

```

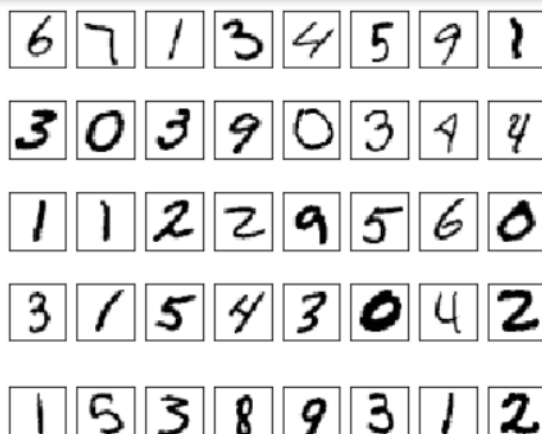
In [1]: import torch
import torchvision
from torch.utils.data import DataLoader
from torchvision.datasets import MNIST
from torchvision import transforms
from torch import nn
import math
import os
os.environ["KMP_DUPLICATE_LIB_OK"]="TRUE"

In [2]: # batch_size 超参, 根据硬件配置相应大小
batch_size = 32 #批处理大小
trans_img = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.1307,), (0.3081,))
])

In [3]: # MNIST 数据集每张图片是灰度图片, 大小为 28x28
trainset = MNIST('data', train=True, download=True, transform=trans_img)
testset = MNIST('data', train=False, download=True, transform=trans_img)
train_loader = DataLoader(trainset, batch_size=batch_size,
    shuffle=True, num_workers=1)
test_loader = DataLoader(testset, batch_size=batch_size,
    shuffle=True, num_workers=1) # 运行环境

In [4]: import matplotlib.pyplot as plt
plt.ion()
cnt = 0
for (img_batch, label) in train_loader:
    cnt += 1
    if cnt > 10:
        break
    fig, ax = plt.subplots(
        nrows=4,
        ncols=8,
        sharex=True,
        sharey=True, )
    ax = ax.flatten()
    for i in range(32):
        img = img_batch[i].numpy().reshape(28, 28)
        ax[i].imshow(img, cmap='Greys', interpolation='nearest')
    ax[0].set_xticks([])
    ax[0].set_yticks([])
    plt.show()
    plt.close()
plt.ioff()

