In [12]:

```
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
```

Data normalization

In [68]:

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

Load the MNIST dataset

In [69]:

```
data_path = './MNIST'

training_set = datasets.MNIST(root = data_path, train= True, download=True, transform= transform)
testing_set = datasets.MNIST(root = data_path, train= False, download=True, transform= transform)
```

Model

- design a neural network that consists of three `fully connected layers` with an activation function of `Sigmoid`
- the activation function for the output layer is `LogSoftmax`

In [70]:

```
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 a stochastic gradient descent algorithm with different mini-batch sizes of 32, 64, 128
- use a constant learning rate for all the mini-batch sizes
- do not use any regularization algorithm such as `dropout` or `weight decay`
- compute the average loss and the average accuracy for all the mini-batches within each epoch

In [76]:

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

In [105]:

```
batch_size = 128
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=training_set, batch_size=batch_size, shuffle=True)
test_loader = DataLoader(dataset=testing_set, 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)
```

```python
            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()

#     # VALIDATION
#     with torch.no_grad():

#         val_epoch_loss = 0
#         val_epoch_acc = 0

#         classifier.eval()
#         for X_val_batch, y_val_batch in test_loader:
#             X_val_batch, y_val_batch = X_val_batch.to(device), y_val_batch.to(device)

#             y_val_pred = classifier(X_val_batch)

#             val_loss = criterion(y_val_pred, y_val_batch)
#             val_acc = multi_acc(y_val_pred, y_val_batch)

#             val_epoch_loss += val_loss.item()
#             val_epoch_acc += val_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

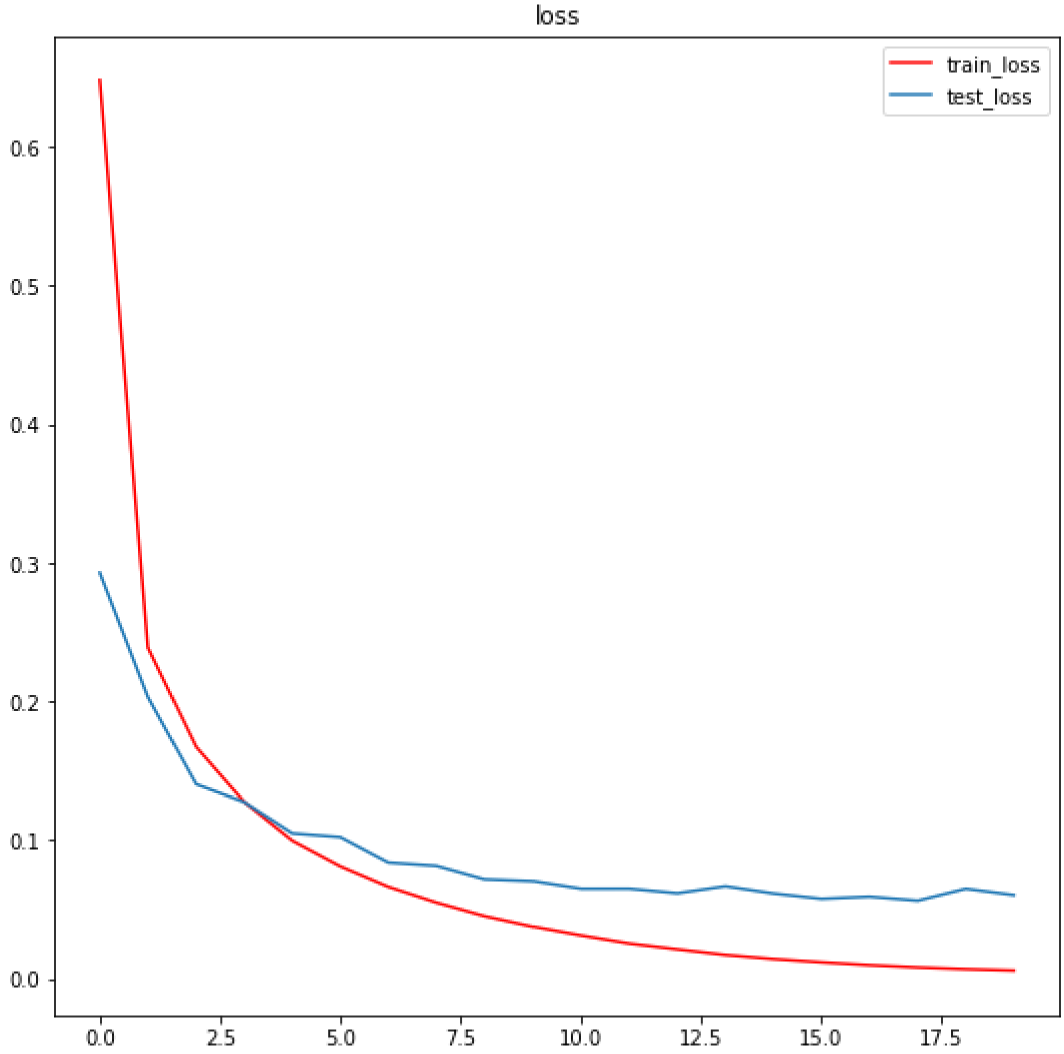
In [74]:

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

[0.0648531833662281, 0.0648531833662281]

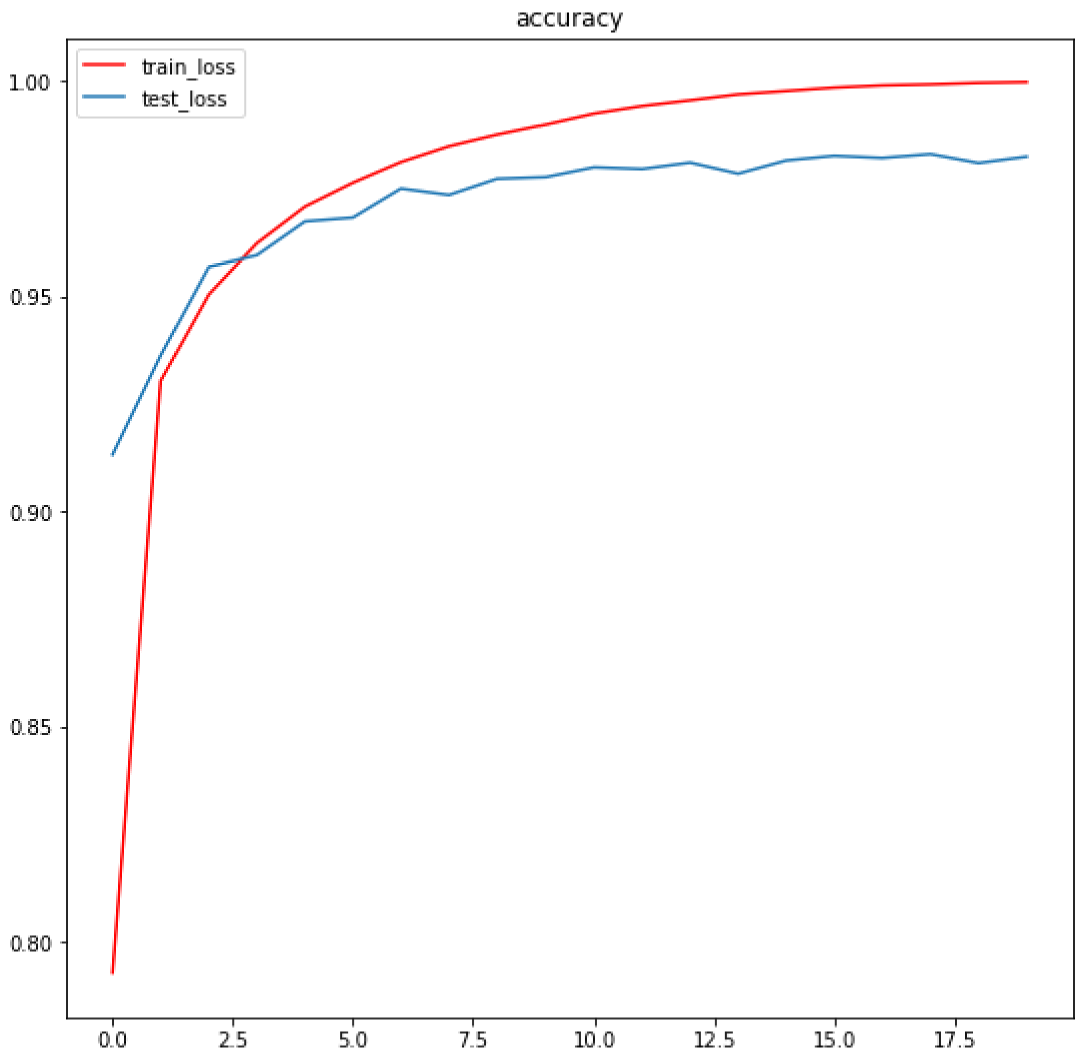
In [106]:

```
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 [107]:

