Lab 5: Spam Detection

Deadline: June 18th, 11:59pm

Late Penalty: There is a penalty-free grace period of one hour past the deadline. Any work that is submitted between 1 hour and 24 hours past the deadline will receive a 20% grade deduction. No other late work is accepted. Quercus submission time will be used, not your local computer time. You can submit your labs as many times as you want before the deadline, so please submit often and early.

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. Use torchtext to build recurrent neural network models.
4. Understand batching for a recurrent neural network, and use torchtext 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 (.html files are also acceptable).

Do not submit any other files produced by your code.

Include a link to your colab file in your submission.

Colab Link

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**.

Colab Link: https://drive.google.com/file/d/1vDnjUn0OESVJuJyYXkYvqRSQnodb9hgY/view?usp=sharing

In [ ]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import numpy as np
import time
import matplotlib.pyplot as plt
```

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) [2 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/gdrive')
```

```
Mounted at /content/gdrive
```

In [ ]:
```
cd gdrive/MyDrive/EngSci 2T1 + PEY/Year 4/Summer/APS360/Labs/Lab_5_Spam_Detection
```

```
/content/gdrive/MyDrive/EngSci 2T1 + PEY/Year 4/Summer/APS360/Labs/Lab_5_Spam_Detection
```

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

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

```
spam    Free entry in 2 a wkly comp to win FA Cup final tkts 21st May 2005. Text FA to 8
7121 to receive entry question(std txt rate)T&C's apply 08452810075over18's

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

Answer:

As shown in the print outs above, the label for a spam message is "spam" and the label for a non-spam message is "ham".

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
    elif line[0] == 'h':
        ham += 1
```

```
print("There are", spam, "spam messages in the data set.")
print("There are", ham, "non-spam messages in the data set.")
```

```
There are 747 spam messages in the data set.
There are 4827 non-spam messages in the data set.
```

Part (c) [4 pt]

We will be using the package `torchtext` to load, process, and batch the data. A tutorial to torchtext is available below. This tutorial uses the same Sentiment140 data set that we explored during lecture.

https://medium.com/@sonicboom8/sentiment-analysis-torchtext-55fb57b1fab8

Unlike what we did during lecture, we will be building a **character level RNN**. That is, we will treat each **character** as a token in our sequence, rather than each **word**.

Identify two advantage and two disadvantage of modelling SMS text messages as a sequence of characters rather than a sequence of words.

Answer:

Advantages:

1. Requires less memory and has faster inference due to a much smaller vocabulary (less than 100 characters vs millions of words)
2. Able to recognize and interpret misspelled words/typos

Disadvantages:

1. Higher computational cost
2. May result in a lower accuracy compared to word level RNN

Part (d) [1 pt]

We will be loading our data set using `torchtext.data.TabularDataset`. The constructor will read directly from the `SMSSpamCollection` file.

For the data file to be read successfuly, we need to specify the **fields** (columns) in the file. In our case, the dataset has two fields:

- a text field containing the sms messages,
- a label field which will be converted into a binary label.

Split the dataset into `train`, `valid`, and `test`. Use a 60-20-20 split. You may find this torchtext API page helpful: https://torchtext.readthedocs.io/en/latest/data.html#dataset

Hint: There is a `Dataset` method that can perform the random split for you.

In [ ]:
```
import torchtext

text_field = torchtext.legacy.data.Field(sequential=True,      # text sequence
                                  tokenize=lambda x: x, # because are building a charac
```

```
                                  include_lengths=True, # to track the length of sequen
                                  batch_first=True,
                                  use_vocab=True)       # to turn each character into a
label_field = torchtext.legacy.data.Field(sequential=False,    # not a sequence
                                   use_vocab=False,     # don't need to track vocabular
                                   is_target=True,
                                   batch_first=True,
                                   preprocessing=lambda x: int(x == 'spam')) # convert

fields = [('label', label_field), ('sms', text_field)]
dataset = torchtext.legacy.data.TabularDataset("SMSSpamCollection", # name of the file
                                        "tsv",               # fields are separated by
                                        fields)
```

In [ ]:

```
dataset[0].sms
```

Out[ ]:

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

In [ ]:

```
dataset[0].label
```

Out[ ]:

```
0
```

In [ ]:

```
np.random.seed(50)
train, valid, test = dataset.split(split_ratio=[0.6,0.2,0.2],
                                   stratified=True,
                                   strata_field='label')
```

Part (e) [2 pt]

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**.

Explain why having a balanced training set is helpful for training our neural network.

Note: if you are not sure, try removing the below code and train your mode.

In [ ]:

```
# save the original training examples
old_train_examples = train.examples
# get all the spam messages in `train`
train_spam = []
for item in train.examples:
    if item.label == 1:
        train_spam.append(item)
# duplicate each spam message 6 more times
train.examples = old_train_examples + train_spam * 6
```

Answer:

It is important to have a balanced training set because it is undesirable to introduce any biases into the neural network model. In this case, since there are many more non-spam messages, the model will be biased towards the non-spam class. As a result, even if the model results in a high training accuracy, it does not indicate that we have learned a good model for this problem.

Part (f) [1 pt]

We need to build the vocabulary on the training data by running the below code. This finds all the possible character tokens in the training set.

Explain what the variables `text_field.vocab.stoi` and `text_field.vocab.itos` represent.

In [ ]:
```
text_field.build_vocab(train)
```

In [ ]:
```
text_field.vocab.stoi
```

Out[ ]:
```
defaultdict(<bound method Vocab._default_unk_index of <torchtext.legacy.vocab.Vocab obje
ct at 0x7f491b47c350>>,
            {'\t': 106,
             '\n': 107,
             ' ': 2,
             '!': 44,
             '"': 80,
             '#': 79,
             '$': 90,
             '%': 93,
             '&': 63,
             "'": 60,
             '(': 76,
             ')': 72,
             '*': 71,
             '+': 75,
             ',': 46,
             '-': 64,
             '.': 16,
             '/': 59,
             '0': 14,
             '1': 23,
             '2': 25,
             '3': 42,
             '4': 37,
             '5': 32,
             '6': 43,
             '7': 40,
             '8': 28,
             '9': 49,
             ':': 65,
             ';': 74,
             '<': 87,
             '<pad>': 1,
             '<unk>': 0,
             '=': 82,
             '>': 81,
             '?': 61,
             '@': 83,
             'A': 41,
             'B': 55,
             'C': 34,
             'D': 54,
             'E': 30,
             'F': 57,
             'G': 58,
             'H': 53,
             'I': 36,
             'J': 73,
             'K': 70,
             'L': 52,
```

```
'M': 51,
'N': 38,
'O': 35,
'P': 47,
'Q': 78,
'R': 45,
'S': 33,
'T': 27,
'U': 50,
'V': 68,
'W': 48,
'X': 66,
'Y': 56,
'Z': 84,
'[': 91,
'\\': 102,
']': 92,
'^': 110,
'_': 98,
'a': 6,
'b': 26,
'c': 17,
'd': 15,
'e': 3,
'f': 24,
'g': 22,
'h': 13,
'i': 9,
'j': 69,
'k': 29,
'l': 11,
'm': 18,
'n': 7,
'o': 4,
'p': 21,
'q': 77,
'r': 8,
's': 10,
't': 5,
'u': 12,
'v': 31,
'w': 20,
'x': 39,
'y': 19,
'z': 67,
'|': 88,
'~': 108,
'\x91': 109,
'\x92': 89,
'\x93': 95,
'\x94': 103,
'\x96': 104,
'¡': 96,
'£': 62,
'»': 111,
'É': 112,
'Ü': 86,
'è': 113,
'é': 105,
'ì': 114,
'ü': 85,
'–': 100,
'—': 115,
'‘': 94,
'’': 99,
```

```
'“': 97,
'…': 101,
'┾': 116,
'≐': 117,
'欽': 118})
```