```



```
In [5]: class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()

        self.features = nn.Sequential(
            nn.Conv2d(1, 32, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True), #inplace = True ,
            nn.Conv2d(32, 32, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
            nn.Conv2d(32, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2)
        )
        self.classifier = nn.Sequential(
            nn.Dropout(p = 0.5),
            nn.Linear(64 * 7 * 7, 512),
            nn.BatchNorm1d(512),
            nn.ReLU(inplace=True),
            nn.Dropout(p = 0.5),
            nn.Linear(512, 512),
            nn.BatchNorm1d(512),
            nn.ReLU(inplace=True),
            nn.Dropout(p = 0.5),
            nn.Linear(512, 10),
        )
```

```
for m in self.features.children():
    if isinstance(m, nn.Conv2d):
        n = m.kernel_size[0] * m.kernel_size[1] * m.out_channels
        m.weight.data.normal_(0, math.sqrt(2. / n))
    elif isinstance(m, nn.BatchNorm2d):
        m.weight.data.fill_(1)
        m.bias.data.zero_()
for m in self.classifier.children():
    if isinstance(m, nn.Linear):
        nn.init.xavier_uniform(m.weight)
    elif isinstance(m, nn.BatchNorm1d):
        m.weight.data.fill_(1)
        m.bias.data.zero_()
def forward(self, x):
    x = self.features(x)
    x = x.view(x.size(0), -1) #这句话是说将最后一次卷积的输出拉伸为一行
    x = self.classifier(x)
    return x
```

```
In [6]: device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        from torch import optim #优化器
        from torch.autograd import Variable
        import warnings
        warnings.filterwarnings("ignore", category=UserWarning)
        model = Net().to(device) #GPU
        learning_rate = 0.001
        criterion = nn.CrossEntropyLoss(size_average=False)
        optimizer = optim.SGD(model.parameters(), lr = learning_rate)
        # 总的训练轮数
        epochs = 50
        train_losses=[]
        test_losses=[]
        for epoch in range(epochs):
            running_loss, running_acc = 0., 0.
            for (img, label) in train_loader:
                img = Variable(img).to(device)
                label = Variable(label).to(device)

                optimizer.zero_grad() #梯度归零;

                output = model(img) ##前向传播
                loss = criterion(output, label) #计算 loss

                loss.backward() #反向传播, 计算当前梯度;
                optimizer.step() #反向传播, 计算当前梯度;
                running_loss += loss.item() #item() 取出张量具体位置的元素元素值
                _, predict = torch.max(output, 1)
                #_, predicted = torch.max(outputs.data, dim): 返回最大值所在索引, dim=1 时, 按行返回最大值所在索引
                correct_num = (predict == label).sum()
                running_acc += correct_num.item()
```

```
running_loss /= len(trainset)
running_acc /= len(trainset)

with torch.no_grad(): #不求梯度
    test_loss, test_acc = 0., 0.
    for images, labels in test_loader:
        images = Variable(images).to(device)
        labels = Variable(labels).to(device)
        output = model(images)
        loss = criterion(output, labels)
        test_loss += loss.item()
        _, predict = torch.max(output, 1)
        correct_num = (predict == labels).sum()
        test_acc += correct_num.item()

test_loss /= len(testset)
test_acc /= len(testset)

train_losses.append(running_loss)
test_losses.append(test_loss)
print("Epoch: {}/{}\n".format(epoch+1, epochs),
      "Training Loss: {:.3f}\n".format(train_losses[-1]),
      "Training Accuracy: {:.3f} %\n".format(100*running_acc),
      "Test Loss: {:.3f}\n".format(test_losses[-1]),
      "Test Accuracy: {:.3f} %\n".format(100*test_acc))
