Lab 5: Spam Detection

In this assignment, we will build a recurrent neural network to classify a SMS text message as "spam" or "not spam". In the process, you will

1. Clean and process text data for machine learning.
2. Understand and implement a character-level recurrent neural network.
3. Understand batching for a recurrent neural network, and develop custom Dataset and DataLoaders with collate_fn to implement RNN batching.

What to submit

Submit a PDF file containing all your code, outputs, and write-up. You can produce a PDF of your Google Colab file by going to File > Print and then save as PDF. The Colab instructions have more information.

Do not submit any other files produced by your code.

Include a link to your colab file in your submission.

Colab Link https://drive.google.com/file/d/1Tr0lCqfFkmYzGEJxw_w usp=sharing

Include a link to your Colab file here. If you would like the TA to look at your Colab file in case your solutions are cut off, **please make sure that your Colab file is publicly accessible at the time of submission**.

In [ ]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import numpy as np
from torch.nn.utils.rnn import pad_sequence
from torch.utils.data import DataLoader, Dataset
```

Part 1. Data Cleaning [15 pt]

We will be using the "SMS Spam Collection Data Set" available at http://archive.ics.uci.edu/ml/datasets/SMS+Spam+Collection

There is a link to download the "Data Folder" at the very top of the webpage. Download the zip file, unzip it, and upload the file `SMSSpamCollection` to Colab.

Part (a) [1 pt]

Open up the file in Python, and print out one example of a spam SMS, and one example of a non-spam SMS.

What is the label value for a spam message, and what is the label value for a non-spam message?

In [ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, cal
l drive.mount("/content/drive", force_remount=True).
```

In [ ]:
```
#label for spam = spam, non-span = ham
for line in open('SMSSpamCollection'):
  if line[0] == 'h':
    print(line)
    break

for line in open('SMSSpamCollection'):
  if line[0] == "s":
    print(line)
    break
```

```
ham     Go until jurong point, crazy.. Available only in bugis n great world
la e buffet... Cine there got amore wat...

spam    Free entry in 2 a wkly comp to win FA Cup final tkts 21st May 2005.
Text FA to 87121 to receive entry question(std txt rate)T&C's apply 08452810
075over18's
```

Part (b) [1 pt]

How many spam messages are there in the data set? How many non-spam messages are there in the data set?

In [ ]:
```
spam = 0
ham = 0
for line in open('SMSSpamCollection'):
  if line[0] == 's':
```

```
        spam += 1
    else:
        ham += 1
print("Spam:")
print(spam)
print("Ham:")
print(ham)
```

```
Spam:
747
Ham:
4827
```

Part (c) [4 pt]

load and parse the data into two lists: sequences and labels. Create character-level stoi and itos dictionaries. Reserve the index 0 for padding. Convert the sequences to list of character ids using stoi dictionary and convert the labels to a list of 0s and 1s by assinging class "ham" to 0 and class "spam" to 1.

In [69]:

```
sequences = []
labels = []

#initialize with pad=0
stoi = {'<pad>': 0}
itos = {0: '<pad>'}
idx = 1

for line in open('SMSSpamCollection', 'r', encoding='utf-8'):
    line = line.strip()
    if not line:
        continue

    # split label vs text
    label, text = line.split('\t', 1)
    labels.append(1 if label == 'spam' else 0)

    seq_ids = []
    for ch in text:
        if ch not in stoi:
            stoi[ch] = idx
            itos[idx] = ch
            idx += 1
        seq_ids.append(stoi[ch])

    sequences.append(seq_ids)
```

Part (d) [4 pt]

Use train_test_split function from sklearn (https://scikit-learn.org/dev/modules/generated/sklearn.model_selection.train_test_split.html) to split the data indices into `train`, `valid`, and `test`. Use a 60-20-20 split.

You saw in part (b) that there are many more non-spam messages than spam messages. This **imbalance** in our training data will be problematic for training. We can fix this disparity by duplicating spam messages in the training set, so that the training set is roughly balanced.

