In [1]:

```
import torch
import numpy as np
from torchvision.datasets import mnist #导入 pytorch内置的mnist数据

from torch import nn
from torch.autograd import Variable
```

文件	内容
train-images-idx3-ubyte.gz	训练集图片 - 55000 张 训练图片, 5000 张验证图片
train-labels-idx1-ubyte.gz	训练集图片对应的数字标签
t10k-images-idx3-ubyte.gz	测试集图片 - 10000 张 图片
t10k-labels-idx1-ubyte.gz	测试集图片对应的数字标签

pytorch下载完会自动解压

In [2]:

```
#使用内置函数下载mnist数据集
train_set = mnist.MNIST('./data',train=True,download=True)
test_set = mnist.MNIST('./data',train=False,download=True)
```

In [3]:

```
a_data, a_label = train_set[0]
```

In [4]:

```
a_data
```

Out[4]:

In [5]:

```
a_label
```

Out[5]:

5

这里读入的数据是PIL库中的格式，可以很方便的将其转换为numpy array

In [6]:

```
a_data = np.array(a_data,dtype='float32')
print(a_data.shape)
```

```
(28, 28)
```

In [13]:

```
print(a_data)
```

```
[[  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
    0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
    0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
    0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
    0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
    0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   3.  18.
   18.  18. 126. 136. 175.  26. 166. 255. 247. 127.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.  30.  36.  94. 154. 170. 253.
  253. 253. 253. 253. 225. 172. 253. 242. 195.  64.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.  49. 238. 253. 253. 253. 253. 253.
  253. 253. 253. 251.  93.  82.  82.  56.  39.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.  18. 219. 253. 253. 253. 253. 253.
  198. 182. 247. 241.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.  80. 156. 107. 253. 253. 205.
   11.   0.  43. 154.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.  14.   1. 154. 253.  90.
    0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0. 139. 253. 190.
    2.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.  11. 190. 253.
   70.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.  35. 241.
  225. 160. 108.   1.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.  81.
  240. 253. 253. 119.  25.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
   45. 186. 253. 253. 150.  27.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
    0.  16.  93. 252. 253. 187.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
    0.   0.   0. 249. 253. 249.  64.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
   46. 130. 183. 253. 253. 207.   2.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.  39. 148.
  229. 253. 253. 253. 250. 182.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.  24. 114. 221. 253.
  253. 253. 253. 201.  78.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.  23.  66. 213. 253. 253. 253.
  253. 198.  81.   2.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.  18. 171. 219. 253. 253. 253. 253. 195.
   80.   9.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.  55. 172. 226. 253. 253. 253. 253. 244. 133.  11.
    0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0. 136. 253. 253. 253. 212. 135. 132.  16.   0.   0.
    0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
    0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
    0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]
```

```
 [  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
    0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]]
```

数据展示出来，里面的0表示黑色，255表示白色 对于神经网络，第一层的输入就是28×28=784，所以必须将得到的数据做一个变换，使用reshape将他们拉平成一个一维向量

流程：

- 定义数据集
- 定义模型
- 定义loss和优化器
- 训练

In [7]:

```
def data_tf(x):
    x=np.array(x,dtype='float32')/ 255
    x=(x - 0.5)/ 0.5
    x=x.reshape((-1,))#拉平
    x=torch.from_numpy(x)
    return x
train_set=mnist.MNIST('./data',train=True,transform=data_tf,download=True)
test_set=mnist.MNIST('./data',train=False,transform=data_tf,download=True)
```

In [8]:

```
a,a_label = train_set[0]
print(a.shape)
print(a_label)
```

```
torch.Size([784])
5
```

In [9]:

```
from torch.utils.data import DataLoader
#使用pytorch自带的DataLoder定义一个数据迭代器
train_data = DataLoader(train_set, batch_size=64,shuffle=True)
test_data = DataLoader(test_set,batch_size=128,shuffle=False)
```