# 保存模型
torch.save(model, 'conv.pth.tar')
```

```

Epoch: 1/50.. Training Loss: 0.294.. Training Accuracy: 90.587 % Test Loss: 0.131.. Test Accuracy: 95.920 %
Epoch: 2/50.. Training Loss: 0.119.. Training Accuracy: 96.377 % Test Loss: 0.096.. Test Accuracy: 96.920 %
Epoch: 3/50.. Training Loss: 0.096.. Training Accuracy: 97.008 % Test Loss: 0.081.. Test Accuracy: 97.530 %
Epoch: 4/50.. Training Loss: 0.081.. Training Accuracy: 97.527 % Test Loss: 0.078.. Test Accuracy: 97.540 %
Epoch: 5/50.. Training Loss: 0.071.. Training Accuracy: 97.815 % Test Loss: 0.064.. Test Accuracy: 97.950 %
Epoch: 6/50.. Training Loss: 0.063.. Training Accuracy: 98.033 % Test Loss: 0.059.. Test Accuracy: 98.080 %
Epoch: 7/50.. Training Loss: 0.058.. Training Accuracy: 98.212 % Test Loss: 0.058.. Test Accuracy: 98.200 %
Epoch: 8/50.. Training Loss: 0.055.. Training Accuracy: 98.318 % Test Loss: 0.050.. Test Accuracy: 98.440 %
Epoch: 9/50.. Training Loss: 0.051.. Training Accuracy: 98.450 % Test Loss: 0.050.. Test Accuracy: 98.280 %
Epoch: 10/50.. Training Loss: 0.046.. Training Accuracy: 98.548 % Test Loss: 0.049.. Test Accuracy: 98.460 %
Epoch: 11/50.. Training Loss: 0.045.. Training Accuracy: 98.655 % Test Loss: 0.048.. Test Accuracy: 98.440 %
Epoch: 12/50.. Training Loss: 0.046.. Training Accuracy: 98.582 % Test Loss: 0.049.. Test Accuracy: 98.590 %
Epoch: 13/50.. Training Loss: 0.042.. Training Accuracy: 98.687 % Test Loss: 0.042.. Test Accuracy: 98.710 %
Epoch: 14/50.. Training Loss: 0.038.. Training Accuracy: 98.802 % Test Loss: 0.040.. Test Accuracy: 98.790 %
Epoch: 15/50.. Training Loss: 0.038.. Training Accuracy: 98.823 % Test Loss: 0.042.. Test Accuracy: 98.750 %
Epoch: 16/50.. Training Loss: 0.034.. Training Accuracy: 98.923 % Test Loss: 0.040.. Test Accuracy: 98.860 %
Epoch: 17/50.. Training Loss: 0.035.. Training Accuracy: 98.962 % Test Loss: 0.037.. Test Accuracy: 98.770 %
Epoch: 18/50.. Training Loss: 0.033.. Training Accuracy: 99.000 % Test Loss: 0.035.. Test Accuracy: 98.870 %
Epoch: 19/50.. Training Loss: 0.033.. Training Accuracy: 98.953 % Test Loss: 0.038.. Test Accuracy: 98.840 %
Epoch: 20/50.. Training Loss: 0.029.. Training Accuracy: 99.068 % Test Loss: 0.035.. Test Accuracy: 98.870 %
Epoch: 21/50.. Training Loss: 0.031.. Training Accuracy: 99.077 % Test Loss: 0.038.. Test Accuracy: 98.800 %
Epoch: 22/50.. Training Loss: 0.028.. Training Accuracy: 99.103 % Test Loss: 0.037.. Test Accuracy: 98.900 %
Epoch: 23/50.. Training Loss: 0.027.. Training Accuracy: 99.168 % Test Loss: 0.033.. Test Accuracy: 98.980 %
Epoch: 24/50.. Training Loss: 0.027.. Training Accuracy: 99.152 % Test Loss: 0.034.. Test Accuracy: 98.970 %
Epoch: 25/50.. Training Loss: 0.026.. Training Accuracy: 99.187 % Test Loss: 0.037.. Test Accuracy: 98.850 %
Epoch: 26/50.. Training Loss: 0.026.. Training Accuracy: 99.210 % Test Loss: 0.034.. Test Accuracy: 99.010 %
Epoch: 27/50.. Training Loss: 0.026.. Training Accuracy: 99.157 % Test Loss: 0.035.. Test Accuracy: 98.870 %
Epoch: 28/50.. Training Loss: 0.024.. Training Accuracy: 99.250 % Test Loss: 0.030.. Test Accuracy: 99.040 %
Epoch: 29/50.. Training Loss: 0.025.. Training Accuracy: 99.218 % Test Loss: 0.034.. Test Accuracy: 98.960 %
Epoch: 30/50.. Training Loss: 0.022.. Training Accuracy: 99.315 % Test Loss: 0.037.. Test Accuracy: 98.840 %
Epoch: 31/50.. Training Loss: 0.022.. Training Accuracy: 99.253 % Test Loss: 0.027.. Test Accuracy: 99.120 %

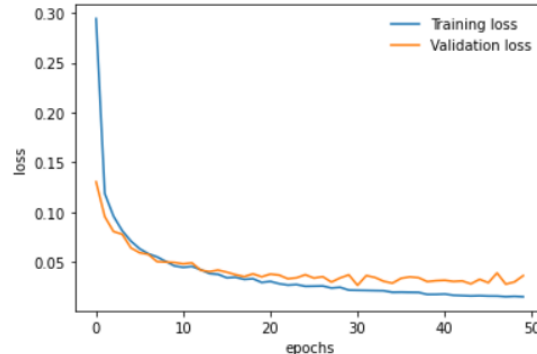
```

```

In [7]: plt.plot(train_losses, label='Training loss')
plt.plot(test_losses, label='Validation loss')
plt.xlabel("epochs")
plt.ylabel("loss")
plt.legend(frameon=False)