In [70]:
```
from sklearn.model_selection import train_test_split

indices = list(range(len(sequences)))

train_index, temp_index = train_test_split(indices, test_size=0.4, random_st

val_index, test_index = train_test_split(temp_index, test_size=0.5, random_s
                                        stratify=[labels[i] for i in temp_ir

#create train, validation, and test sets
train_x = [sequences[idx] for idx in train_index]
train_y = [labels[idx] for idx in train_index]
val_x = [sequences[idx] for idx in val_index]
val_y = [labels[idx] for idx in val_index]
test_x = [sequences[idx] for idx in test_index]
test_y = [labels[idx] for idx in test_index]

print(f"Training set size: {len(train_x)}")
print(f"Validation set size: {len(val_x)}")
print(f"Test set size: {len(test_x)}")

train_ham = sum(1 for label in train_y if label == 0)
train_spam_count = sum(1 for label in train_y if label == 1)
print(f"Train set before balancing: Ham={train_ham}, Spam={train_spam_count}

#balance the train classes
train_spam = []
for idx, item in enumerate(train_x):
    if train_y[idx] == 1:
        train_spam.append(item)

#duplicate spam message
train_x = train_x + train_spam * 6
train_y = train_y + [1] * (len(train_spam) * 6)

train_ham_after = sum(1 for label in train_y if label == 0)
train_spam_after = sum(1 for label in train_y if label == 1)
print(f"Train set after balancing: Ham={train_ham_after}, Spam={train_spam_a
print(f"Final training set size: {len(train_x)}")
```

```
Training set size: 3344
Validation set size: 1115
Test set size: 1115
Train set before balancing: Ham=2896, Spam=448
Train set after balancing: Ham=2896, Spam=3136
Final training set size: 6032
```

Part (e) [4 pt]

Since each sequence has a different length, we cannot use the default DataLoader. We need to change the DataLoader such that it can pad differnt sequence sizes within the batch. To do this, we need to introduce a **collate_fn** to the DataLoader such that it uses **pad_sequence** function (https://pytorch.org/docs/stable/generated/torch.nn.utils.rnn.pad_sequence.html) to pad the sequences within the batch to the same size.

We also need a custom Dataset class to return a pair of sequence and label for each example. Complete the code below to address these.

Hint:

- https://stanford.edu/~shervine/blog/pytorch-how-to-generate-data-parallel
- https://plainenglish.io/blog/understanding-collate-fn-in-pytorch-f9d1742647d3

In [71]:
```
class MyDataset(Dataset):
    def __init__(self, sequences, labels):
        self.sequences = sequences
        self.labels = labels

    def __len__(self):
        return len(self.sequences)

    def __getitem__(self, idx):
        sequence = torch.tensor(self.sequences[idx], dtype=torch.long)
        label = torch.tensor(self.labels[idx], dtype=torch.long)
        return sequence, label

def collate_sequences(batch):
    sequences = [item[0] for item in batch]
    labels = torch.tensor([item[1] for item in batch], dtype=torch.long)

    padded_sequences = pad_sequence(sequences, batch_first=True, padding_val

    return padded_sequences, labels

#DataLoaders
train_loader = DataLoader(dataset=MyDataset(train_x, train_y), batch_size=32
val_loader = DataLoader(dataset=MyDataset(val_x, val_y), batch_size=32, shuf
test_loader = DataLoader(dataset=MyDataset(test_x, test_y), batch_size=32, s
```

Part (f) [1 pt]

Take a look at 10 batches in `train_loader`. What is the maximum length of the input sequence in each batch? How many `<pad>` tokens are used in each of the 10 batches?

