In [3]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import copy
import time
import tensorflow as tf

# train
import torch
from torch import nn
from torch.nn import functional as F

# load data
from torch.utils.data import DataLoader
from torchvision import datasets, transforms
```

1. Data

- you can use any data normalisation method
- one example of the data normalisation is whitenning as given by:

In [4]:

```
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.1307,),(0.3081,)),  # mean value = 0.1307, standard deviation value = 0.
])
```

- load the MNIST dataset
- use the original `training` dataset for `testing` your model
- use the original `testing` dataset for `training` your model

In [5]:

```
data_path = './MNIST'

data_test   = datasets.MNIST(root = data_path, train= True, download=True, transform= transform)
data_train  = datasets.MNIST(root = data_path, train= False, download=True, transform= transform)
```

- Note that the number of your `training` data must be 10,000
- Note that the number of your `testing` data must be 60,000

In [6]:

```
print("the number of your training data (must be 10,000) =", data_train.__len__())
print("the number of your testing data (must be 60,000) =", data_test.__len__())
```

```
the number of your training data (must be 10,000) = 10000
the number of your testing data (must be 60,000) = 60000
```

Model

- design a neural network architecture with three layers (input layer, one hidden layer and output layer)
- the input dimension of the input layer should be 784 (28 * 28)
- the output dimension of the output layer should be 10 (class of digits)
- all the layers should be `fully connected layers`
- use any type of activation functions

In [32]:

```
class classification(nn.Module):
    def __init__(self):
        super(classification, self).__init__()

        # construct layers for a neural network
        self.classifier1 = nn.Sequential(
            nn.Linear(in_features=28*28, out_features=20*20),
            nn.Sigmoid(),
        )
        self.classifier2 = nn.Sequential(
            nn.Linear(in_features=20*20, out_features=10*10),
            nn.Sigmoid(),
        )
        self.classifier3 = nn.Sequential(
            nn.Linear(in_features=10*10, out_features=10),
            nn.LogSoftmax(dim=1),
        )


    def forward(self, inputs):                 # [batchSize, 1, 28, 28]
        x = inputs.view(inputs.size(0), -1)    # [batchSize, 28*28]
        x = self.classifier1(x)                # [batchSize, 20*20]
        x = self.classifier2(x)                # [batchSize, 10*10]
        out = self.classifier3(x)              # [batchSize, 10]

        return out
```

Optimization

- use any stochastic gradient descent algorithm for the optimization
- use any size of the mini-batch
- use any optimization algorithm (for example, Momentum, AdaGrad, RMSProp, Adam)
- use any regularization algorithm (for example, Dropout, Weight Decay)
- use any annealing scheme for the learning rate (for example, constant, decay, staircase)

In [2]:

```
def accuracy(log_pred, y_true):
    y_pred = torch.argmax(log_pred, dim=1)
    return (y_pred == y_true).to(torch.float).mean()
```

In [33]:

```
batch_size = 32
lr=0.5
n_epochs = 20

no_cuda = True
use_cuda = not no_cuda and torch.cuda.is_available()
device = torch.device("cuda" if use_cuda else "cpu")

train_loader = DataLoader(dataset=data_train, batch_size=batch_size, shuffle=True)
test_loader = DataLoader(dataset=data_test, batch_size=batch_size, shuffle=True)

classifier = classification().to(device)
optimizer = torch.optim.SGD(classifier.parameters(), lr)

criterion = nn.NLLLoss()

accuracy_stats = {
    'train': [],
    "test": []
}
loss_stats = {
    'train': [],
    "test": []
}

for epoch in range(n_epochs):

    # TRAINING
    train_epoch_loss = 0
    train_epoch_acc = 0

    classifier.train()

    for X_train_batch, y_train_batch in train_loader:
        X_train_batch, y_train_batch = X_train_batch.to(device), y_train_batch.to(device)

        optimizer.zero_grad()

        y_train_pred = classifier(X_train_batch)

        train_loss = criterion(y_train_pred, y_train_batch)
        train_acc = accuracy(y_train_pred, y_train_batch)

        train_loss.backward()
        optimizer.step()

        train_epoch_loss += train_loss.item()
        train_epoch_acc += train_acc.item()

    with torch.no_grad():
        test_epoch_loss = 0
        test_epoch_acc = 0

        classifier.eval()

        for X_test_batch, y_test_batch in test_loader:
            X_test_batch, y_test_batch = X_test_batch.to(device), y_test_batch.to(device)

            y_test_pred = classifier(X_test_batch)
```

```
            test_loss = criterion(y_test_pred, y_test_batch)
            test_acc = accuracy(y_test_pred, y_test_batch)