```

Out[7]: <matplotlib.legend.Legend at 0x23ae6452c70>



```

In [9]: device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = torch.load('conv.pth.tar')
print('testing cnn model')
testloss, testacc = 0., 0.
for (img, label) in test_loader:
    img = Variable(img).to(device)
    label = Variable(label).to(device)
    out = model(img)
    loss = criterion(out, label)
    testloss += loss.item()
    _, predict = torch.max(out, 1)
    correct_num = (predict == label).sum()
    testacc += correct_num.item()
testloss /= len(testset)
testacc /= len(testset)
print('cnn model, Test: Loss: %.5f, Acc: %.2f' %
      (testloss, 100 * testacc))

```

```

testing cnn model
cnn model, Test: Loss: 0.03346, Acc: 99.09

```

```

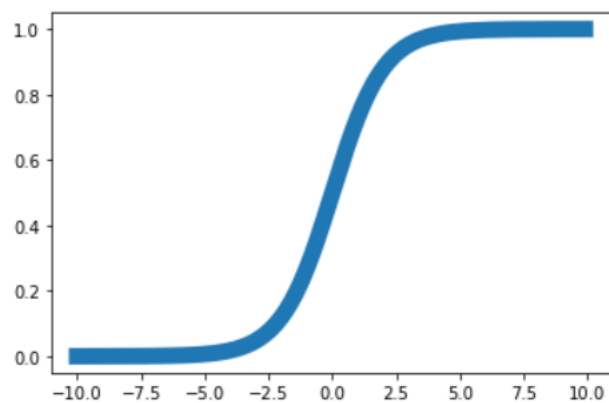
In [1]: %matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import math
#显示中文
plt.rcParams['font.sans-serif'] = ['Arial Unicode MS']

In [3]: def sigmoid(x):
        return 1/(1+np.exp(-x))

In [4]: def df_sigmoid(x):
        s = sigmoid(x)
        return np.multiply(s, (np.ones(len(x)) - s))

In [5]: x = np.arange(-10., 10., 0.1)
y_sigmoid = sigmoid(x)
#df = np.multiply(y_sigmoid, (np.ones(len(x)) - y_sigmoid))
df = df_sigmoid(x)
plt.plot(x, y_sigmoid, label = u'Sigmoid', linewidth=10)
plt.show()

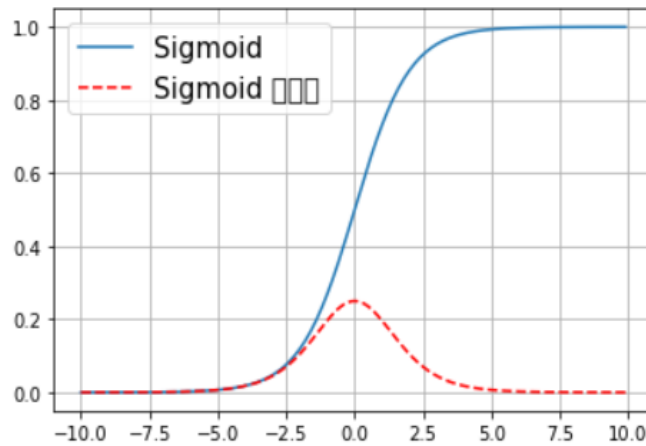
```



```

In [6]: x = np.arange(-10., 10., 0.1)
y_sigmoid = sigmoid(x)
#df = np.multiply(y_sigmoid, (np.ones(len(x)) - y_sigmoid))
df = df_sigmoid(x)
plt.plot(x, y_sigmoid, label = u'Sigmoid')
plt.plot(x, df, 'r', linestyle = '--', label = u'Sigmoid 的导数')
plt.grid() #生成网格线
plt.legend(fontsize = 15)

```

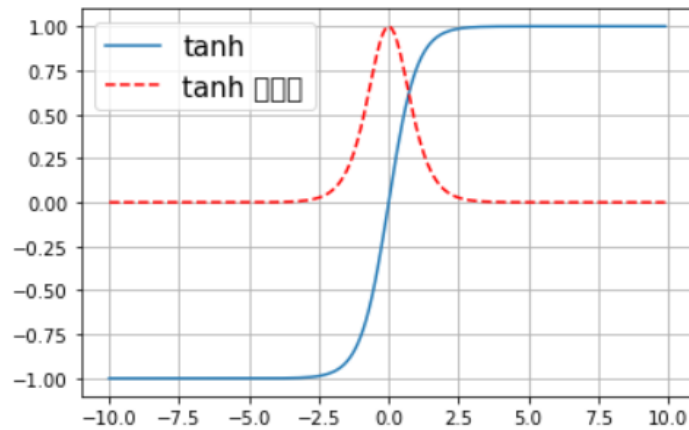


```
In [7]: def tanh(x):
        return np.tanh(x)
        #return (1-np.exp(-2x))/(1+np.exp(-2x))
```

```
In [8]: def df_tanh(x):
        t = tanh(x)
        return 1 - np.power(t, 2) #np.power() 幂次方
```

```
In [9]: x = np.arange(-10., 10., 0.1)
        y_tanh = tanh(x)
        df = df_tanh(x)
        plt.plot(x, y_tanh, label = u'tanh')
        plt.plot(x, df, 'r', linestyle = '--', label = u'tanh 的导数')
        plt.grid()
        plt.legend(fontsize = 15)
```