In [72]:
```
#counter - only up to 10
batch_count = 0

for batch in train_loader:
    if batch_count >= 10:
```

```
        break

    sequences, _ = batch
    batch_size = sequences.size(0)
    max_length = sequences.size(1)

    pad_count = torch.sum(sequences == 0).item()

    print(f"Batch {batch_count + 1}:")
    print(f"  Maximum sequence length: {max_length}")
    print(f"  Number of padding tokens: {pad_count}")

    batch_count += 1
```

```
Batch 1:
  Maximum sequence length: 162
  Number of padding tokens: 2151
Batch 2:
  Maximum sequence length: 166
  Number of padding tokens: 2018
Batch 3:
  Maximum sequence length: 281
  Number of padding tokens: 5675
Batch 4:
  Maximum sequence length: 327
  Number of padding tokens: 6502
Batch 5:
  Maximum sequence length: 175
  Number of padding tokens: 2392
Batch 6:
  Maximum sequence length: 160
  Number of padding tokens: 2004
Batch 7:
  Maximum sequence length: 177
  Number of padding tokens: 2568
Batch 8:
  Maximum sequence length: 160
  Number of padding tokens: 1994
Batch 9:
  Maximum sequence length: 166
  Number of padding tokens: 1887
Batch 10:
  Maximum sequence length: 276
  Number of padding tokens: 4892
```

Part 2. Model Building [8 pt]

Build a recurrent neural network model, using an architecture of your choosing. Use the one-hot embedding of each character as input to your recurrent network. Use one or more fully-connected layers to make the prediction based on your recurrent network output.

Instead of using the RNN output value for the final token, another often used strategy is to max-pool over the entire output array. That is, instead of calling something like:

```
out, _ = self.rnn(x)
self.fc(out[:, -1, :])
```

where `self.rnn` is an `nn.RNN`, `nn.GRU`, or `nn.LSTM` module, and `self.fc` is a fully-connected layer, we use:

```
out, _ = self.rnn(x)
self.fc(torch.max(out, dim=1)[0])
```

This works reasonably in practice. An even better alternative is to concatenate the max-pooling and average-pooling of the RNN outputs:

```
out, _ = self.rnn(x)
out = torch.cat([torch.max(out, dim=1)[0],
                 torch.mean(out, dim=1)], dim=1)
self.fc(out)
```

We encourage you to try out all these options. The way you pool the RNN outputs is one of the "hyperparameters" that you can choose to tune later on.

In [73]:
```python
# You might find this code helpful for obtaining
# PyTorch one-hot vectors.

ident = torch.eye(10)
print(ident[0]) # one-hot vector
print(ident[1]) # one-hot vector
x = torch.tensor([[1, 2], [3, 4]])
print(ident[x]) # one-hot vectors
```

```
tensor([1., 0., 0., 0., 0., 0., 0., 0., 0., 0.])
tensor([0., 1., 0., 0., 0., 0., 0., 0., 0., 0.])
tensor([[[0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
         [0., 0., 1., 0., 0., 0., 0., 0., 0., 0.]],

        [[0., 0., 0., 1., 0., 0., 0., 0., 0., 0.],
         [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.]]])
```

In [74]:
```python
class SpamRNN(nn.Module):
    def __init__(self, vocab_size, embedding_dim, hidden_dim, output_dim, nu
        super(SpamRNN, self).__init__()

        # one-hot embedding layer
        self.embedding = nn.Embedding(vocab_size, embedding_dim)

        with torch.no_grad():
            self.embedding.weight.copy_(torch.eye(vocab_size))
            self.embedding.weight.requires_grad = False

        self.lstm = nn.LSTM(embedding_dim, hidden_dim, num_layers=num_layers
                            batch_first=True, dropout=dropout if num_layers >
```

```
        self.fc1 = nn.Linear(hidden_dim * 2, hidden_dim)
        self.fc2 = nn.Linear(hidden_dim, output_dim)

        self.dropout = nn.Dropout(dropout)
        self.relu = nn.ReLU()

    def forward(self, x):

        embedded = self.embedding(x)

        out, (hidden, cell) = self.lstm(embedded)

        max_pool = torch.max(out, dim=1)[0]
        avg_pool = torch.mean(out, dim=1)
        combined = torch.cat([max_pool, avg_pool], dim=1)

        out = self.dropout(combined)
        out = self.relu(self.fc1(out))
        out = self.dropout(out)
        out = self.fc2(out)

        return out

vocab_size = len(stoi) + 1
embedding_dim = vocab_size
hidden_dim = 128
output_dim = 2

model = SpamRNN(vocab_size, embedding_dim, hidden_dim, output_dim)
```

Part 3. Training [16 pt]

Part (a) [4 pt]

Complete the `get_accuracy` function, which will compute the accuracy (rate) of your model across a dataset (e.g. validation set).