In [ ]:
```
text_field.vocab.itos
```

Out[ ]:
```
['<unk>',
 '<pad>',
 ' ',
 'e',
 'o',
 't',
 'a',
 'n',
 'r',
 'i',
 's',
 'l',
 'u',
 'h',
 '0',
 'd',
 '.',
 'c',
 'm',
 'y',
 'w',
 'p',
 'g',
 '1',
 'f',
 '2',
 'b',
 'T',
 '8',
 'k',
 'E',
 'v',
 '5',
 'S',
 'C',
 'O',
 'I',
 '4',
 'N',
 'x',
 '7',
 'A',
 '3',
 '6',
 '!',
 'R',
 ',',
 'P',
 'W',
 '9',
 'U',
 'M',
 'L',
 'H',
 'D',
 'B',
```

```
 'Y',
 'F',
 'G',
 '/',
 "'",
 '?',
 '£',
 '&',
 '-',
 ':',
 'X',
 'z',
 'V',
 'j',
 'K',
 '*',
 ')',
 'J',
 ';',
 '+',
 '(',
 'q',
 'Q',
 '#',
 '"',
 '>',
 '=',
 '@',
 'Z',
 'ü',
 'Ü',
 '<',
 '|',
 '\x92',
 '$',
 '[',
 ']',
 '%',
 '‘',
 '\x93',
 '¡',
 '“',
 '_',
 '’',
 '–',
 '…',
 '\\',
 '\x94',
 '\x96',
 'é',
 '\t',
 '\n',
 '~',
 '\x91',
 '^',
 '»',
 'É',
 'è',
 'ì',
 '—',
 '┼',
 '≡',
 '鈥']
```

Answer:

As shown in the code above, the variable `text_field.vocab.stoi` is a dictionary mapping of character tokens to integer indices, where `stoi` stands for string to integer.

The variable `text_field.vocab.itos` represents a list mapping integer indices to the character tokens, where `itos` stands for integer to string.

Part (g) [2 pt]

The tokens `<unk>` and `<pad>` were not in our SMS text messages. What do these two values represent?

Answer:

The `<unk>` token represents an unknown token, which means that the token is unrecognized.

The `<pad>` token represents padding. Since the SMS text messages vary in length, padding is applied to ensure training data in the same batch have equal lengths.

Part (h) [2 pt]

Since text sequences are of variable length, `torchtext` provides a `BucketIterator` data loader, which batches similar length sequences together. The iterator also provides functionalities to pad sequences automatically.

Take a look at 10 batches in `train_iter` . 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 [ ]:
```
train_iter = torchtext.legacy.data.BucketIterator(train,
                                           batch_size=32,
                                           sort_key=lambda x: len(x.sms), # to minimize
                                           sort_within_batch=True,        # sort within
                                           repeat=False)                  # repeat the
```

In [ ]:
```
i = 0
for batch in train_iter:
    if i == 10:
        break
    pad = 0
    print("Batch", i+1, ":")
    print("\tMaximum Length =", int(batch.sms[1][0]))
    for sms in batch.sms[1]:
        pad += batch.sms[1][0] - sms
    print("\tNumber of <pad> tokens =", int(pad))
    i += 1
```

```
Batch 1 :
        Maximum Length = 55
        Number of <pad> tokens = 33
Batch 2 :
        Maximum Length = 25
        Number of <pad> tokens = 25
Batch 3 :
        Maximum Length = 76
        Number of <pad> tokens = 35
Batch 4 :
        Maximum Length = 143
```

```
        Number of <pad> tokens = 0
Batch 5 :
        Maximum Length = 156
        Number of <pad> tokens = 0
Batch 6 :
        Maximum Length = 88
        Number of <pad> tokens = 56
Batch 7 :
        Maximum Length = 50
        Number of <pad> tokens = 18
Batch 8 :
        Maximum Length = 144
        Number of <pad> tokens = 1
Batch 9 :
        Maximum Length = 149
        Number of <pad> tokens = 32
Batch 10 :
        Maximum Length = 80
        Number of <pad> tokens = 55
```

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 [ ]:
```
# 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 [ ]:
```
class RNN(nn.Module):
    def __init__(self, hidden_size):
        super(RNN, self).__init__()
        self.name = "rnn"
        self.emb = torch.eye(len(text_field.vocab.itos))
        self.hidden_size = hidden_size
        self.rnn = nn.RNN(len(text_field.vocab.itos), hidden_size, batch_first=True)
        self.fc = nn.Linear(hidden_size, 2)

    def forward(self, x):
        x = self.emb[x]
        h0 = torch.zeros(1, x.size(0), self.hidden_size)
        out, _ = self.rnn(x, h0)
        out = self.fc(out[:, -1, :])
        return out
```

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). You may modify `torchtext.data.BucketIterator` to make your computation faster.

In [ ]:
```
def get_accuracy(model, data_loader):
    """ 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
    """
    correct, total = 0, 0
    for batch in data_loader:
        messages = batch.sms
        labels = batch.label
        output = model(messages[0])
        pred = output.max(1, keepdim=True)[1]
        correct += pred.eq(labels.view_as(pred)).sum().item()
        total += labels.shape[0]
    return correct / total
```

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 [ ]:
```
def get_val_loss(model, valid_loader, criterion):
    total_val_loss = 0.0
    i = 0
    for batch in valid_loader:
        messages = batch.sms
        labels = batch.label
        pred = model(messages[0])
        loss = criterion(pred, labels)
        total_val_loss += loss.item()
        i += 1
    val_loss = float(total_val_loss)/(i + 1)
    return val_loss
```

In [ ]:
```
def train(model, train_loader, valid_loader, num_epochs=5, learning_rate=1e-5):
    torch.manual_seed(1000)
    criterion = nn.CrossEntropyLoss()
    optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
    train_acc, train_loss, val_acc, val_loss = [], [], [], []
    epochs = []

