In [2]:
```
import torch
print("Torch Version: {}".format(torch.__version__))
```

```
Torch Version: 1.8.1
```

In [3]:
```
import numpy as np
print("Numpy Version: {}".format(np.__version__))
```

```
Numpy Version: 1.19.2
```

In [4]:
```
import matplotlib
print("Matplotlib Version: {}".format(matplotlib.__version__))
```

```
Matplotlib Version: 3.3.2
```

In [5]:
```
import torchvision
print("Torchvision Version: {}".format(torchvision.__version__))
```

```
Torchvision Version: 0.9.1
```

In [6]:
```
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 [7]:
```
batch_size = 20

valid_size = 0.2

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

train_data = datasets.FashionMNIST('F_MNIST_data/', download=True, train=True, transform=transform)

test_data = datasets.FashionMNIST('F_MNIST_data/', download=True, train=False, 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)

classes = ['T-shirt/top',
            'Trouser',
            'Pullover',
            'Dress',
            'Coat',
            'Sandal',
            'Shirt',
            'Sneaker',
            'Bag',
            'Ankle Boot']
```

In [8]:
```
class Net(nn.Module):
  def __init__(self):
    super().__init__()
    self.fc1 = nn.Linear(784, 512)
    self.fc2 = nn.Linear(512, 256)
    self.fc3 = nn.Linear(256, 128)
    self.fc4 = nn.Linear(128, 64)
    self.fc5 = nn.Linear(64, 10)
    self.dropout = nn.Dropout(p=0.2)

  def forward(self, x):
    x = x.view(x.shape[0], -1)

    x = self.dropout(F.relu(self.fc1(x)))
    x = self.dropout(F.relu(self.fc2(x)))
    x = self.dropout(F.relu(self.fc3(x)))
    x = self.dropout(F.relu(self.fc4(x)))
    x = F.log_softmax(self.fc5(x), dim=1)

    return x
```

In [9]:
```
model = Net()
model = model.to(device)
criterion = nn.NLLLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01)
```

In [42]:

```
epochs = 50
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(),'fashion_mnist_ann.pt')
        valid_loss_min = valid_loss
```

```
Epoch: 1        Training Loss: 1.358861         Validation Loss: 0.769927
Validation loss decreased (inf --> 0.769927).  Saving model ...
Epoch: 2        Training Loss: 0.663367         Validation Loss: 0.583180
Validation loss decreased (0.769927 --> 0.583180).  Saving model ...
Epoch: 3        Training Loss: 0.548222         Validation Loss: 0.521153
Validation loss decreased (0.583180 --> 0.521153).  Saving model ...
Epoch: 4        Training Loss: 0.486952         Validation Loss: 0.484718
Validation loss decreased (0.521153 --> 0.484718).  Saving model ...
Epoch: 5        Training Loss: 0.452480         Validation Loss: 0.442287
Validation loss decreased (0.484718 --> 0.442287).  Saving model ...
Epoch: 6        Training Loss: 0.425699         Validation Loss: 0.414073
Validation loss decreased (0.442287 --> 0.414073).  Saving model ...
Epoch: 7        Training Loss: 0.404787         Validation Loss: 0.406415
Validation loss decreased (0.414073 --> 0.406415).  Saving model ...
Epoch: 8        Training Loss: 0.388965         Validation Loss: 0.382574
Validation loss decreased (0.406415 --> 0.382574).  Saving model ...
Epoch: 9        Training Loss: 0.372344         Validation Loss: 0.371904
Validation loss decreased (0.382574 --> 0.371904).  Saving model ...
Epoch: 10       Training Loss: 0.359971         Validation Loss: 0.366394
Validation loss decreased (0.371904 --> 0.366394).  Saving model ...
Epoch: 11       Training Loss: 0.348125         Validation Loss: 0.362578
Validation loss decreased (0.366394 --> 0.362578).  Saving model ...
Epoch: 12       Training Loss: 0.340430         Validation Loss: 0.354380
Validation loss decreased (0.362578 --> 0.354380).  Saving model ...
Epoch: 13       Training Loss: 0.327693         Validation Loss: 0.373747
Epoch: 14       Training Loss: 0.321065         Validation Loss: 0.357246
Epoch: 15       Training Loss: 0.314037         Validation Loss: 0.354296
Validation loss decreased (0.354380 --> 0.354296).  Saving model ...
Epoch: 16       Training Loss: 0.304257         Validation Loss: 0.343482
Validation loss decreased (0.354296 --> 0.343482).  Saving model ...
Epoch: 17       Training Loss: 0.297523         Validation Loss: 0.338897
Validation loss decreased (0.343482 --> 0.338897).  Saving model ...
Epoch: 18       Training Loss: 0.290501         Validation Loss: 0.337632
Validation loss decreased (0.338897 --> 0.337632).  Saving model ...
Epoch: 19       Training Loss: 0.285073         Validation Loss: 0.346223
Epoch: 20       Training Loss: 0.279887         Validation Loss: 0.345977
Epoch: 21       Training Loss: 0.273485         Validation Loss: 0.337106
Validation loss decreased (0.337632 --> 0.337106).  Saving model ...
Epoch: 22       Training Loss: 0.267907         Validation Loss: 0.339344
Epoch: 23       Training Loss: 0.261199         Validation Loss: 0.347261
Epoch: 24       Training Loss: 0.257007         Validation Loss: 0.349846
Epoch: 25       Training Loss: 0.253143         Validation Loss: 0.323562
Validation loss decreased (0.337106 --> 0.323562).  Saving model ...
Epoch: 26       Training Loss: 0.247418         Validation Loss: 0.334285
Epoch: 27       Training Loss: 0.242037         Validation Loss: 0.324759
Epoch: 28       Training Loss: 0.237751         Validation Loss: 0.341492
```