In [75]:
```
def get_accuracy(model, data):
    """ Compute the accuracy of the `model` across a dataset `data`

    Example usage:

    >>> model = MyRNN() # to be defined
    >>> get_accuracy(model, valid) # the variable `valid` is from above
    """
    model.eval()
    correct = 0
    total = 0

    with torch.no_grad():
        for batch in data:
            sequences, labels = batch
            outputs = model(sequences)
```

```
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    accuracy = correct / total
    return accuracy
```

Part (b) [4 pt]

Train your model. Plot the training curve of your final model. Your training curve should have the training/validation loss and accuracy plotted periodically.

Note: Not all of your batches will have the same batch size. In particular, if your training set does not divide evenly by your batch size, there will be a batch that is smaller than the rest.

In [76]:
```
import matplotlib.pyplot as plt

def train_model(model, train_loader, val_loader, num_epochs, learning_rate,

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=learning_rate)

    history = {
        'train_losses': [],
        'val_losses': [],
        'train_accuracies': [],
        'val_accuracies': []
    }

    print_every = 1  #print every epoch

    #training loop
    for epoch in range(num_epochs):
        model.train()
        running_loss = 0.0
        for batch in train_loader:
            sequences, labels = batch
            sequences, labels = sequences.to(device), labels.to(device)

            optimizer.zero_grad()

            #forward pass
            outputs = model(sequences)
            loss = criterion(outputs, labels)

            #backward pass and optimize
            loss.backward()
            optimizer.step()

            running_loss += loss.item()

        avg_train_loss = running_loss / len(train_loader)
```

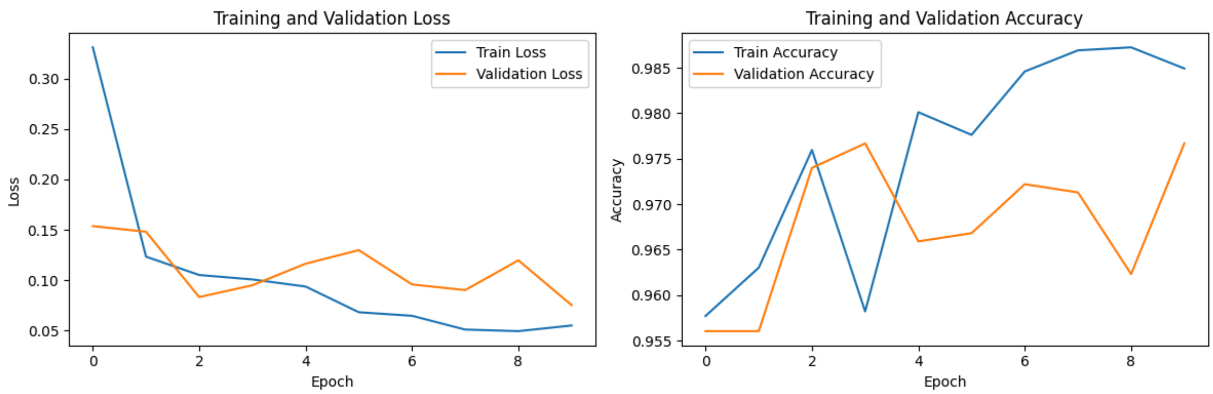
```
        history['train_losses'].append(avg_train_loss)
        train_acc = get_accuracy(model, train_loader)
        history['train_accuracies'].append(train_acc)

        #validation phase
        model.eval()
        val_loss = 0.0
        with torch.no_grad():
            for batch in val_loader:
                sequences, labels = batch
                sequences, labels = sequences.to(device), labels.to(device)
                outputs = model(sequences)
                loss = criterion(outputs, labels)
                val_loss += loss.item()

        avg_val_loss = val_loss / len(val_loader)
        history['val_losses'].append(avg_val_loss)
        val_acc = get_accuracy(model, val_loader)
        history['val_accuracies'].append(val_acc)

        if (epoch + 1) % print_every == 0:
            print(f'Epoch [{epoch+1}/{num_epochs}]')
            print(f'Train Loss: {avg_train_loss:.4f}, Train Acc: {train_acc:
            print(f'Val Loss: {avg_val_loss:.4f}, Val Acc: {val_acc:.4f}')

    return history

def plot_training_history(history):
    plt.figure(figsize=(12, 4))

    # Plot loss
    plt.subplot(1, 2, 1)
    plt.plot(history['train_losses'], label='Train Loss')
    plt.plot(history['val_losses'], label='Validation Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title('Training and Validation Loss')
    plt.legend()

    # Plot accuracy
    plt.subplot(1, 2, 2)
    plt.plot(history['train_accuracies'], label='Train Accuracy')
    plt.plot(history['val_accuracies'], label='Validation Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.title('Training and Validation Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()
```

