HW6-Q3

In [15]:
```
import torch
import torch.nn as nn
import torchvision
import torchvision.transforms as transforms
import torch.utils.data as data
import torch.optim as optim
import matplotlib.pyplot as plt

train_set=torchvision.datasets.CIFAR10(root="./data",train=True,download=True,
                                       transform=transforms.ToTensor())
test_set=torchvision.datasets.CIFAR10(root="./data",train=False,download=True,
                                      transform=transforms.ToTensor())

train_loader=data.DataLoader(train_set,batch_size=100,shuffle=True)
test_loader=data.DataLoader(test_set,batch_size=100,shuffle=False)

class MLP(nn.Module):
    def __init__(self):
        super(MLP,self).__init__()
        self.network=nn.Sequential(
            nn.Flatten(),
            nn.Linear(3*32*32,256),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(256,128),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(128,10)
        )
    def forward(self,x):
        return self.network(x)

model=MLP()

learning_rate=0.01
l2_lambda=0.0001

loss_func=nn.CrossEntropyLoss()
optimizer=optim.SGD(model.parameters(),lr=learning_rate,weight_decay=l2_lambda)
```

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Files already downloaded and verified
Files already downloaded and verified
```

In [16]:
```
num_epoch=100

for epoch in range(num_epoch):
    model.train()
    running_loss=0
    for images,labels in train_loader:
        outputs=model(images)
        loss=loss_func(outputs,labels)
        running_loss+=loss
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

```
    print('Epoch {} - loss: {}'.format(epoch,running_loss))

all_preds=[]
all_labels=[]

model.eval()
with torch.no_grad():
    for images,labels in test_loader:
        outputs=model(images)
        loss=loss_func(outputs,labels)
        _,predicted=torch.max(outputs,1)
        all_preds.extend(predicted.numpy())
        all_labels.extend(labels.numpy())
```

```
Epoch 0 - loss: 1115.5830078125
Epoch 1 - loss: 1021.7300415039062
Epoch 2 - loss: 978.0801391601562
Epoch 3 - loss: 952.0846557617188
Epoch 4 - loss: 932.6698608398438
Epoch 5 - loss: 916.4351196289062
Epoch 6 - loss: 902.0715942382812
Epoch 7 - loss: 889.9658203125
Epoch 8 - loss: 879.0838623046875
Epoch 9 - loss: 869.3945922851562
Epoch 10 - loss: 860.4180297851562
Epoch 11 - loss: 851.1945190429688
Epoch 12 - loss: 843.663330078125
Epoch 13 - loss: 835.9638671875
Epoch 14 - loss: 830.2979125976562
Epoch 15 - loss: 823.1368408203125
Epoch 16 - loss: 816.7457275390625
Epoch 17 - loss: 811.6392211914062
Epoch 18 - loss: 805.4404907226562
Epoch 19 - loss: 799.4823608398438
Epoch 20 - loss: 793.977294921875
Epoch 21 - loss: 788.6806030273438
Epoch 22 - loss: 783.8004760742188
Epoch 23 - loss: 778.8466186523438
Epoch 24 - loss: 775.9365844726562
Epoch 25 - loss: 771.15673828125
Epoch 26 - loss: 767.33349609375
Epoch 27 - loss: 762.5327758789062
Epoch 28 - loss: 760.2673950195312
Epoch 29 - loss: 755.841796875
Epoch 30 - loss: 752.6836547851562
Epoch 31 - loss: 748.1321411132812
Epoch 32 - loss: 745.6010131835938
Epoch 33 - loss: 741.7354125976562
Epoch 34 - loss: 738.0830688476562
Epoch 35 - loss: 734.119140625
Epoch 36 - loss: 730.2850341796875
Epoch 37 - loss: 727.86328125
Epoch 38 - loss: 724.5682983398438
Epoch 39 - loss: 722.3261108398438
Epoch 40 - loss: 720.2451171875
Epoch 41 - loss: 715.8592529296875
Epoch 42 - loss: 712.8264770507812
Epoch 43 - loss: 711.372802734375
Epoch 44 - loss: 707.0244140625
Epoch 45 - loss: 705.709228515625
Epoch 46 - loss: 702.57177734375
Epoch 47 - loss: 698.5643920898438
Epoch 48 - loss: 698.3269653320312
Epoch 49 - loss: 693.7485961914062
Epoch 50 - loss: 692.7638549804688
Epoch 51 - loss: 691.4204711914062
Epoch 52 - loss: 687.90625
Epoch 53 - loss: 684.0046997070312
Epoch 54 - loss: 681.9351806640625
Epoch 55 - loss: 679.922119140625
Epoch 56 - loss: 681.682373046875
Epoch 57 - loss: 679.185546875
Epoch 58 - loss: 675.5855712890625
Epoch 59 - loss: 672.2362670898438
```