    start_time = time.time()
    for epoch in range(num_epochs):
        total_train_loss = 0.0
        i = 0
        for batch in train_loader:
            messages = batch.sms
            labels = batch.label
            optimizer.zero_grad()
            pred = model(messages[0])
            loss = criterion(pred, labels)
            loss.backward()
            optimizer.step()
            total_train_loss += loss.item()
            i += 1
        epochs.append(epoch)
        train_acc.append(get_accuracy(model, train_loader))
        train_loss.append(float(total_train_loss)/(i + 1))
        val_acc.append(get_accuracy(model, valid_loader))
        val_loss.append(get_val_loss(model, valid_loader, criterion))
        print(("Epoch {}: Train acc: {}, Train loss: {} |"+
               "Validation acc: {}, Validation loss: {}").format(
                   epoch + 1,
                   train_acc[-1],
                   train_loss[-1],
                   val_acc[-1],
                   val_loss[-1]))
    print('Finished Training')
    end_time = time.time()
    elapsed_time = end_time - start_time
    print("Total time elapsed: {:.2f} seconds".format(elapsed_time))

    # Plotting
    plt.title("Train vs Validation Loss")
```

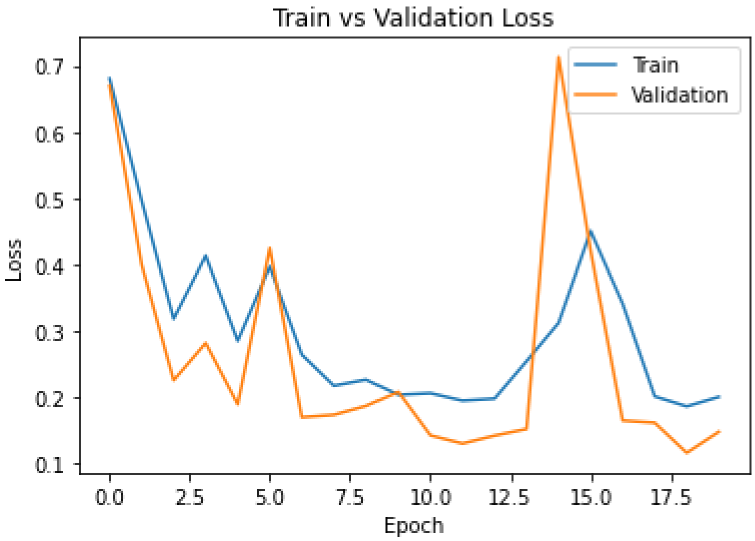
```
    plt.plot(epochs, train_loss, label="Train")
    plt.plot(epochs, val_loss, label="Validation")
    plt.xlabel("Epoch")
    plt.ylabel("Loss")
    plt.legend(loc='best')
    plt.show()

    plt.title("Train vs Validation Accuracy")
    plt.plot(epochs, train_acc, label="Train")
    plt.plot(epochs, val_acc, label="Validation")
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy")
    plt.legend(loc='best')
    plt.show()

    print("Final Training Accuracy: {}".format(train_acc[-1]))
    print("Final Validation Accuracy: {}".format(val_acc[-1]))
```

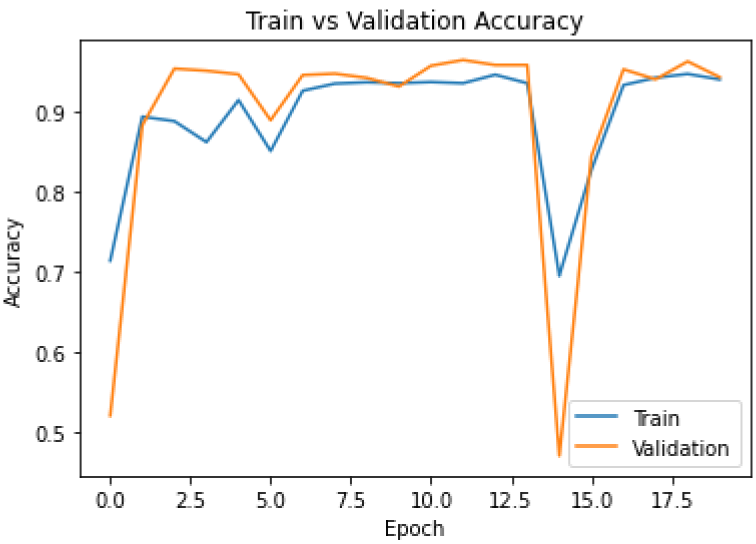
In [ ]:

```
valid_iter = torchtext.legacy.data.BucketIterator(valid,
                                           batch_size=32,
                                           sort_key=lambda x: len(x.sms), # to minimize
                                           sort_within_batch=True,        # sort within
                                           repeat=False)                  # repeat the
model = RNN(50)
train(model, train_iter, valid_iter, num_epochs=20, learning_rate=2e-4)
```

```
Epoch 1: Train acc: 0.7141435914442049, Train loss: 0.6804776721879056 |Validation acc:
0.5210762331838565, Validation loss: 0.6698493676053153
Epoch 2: Train acc: 0.8942132316365445, Train loss: 0.4965032028524499 |Validation acc:
0.8834080717488789, Validation loss: 0.4002683055069711
Epoch 3: Train acc: 0.8885756922566739, Train loss: 0.3184615362631647 |Validation acc:
0.9542600896860987, Validation loss: 0.22565977896253267
Epoch 4: Train acc: 0.8623777151384513, Train loss: 0.4132004074360195 |Validation acc:
0.9515695067264573, Validation loss: 0.28194522733489674
Epoch 5: Train acc: 0.9149394793566573, Train loss: 0.28518127595123494 |Validation acc:
0.947085201793722, Validation loss: 0.18944910044471422
Epoch 6: Train acc: 0.8512684463604709, Train loss: 0.39714714010295116 |Validation acc:
0.8896860986547085, Validation loss: 0.4248014572593901
Epoch 7: Train acc: 0.9265461780799205, Train loss: 0.26450181503437065 |Validation acc:
0.9461883408071748, Validation loss: 0.16993081517931488
Epoch 8: Train acc: 0.9354999170950091, Train loss: 0.21749202187516187 |Validation acc:
0.9479820627802691, Validation loss: 0.17355751535958713
Epoch 9: Train acc: 0.9371580169126181, Train loss: 0.2266298216620558 |Validation acc:
0.9426008968609866, Validation loss: 0.18699265540473992
Epoch 10: Train acc: 0.9359973470402918, Train loss: 0.2038432311070593 |Validation acc:
0.9318385650224216, Validation loss: 0.2082437134037415
Epoch 11: Train acc: 0.93748963687614, Train loss: 0.20630390554862588 |Validation acc:
0.957847533632287, Validation loss: 0.14254902354958984
Epoch 12: Train acc: 0.9359973470402918, Train loss: 0.1950058726593852 |Validation acc:
0.9650224215246637, Validation loss: 0.13023561580727497
Epoch 13: Train acc: 0.9466091858729896, Train loss: 0.19805037038106668 |Validation ac
c: 0.9587443946188341, Validation loss: 0.14214143105265167
Epoch 14: Train acc: 0.9359973470402918, Train loss: 0.25459308167919514 |Validation ac
c: 0.9587443946188341, Validation loss: 0.15223710839119223
Epoch 15: Train acc: 0.6957386834687448, Train loss: 0.31242987642946995 |Validation ac
c: 0.47085201793721976, Validation loss: 0.713133735789193
Epoch 16: Train acc: 0.8277234289504228, Train loss: 0.4504673296683713 |Validation acc:
0.8448430493273542, Validation loss: 0.42072220063871807
Epoch 17: Train acc: 0.9336760072956392, Train loss: 0.34111918430579335 |Validation ac
c: 0.9533632286995516, Validation loss: 0.164895406510267
Epoch 18: Train acc: 0.9427955562924888, Train loss: 0.20142880448777425 |Validation ac
c: 0.9408071748878923, Validation loss: 0.16166115562534994
Epoch 19: Train acc: 0.947604045763555, Train loss: 0.18631989463771645 |Validation acc:
```

