 82.5800 %
```

```
# 2.9 Save the model checkpoint
torch.save(model.state_dict(), 'model.ckpt')
```

Submission Instructions

Once you are finished, follow these steps:

Restart the kernel and re-run this notebook from beginning to end by going to Kernel > Restart Kernel and Run All Cells. If this process stops halfway through, that means there was an error. Correct the error and repeat Step 1 until the notebook runs from beginning to end. Double check that there is a number next to each code cell and that these numbers are in order. Then, submit your lab as follows:

Go to File > Print > Save as PDF. Double check that the entire notebook, from beginning to end, is in this PDF file. Make sure Solution for Exercise 5 are in for marks. Upload the PDF to Spectrum.

0 秒 完成时间：21:05