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. 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.

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:

As we are using the older version of the torchtext, please run the following to downgrade the torchtext version:

!pip install -U torch==1.8.0+cu111 torchtext==0.9.0 -f https://download.pytorch.org/whl/torch_stable.html

If you are interested to use the most recent version if torchtext, you can look at the following document to see how to convert the legacy version to the new version:

https://colab.research.google.com/github/pytorch/text/blob/master/examples/legacy_tutorial/migration_tutorial.ipynb

```
!pip install -U torch==1.8.0+cu111 torchtext==0.9.0 -f https://download.pytorch.org/wh
```

```
    Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-whe
    Looking in links: https://download.pytorch.org/whl/torch_stable.html
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      Downloading https://download.pytorch.org/whl/cu111/torch-1.8.0%2Bcu111-cp39-cp
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    Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.9/dist-pac
    Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.9/di
    Installing collected packages: torch, torchtext
      Attempting uninstall: torch
        Found existing installation: torch 1.13.1+cu116
        Uninstalling torch-1.13.1+cu116:
          Successfully uninstalled torch-1.13.1+cu116
      Attempting uninstall: torchtext
        Found existing installation: torchtext 0.14.1
        Uninstalling torchtext-0.14.1:
          Successfully uninstalled torchtext-0.14.1
    ERROR: pip's dependency resolver does not currently take into account all the pa
    torchvision 0.14.1+cu116 requires torch==1.13.1, but you have torch 1.8.0+cu111 
    torchaudio 0.13.1+cu116 requires torch==1.13.1, but you have torch 1.8.0+cu111 w
    Successfully installed torch-1.8.0+cu111 torchtext-0.9.0
```

```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import numpy as np
```

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.

```
mPath = '/content/drive/MyDrive/Colab Notebooks/smsspamcollection/SMSSpamCollection'
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
    Mounted at /content/drive
```

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?

```
reg, spm = 0, 0
for line in open(mPath):
  if 'ham' in line and reg < 1:
    print("Regular Text Example: "+line)
    reg +=1

  if 'spam' in line and spm < 1:
    print("Spam Example: "+ line)
    spm += 1

  if reg == spm:
    break
```

```
    Regular Text Example: ham       Go until jurong point, crazy.. Available only in

    Spam Example: spam      Free entry in 2 a wkly comp to win FA Cup final tkts 21s
```

The label value for a spam message is 'spam' and the label for the 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?

```
regCt, spmCt = 0, 0
for line in open(mPath):
  if 'ham' in line:
    regCt +=1

  if 'spam' in line:
        spmCt += 1

print("Spam Message Count:" + str(spmCt) + '\nNon-Spam Message count: ' + str(regCt))
```

```
Spam Message Count:747
Non-Spam Message count: 4831
```

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.

Advantages

- Requires less memeory because there are around 97 English characters but thousands of words.
- Rich morphology with other languages such as such as Finish, Turkish, Russian etc. Using word-based RNN LMs to model such languages is difficult if possible at all and is not advised.

Disadvantages

- Char-based RNN models require much bigger hidden layer to successfully model long-term dependencies which means higher computational costs.
- Is not very good with handling new encounters such as misspelled words

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.

```
import torchtext
import os
from torchtext import data


text_field = torchtext.legacy.data.Field(sequential=True,      # text sequence
                                  tokenize=lambda x: x, # because are building a chara
                                  include_lengths=True, # to track the length of seque
                                  batch_first=True,
                                  use_vocab=True)       # to turn each character into
label_field = torchtext.legacy.data.Field(sequential=False,    # not a sequence
                                   use_vocab=False,     # don't need to track vocabula
                                   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(mPath, # name of the file
                                        "tsv",               # fields are separated by
                                        fields)

train, valid, test = dataset.split(split_ratio=[0.6,0.2,0.2])


#print(dataset[0].sms)
#dataset[0].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.

Having a balanced training set is helpful because the modelt is as good as the data we train it on, in the sense that if there are more non-spam messages, we are more likely to get a response that is identifies spam as non-spam just because the volume of non-spam in the data is larger than the spam.

```
# 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
```

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.

```
text_field.build_vocab(train)
#text_field.vocab.stoi
#text_field.vocab.itos
```

text_field.vocab.stoi is a dictionary mapping each character that appeared in the training set to a numerical identifier, and text_field.vocab.itos is a list of the characters in the training set in order of their respective numerical identifiers.

Part (g) [2 pt]

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

unk represents an unknown character that doesn't exist in the vocabulary (ie. it may represent a word that didn't appear often enough in the dataset so it was removed from the vocabulary), and pad is a token used to increase the size of SMS messages so that all SMS messages in a batch have the same length.

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?