```
0.9632286995515695, Validation loss: 0.11617447052978808
Epoch 20: Train acc: 0.9406400265295971, Train loss: 0.2006524994577232 |Validation acc:
0.9434977578475336, Validation loss: 0.14794848207384348
Finished Training
Total time elapsed: 97.70 seconds
```






```
Final Training Accuracy: 0.9406400265295971
Final Validation Accuracy: 0.9434977578475336
```

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.

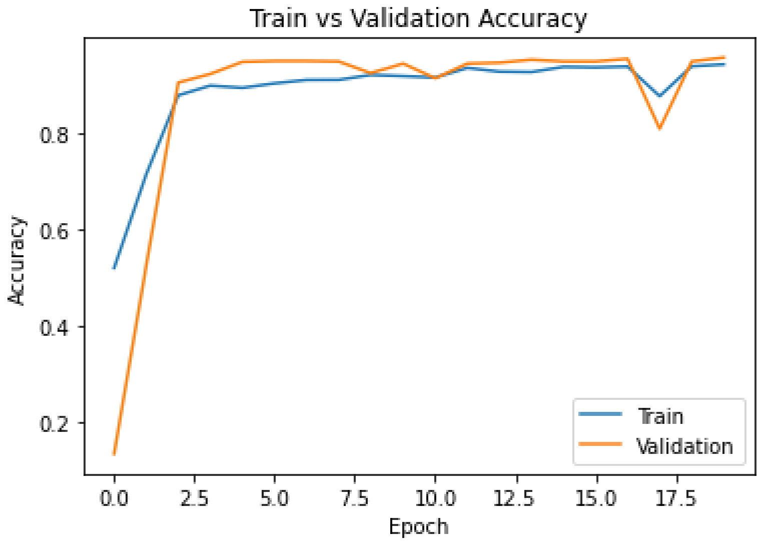
For this assignment, you should tune more than just your learning rate and epoch. Choose at least 2 hyperparameters that are unrelated to the optimizer.

In [ ]:

```
# Since the training curves of the model in Part (b) were noisy, learning_rate is decre
model_1 = RNN(50)
train(model_1, train_iter, valid_iter, num_epochs=20, learning_rate=1e-4)

# Results:
```

```
# Final Training Accuracy: 0.9436246062012933
# Final Validation Accuracy: 0.957847533632287
```

```
Epoch 1: Train acc: 0.5206433427292323, Train loss: 0.6903340483966627 |Validation acc:
0.13542600896860987, Validation loss: 0.7396099650197558
Epoch 2: Train acc: 0.7149726413530094, Train loss: 0.6690227590109172 |Validation acc:
0.525560538116592, Validation loss: 0.6657121595409181
Epoch 3: Train acc: 0.8792903332780634, Train loss: 0.5217389828280399 |Validation acc:
0.905829596412556, Validation loss: 0.37643614245785606
Epoch 4: Train acc: 0.8995191510528934, Train loss: 0.37207915084926707 |Validation acc:
0.9237668161434978, Validation loss: 0.3236350541313489
Epoch 5: Train acc: 0.8948764715635882, Train loss: 0.32155652532452034 |Validation acc:
0.9488789237668162, Validation loss: 0.2462928079896503
Epoch 6: Train acc: 0.9041618305421987, Train loss: 0.3088581658507648 |Validation acc:
0.9506726457399103, Validation loss: 0.2247312255203724
Epoch 7: Train acc: 0.9112916597579174, Train loss: 0.30459735405288246 |Validation acc:
0.9506726457399103, Validation loss: 0.21617909810609287
Epoch 8: Train acc: 0.9114574697396783, Train loss: 0.31656184247449826 |Validation acc:
0.9497757847533632, Validation loss: 0.2069790725492769
Epoch 9: Train acc: 0.9217376886088543, Train loss: 0.2707316149418291 |Validation acc:
0.9255605381165919, Validation loss: 0.2510863290064865
Epoch 10: Train acc: 0.9192505388824407, Train loss: 0.250418108505638 |Validation acc:
0.9452914798206278, Validation loss: 0.2038864197416438
Epoch 11: Train acc: 0.9162659592107445, Train loss: 0.24597041153986204 |Validation ac
c: 0.9147982062780269, Validation loss: 0.2541445634431309
Epoch 12: Train acc: 0.9363289670038136, Train loss: 0.249507427607712 |Validation acc:
0.9452914798206278, Validation loss: 0.2296621778772937
Epoch 13: Train acc: 0.9285358978610513, Train loss: 0.2340851051242728 |Validation acc:
0.947085201793722, Validation loss: 0.22126217828028732
Epoch 14: Train acc: 0.9277068479522467, Train loss: 0.22029609633119482 |Validation ac
c: 0.9533632286995516, Validation loss: 0.1681025337634815
Epoch 15: Train acc: 0.9384844967667053, Train loss: 0.24914016075628367 |Validation ac
c: 0.9497757847533632, Validation loss: 0.17783430384265053
Epoch 16: Train acc: 0.93748963687614, Train loss: 0.21806052491853112 |Validation acc:
0.9497757847533632, Validation loss: 0.1797734952221314
Epoch 17: Train acc: 0.939147736693749, Train loss: 0.20676536771811937 |Validation acc:
0.9551569506726457, Validation loss: 0.16786408155328697
Epoch 18: Train acc: 0.8776322334604543, Train loss: 0.20116905517091876 |Validation ac
c: 0.809865470852018, Validation loss: 0.46162457888325054
Epoch 19: Train acc: 0.9396451666390316, Train loss: 0.2118614126486998 |Validation acc:
0.9497757847533632, Validation loss: 0.1768091426541408
Epoch 20: Train acc: 0.9436246062012933, Train loss: 0.1978954168330682 |Validation acc:
0.957847533632287, Validation loss: 0.1567128234439426
Finished Training
Total time elapsed: 97.72 seconds
```