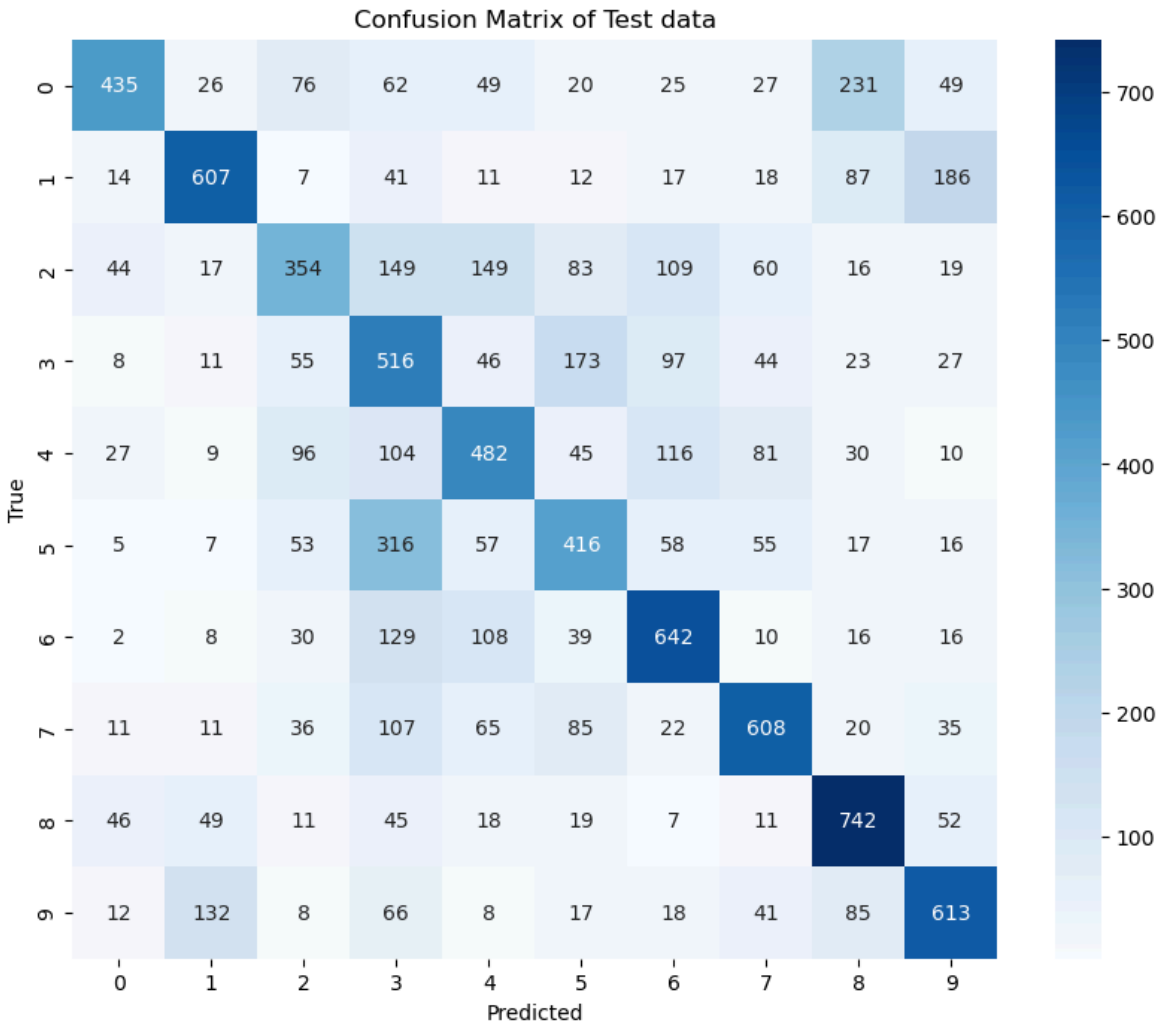
```
Epoch 60 - loss: 670.3721923828125
Epoch 61 - loss: 667.3853149414062
Epoch 62 - loss: 667.07080078125
Epoch 63 - loss: 664.8051147460938
Epoch 64 - loss: 662.336181640625
Epoch 65 - loss: 660.668701171875
Epoch 66 - loss: 658.658447265625
Epoch 67 - loss: 658.1076049804688
Epoch 68 - loss: 656.8859252929688
Epoch 69 - loss: 652.122314453125
Epoch 70 - loss: 650.6231079101562
Epoch 71 - loss: 651.99755859375
Epoch 72 - loss: 648.3004150390625
Epoch 73 - loss: 646.3712768554688
Epoch 74 - loss: 642.7102661132812
Epoch 75 - loss: 642.4271850585938
Epoch 76 - loss: 640.4236450195312
Epoch 77 - loss: 639.564453125
Epoch 78 - loss: 639.0795288085938
Epoch 79 - loss: 637.21826171875
Epoch 80 - loss: 634.5625610351562
Epoch 81 - loss: 632.9602661132812
Epoch 82 - loss: 633.1918334960938
Epoch 83 - loss: 629.15966796875
Epoch 84 - loss: 628.8482055664062
Epoch 85 - loss: 627.7118530273438
Epoch 86 - loss: 626.3252563476562
Epoch 87 - loss: 623.9664306640625
Epoch 88 - loss: 622.150634765625
Epoch 89 - loss: 621.0182495117188
Epoch 90 - loss: 620.7442016601562
Epoch 91 - loss: 619.5210571289062
Epoch 92 - loss: 616.933837890625
Epoch 93 - loss: 616.4555053710938
Epoch 94 - loss: 615.8231811523438
Epoch 95 - loss: 612.2374267578125
Epoch 96 - loss: 611.1432495117188
Epoch 97 - loss: 611.5711059570312
Epoch 98 - loss: 609.9839477539062
Epoch 99 - loss: 605.0579833984375
```