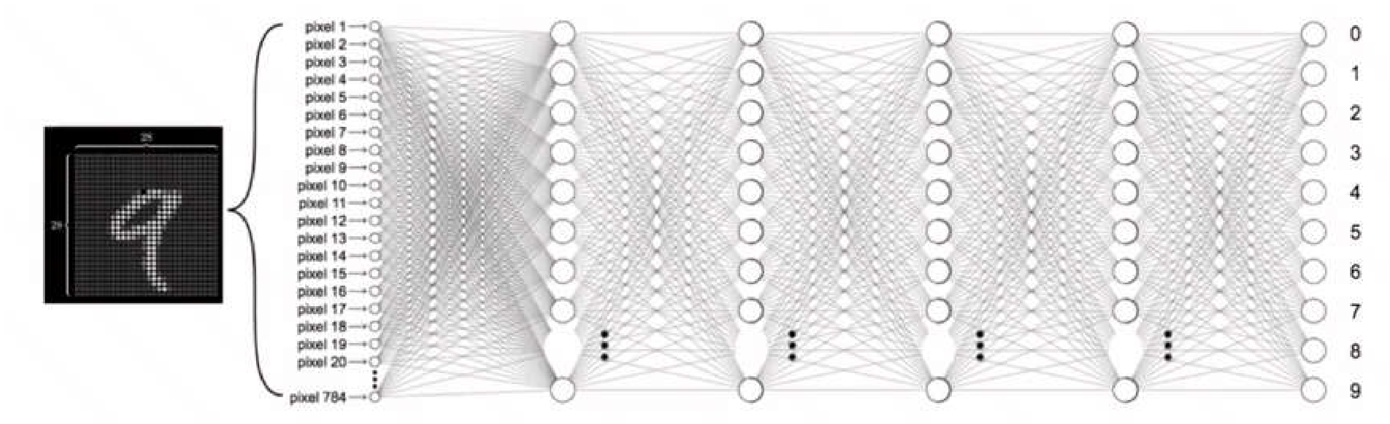
In [10]:

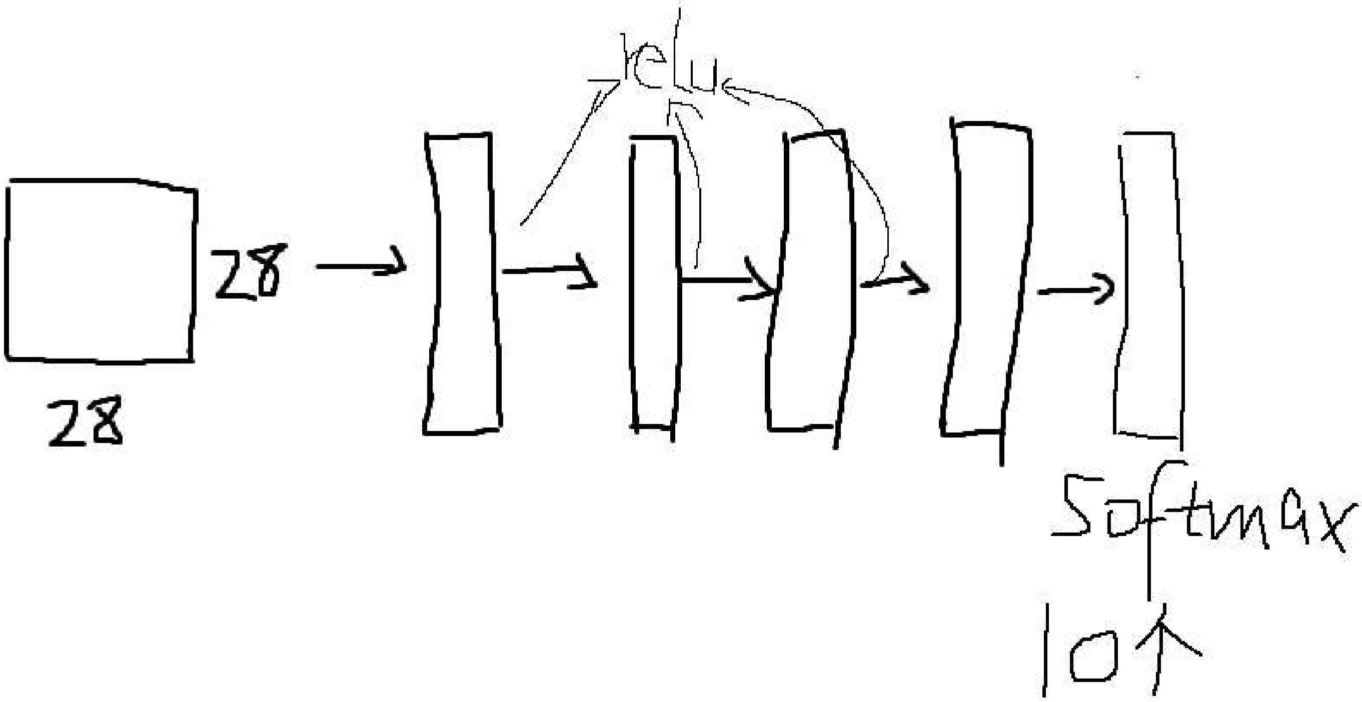
```
a,a_label = next(iter(train_data))
```