In [77]:

```
#baseline model
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

baseline_config = {
    'hidden_dim': 128,
```

```
    'num_layers': 2,
    'dropout': 0.5,
    'num_epochs': 10,
    'learning_rate': 0.001
}

baseline_model = SpamRNN(vocab_size=len(stoi)+1,
                        embedding_dim=len(stoi)+1,
                        hidden_dim=baseline_config['hidden_dim'],
                        output_dim=2,
                        num_layers=baseline_config['num_layers'],
                        dropout=baseline_config['dropout']).to(device)

baseline_history = train_model(baseline_model,
                              train_loader,
                              val_loader,
                              baseline_config['num_epochs'],
                              baseline_config['learning_rate'],
                              device)

#plot
plot_training_history(baseline_history)
```

```
Epoch [1/10]
Train Loss: 0.3310, Train Acc: 0.9577
Val Loss: 0.1537, Val Acc: 0.9561
Epoch [2/10]
Train Loss: 0.1234, Train Acc: 0.9630
Val Loss: 0.1481, Val Acc: 0.9561
Epoch [3/10]
Train Loss: 0.1052, Train Acc: 0.9760
Val Loss: 0.0833, Val Acc: 0.9740
Epoch [4/10]
Train Loss: 0.1008, Train Acc: 0.9582
Val Loss: 0.0951, Val Acc: 0.9767
Epoch [5/10]
Train Loss: 0.0938, Train Acc: 0.9801
Val Loss: 0.1165, Val Acc: 0.9659
Epoch [6/10]
Train Loss: 0.0683, Train Acc: 0.9776
Val Loss: 0.1299, Val Acc: 0.9668
Epoch [7/10]
Train Loss: 0.0648, Train Acc: 0.9846
Val Loss: 0.0959, Val Acc: 0.9722
Epoch [8/10]
Train Loss: 0.0511, Train Acc: 0.9869
Val Loss: 0.0903, Val Acc: 0.9713
Epoch [9/10]
Train Loss: 0.0495, Train Acc: 0.9872
Val Loss: 0.1198, Val Acc: 0.9623
Epoch [10/10]
Train Loss: 0.0552, Train Acc: 0.9849
Val Loss: 0.0754, Val Acc: 0.9767
```



Part (c) [4 pt]

Choose at least 4 hyperparameters to tune. Explain how you tuned the hyperparameters. You don't need to include your training curve for every model you trained. Instead, explain what hyperparemters you tuned, what the best validation accuracy was, and the reasoning behind the hyperparameter decisions you made.

For this assignment, you should tune more than just your learning rate and epoch. Choose at least 2 hyperparameters that are unrelated to the optimizer.