In [17]:

```python
import seaborn as sns
from sklearn.metrics import confusion_matrix

cm=confusion_matrix(all_labels,all_preds)

plt.figure(figsize=(10, 8))
sns.heatmap(cm,annot=True,fmt="d",cmap="Blues")
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix of Test data')
plt.show()
```



(a) Consider class m. List the class most likely confused for class m for each object type.

In [22]:
```
import numpy as np
for i in range(10):
    confused_classes=np.argsort(-cm[i,:])   #minus + sort increase = the biggest
    for confused_class in confused_classes:
        if confused_class!=i:
            print('For class {} ({}), the most likely confused class is {} ({})'
                  i,test_set.classes[i],confused_class,test_set.classes[confuse
            break
```

```
For class 0 (airplane), the most likely confused class is 8 (ship)
For class 1 (automobile), the most likely confused class is 9 (truck)
For class 2 (bird), the most likely confused class is 3 (cat)
For class 3 (cat), the most likely confused class is 5 (dog)
For class 4 (deer), the most likely confused class is 6 (frog)
For class 5 (dog), the most likely confused class is 3 (cat)
For class 6 (frog), the most likely confused class is 3 (cat)
For class 7 (horse), the most likely confused class is 3 (cat)
For class 8 (ship), the most likely confused class is 9 (truck)
For class 9 (truck), the most likely confused class is 1 (automobile)
```

(b) Which two classes (object types) are most likely to be confused overall?

In [23]:
```
cm_no_diagnal=cm-np.eye(10)*cm.diagonal()
idx_max_error=np.argmax(cm_no_diagnal,axis=None)
most_confused_classes = np.unravel_index(idx_max_error,cm.shape)
print('class {} ({}) and class {} ({}) are most likely to be confused overall'.f
    most_confused_classes[0],test_set.classes[most_confused_classes[0]],most_con
```

```
class 5 (dog) and class 3 (cat) are most likely to be confused overall
```