```
Epoch: 29       Training Loss: 0.231133         Validation Loss: 0.321932
Validation loss decreased (0.323562 --> 0.321932).  Saving model ...
Epoch: 30       Training Loss: 0.228064         Validation Loss: 0.329132
Epoch: 31       Training Loss: 0.226681         Validation Loss: 0.353209
Epoch: 32       Training Loss: 0.220912         Validation Loss: 0.351970
Epoch: 33       Training Loss: 0.218139         Validation Loss: 0.330462
Epoch: 34       Training Loss: 0.212439         Validation Loss: 0.334524
Epoch: 35       Training Loss: 0.208175         Validation Loss: 0.335599
Epoch: 36       Training Loss: 0.205895         Validation Loss: 0.349774
Epoch: 37       Training Loss: 0.202952         Validation Loss: 0.319005
Validation loss decreased (0.321932 --> 0.319005).  Saving model ...
Epoch: 38       Training Loss: 0.198813         Validation Loss: 0.334688
Epoch: 39       Training Loss: 0.196446         Validation Loss: 0.337607
Epoch: 40       Training Loss: 0.192292         Validation Loss: 0.340911
Epoch: 41       Training Loss: 0.191735         Validation Loss: 0.339332
Epoch: 42       Training Loss: 0.185891         Validation Loss: 0.324097
Epoch: 43       Training Loss: 0.183762         Validation Loss: 0.344853
Epoch: 44       Training Loss: 0.181242         Validation Loss: 0.358128
Epoch: 45       Training Loss: 0.178423         Validation Loss: 0.342752
Epoch: 46       Training Loss: 0.173301         Validation Loss: 0.368151
Epoch: 47       Training Loss: 0.171478         Validation Loss: 0.329854
Epoch: 48       Training Loss: 0.167631         Validation Loss: 0.339990
Epoch: 49       Training Loss: 0.166009         Validation Loss: 0.351595
Epoch: 50       Training Loss: 0.166257         Validation Loss: 0.355389
```

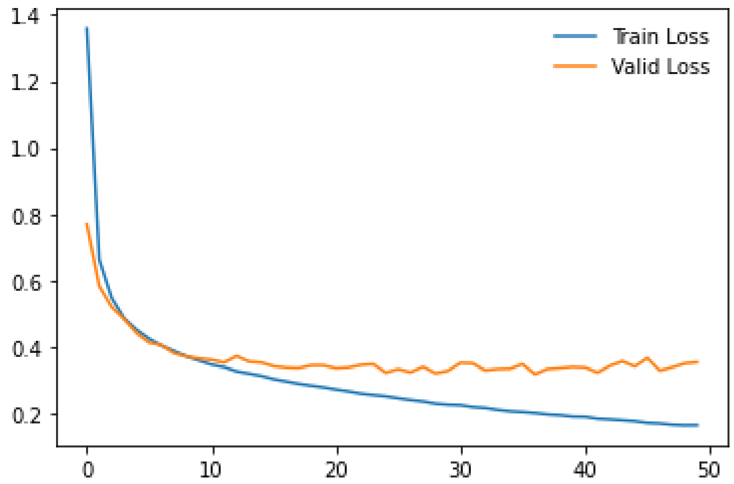
In [11]:

```
model.load_state_dict(torch.load("fashion_mnist_ann.pt"))
```

Out[11]: <All keys matched successfully>

In [46]:

```
plt.plot(train_losses, label="Train Loss")
plt.plot(valid_losses, label="Valid Loss")
plt.legend(frameon=False)
plt.show()
```



In [49]:

```
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 %5s: %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: 0.334308

Test Accuracy of     0: 88% (883/1000)
Test Accuracy of     1: 96% (963/1000)
Test Accuracy of     2: 83% (830/1000)
Test Accuracy of     3: 88% (886/1000)
Test Accuracy of     4: 85% (855/1000)
Test Accuracy of     5: 96% (968/1000)
Test Accuracy of     6: 63% (637/1000)
Test Accuracy of     7: 95% (952/1000)
Test Accuracy of     8: 97% (975/1000)
Test Accuracy of     9: 95% (958/1000)

Test Accuracy (Overall): 89% (8907/10000)
```

In [13]:

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

output = model(images)
_, preds = torch.max(output, 1)
images = images.cpu().numpy()

fig = plt.figure(figsize=(25, 4))
for idx in range(20):
    ax = fig.add_subplot(2, 10, idx+1, xticks=[], yticks=[])
    ax.imshow(np.squeeze(images[idx]), cmap='gray')
    ax.set_title("{} ({})".format(classes[(preds[idx].item())], classes[(labels[idx].item())]),
                 color=("green" if preds[idx]==labels[idx] else "red"))
```