```
Final Training Accuracy: 0.9436246062012933
Final Validation Accuracy: 0.957847533632287
```

In [ ]:

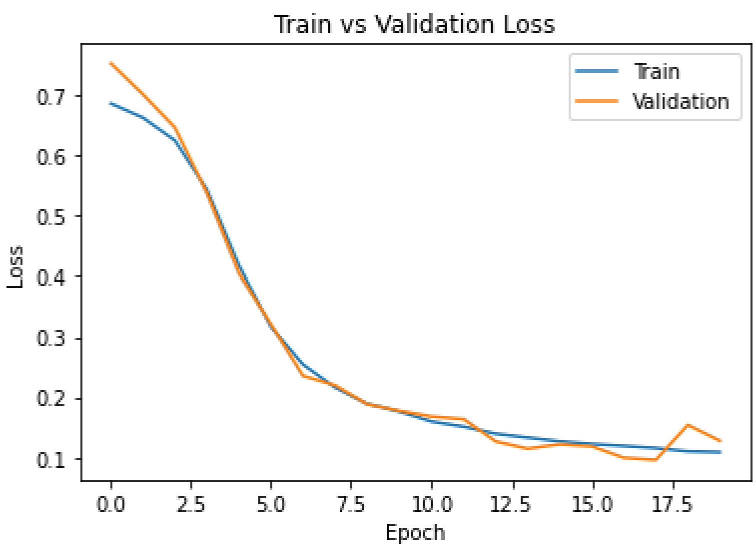
```python
# In Part 2, it is stated that the way the RNN outputs are pooled can be tuned as well
# A new architecture that uses max-pool over the entire output array is proposed
class RNN_max(nn.Module):
    def __init__(self, hidden_size):
        super(RNN_max, self).__init__()
        self.name = "rnn_max"
        self.emb = torch.eye(len(text_field.vocab.itos))
        self.hidden_size = hidden_size
        self.rnn = nn.RNN(len(text_field.vocab.itos), hidden_size, batch_first=True)
        self.fc = nn.Linear(hidden_size, 2)

    def forward(self, x):
        x = self.emb[x]
        h0 = torch.zeros(1, x.size(0), self.hidden_size)
        out, _ = self.rnn(x, h0)
        out = self.fc(torch.max(out, dim=1)[0])
        return out
```

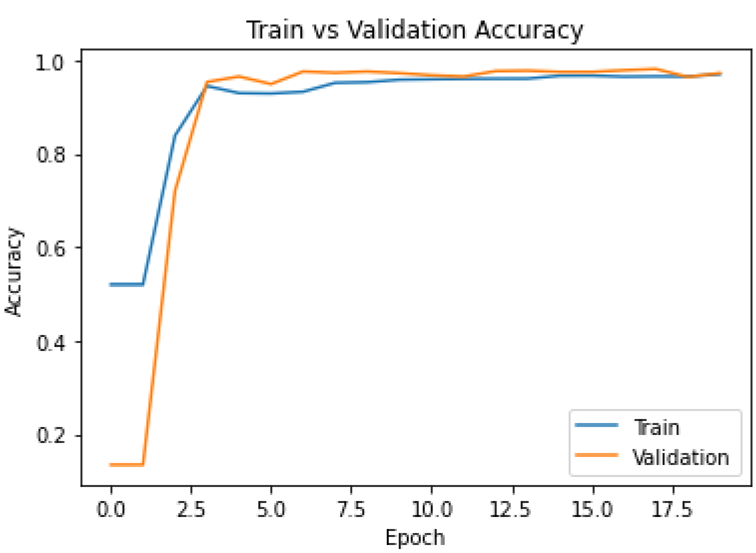
In [ ]:

```python
model_2 = RNN_max(50)
train(model_2, train_iter, valid_iter, num_epochs=20, learning_rate=1e-4)

# Results:
# Final Training Accuracy: 0.9699883933012767
# Final Validation Accuracy: 0.9721973094170404
```

```
Epoch 1: Train acc: 0.5199801028021886, Train loss: 0.6864059423145495 |Validation acc: 
0.13452914798206278, Validation loss: 0.7529377225372527
Epoch 2: Train acc: 0.5201459127839496, Train loss: 0.6629379542250382 |Validation acc: 
0.13452914798206278, Validation loss: 0.7016291419665018
Epoch 3: Train acc: 0.8386668877466423, Train loss: 0.6250654971913288 |Validation acc: 
0.7201793721973094, Validation loss: 0.646301786104838
Epoch 4: Train acc: 0.9446194660918588, Train loss: 0.5436547732666919 |Validation acc: 
0.9533632286995516, Validation loss: 0.5371421931518449
Epoch 5: Train acc: 0.9295307577516166, Train loss: 0.4180502640573602 |Validation acc: 
0.9650224215246637, Validation loss: 0.4045275491144922
Epoch 6: Train acc: 0.9287017078428121, Train loss: 0.31714222078260623 |Validation acc: 
0.9488789237668162, Validation loss: 0.32067176575462025
Epoch 7: Train acc: 0.932349527441552, Train loss: 0.254495153262427 |Validation acc: 0.
9757847533632287, Validation loss: 0.23551247227523062
Epoch 8: Train acc: 0.9515834853258166, Train loss: 0.21629952992263593 |Validation acc: 
0.9730941704035875, Validation loss: 0.219858322913448
```