In [11]:

```
#打印出一个批次的数据大小
print(a.shape)
print(a_label.shape)
```

```
torch.Size([64, 784])
torch.Size([64])
```





In [12]:

```
#使用Sequential 定义4层神经网络
net = nn.Sequential(
    nn.Linear(784,400),
    nn.ReLU(),
    nn.Linear(400,200),
    nn.ReLU(),
    nn.Linear(200,100),
    nn.ReLU(),
    nn.Linear(100,10)
)
```

In [13]:

```
net
```

Out[13]:

```
Sequential(
  (0): Linear(in_features=784, out_features=400, bias=True)
  (1): ReLU()
  (2): Linear(in_features=400, out_features=200, bias=True)
  (3): ReLU()
  (4): Linear(in_features=200, out_features=100, bias=True)
  (5): ReLU()
  (6): Linear(in_features=100, out_features=10, bias=True)
)
```

交叉熵在pytorch中已经内置了，交叉熵的数值稳定性更差，所以内置的函数已经帮我们解决了这个问题

In [14]:

```
#定义loss函数
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(net.parameters(),1e-1) #使用随机梯度下降，学习率0.1
```

In [15]:

```
# 开始训练
losses = []
acces = []
eval_losses = []
eval_acces = []

for e in range(20):
    train_loss = 0
    train_acc = 0
    net.train()
    for im, label in train_data:
        im = Variable(im)
        label = Variable(label)
        # 前向传播
        out = net(im)
        loss = criterion(out, label)
        # 反向传播
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        # 记录误差
        #train_loss += loss.data[0] #报错 版本问题
        train_loss += loss.item()
        # 计算分类的准确率
        _, pred = out.max(1)
        num_correct = (pred == label).sum().item()
        acc = num_correct / im.shape[0]
        train_acc += acc

    losses.append(train_loss / len(train_data))
    acces.append(train_acc / len(train_data))
    # 在测试集上检验效果
    eval_loss = 0
    eval_acc = 0
    net.eval() # 将模型改为预测模式
    for im, label in test_data:
        im = Variable(im)
        label = Variable(label)
        out = net(im)
        loss = criterion(out, label)
        # 记录误差
        eval_loss += loss.item()
        # 记录准确率
        _, pred = out.max(1)
        num_correct = (pred == label).sum().item()
        acc = num_correct / im.shape[0]
        eval_acc += acc

    eval_losses.append(eval_loss / len(test_data))
    eval_acces.append(eval_acc / len(test_data))
    print('epoch: {}, Train Loss: {:.6f}, Train Acc: {:.6f}, Eval Loss: {:.6f}, Eval Acc: {:.6f
          .format(e, train_loss / len(train_data), train_acc / len(train_data),
                     eval_loss / len(test_data), eval_acc / len(test_data)))
```

```
epoch: 0, Train Loss: 0.524639, Train Acc: 0.830307, Eval Loss: 0.196595, Eval Acc:
0.937896
```

```
epoch: 1, Train Loss: 0.169251, Train Acc: 0.947844, Eval Loss: 0.202472, Eval Acc:
0.932555
epoch: 2, Train Loss: 0.118582, Train Acc: 0.962903, Eval Loss: 0.091459, Eval Acc:
0.970332
epoch: 3, Train Loss: 0.090689, Train Acc: 0.971249, Eval Loss: 0.092443, Eval Acc:
0.973299
epoch: 4, Train Loss: 0.074384, Train Acc: 0.976912, Eval Loss: 0.103744, Eval Acc:
0.968948
epoch: 5, Train Loss: 0.062870, Train Acc: 0.979061, Eval Loss: 0.092980, Eval Acc:
0.972211
epoch: 6, Train Loss: 0.052165, Train Acc: 0.983426, Eval Loss: 0.079641, Eval Acc:
0.976167
epoch: 7, Train Loss: 0.045725, Train Acc: 0.985724, Eval Loss: 0.069120, Eval Acc:
0.978639
epoch: 8, Train Loss: 0.036937, Train Acc: 0.987773, Eval Loss: 0.078571, Eval Acc:
0.976365
epoch: 9, Train Loss: 0.031771, Train Acc: 0.989855, Eval Loss: 0.087811, Eval Acc:
0.974090
epoch: 10, Train Loss: 0.028822, Train Acc: 0.990905, Eval Loss: 0.101254, Eval Acc:
0.972310
epoch: 11, Train Loss: 0.024348, Train Acc: 0.992221, Eval Loss: 0.077674, Eval Acc:
0.978837
epoch: 12, Train Loss: 0.021247, Train Acc: 0.993104, Eval Loss: 0.078959, Eval Acc:
0.976365
epoch: 13, Train Loss: 0.021948, Train Acc: 0.993354, Eval Loss: 0.071681, Eval Acc:
0.980716
epoch: 14, Train Loss: 0.016164, Train Acc: 0.994753, Eval Loss: 0.067969, Eval Acc:
0.981013
epoch: 15, Train Loss: 0.012936, Train Acc: 0.996102, Eval Loss: 0.066740, Eval Acc:
0.983188
epoch: 16, Train Loss: 0.017260, Train Acc: 0.995003, Eval Loss: 0.064093, Eval Acc:
0.983881
epoch: 17, Train Loss: 0.010002, Train Acc: 0.996885, Eval Loss: 0.075244, Eval Acc:
0.981705
epoch: 18, Train Loss: 0.010850, Train Acc: 0.996452, Eval Loss: 0.077619, Eval Acc:
0.980024
epoch: 19, Train Loss: 0.011614, Train Acc: 0.996085, Eval Loss: 0.373819, Eval Acc:
0.938489
```