```
train_iter = torchtext.legacy.data.BucketIterator(train,
                                           batch_size=32,
                                           sort_key=lambda x: len(x.sms), # to minimiz
                                           sort_within_batch=True,        # sort withi
                                           repeat=False)                  # repeat the

val_iter = torchtext.legacy.data.BucketIterator(valid,
                                           batch_size=32,
                                           sort_key=lambda x: len(x.sms), # to minimiz
                                           sort_within_batch=True,        # sort withi
                                           repeat=False)                  # repeat the

test_iter = torchtext.legacy.data.BucketIterator(test,
                                           batch_size=32,
                                           sort_key=lambda x: len(x.sms), # to minimiz
                                           sort_within_batch=True,        # sort withi
                                           repeat=False)                  # repeat the


i = 0
padCounts = [0, 0, 0, 0, 0, 0, 0, 0, 0 ,0] # The number of pad tokens in each batch
maxLengths = [0, 0, 0, 0, 0, 0, 0, 0, 0 ,0] # The maximum SMS length in that batch

for batch in train_iter:
  if i < 10:
    for sms in batch.sms[0]:
      if len(sms) > maxLengths[i]:
        maxLengths[i] = len(sms)
      for token in sms:
        if token == text_field.vocab.stoi["<pad>"]:
          padCounts[i] += 1
    i += 1

print(padCounts)
print(maxLengths)
```

Show hidden output

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.

```
# 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
```

Show hidden output

```
class RNN(nn.Module):
  def __init__(self, vocab_size, hidden_size, n_layers=1):
    super(RNN, self).__init__()

    # identity matrix for generating one-hot vectors
    self.ident = torch.eye(vocab_size)
    # recurrent neural network
    self.rnn = nn.GRU(vocab_size, hidden_size, n_layers, batch_first=True)

    # a fully-connected layer that classifies the input into SPAM/HAM
    self.classifier = nn.Linear(hidden_size, 2)

  def forward(self, x):
    one_hot = []
    for sms in x:
      one_hot.append(self.ident[sms])   # generate one-hot vectors of input

    inp_x = torch.stack(one_hot)

    output, _ = self.rnn(inp_x)           # get the next output and hidden state
    out =  torch.max(output, dim=1)[0]    # max pooling the GRU output
    out = self.classifier(out)            # predict SPAM/HAM
    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.

```
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
    """
    correct, total = 0, 0
    for sms, labels in data:
        output = model(sms[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]

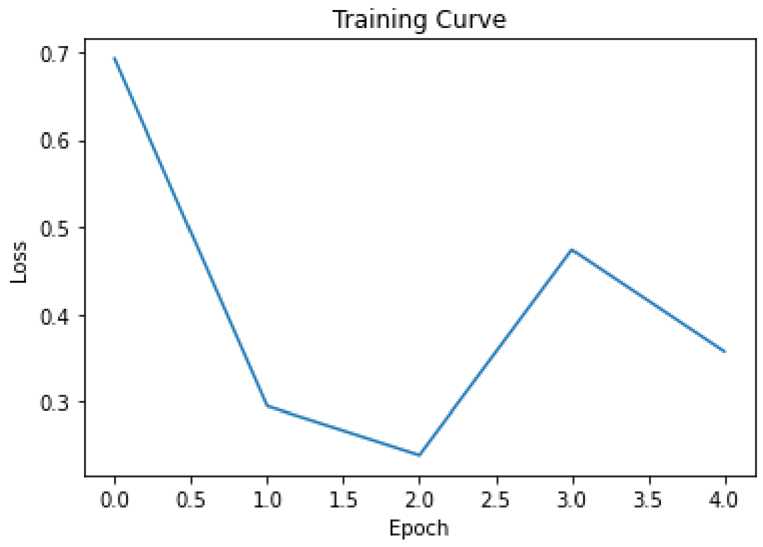
Train your model. Plot the training curve of your final model. Your training curve should have the training/validation loss and accuracy plotted periodically.

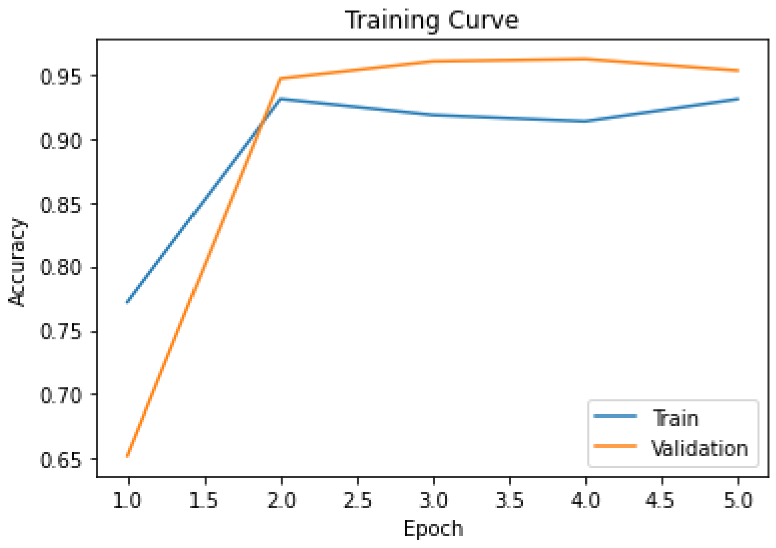
Note: Not all of your batches will have the same batch size. In particular, if your training set does not divide evenly by your batch size, there will be a batch that is smaller than the rest.