```
Epoch 9: Train acc: 0.9529099651799038, Train loss: 0.1892612285519901 |Validation acc:
0.9757847533632287, Validation loss: 0.1884918984853559
Epoch 10: Train acc: 0.9582158845962527, Train loss: 0.17592544554683723 |Validation ac
c: 0.9721973094170404, Validation loss: 0.1774116497900751
Epoch 11: Train acc: 0.9592107444868181, Train loss: 0.1596182099102359 |Validation acc:
0.967713004484305, Validation loss: 0.16809018949667612
Epoch 12: Train acc: 0.9600397943956226, Train loss: 0.15108841550781538 |Validation ac
c: 0.9650224215246637, Validation loss: 0.16362176131871012
Epoch 13: Train acc: 0.9603714143591444, Train loss: 0.13934205893525167 |Validation ac
c: 0.9766816143497757, Validation loss: 0.12665037334793144
Epoch 14: Train acc: 0.9605372243409053, Train loss: 0.13300600263633225 |Validation ac
c: 0.9775784753363229, Validation loss: 0.11467103566974401
Epoch 15: Train acc: 0.9666721936660587, Train loss: 0.12672864273680667 |Validation ac
c: 0.9748878923766816, Validation loss: 0.1219657248713904
Epoch 16: Train acc: 0.9668380036478196, Train loss: 0.12236000161225859 |Validation ac
c: 0.9748878923766816, Validation loss: 0.11857040309243733
Epoch 17: Train acc: 0.9648482838666887, Train loss: 0.11913930052695305 |Validation ac
c: 0.97847533632287, Validation loss: 0.09954664406056206
Epoch 18: Train acc: 0.9653457138119714, Train loss: 0.11559367523479619 |Validation ac
c: 0.9811659192825112, Validation loss: 0.09594070673402813
Epoch 19: Train acc: 0.9650140938484497, Train loss: 0.1101354196152993 |Validation acc:
0.9641255605381166, Validation loss: 0.15401534415367577
Epoch 20: Train acc: 0.9699883933012767, Train loss: 0.10883524032603753 |Validation ac
c: 0.9721973094170404, Validation loss: 0.12784125304056537
Finished Training
Total time elapsed: 96.49 seconds
```






```
Final Training Accuracy: 0.9699883933012767
```

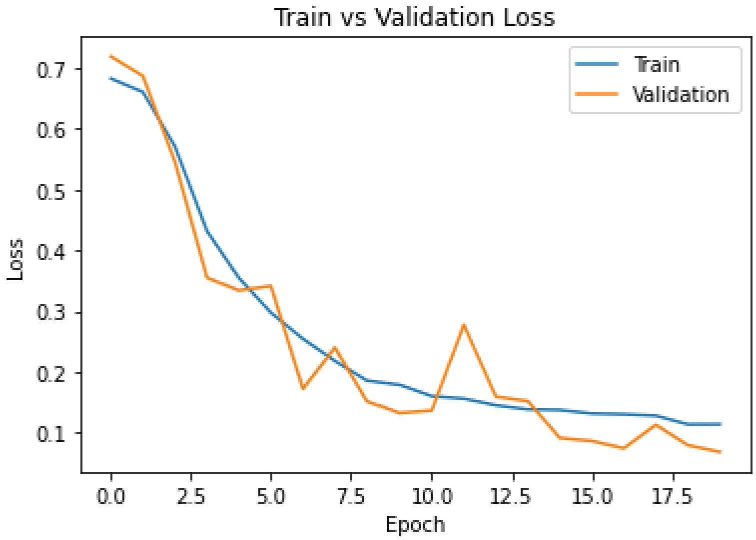
```
Final Validation Accuracy: 0.9721973094170404
```

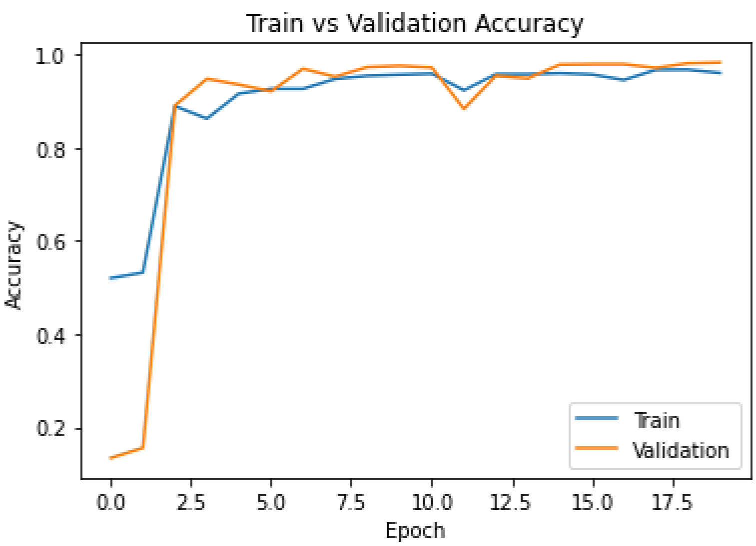
In [ ]:
```
# Since changing the way the RNN outputs are pooled increased the training and validati
# a new architecture that concatenates the max-pooling and average-pooling of the RNN o
class RNN_cat(nn.Module):
    def __init__(self, hidden_size):
        super(RNN_cat, self).__init__()
        self.name = "rnn_cat"
        self.emb = torch.eye(len(text_field.vocab.itos))
        self.hidden_size = hidden_size
        self.rnn = nn.RNN(len(text_field.vocab.itos), hidden_size, batch_first=True)
        self.fc = nn.Linear(hidden_size*2, 2)

    def forward(self, x):
        x = self.emb[x]
        h0 = torch.zeros(1, x.size(0), self.hidden_size)
        out, _ = self.rnn(x, h0)
        out = torch.cat([torch.max(out, dim=1)[0],
                         torch.mean(out, dim=1)], dim=1)
        return self.fc(out)
```

In [ ]:
```
model_3 = RNN_cat(50)
train(model_3, train_iter, valid_iter, num_epochs=20, learning_rate=1e-4)