Answer

Tune 1:

From the baseline model there seems to be a large gap between the training and validation accuracy and the validation loss plateaus very early on. Therefore, this model seems to be memorizing training data (overfitting) due to the high capacity. I will try to improve this by changing the parameters by increasing the dropout to 0.7 to increase regularization, reduce the hidden dimensions to 64 to reduce model capacity, and increase the number of epochs to 15.

tune1_config = {'hidden_dim': 64, 'num_layers': 2, 'dropout': 0.7, 'num_epochs': 15, 'learning_rate': 0.001 }

Tune 2:

The results of the previous tune imporved greatly. The loss curves decrease together now and more earlier, and the space between the accuracy curves are closer together. However it seems to straighten out early on in the epochs which might mean that the model learns to generalize the patterns too quickly. To fix this I will try to increase the hidden layers a little bit for more capacity, reduce the regularization, increase training time, and rate.

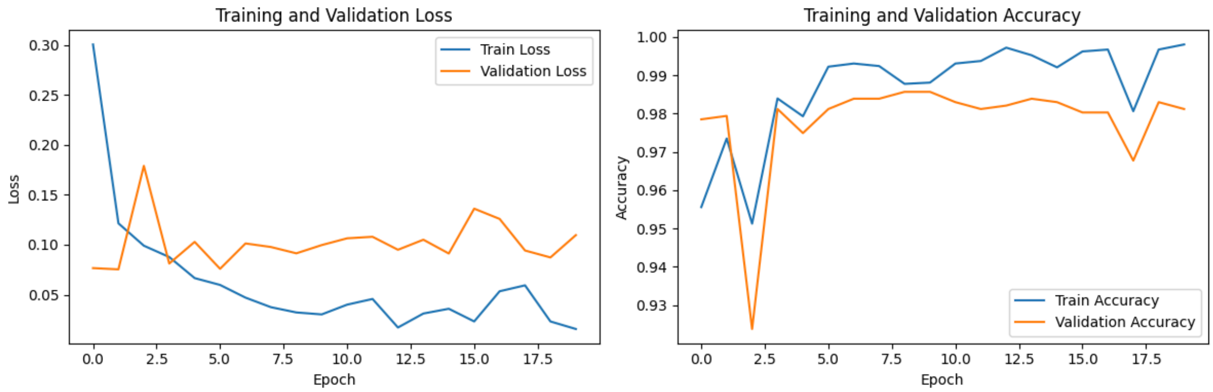
tune4_config = {'hidden_dim': 96, 'num_layers': 2, 'dropout': 0.5, 'num_epochs': 20,'learning_rate': 0.002}

I think this produced the best results, the loss and accuracy charts now have a constant decrease/increase thoughtout the epochs.

In [ ]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

tune1_config = {
    'hidden_dim': 96,
    'num_layers': 2,
    'dropout': 0.5,
    'num_epochs': 20,
    'learning_rate': 0.002
}

tune1_model = SpamRNN(vocab_size=len(stoi)+1,
                      embedding_dim=len(stoi)+1,
                      hidden_dim=tune1_config['hidden_dim'],
                      output_dim=2,
                      num_layers=tune1_config['num_layers'],
                      dropout=tune1_config['dropout']).to(device)

tune1_history = train_model(tune1_model,
                            train_loader,
                            val_loader,
                            tune1_config['num_epochs'],
                            tune1_config['learning_rate'],
                            device)