```
import numpy as np
import matplotlib.pyplot as plt


def train_rnn_network(model, train, valid, num_epochs=5, learning_rate=1e-4):
    optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
    criterion = nn.CrossEntropyLoss()
    it = 0
    losses, train_acc, valid_acc = [], [], []
    epochs = []
    for epoch in range(num_epochs):
        avg_loss = 0
        for sms, labels in train:
            # target = sms[:, 1:]
            # inp = sms[:, :-1]
            optimizer.zero_grad()
            pred = model(sms[0])
            loss = criterion(pred, labels)
            loss.backward()
            optimizer.step()

        losses.append(float(loss))
        epochs.append(epoch+1)
        train_acc.append(get_accuracy(model, train))
        valid_acc.append(get_accuracy(model, valid))
        print("Epoch %d; Loss %f; Train Acc %f; Val Acc %f" % (
              epoch+1, loss, train_acc[-1], valid_acc[-1]))
    # plotting
    plt.title("Training Curve")
    plt.plot(losses, label="Train")
    plt.xlabel("Epoch")
    plt.ylabel("Loss")
    plt.show()

    plt.title("Training Curve")
    plt.plot(epochs, train_acc, label="Train")
    plt.plot(epochs, valid_acc, label="Validation")
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy")
    plt.legend(loc='best')
    plt.show()
```

```
RNN1 = RNN(len(text_field.vocab.itos), len(text_field.vocab.itos), n_layers=1)
train_rnn_network(RNN1, train_iter, val_iter, num_epochs=5, learning_rate=1e-4)
```

```
    Epoch 1; Loss 0.692628; Train Acc 0.772028; Val Acc 0.652018
    Epoch 2; Loss 0.294976; Train Acc 0.931063; Val Acc 0.947085
    Epoch 3; Loss 0.238955; Train Acc 0.918499; Val Acc 0.960538
    Epoch 4; Loss 0.473924; Train Acc 0.913539; Val Acc 0.962332
    Epoch 5; Loss 0.357432; Train Acc 0.930898; Val Acc 0.953363
```





Double-click (or enter) to edit

```
torch.save(RNN1.state_dict(), "first_model")
```

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.

- First, I increased the number of layers in the GRU (to 2) to see if that would improve performance at all. Since this would increase the number of weights in the neural network, I also increased the number of epochs to 10.

  Results: Epoch 10; Loss 0.347943; Train Acc 0.957642; Val Acc 0.953363

  The performance was very good, and it didn't appear to overfit the training set since the validation accuracy was as good (if not better) than the training accuracy for most of the epochs.

- Next, I decided to try a slightly different architecture by using a concatenation of the max pooling and average pooling of the GRU output as the input to the fully connected layer. I kept everything else the same as the current model. The new class is declared below as "MyRNN".

  Results: Epoch 10; Loss 0.344888; Train Acc 0.962075; Val Acc 0.949776

- It was better on the training set but slightly worse on the validation set. However, I think it might have been a little bit overfit since it converged near those values really quickly. I decided to try again with a higher learning rate (5e-4) to avoid local minima.

  Results: Epoch 10; Loss 0.375822; Train Acc 0.966015; Val Acc 0.969507

- This was the best performing model yet, but it appeared to converge at around 5 epochs and the other 5 epochs past that were overfitting with just extremely small gains in accuracy. So I decided to try training the same model but only for 5 epochs this time.

  Results: Epoch 5; Loss 0.314648; Train Acc 0.960598; Val Acc 0.963229

  I decided to go with this model since it was just marginally below the numbers of the fourth model, but it was trained significantly less so it's less likely to be overfitted to the training data.