# Results:
# Final Training Accuracy: 0.9597081744321008
# Final Validation Accuracy: 0.9820627802690582
```

```
Epoch 1: Train acc: 0.5199801028021886, Train loss: 0.6829111055323952 |Validation acc:
0.13452914798206278, Validation loss: 0.7191536360316806
Epoch 2: Train acc: 0.5317526115072128, Train loss: 0.6606561965063998 |Validation acc:
0.15605381165919283, Validation loss: 0.6870254576206207
Epoch 3: Train acc: 0.8887415022384347, Train loss: 0.5713585249687496 |Validation acc:
0.8896860986547085, Validation loss: 0.5455599890814887
Epoch 4: Train acc: 0.8617144752114078, Train loss: 0.4322897091507912 |Validation acc:
0.947085201793722, Validation loss: 0.35540933658679325
Epoch 5: Train acc: 0.91543690930194, Train loss: 0.35486842691898346 |Validation acc:
0.9345291479820628, Validation loss: 0.334542453289032
Epoch 6: Train acc: 0.925717128171116, Train loss: 0.29781997635176305 |Validation acc:
0.9201793721973094, Validation loss: 0.3418952338397503
Epoch 7: Train acc: 0.925717128171116, Train loss: 0.25482927074557854 |Validation acc:
0.968609865470852, Validation loss: 0.17259083771043354
Epoch 8: Train acc: 0.9467749958547504, Train loss: 0.2185006145583956 |Validation acc:
0.9515695067264573, Validation loss: 0.24024947318765852
Epoch 9: Train acc: 0.9535732051069474, Train loss: 0.18600512070483283 |Validation acc:
0.9721973094170404, Validation loss: 0.15196826246877512
Epoch 10: Train acc: 0.9560603548333609, Train loss: 0.17898655318115886 |Validation ac
c: 0.9748878923766816, Validation loss: 0.13282323711448246
Epoch 11: Train acc: 0.9580500746144918, Train loss: 0.16040640539048534 |Validation ac
c: 0.9713004484304932, Validation loss: 0.13707797332770294
Epoch 12: Train acc: 0.9225667385176588, Train loss: 0.15639349662355687 |Validation ac
c: 0.8825112107623319, Validation loss: 0.2779569073269765
Epoch 13: Train acc: 0.9570552147239264, Train loss: 0.14546924589299842 |Validation ac
c: 0.9533632286995516, Validation loss: 0.1597701623621914
Epoch 14: Train acc: 0.9570552147239264, Train loss: 0.13870882157628472 |Validation ac
c: 0.9479820627802691, Validation loss: 0.1524360270963775
Epoch 15: Train acc: 0.9590449345050572, Train loss: 0.13771911606094556 |Validation ac
c: 0.9775784753363229, Validation loss: 0.0917315689019031
Epoch 16: Train acc: 0.9565577847786437, Train loss: 0.1318810817540476 |Validation acc:
0.97847533632287, Validation loss: 0.08685739607446724
Epoch 17: Train acc: 0.9446194660918588, Train loss: 0.13068280584227882 |Validation ac
c: 0.97847533632287, Validation loss: 0.07481918608148892
Epoch 18: Train acc: 0.9663405737025369, Train loss: 0.12833534240673639 |Validation ac
```

```
c: 0.9704035874439462, Validation loss: 0.11338703758600685
Epoch 19: Train acc: 0.9666721936660587, Train loss: 0.11415863792460999 |Validation ac
c: 0.9802690582959641, Validation loss: 0.07986906952121192
Epoch 20: Train acc: 0.9597081744321008, Train loss: 0.11427171845969401 |Validation ac
c: 0.9820627802690582, Validation loss: 0.06881144906704624
Finished Training
Total time elapsed: 100.55 seconds
```





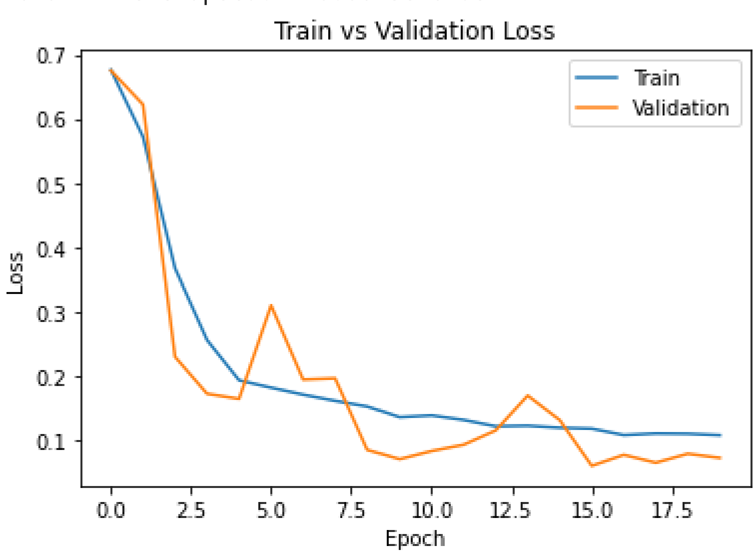

```
Final Training Accuracy: 0.9597081744321008
Final Validation Accuracy: 0.9820627802690582
```

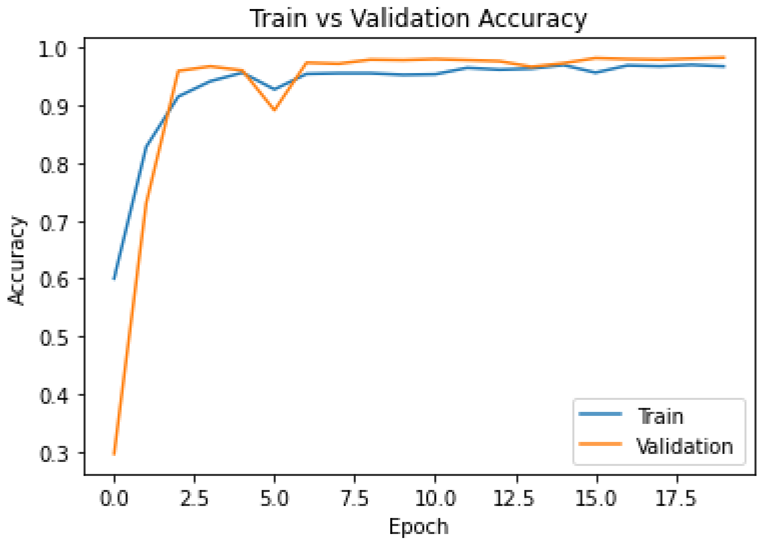
In [ ]:

```
# Since model_3 performed the best so far, the number of hidden units is increased from

model_4 = RNN_cat(100)
train(model_4, train_iter, valid_iter, num_epochs=20, learning_rate=1e-4)

# Results:
# Final Training Accuracy: 0.96766705355566241
# Final Validation Accuracy: 0.9829596412556054
```

```
Epoch 1: Train acc: 0.6000663239927043, Train loss: 0.6759776761657313 |Validation acc:
0.29596412556053814, Validation loss: 0.6750204347901874
Epoch 2: Train acc: 0.8278892389321837, Train loss: 0.5719994723012573 |Validation acc:
0.7300448430493274, Validation loss: 0.6222045603725646
Epoch 3: Train acc: 0.915271099320179, Train loss: 0.3676341379943647 |Validation acc:
0.9596412556053812, Validation loss: 0.2304677309261428
Epoch 4: Train acc: 0.9418006964019234, Train loss: 0.2565362821480161 |Validation acc:
0.967713004484305, Validation loss: 0.1730135733054744
```