plot_training_history(tune1_history)
```

```
Epoch [1/20]
Train Loss: 0.3006, Train Acc: 0.9556
Val Loss: 0.0766, Val Acc: 0.9785
Epoch [2/20]
Train Loss: 0.1215, Train Acc: 0.9735
Val Loss: 0.0754, Val Acc: 0.9794
Epoch [3/20]
Train Loss: 0.0991, Train Acc: 0.9513
Val Loss: 0.1790, Val Acc: 0.9238
Epoch [4/20]
Train Loss: 0.0877, Train Acc: 0.9839
Val Loss: 0.0812, Val Acc: 0.9812
Epoch [5/20]
Train Loss: 0.0666, Train Acc: 0.9793
Val Loss: 0.1029, Val Acc: 0.9749
Epoch [6/20]
Train Loss: 0.0598, Train Acc: 0.9922
Val Loss: 0.0759, Val Acc: 0.9812
Epoch [7/20]
Train Loss: 0.0471, Train Acc: 0.9930
Val Loss: 0.1013, Val Acc: 0.9839
Epoch [8/20]
Train Loss: 0.0375, Train Acc: 0.9924
Val Loss: 0.0977, Val Acc: 0.9839
Epoch [9/20]
Train Loss: 0.0322, Train Acc: 0.9877
Val Loss: 0.0914, Val Acc: 0.9857
Epoch [10/20]
Train Loss: 0.0302, Train Acc: 0.9881
Val Loss: 0.0997, Val Acc: 0.9857
Epoch [11/20]
Train Loss: 0.0400, Train Acc: 0.9930
Val Loss: 0.1065, Val Acc: 0.9830
Epoch [12/20]
Train Loss: 0.0457, Train Acc: 0.9937
Val Loss: 0.1080, Val Acc: 0.9812
Epoch [13/20]
Train Loss: 0.0171, Train Acc: 0.9972
Val Loss: 0.0950, Val Acc: 0.9821
Epoch [14/20]
Train Loss: 0.0311, Train Acc: 0.9952
Val Loss: 0.1050, Val Acc: 0.9839
Epoch [15/20]
Train Loss: 0.0359, Train Acc: 0.9920
Val Loss: 0.0912, Val Acc: 0.9830
Epoch [16/20]
Train Loss: 0.0232, Train Acc: 0.9962
Val Loss: 0.1361, Val Acc: 0.9803
Epoch [17/20]
Train Loss: 0.0534, Train Acc: 0.9967
Val Loss: 0.1259, Val Acc: 0.9803
Epoch [18/20]
Train Loss: 0.0593, Train Acc: 0.9806
Val Loss: 0.0942, Val Acc: 0.9677
Epoch [19/20]
Train Loss: 0.0232, Train Acc: 0.9967
```

```
Val Loss: 0.0873, Val Acc: 0.9830
Epoch [20/20]
Train Loss: 0.0156, Train Acc: 0.9980
Val Loss: 0.1097, Val Acc: 0.9812
```



Part (d) [2 pt]

Before we deploy a machine learning model, we usually want to have a better understanding of how our model performs beyond its validation accuracy. An important metric to track is *how well our model performs in certain subsets of the data*.

In particular, what is the model's error rate amongst data with negative labels? This is called the **false positive rate**.

What about the model's error rate amongst data with positive labels? This is called the **false negative rate**.

Report your final model's false positive and false negative rate across the validation set.

In [78]:
```
valid_spam_indices = [i for i, label in enumerate(val_y) if label == 1]
valid_nospam_indices = [i for i, label in enumerate(val_y) if label == 0]

valid_spam_x = [val_x[i] for i in valid_spam_indices]
valid_spam_y = [val_y[i] for i in valid_spam_indices]
valid_nospam_x = [val_x[i] for i in valid_nospam_indices]
valid_nospam_y = [val_y[i] for i in valid_nospam_indices]

valid_spam_loader = DataLoader(dataset=MyDataset(valid_spam_x, valid_spam_y)
                               batch_size=32,
                               shuffle=False,
                               collate_fn=collate_sequences)
valid_nospam_loader = DataLoader(dataset=MyDataset(valid_nospam_x, valid_nos
                                 batch_size=32,
                                 shuffle=False,
                                 collate_fn=collate_sequences)

fn = 1 - get_accuracy(tune1_model, valid_spam_loader)
fp = 1 - get_accuracy(tune1_model, valid_nospam_loader)

print("False Negative Rate: ", fn*100, "%")
print("False Positive Rate: ", fp*100, "%")
```