            test_epoch_loss += test_loss.item()
            test_epoch_acc += test_acc.item()

    loss_stats['train'].append(train_epoch_loss/len(train_loader))
    loss_stats['test'].append(test_epoch_loss/len(test_loader))
    accuracy_stats['train'].append(train_epoch_acc/len(train_loader))
    accuracy_stats['test'].append(test_epoch_acc/len(test_loader))

print('done')
```

done

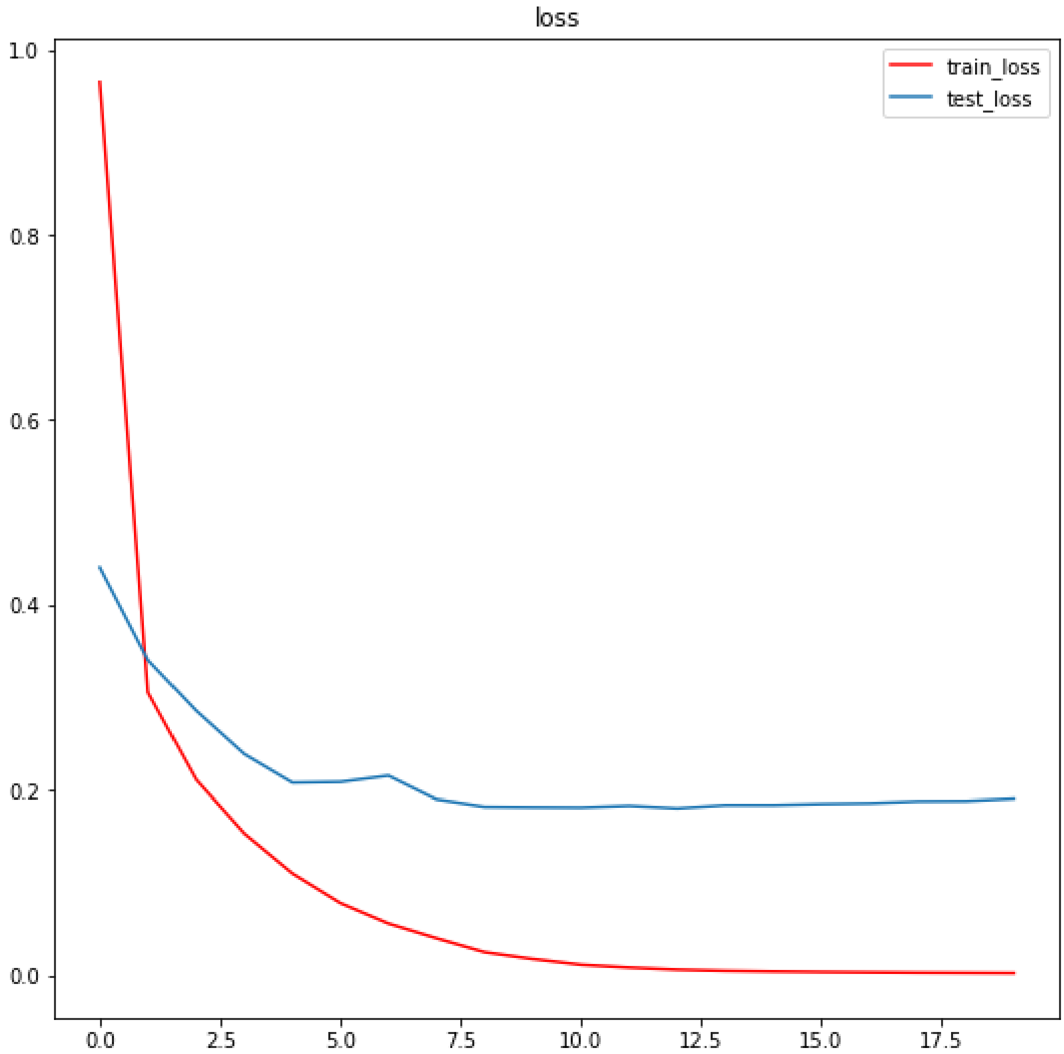
In [74]:

```
print(loss_stats['test'])
```

[0.0648531833662281, 0.0648531833662281]

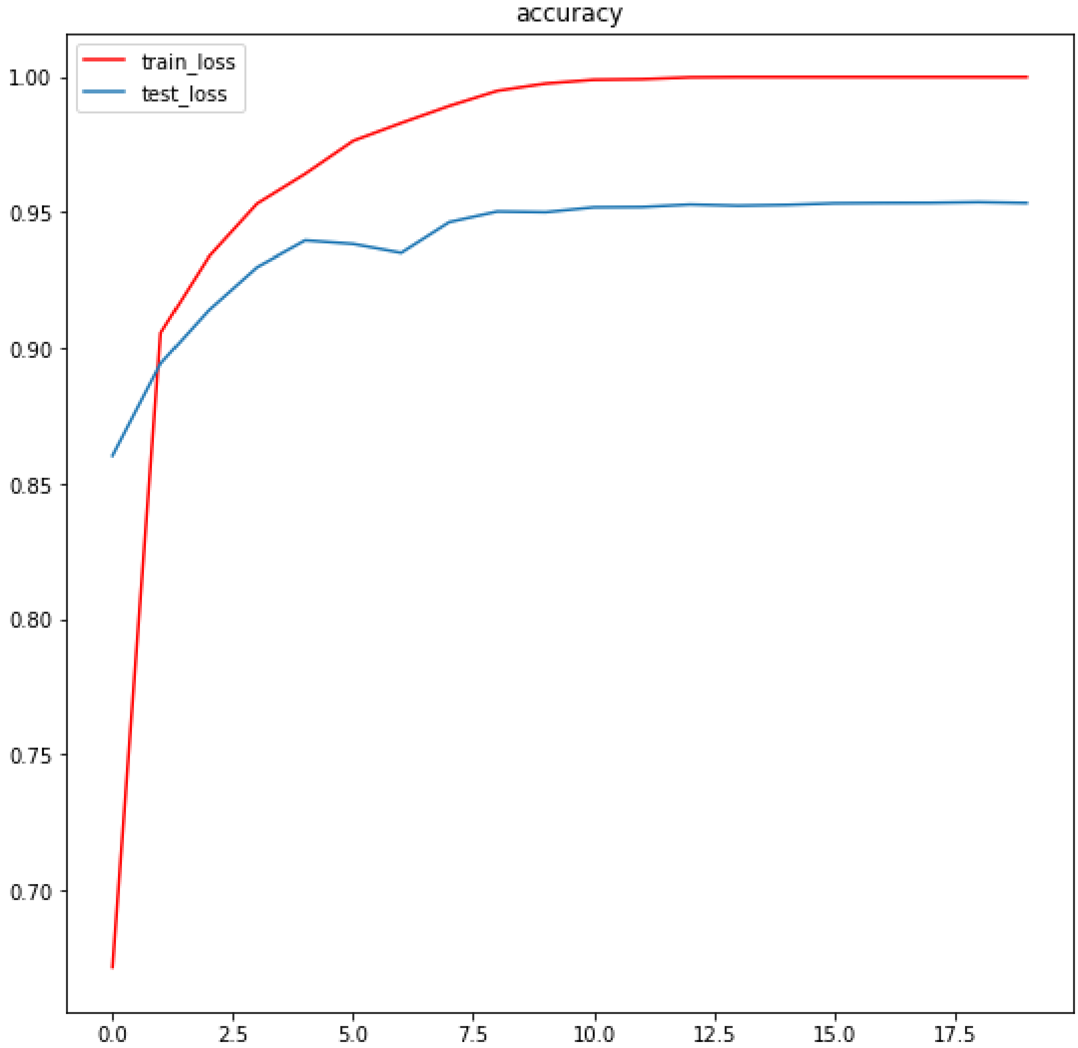
In [34]:

```
plt.figure(1,figsize=(9,9))
plt.plot(np.array(range(n_epochs)), loss_stats['train'], c='r', label='train_loss')
plt.plot(np.array(range(n_epochs)), loss_stats['test'], label='test_loss')
plt.legend()
plt.title('loss')
plt.show()
```



In [35]:

```
plt.figure(1,figsize=(9,9))
plt.plot(np.array(range(n_epochs)), accuracy_stats['train'], c='r', label='train_loss')
plt.plot(np.array(range(n_epochs)), accuracy_stats['test'], label='test_loss')
plt.legend()
plt.title('accuracy')
plt.show()
```



In [86]:

```
final_train_loss = []
final_test_loss = []
final_train_acc = []
final_test_acc = []
```

In [108]:

```
final_train_loss.append(loss_stats['train'][-1])
final_test_loss.append(loss_stats['test'][-1])
final_train_acc.append(accuracy_stats['train'][-1])
final_test_acc.append(accuracy_stats['test'][-1])
```

In [104]:

```
print('%.6f' % final_train_loss[1])
```

0.001297

In [115]:

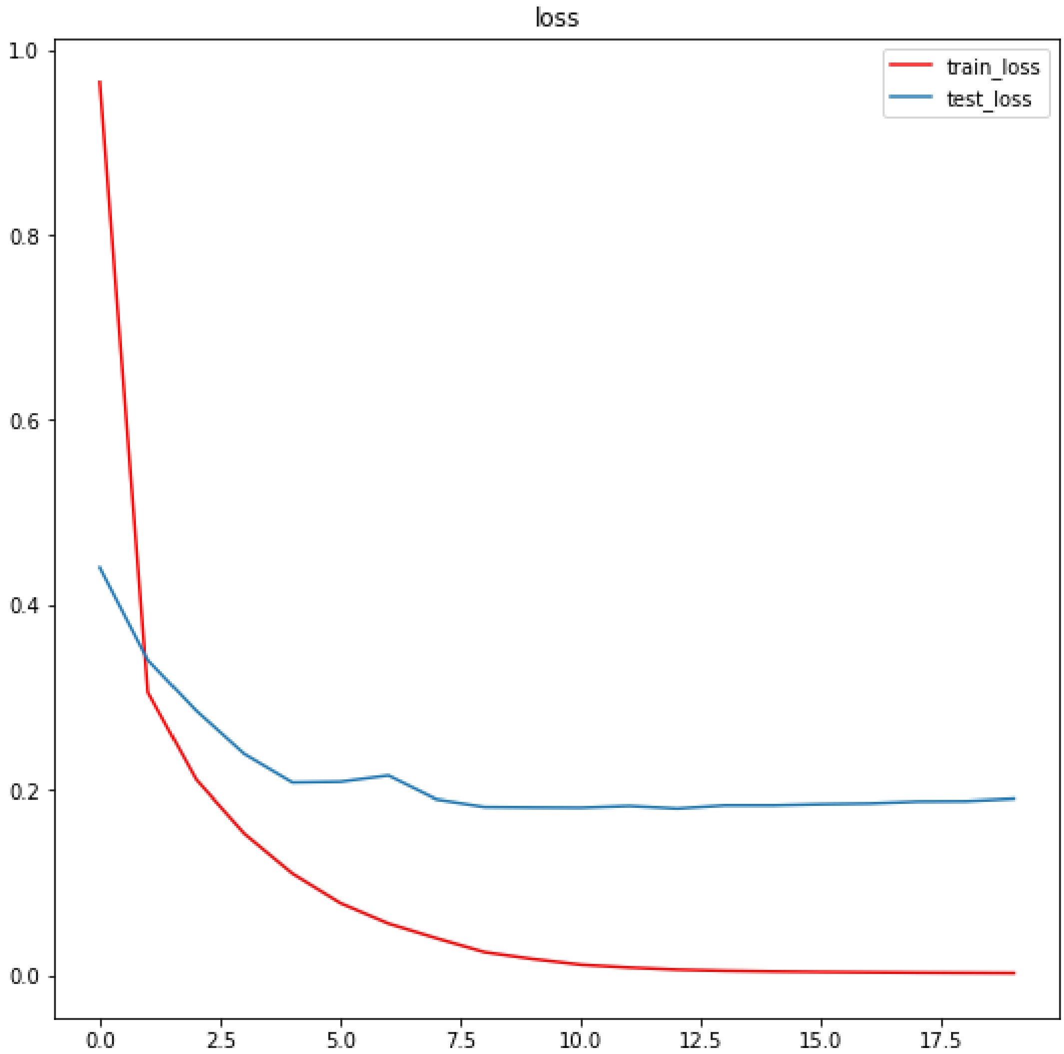
```
print('mini-batch size = 32 | training accuracy = %.6f'% final_train_acc[0], '| testing accuracy = %
print('mini-batch size = 64 | training accuracy = %.6f'% final_train_acc[1], '| testing accuracy = %
print('mini-batch size = 128 | training accuracy = %.6f'% final_train_acc[2], '| testing accuracy =
```

