In [23]:

```
import torch
print("Torch Version: {}".format(torch.__version__))
```

```
Torch Version: 1.8.1
```

In [25]:

```
import numpy as np
print("Numpy Version: {}".format(np.__version__))
```

```
Numpy Version: 1.19.2
```

In [27]:

```
import matplotlib
print("Matplotlib Version: {}".format(matplotlib.__version__))
```

```
Matplotlib Version: 3.3.2
```

In [29]:

```
import torchvision
print("Torchvision Version: {}".format(torchvision.__version__))
```

```
Torchvision Version: 0.9.1
```

In [31]:

```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from torch import nn, optim
import torch.nn.functional as F
from torch.utils.data import DataLoader
from torchvision import datasets,transforms
from torch.utils.data.sampler import SubsetRandomSampler

%matplotlib inline
device = 'cuda' if torch.cuda.is_available() else 'cpu'
```

In [33]:

```
batch_size = 20

valid_size = 0.2

transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5), (0.5,))
    ])

train_data = datasets.MNIST('MNIST_data', train=True, download=True, transform=transform)

test_data = datasets.MNIST('MNIST_data', train=False, download=True, transform=transform)

num_train = len(train_data)
indices = list(range(num_train))
np.random.shuffle(indices)
split = int(np.floor(valid_size * num_train))
train_idx, valid_idx = indices[split:], indices[:split]

train_sampler = SubsetRandomSampler(train_idx)
valid_sampler = SubsetRandomSampler(valid_idx)

train_loader = DataLoader(train_data, batch_size=batch_size, sampler=train_sampler)

valid_loader = DataLoader(train_data, batch_size=batch_size, sampler=valid_sampler)

test_loader = DataLoader(test_data, batch_size=batch_size)
```

In [ ]:

```
class Net(nn.Module):
  def __init__(self):
    super().__init__()
    self.fc1 = nn.Linear(784, 256)
    self.fc2 = nn.Linear(256, 128)
    self.fc3 = nn.Linear(128, 64)
    self.fc4 = nn.Linear(64, 10)

  def forward(self, x):
    x = x.view(x.shape[0], -1)  # flattering the input tensor

    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = F.relu(self.fc3(x))
    x = F.log_softmax(self.fc4(x), dim=1)

    return x
```

In [32]:

```
model = Classifier()
model = model.to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.003)
```