```
class MyRNN(nn.Module):
  def __init__(self, vocab_size, hidden_size, n_layers=1):
    super(MyRNN, self).__init__()

    # identity matrix for generating one-hot vectors
    self.ident = torch.eye(vocab_size)

    # recurrent neural network
    self.rnn = nn.GRU(vocab_size, hidden_size, n_layers, batch_first=True)
    # a fully-connected layer that classifies the input into SPAM/HAM
    self.classifier = nn.Linear(2*hidden_size, 2)  # 2*hidden_size because of the conc

  def forward(self, x):
    one_hot = []
    for sms in x:
      one_hot.append(self.ident[sms])   # generate one-hot vectors of input

    inp_x = torch.stack(one_hot)

    output, _ = self.rnn(inp_x)          # get the next output and hidden state
    out = torch.cat([torch.max(output, dim=1)[0], torch.mean(output, dim=1)], dim=1)
    out = self.classifier(out)          # predict SPAM/HAM
    return out

RNN_5 = MyRNN(len(text_field.vocab.itos), len(text_field.vocab.itos), n_layers=2)
train_rnn_network(RNN_5, train_iter, val_iter, num_epochs=5, learning_rate=5e-4)
```

```
    Epoch 1; Loss 0.270917; Train Acc 0.938502; Val Acc 0.958744
```

```
torch.save(RNN_5.state_dict(), "/content/fifth_model")
```

```
    Epoch 4; Loss 0.074549; Train Acc 0.969747; Val Acc 0.978475
```

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.

```
# 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)

valid_spam_iter = torchtext.legacy.data.BucketIterator(valid_spam,
                                           batch_size=32,
                                           sort_key=lambda x: len(x.sms), # to minimiz
                                           sort_within_batch=True,        # sort withi
                                           repeat=False)                  # repeat the

# 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_nospam_iter = torchtext.legacy.data.BucketIterator(valid_nospam,
                                           batch_size=32,
                                           sort_key=lambda x: len(x.sms), # to minimiz
                                           sort_within_batch=True,        # sort withi
                                           repeat=False)                  # repeat the
```

```
final_model = MyRNN(len(text_field.vocab.itos), len(text_field.vocab.itos), n_layers=2
state = torch.load("fifth_model")
final_model.load_state_dict(state)
```

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

```
print("The model's false positive rate is {}.".format(1 - get_accuracy(final_model, va

print("The model's false negative rate is {}.".format(1 - get_accuracy(final_model, va
```

```
    The model's false positive rate is 0.015337423312883458.
    The model's false negative rate is 0.04379562043795615.
```

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?

A false positive would result in the phone blocking a valid message from the user. This could be bad because the algorithm would essentially be discarding important and useful content. On the other hand, a false negative would mean that the user receives a spam message. This could be annoying, but the user is capable of deleting the spam message themselves.

Part 4. Evaluation [11 pt]

Part (a) [1 pt]

Report the final test accuracy of your model.

```
print("The final test accuracy of my model is {}.".format(get_accuracy(final_model, te
```

Show hidden output

Part (b) [3 pt]

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

```
# Create a Dataset of only spam validation examples
test_spam = torchtext.legacy.data.Dataset(
    [e for e in test.examples if e.label == 1],
    test.fields)

test_spam_iter = torchtext.legacy.data.BucketIterator(test_spam,
                                                   batch_size=32,
                                                   sort_key=lambda x: len(x.sms), # to minimi
```

```
                                           sort_within_batch=True,         # sort withi
                                           repeat=False)                   # repeat the

# Create a Dataset of only non-spam validation examples
test_nospam = torchtext.legacy.data.Dataset(
    [e for e in test.examples if e.label == 0],
    test.fields)

test_nospam_iter = torchtext.legacy.data.BucketIterator(test_nospam,
                                           batch_size=32,
                                           sort_key=lambda x: len(x.sms), # to minimiz
                                           sort_within_batch=True,         # sort withi
                                           repeat=False)                   # repeat the

print("The model's false positive rate is {}.".format(1 - get_accuracy(final_model, te

print("The model's false negative rate is {}.".format(1 - get_accuracy(final_model, te
```

Show hidden output

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.

```
msg = "machine learning is sooo cool!"
msg_tokens = []

for char in msg:
  msg_tokens.append(torch.tensor(text_field.vocab.stoi[char]))

x = torch.stack(msg_tokens)
x.unsqueeze_(0)

print("According to my model, the probability that the SMS message is spam is {}.".for
```

Show hidden output

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.

Spam detection is definitely not an easy task. If it were, we wouldnt have spam in out inboxes right now. Spam generators are getting better and better at making spam messages undistinguishable from real messages which makes training models to recognize it even harder.

A baseline model for spam detection could be using a simple heuristic engine. Such a heuristic filter would work by scanning incoming emails for suspicious words (ex. "free" or "prince") and then assign points whenever it encounters a suspicous word or phrase. The database of suspicious words and phrases could be created by an expert, or just by parsing the spam dataset for words that commonly occur in that set and don't occur as much in the ham dataset.