```
False Negative Rate:  6.666666666666665 %
False Positive Rate:  1.1398963730569922 %
```

Part (e) [2 pt]

The impact of a false positive vs a false negative can be drastically different. If our spam detection algorithm was deployed on your phone, what is the impact of a false positive on the phone's user? What is the impact of a false negative?

Answer

A false positive is when a real message would be marked as spam. Bad because you might miss an important message and sent directly to spam.

A false negative is when a spam message would be marked as real. Bad because spam messages will show up in your inbox.

Part 4. Evaluation [11 pt]

Part (a) [1 pt]

Report the final test accuracy of your model.

In [79]:
```
final_test_accuracy = get_accuracy(tune1_model, test_loader)
print("The final test accuracy is:", final_test_accuracy*100, "%")
```

```
The final test accuracy is: 96.95067264573991 %
```

Part (b) [3 pt]

Report the false positive rate and false negative rate of your model across the test set.

In [80]:
```
test_spam_indices = [i for i, label in enumerate(test_y) if label == 1]
test_nospam_indices = [i for i, label in enumerate(test_y) if label == 0]

test_spam_x = [test_x[i] for i in test_spam_indices]
test_spam_y = [test_y[i] for i in test_spam_indices]
test_nospam_x = [test_x[i] for i in test_nospam_indices]
test_nospam_y = [test_y[i] for i in test_nospam_indices]

test_spam_loader = DataLoader(dataset=MyDataset(test_spam_x, test_spam_y),
                              batch_size=32,
                              shuffle=False,
                              collate_fn=collate_sequences)
test_nospam_loader = DataLoader(dataset=MyDataset(test_nospam_x, test_nospam
                                batch_size=32,
                                shuffle=False,
                                collate_fn=collate_sequences)

test_fn = 1 - get_accuracy(tune1_model, test_spam_loader)
```

```
test_fp = 1 - get_accuracy(tune1_model, test_nospam_loader)

print("Test False Negative Rate: ", test_fn*100, "%")
print("Test False Positive Rate: ", test_fp*100, "%")
```

```
Test False Negative Rate:  8.053691275167784 %
Test False Positive Rate:  2.2774327122153215 %
```

Part (c) [3 pt]

What is your model's prediction of the **probability** that the SMS message "machine learning is sooo cool!" is spam?

Hint: To begin, use `stoi` to look up the index of each character in the vocabulary.

In [81]:
```
msg = "machine learning is sooo cool!"

msg_sequence = [stoi.get(char, 0) for char in msg]

msg_tensor = torch.tensor(msg_sequence, dtype=torch.long).unsqueeze(0).to(de

baseline_model.eval()

with torch.no_grad():
    output = baseline_model(msg_tensor)
    probabilities = torch.softmax(output, dim=1)
    spam_probability = probabilities[0, 1].item()

print(f"Probability that the message '{msg}' is spam: {spam_probability * 10
```

```
Probability that the message 'machine learning is sooo cool!' is spam: 2.23%
```

Part (d) [4 pt]

Do you think detecting spam is an easy or difficult task?

Since machine learning models are expensive to train and deploy, it is very important to compare our models against baseline models: a simple model that is easy to build and inexpensive to run that we can compare our recurrent neural network model against.

Explain how you might build a simple baseline model. This baseline model can be a simple neural network (with very few weights), a hand-written algorithm, or any other strategy that is easy to build and test.

Do not actually build a baseline model. Instead, provide instructions on how to build it.

Answer

I think that detecting spam can be complex because you don't know what people consider as spam, or many spam emails have gotten better at sounding not like spam.

For example, emails regarding sales at stores, some might prefer seeing that while others may not.

I think the Bag-of-Words approach is a good idea for a baseline for spam detection because it catches important signal words while being simple and fast. To implement this you can create a vocabulary of frequently used words from your data, then convert each email into a fixed-length vector where each position represents the count or presence of a specific word from your vocabulary. You would then train a simple classifier, where the model learns which words are most seen in spam versus actual important emails. This ignores word order and grammar but captures the key discriminative vocabulary patterns that distinguish spam (words like "free," "winner," "urgent," "congratulations") from normal emails.