Out[9]: <matplotlib.legend.Legend at 0x1678f02cfd0>

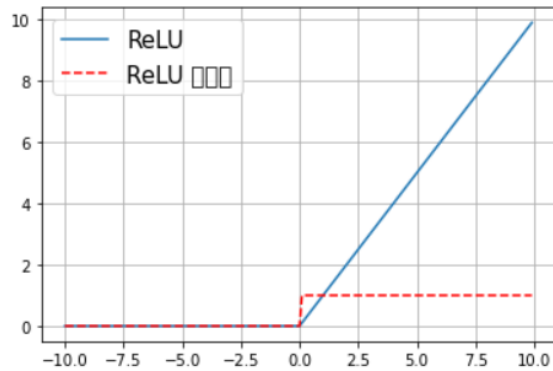


```
In [10]: def ReLU(x):
          arr = []
          for i in x:
              arr.append(0 if i<0 else i )
          return arr
```

```
In [11]: def df_ReLU(x):
          arr = []
          for i in x:
              arr.append(0 if i<0 else 1 )
          return arr
```

```
In [12]: x = np.arange(-10., 10., 0.1)
          y_ReLU = ReLU(x)
          df = df_ReLU(x)
          plt.plot(x, y_ReLU, label = u'ReLU')
          plt.plot(x, df, 'r', linestyle = '--', label = u'ReLU 的导数')
          plt.grid()
          plt.legend(fontsize = 15)
```

```
Out[12]: <matplotlib.legend.Legend at 0x1678eefedc0>
```

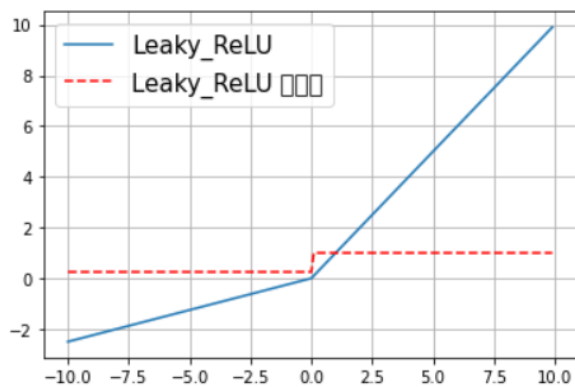


```
In [13]: def Leaky_ReLU(x, alpha):
         arr = []
         for i in x:
             arr.append(alpha*i if i<0 else i )
         return arr
```

```
In [14]: def df_Leaky_ReLU(x, alpha):
         arr = []
         for i in x:
             arr.append(alpha if i<0 else 1 )
         return arr
```

```
In [15]: x = np.arange(-10., 10., 0.1)
         alpha =0.25
         y_LeakyReLU = Leaky_ReLU(x, alpha)
         df = df_Leaky_ReLU(x, alpha)
         plt.plot(x, y_LeakyReLU, label = u'Leaky_ReLU')
         plt.plot(x, df, 'r', linestyle = '--', label = u'Leaky_ReLU 的导数')
         plt.grid()
         plt.legend(fontsize = 15)
```

Out[15]: <matplotlib.legend.Legend at 0x1678f06a820>

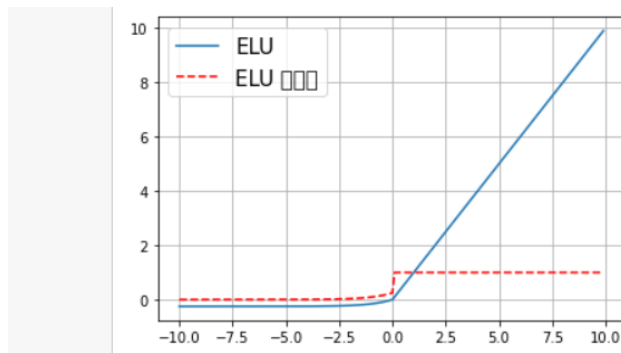


```
In [16]: def ELU(x, alpha):
         arr = []
         for i in x:
             arr.append(alpha*(np.exp(i) -1) if i<0 else i )
         return arr
         def df_ELU(x, alpha):
             arr = []
             for i in x:
                 arr.append(alpha*(np.exp(i)) if i<0 else 1 )
             return arr
```



```
In [17]: x = np.arange(-10., 10., 0.1)
alpha = 0.25
y_ELU = ELU(x, alpha)
df = df_ELU(x, alpha)
plt.plot(x, y_ELU, label = u'ELU')
plt.plot(x, df, 'r', linestyle = '--', label = u'ELU 的导数')
plt.grid()
plt.legend(fontsize = 15)
```