画出 loss 曲线和 准确率曲线

In [16]:

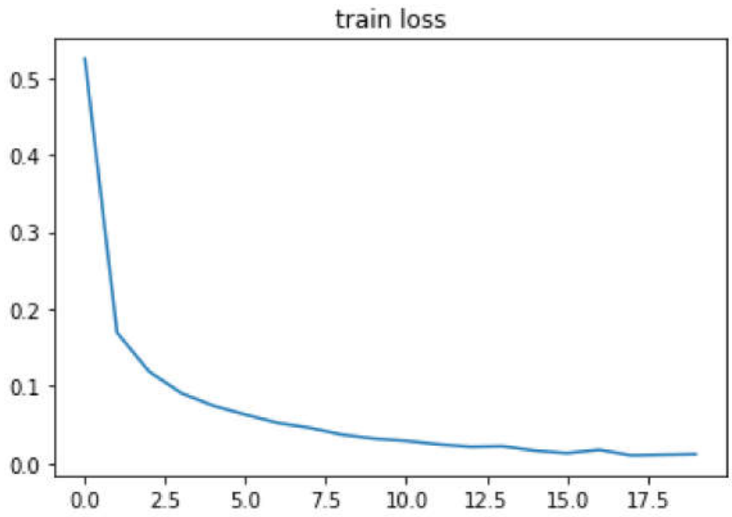
```python
import matplotlib.pyplot as plt
%matplotlib inline
```

In [17]:

```
plt.title('train loss')
plt.plot(np.arange(len(losses)), losses)
```