```
Epoch 5: Train acc: 0.9567235947604046, Train loss: 0.19393194319778367 |Validation acc:
0.9605381165919282, Validation loss: 0.1650052677012152
Epoch 6: Train acc: 0.9277068479522467, Train loss: 0.18250038692433584 |Validation acc:
0.8914798206278027, Validation loss: 0.310514197167423
Epoch 7: Train acc: 0.9545680649975129, Train loss: 0.17159915766433664 |Validation acc:
0.9739910313901345, Validation loss: 0.19507517996761534
Epoch 8: Train acc: 0.9557287348698391, Train loss: 0.16195517340184826 |Validation acc:
0.9721973094170404, Validation loss: 0.19701212665273082
Epoch 9: Train acc: 0.9557287348698391, Train loss: 0.1532196528523376 |Validation acc:
0.979372197309417, Validation loss: 0.08571400731388065
Epoch 10: Train acc: 0.9529099651799038, Train loss: 0.13658128936627978 |Validation ac
c: 0.97847533632287, Validation loss: 0.07120659207511279
Epoch 11: Train acc: 0.9539048250704693, Train loss: 0.13929277831002285 |Validation ac
c: 0.9802690582959641, Validation loss: 0.08387348987162113
Epoch 12: Train acc: 0.9651799038302106, Train loss: 0.1322309566024495 |Validation acc:
0.97847533632287, Validation loss: 0.0936959056287176
Epoch 13: Train acc: 0.9618637041949926, Train loss: 0.1223948716284021 |Validation acc:
0.9766816143497757, Validation loss: 0.11590949984060393
Epoch 14: Train acc: 0.9636876139943624, Train loss: 0.12322672696195935 |Validation ac
c: 0.9668161434977578, Validation loss: 0.17013757810410526
Epoch 15: Train acc: 0.9699883933012767, Train loss: 0.12003948594394483 |Validation ac
c: 0.9730941704035875, Validation loss: 0.13199541733289757
Epoch 16: Train acc: 0.9567235947604046, Train loss: 0.11867616201848968 |Validation ac
c: 0.9820627802690582, Validation loss: 0.06081056550869511
Epoch 17: Train acc: 0.9693251533742331, Train loss: 0.10867868696192377 |Validation ac
c: 0.9802690582959641, Validation loss: 0.07790554801209106
Epoch 18: Train acc: 0.967832863538385, Train loss: 0.11118614061882622 |Validation acc:
0.979372197309417, Validation loss: 0.06568223698478606
Epoch 19: Train acc: 0.9703200132647986, Train loss: 0.11070939040938882 |Validation ac
c: 0.9811659192825112, Validation loss: 0.07962419046089053
Epoch 20: Train acc: 0.9676670535566241, Train loss: 0.10850700417435483 |Validation ac
c: 0.9829596412556054, Validation loss: 0.07319209440093902
Finished Training
Total time elapsed: 146.06 seconds
```






```
Final Training Accuracy: 0.9676670535566241
Final Validation Accuracy: 0.9829596412556054
```

Answer:

`model_4` produces the best results, with a final validation accuracy of `98.3%` .

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 [ ]:
```
# Create a Dataset of only spam validation examples
valid_spam = torchtext.legacy.data.Dataset(
    [e for e in valid.examples if e.label == 1],
    valid.fields)
# Create a Dataset of only non-spam validation examples
valid_nospam = torchtext.legacy.data.Dataset(
    [e for e in valid.examples if e.label == 0],
    valid.fields)

valid_spam_iter = torchtext.legacy.data.BucketIterator(valid_spam,
                                           batch_size=32,
                                           sort_key=lambda x: len(x.sms),
                                           sort_within_batch=True,
                                           repeat=False)

valid_nospam_iter = torchtext.legacy.data.BucketIterator(valid_nospam,
                                           batch_size=32,
                                           sort_key=lambda x: len(x.sms),
                                           sort_within_batch=True,
```

```
                                            repeat=False)

valid_false_positive = 1 - get_accuracy(model_4, valid_nospam_iter)
valid_false_negative = 1 - get_accuracy(model_4, valid_spam_iter)

print("The false positive rate is", valid_false_positive*100, "%")
print("The false negative rate is", valid_false_negative*100, "%")
```

```
The false positive rate is 1.4507772020725396 %
The false negative rate is 4.0000000000000036 %
```

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:

If the spam detection algorithm was deployed on my phone, a high false positive rate would mean that normal texts I receive can potentially be marked as spam as well. This could lead to the negligence or deletion of important texts that I might receive. On the other hand, a high false negative rate would mean that the algorithm is often labeling spam texts as normal texts, which means that it is not performing very well at reducing the amount of spam texts I might receive.

Part 4. Evaluation [11 pt]

Part (a) [1 pt]

Report the final test accuracy of your model.

In [ ]:
```
test_iter = torchtext.legacy.data.BucketIterator(test,
                                            batch_size=32,
                                            sort_key=lambda x: len(x.sms),
                                            sort_within_batch=True,
                                            repeat=False)

test_acc = get_accuracy(model_4, test_iter)
print("The final test accuracy of my model is", test_acc*100, "%")
```

```
The final test accuracy of my model is 97.3967684021544 %
```

Part (b) [3 pt]

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

In [ ]:
```
test_spam = torchtext.legacy.data.Dataset(
    [e for e in test.examples if e.label == 1],
    test.fields)

test_nospam = torchtext.legacy.data.Dataset(
    [e for e in test.examples if e.label == 0],
    test.fields)

test_spam_iter = torchtext.legacy.data.BucketIterator(test_spam,
                                            batch_size=32,
```

```
                                            sort_key=lambda x: len(x.sms),
                                            sort_within_batch=True,
                                            repeat=False)

test_nospam_iter = torchtext.legacy.data.BucketIterator(test_nospam,
                                            batch_size=32,
                                            sort_key=lambda x: len(x.sms),
                                            sort_within_batch=True,
                                            repeat=False)

test_false_positive = 1 - get_accuracy(model_4, test_nospam_iter)
test_false_negative = 1 - get_accuracy(model_4, test_spam_iter)

print("The false positive rate is", test_false_positive*100, "%")
print("The false negative rate is", test_false_negative*100, "%")
```

```
The false positive rate is 1.9689119170984481 %
The false negative rate is 7.38255033557047 %
```

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 `text_field.vocab.stoi` to look up the index of each character in the vocabulary.

In [ ]:

```
msg = "machine learning is sooo cool!"
msg_stoi = []
for i in range(len(msg)):
    msg_stoi.append(text_field.vocab.stoi[msg[i]])

test_msg = torch.LongTensor(msg_stoi).unsqueeze(dim=0)
pred = model_4(test_msg)
prob = F.softmax(pred, dim=1)
print("The probability that \"machine learning is sooo cool!\" is spam is", float(prob[
```

```
The probability that "machine learning is sooo cool!" is spam is 5.805425643920898 %
```

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:

In my opinion, it is not difficult to achieve high accuracies for spam detection using a recurrent neural network model. However, even with a high overall accuracy, the impact of false positives and false negatives can still be significant. So, it is important to reduce these errors as much as possible, which is the difficult part.

A simple baseline model could be built through targeting keywords in common spam messages and labeling any messages containing these keywords as spams. This can be an easy to build and inexpensive model to compare the recurrent neural network against.