Out[17]: <matplotlib.legend.Legend at 0x1678f08bdc0>

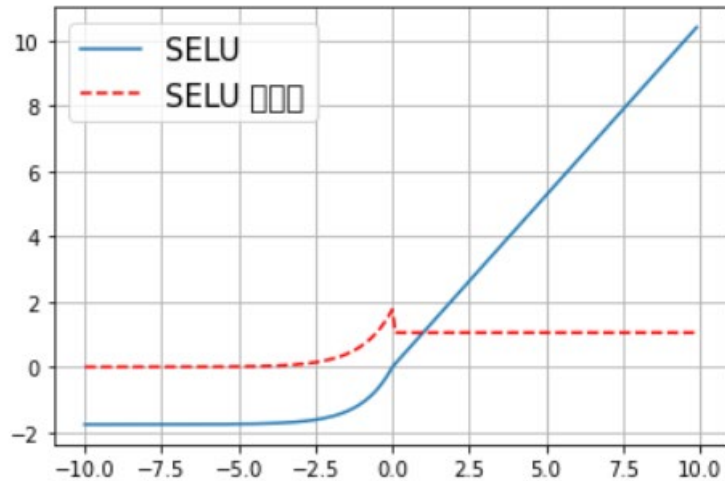


```
In [19]: def SELU(x, alpha):
arr = []
alpha = 1.6732632423543772848170429916717
lambda_ = 1.0507009873554804934193349852946
for i in x:
    arr.append(lambda_*alpha*(np.exp(i) - 1) if i < 0 else lambda_*i)
return arr
```

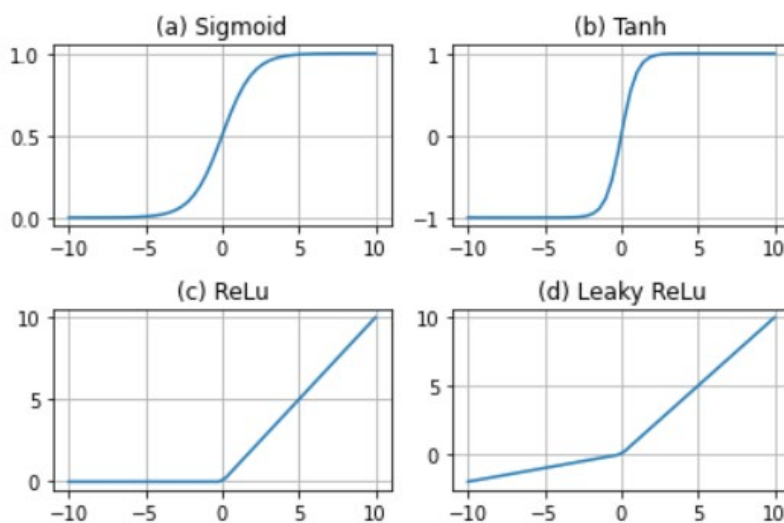
```
In [20]: def df_SELU(x, alpha):
arr = []
alpha = 1.6732632423543772848170429916717
lambda_ = 1.0507009873554804934193349852946
for i in x:
    arr.append(lambda_*alpha*(np.exp(i) ) if i < 0 else lambda_)
return arr
```

```
In [21]: x = np.arange(-10., 10., 0.1)
alpha = 0.25
y_SELU = SELU(x, alpha)
df = df_SELU(x, alpha)
plt.plot(x, y_SELU, label = u'SELU')
plt.plot(x, df, 'r', linestyle = '--', label = u'SELU 的导数')
plt.grid()
plt.legend(fontsize = 15)
```