```
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]:

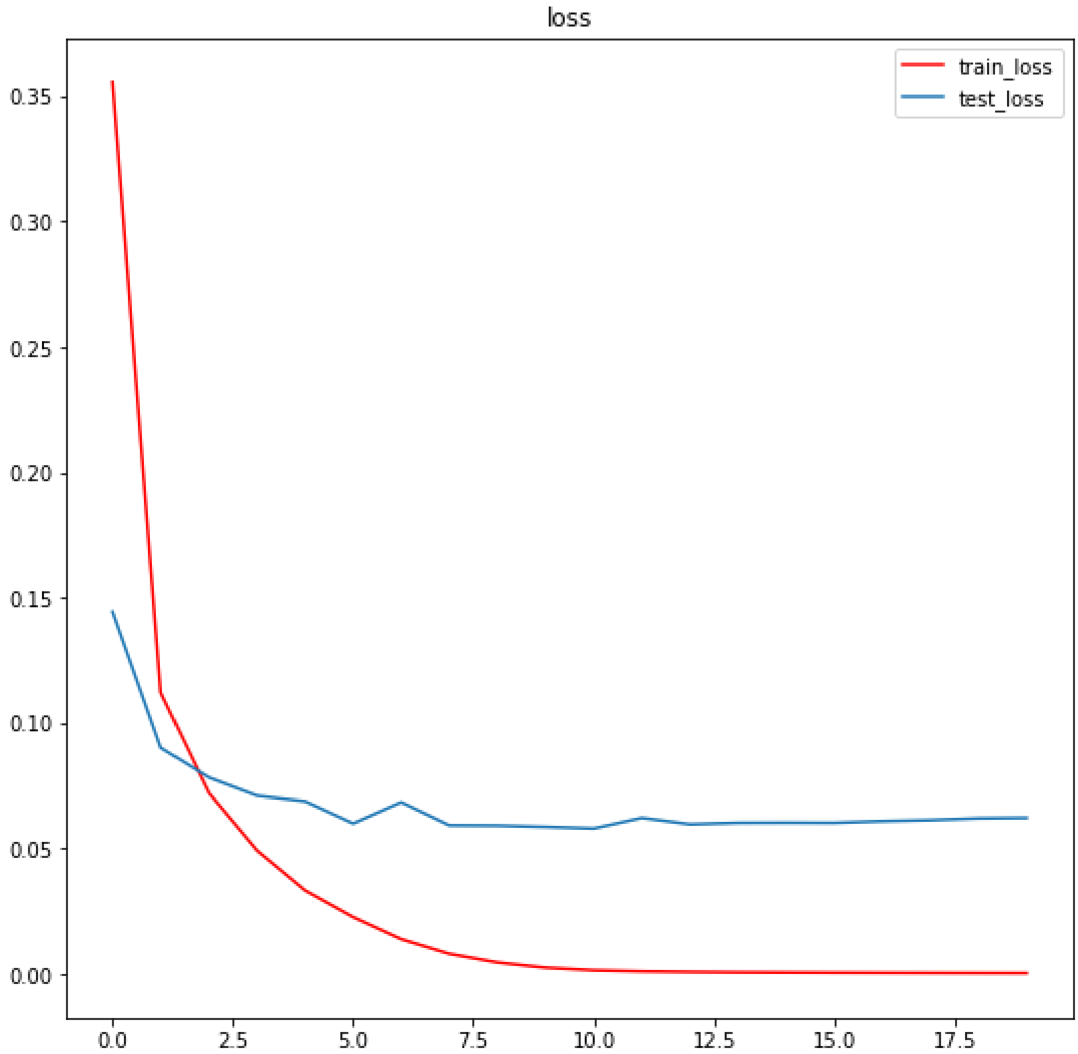
```
print('%.6f' % final_train_loss[1])
```

```
0.001297
```