```
mini-batch size = 32 | training accuracy = 1.000000 | testing accuracy = 0.985124
mini-batch size = 64 | training accuracy = 1.000000 | testing accuracy = 0.982882
mini-batch size = 128 | training accuracy = 0.999650 | testing accuracy = 0.982298
```

1. Plot the training and testing losses over epochs [2pt]

In [36]:

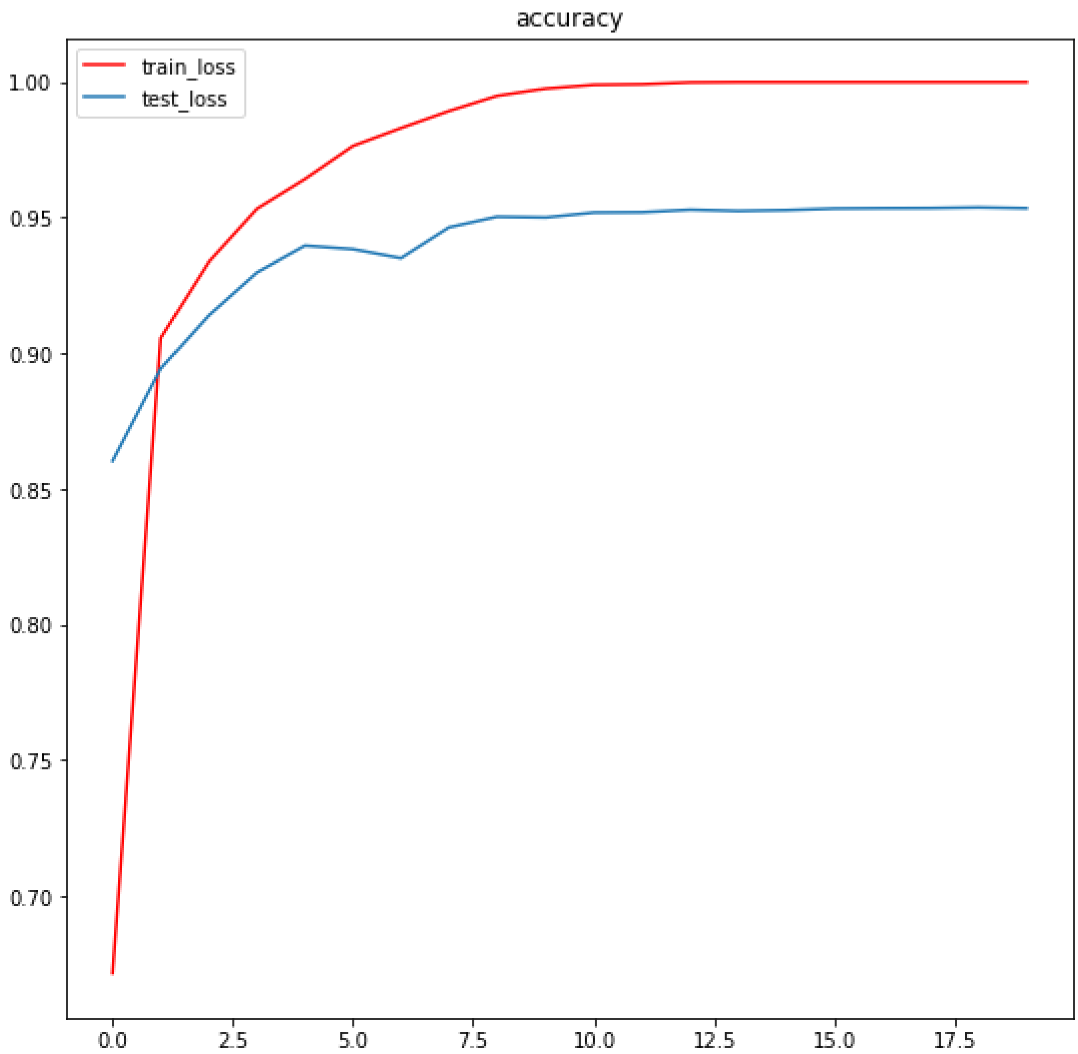
```
plt.figure(1,figsize=(9,9))
plt.plot(np.array(range(n_epochs)), loss_stats['train'], c='r', label='train_loss')
plt.plot(np.array(range(n_epochs)), loss_stats['test'], label='test_loss')
plt.legend()
plt.title('loss')
plt.show()
```



2. Plot the training and testing accuracies over epochs [2pt]

In [37]:

```
plt.figure(1,figsize=(9,9))
plt.plot(np.array(range(n_epochs)), accuracy_stats['train'], c='r', label='train_loss')
plt.plot(np.array(range(n_epochs)), accuracy_stats['test'], label='test_loss')
plt.legend()
plt.title('accuracy')
plt.show()
```



3. Print the final training and testing losses at convergence [2pt]

In [39]:

```
print('train loss : %.6f' %loss_stats['train'][-1])
print('test loss : %.6f' %loss_stats['test'][-1])
```

```
train loss : 0.002180
test loss : 0.190550
```

4. Print the final training and testing accuracies at convergence [20pt]

In [41]:

```
print('train accuracy " %.6f' %accuracy_stats['train'][-1])
print('test accuracy " %.6f' %accuracy_stats['test'][-1])
```

```
train accuracy " 1.000000
test accuracy " 0.953483
```