Out[21]: <matplotlib.legend.Legend at 0x1678f05b2b0>



```
In [22]: import matplotlib.pyplot as plt
import numpy as np
x = np.linspace(-10,10)
y_sigmoid = 1/(1+np.exp(-x))
y_tanh = (np.exp(x)-np.exp(-x))/(np.exp(x)+np.exp(-x))
fig = plt.figure()
# plot sigmoid
ax = fig.add_subplot(221)
ax.plot(x,y_sigmoid)
ax.grid()
ax.set_title(' (a) Sigmoid')
# plot tanh
ax = fig.add_subplot(222)
ax.plot(x,y_tanh)
ax.grid()
ax.set_title(' (b) Tanh')
# plot relu
ax = fig.add_subplot(223)
y_relu = np.array([0*item if item<0 else item for item in x ])
ax.plot(x,y_relu)
ax.grid()
ax.set_title(' (c) ReLu')
#plot leaky relu
ax = fig.add_subplot(224)
y_relu = np.array([0.2*item if item<0 else item for item in x ])
ax.plot(x,y_relu)
ax.grid()
ax.set_title(' (d) Leaky ReLu')
plt.tight_layout()
```

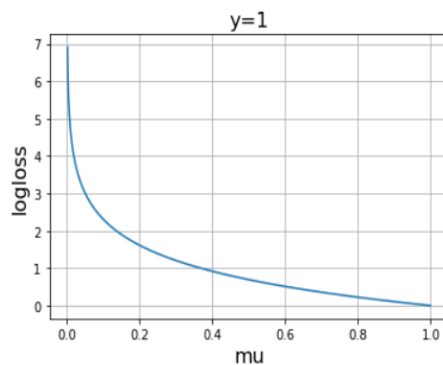


```
In [27]: import matplotlib.pyplot as plt # python 的可视化模块, 我有教程 (https://morvanzhou.github.io/tutorials/data-manipulation/p)
import torch
import torch.nn.functional as F # 激励函数都在这
from torch.autograd import Variable # 自动求导 变量
# 做一些假数据来观看图像
x = torch.linspace(-5, 5, 200) # x data (tensor), shape=(100, 1)
x = Variable(x)
x_np = x.data.numpy() # 换成 numpy array, 出图时用
# 几种常用的 激励函数
y_relu = F.relu(x).data.numpy()
y_sigmoid = F.sigmoid(x).data.numpy()
y_tanh = F.tanh(x).data.numpy()
y_softplus = F.softplus(x).data.numpy() # Softplus(x)=log(1+e^x)
plt.figure(1, figsize=(8, 6))
plt.subplot(221)
plt.plot(x_np, y_relu, c='red', label='relu')
plt.ylim((-1, 5))
plt.legend(loc='best') # 图例所有 figure 位置
plt.subplot(222)
plt.plot(x_np, y_sigmoid, c='red', label='sigmoid')
plt.ylim((-0.2, 1.2))
plt.legend(loc='best')
plt.subplot(223)
plt.plot(x_np, y_tanh, c='red', label='tanh')
plt.ylim((-1.2, 1.2))
plt.legend(loc='best')
plt.subplot(224)
plt.plot(x_np, y_softplus, c='red', label='softplus')
plt.ylim((-0.2, 6))
plt.legend(loc='best')
plt.show()
```

```
In [28]: x = np.arange(0, 1, 0.001)
logloss = -np.log( x)
plt.plot(x, logloss)
plt.grid()
plt.xlabel('mu', fontsize = 16)
plt.ylabel('logloss', fontsize = 16)
plt.title('y=1', fontsize = 16)
```

C:\Users\Administrator\AppData\Local\Temp\ipykernel\_1980\51743719.py:2: RuntimeWarning: divide by zero encountered in log  
logloss = -np.log( x)

Out[28]: Text(0.5, 1.0, 'y=1')



```
In [29]: x = np.arange(0, 1, 0.001)
logloss = -np.log(1- x)
plt.plot(x, logloss)
plt.grid()
plt.xlabel('mu', fontsize = 16)
plt.ylabel('logloss', fontsize = 16)
plt.title('y=0', fontsize = 16)
```

Out[29]: Text(0.5, 1.0, 'y=0')