1. Plot the training and testing losses with a batch size of 32 [4pt]

In [100]:

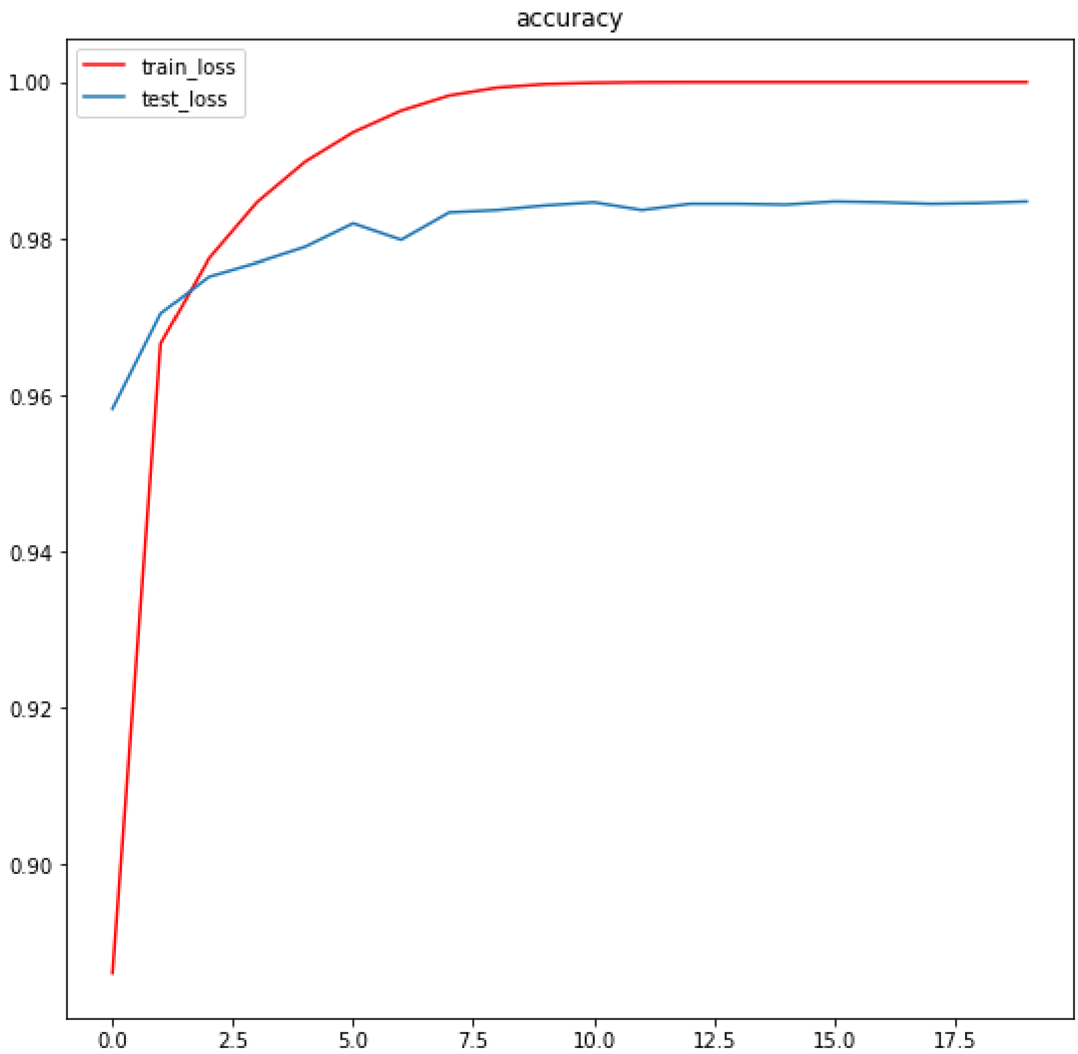
```
plt.figure(1,figsize=(9,9))
plt.plot(np.array(range(n_epochs)), loss_stats['train'], c='r', label='train_loss')
plt.plot(np.array(range(n_epochs)), loss_stats['test'], label='test_loss')
plt.legend()
plt.title('loss')
plt.show()
```