Out[17]:

```
[<matplotlib.lines.Line2D at 0x26a1aebe240>]
```

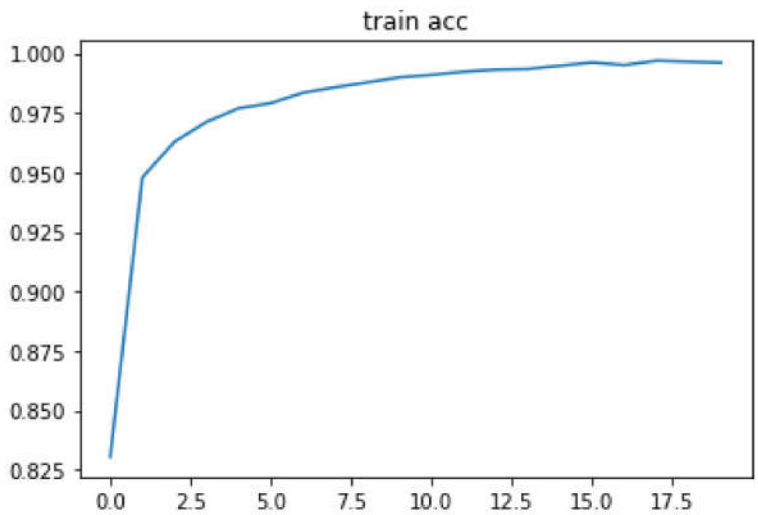


In [18]:

```
plt.plot(np.arange(len(acces)), acces)
plt.title('train acc')
```

Out[18]:

```
Text(0.5,1,'train acc')
```

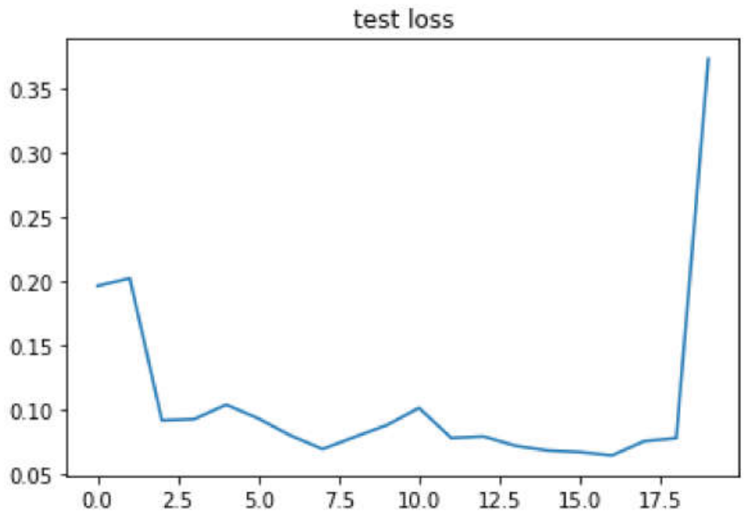


In [19]:

```
plt.plot(np.arange(len(eval_losses)), eval_losses)
plt.title('test loss')
```

Out[19]:

Text(0.5,1,'test loss')

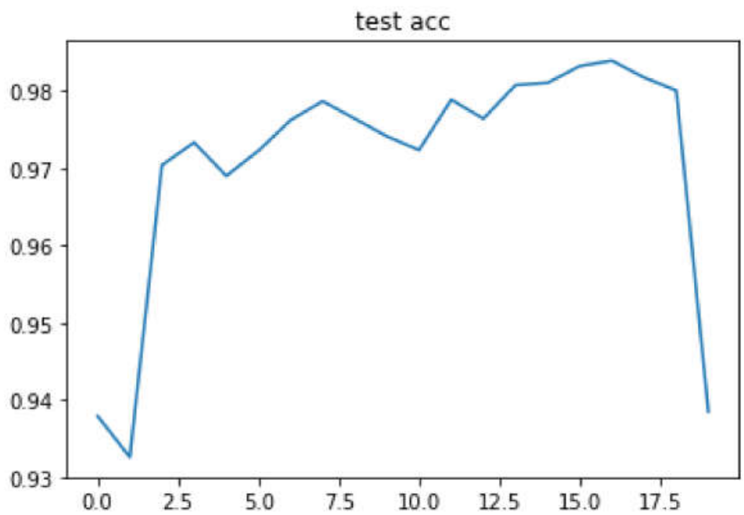


In [20]:

```
plt.plot(np.arange(len(eval_acces)), eval_acces)
plt.title('test acc')
```

Out[20]:

Text(0.5,1,'test acc')



- 三层网络在训练集达到99.9的准确率，测试集上达到98.2的准确率

训练集没有出现过拟合现象，但是测试集稍微有点，原因不知道，还是有点问题，可以调节下，batch_size,或者学习率。

pytorch里集成了许多api函数，各种激活函数(relu,sigmoid等等)，还有它在梯度下降，反向传播中也集成了许多，具体可以去官网查看手册。

In [ ]:

```

```