In [36]:

```
epochs = 30
train_losses, valid_losses = [], []
valid_loss_min = np.Inf

for e in range(epochs):
    train_loss, valid_loss = 0.0, 0.0
    model.train()
    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device)

        optimizer.zero_grad()
        output = model(images)
        loss = criterion(output, labels)
        loss.backward()
        optimizer.step()
        train_loss += loss.item()*images.size(0)

    model.eval
    for images, labels in valid_loader:
        images, labels = images.to(device), labels.to(device)

        output = model(images)
        loss = criterion(output, labels)
        valid_loss += loss.item()*images.size(0)


    train_loss = train_loss/len(train_loader.sampler)
    train_losses.append(train_loss)
    valid_loss = valid_loss/len(valid_loader.sampler)
    valid_losses.append(valid_loss)

    print('Epoch: {} \tTraining Loss: {:.6f} \tValidation Loss: {:.6f}'.format(
        e+1, train_loss, valid_loss))

    if valid_loss <= valid_loss_min:
        print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.format(
        valid_loss_min,
        valid_loss))
        torch.save(model.state_dict(), 'mnist_ann.pt')
        valid_loss_min = valid_loss
```

```
Epoch: 1        Training Loss: 0.331936         Validation Loss: 0.316636
Validation loss decreased (inf --> 0.316636).  Saving model ...
Epoch: 2        Training Loss: 0.303024         Validation Loss: 0.296594
Validation loss decreased (0.316636 --> 0.296594).  Saving model ...
Epoch: 3        Training Loss: 0.278292         Validation Loss: 0.267787
Validation loss decreased (0.296594 --> 0.267787).  Saving model ...
Epoch: 4        Training Loss: 0.255892         Validation Loss: 0.249430
Validation loss decreased (0.267787 --> 0.249430).  Saving model ...
Epoch: 5        Training Loss: 0.234609         Validation Loss: 0.236686
Validation loss decreased (0.249430 --> 0.236686).  Saving model ...
Epoch: 6        Training Loss: 0.214459         Validation Loss: 0.216773
Validation loss decreased (0.236686 --> 0.216773).  Saving model ...
Epoch: 7        Training Loss: 0.196832         Validation Loss: 0.212171
Validation loss decreased (0.216773 --> 0.212171).  Saving model ...
Epoch: 8        Training Loss: 0.180280         Validation Loss: 0.181335
Validation loss decreased (0.212171 --> 0.181335).  Saving model ...
Epoch: 9        Training Loss: 0.165568         Validation Loss: 0.177877
Validation loss decreased (0.181335 --> 0.177877).  Saving model ...
Epoch: 10       Training Loss: 0.152678         Validation Loss: 0.161196
Validation loss decreased (0.177877 --> 0.161196).  Saving model ...
Epoch: 11       Training Loss: 0.141372         Validation Loss: 0.144571
Validation loss decreased (0.161196 --> 0.144571).  Saving model ...
Epoch: 12       Training Loss: 0.130932         Validation Loss: 0.144412
Validation loss decreased (0.144571 --> 0.144412).  Saving model ...
Epoch: 13       Training Loss: 0.122724         Validation Loss: 0.128777
Validation loss decreased (0.144412 --> 0.128777).  Saving model ...
Epoch: 14       Training Loss: 0.114138         Validation Loss: 0.124194
Validation loss decreased (0.128777 --> 0.124194).  Saving model ...
Epoch: 15       Training Loss: 0.107077         Validation Loss: 0.120858
Validation loss decreased (0.124194 --> 0.120858).  Saving model ...
Epoch: 16       Training Loss: 0.100580         Validation Loss: 0.112536
Validation loss decreased (0.120858 --> 0.112536).  Saving model ...
Epoch: 17       Training Loss: 0.094357         Validation Loss: 0.112285
Validation loss decreased (0.112536 --> 0.112285).  Saving model ...
Epoch: 18       Training Loss: 0.088760         Validation Loss: 0.105653
Validation loss decreased (0.112285 --> 0.105653).  Saving model ...
Epoch: 19       Training Loss: 0.084454         Validation Loss: 0.103083
Validation loss decreased (0.105653 --> 0.103083).  Saving model ...
Epoch: 20       Training Loss: 0.079355         Validation Loss: 0.099246
Validation loss decreased (0.103083 --> 0.099246).  Saving model ...
Epoch: 21       Training Loss: 0.074687         Validation Loss: 0.094391
Validation loss decreased (0.099246 --> 0.094391).  Saving model ...
Epoch: 22       Training Loss: 0.070907         Validation Loss: 0.095798
Epoch: 23       Training Loss: 0.067106         Validation Loss: 0.091535
Validation loss decreased (0.094391 --> 0.091535).  Saving model ...
Epoch: 24       Training Loss: 0.063286         Validation Loss: 0.094253
```

```
Epoch: 25 	Training Loss: 0.060219 	Validation Loss: 0.092203
Epoch: 26 	Training Loss: 0.057201 	Validation Loss: 0.092112
Epoch: 27 	Training Loss: 0.053932 	Validation Loss: 0.092661
Epoch: 28 	Training Loss: 0.052097 	Validation Loss: 0.086928
Validation loss decreased (0.091535 --> 0.086928).  Saving model ...
Epoch: 29 	Training Loss: 0.048747 	Validation Loss: 0.083981
Validation loss decreased (0.086928 --> 0.083981).  Saving model ...
Epoch: 30 	Training Loss: 0.046583 	Validation Loss: 0.084904
```

In [37]:

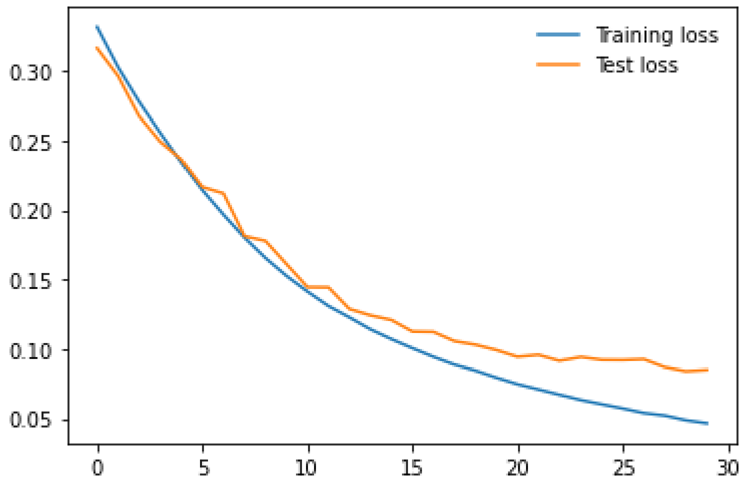
```python
model.load_state_dict(torch.load('mnist_ann.pt', map_location=torch.device(device)))
```

Out[37]:

```
<All keys matched successfully>
```

In [39]:

```python
plt.plot(train_losses, label='Training loss')
plt.plot(valid_losses, label ='Test loss')
plt.legend(frameon=False)
plt.show()
```



In [56]:

```python
test_loss = 0.0
class_correct = list(0. for i in range(10))
class_total = list(0. for i in range(10))

model.eval()

for images, labels in test_loader:
    images, labels = images.to(device), labels.to(device)

    output = model(images)
    loss = criterion(output, labels)
    test_loss += loss.item()*images.size(0)
    _, pred = torch.max(output, 1)
    correct = np.squeeze(pred.eq(labels.data.view_as(pred)))

    for i in range(batch_size):
        label = labels.data[i]
        class_correct[label] += correct[i].item()
        class_total[label] += 1


test_loss = test_loss/len(test_loader.dataset)
print('Test Loss: {:.6f}\n'.format(test_loss))

for i in range(10):
    if class_total[i] > 0:
        print('Test Accuracy of %2s: %2d%% (%2d/%2d)' % (
            str([i]), 100 * class_correct[i] / class_total[i],
            np.sum(class_correct[i]), np.sum(class_total[i])))
    else:
        print('Test Accuracy of %5s: N/A (no training examples)' % (classes[i]))

print('\nTest Accuracy (Overall): %2d%% (%2d/%2d)' % (
    100. * np.sum(class_correct) / np.sum(class_total),
    np.sum(class_correct), np.sum(class_total)))
```

```
Test Loss: 0.082571

Test Accuracy of [0]: 98% (966/980)
Test Accuracy of [1]: 99% (1125/1135)
Test Accuracy of [2]: 97% (1006/1032)
Test Accuracy of [3]: 97% (987/1010)
Test Accuracy of [4]: 96% (952/982)
Test Accuracy of [5]: 97% (871/892)
Test Accuracy of [6]: 97% (936/958)
Test Accuracy of [7]: 95% (980/1028)
Test Accuracy of [8]: 97% (948/974)
Test Accuracy of [9]: 96% (978/1009)

Test Accuracy (Overall): 97% (9749/10000)
```

In [77]:

```
images, labels = next(iter(train_loader))
image, labels = images.to(device), labels.to(device)

img = images[1].view(1,784)

with torch.no_grad():
  log_ps = model(img)

ps = F.softmax(log_ps, dim=1)
fig = plt.figure(figsize=(6,9))
ax1 = plt.subplot(121)
ax1.imshow(img.resize_(1, 28, 28).cpu().numpy().squeeze())
ax1.axis('off')

ax2 = plt.subplot(122)
ax2.set_yticks(np.arange(10))
ax2.set_xticks(np.arange(0,1.1,0.25))
ax2.set_xlim(0,1.1)
ax2.set_aspect(0.1)
ax2.set_title('Class Probability')
plt.barh(np.arange(10),ps.data.cpu().numpy().squeeze())

plt.tight_layout()

```