2. Plot the training and testing accuracies with a batch size of 32 [4pt]

In [102]:

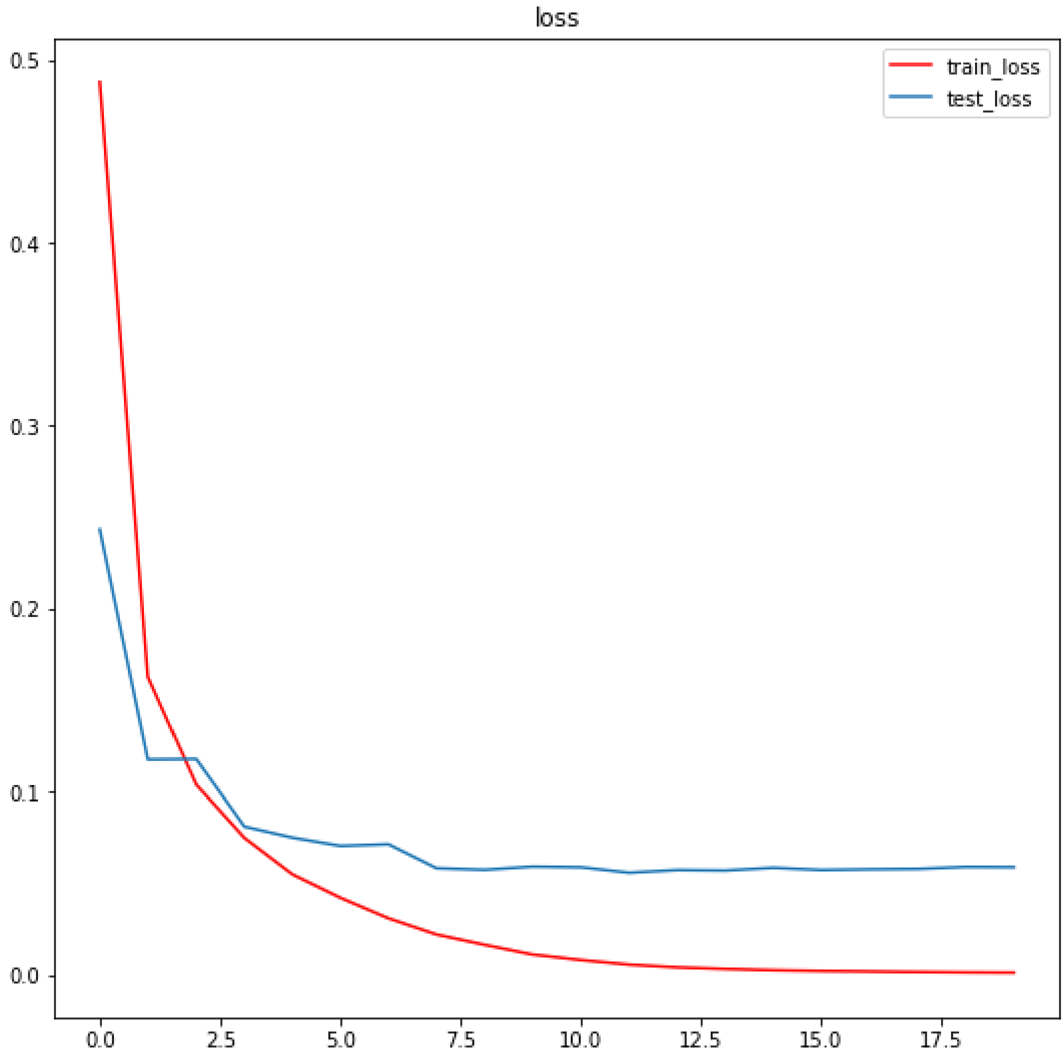
```
plt.figure(1,figsize=(9,9))
plt.plot(np.array(range(n_epochs)), accuracy_stats['train'], c='r', label='train_loss')
plt.plot(np.array(range(n_epochs)), accuracy_stats['test'], label='test_loss')
plt.legend()
plt.title('accuracy')
plt.show()
```



3. Plot the training and testing losses with a batch size of 64 [4pt]

In [91]:

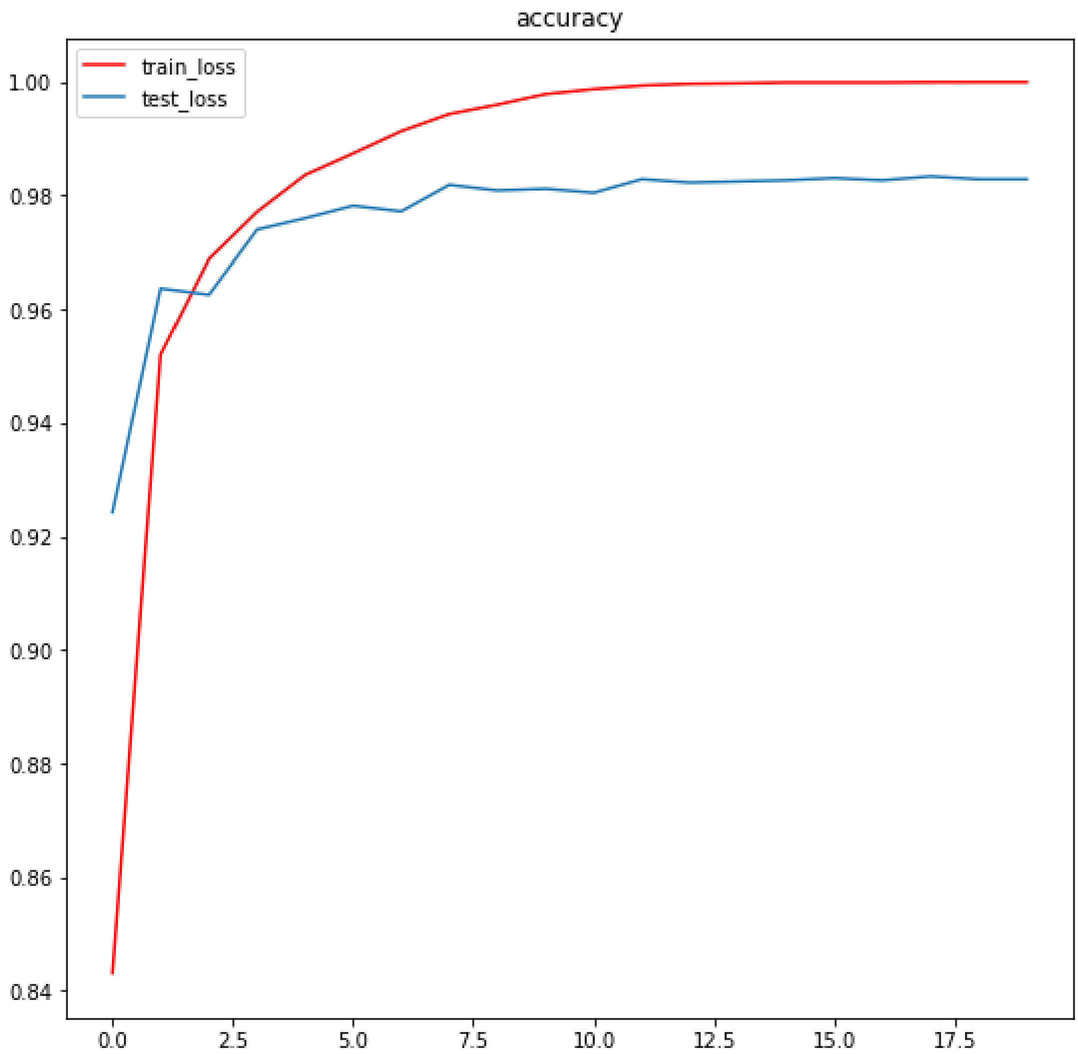
```
plt.figure(1,figsize=(9,9))
plt.plot(np.array(range(n_epochs)), loss_stats['train'], c='r', label='train_loss')
plt.plot(np.array(range(n_epochs)), loss_stats['test'], label='test_loss')
plt.legend()
plt.title('loss')
plt.show()
```



4. Plot the training and testing accuracies with a batch size of 64 [4pt]

In [96]:

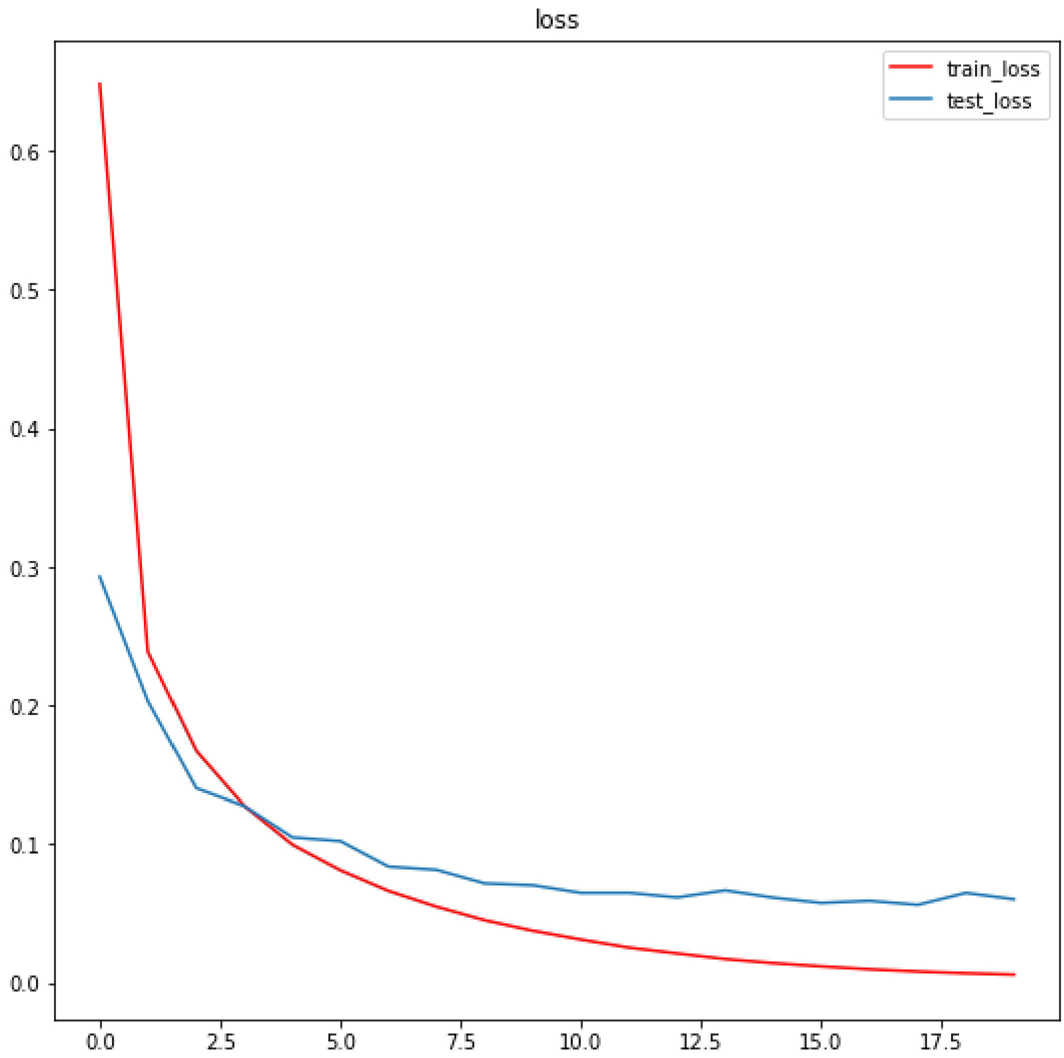
```
plt.figure(1,figsize=(9,9))
plt.plot(np.array(range(n_epochs)), accuracy_stats['train'], c='r', label='train_loss')
plt.plot(np.array(range(n_epochs)), accuracy_stats['test'], label='test_loss')
plt.legend()
plt.title('accuracy')
plt.show()
```



5. Plot the training and testing losses with a batch size of 128 [4pt]

In [109]:

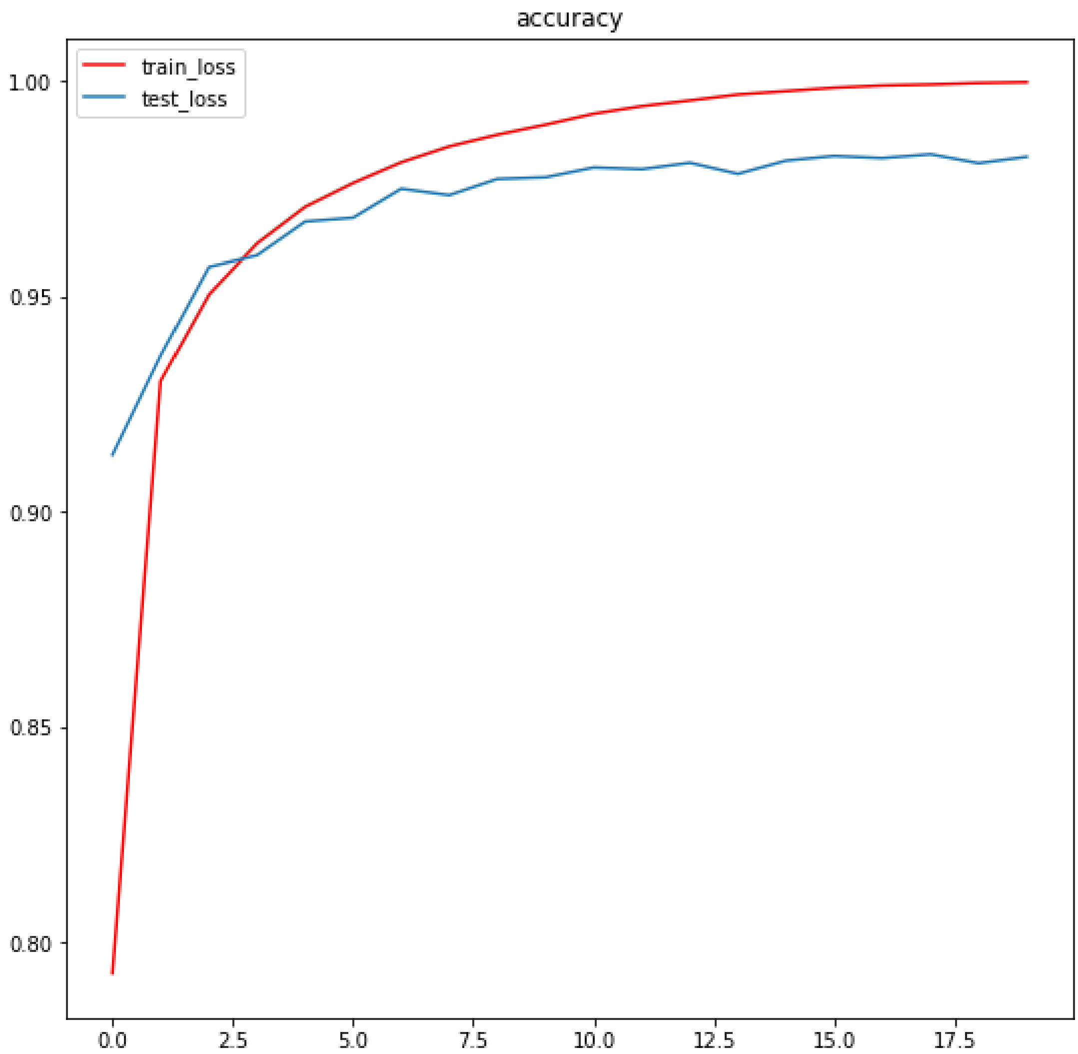
```
plt.figure(1,figsize=(9,9))
plt.plot(np.array(range(n_epochs)), loss_stats['train'], c='r', label='train_loss')
plt.plot(np.array(range(n_epochs)), loss_stats['test'], label='test_loss')
plt.legend()
plt.title('loss')
plt.show()
```



6. Plot the training and testing accuracies with a batch size of 128 [4pt]

In [110]:

```
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()
```



7. Print the loss at convergence with different mini-batch sizes [3pt]

In [114]:

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

```
mini-batch size = 32 | training loss = 0.000395 | testing loss = 0.061291
mini-batch size = 64 | training loss = 0.001297 | testing loss = 0.058929
mini-batch size = 128 | training loss = 0.005865 | testing loss = 0.060326
```

8. Print the accuracy at convergence with different mini-batch sizes [3pt]

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
```