Assignment 5

March 10, 2019

```
In [1]: # Part 1 (a)
        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 8712

ham        Go until jurong point, crazy.. Available only in bugis n great world la e buffet...
```

```
In [2]: # Part 1 (b)
        num_spam = 0
        for line in open('SMSSpamCollection'):
            if line[0] == 's':
                num_spam += 1
        print(num_spam)

        num_non = 0
        for line in open('SMSSpamCollection'):
            if line[0] == 'h':
                num_non += 1
        print(num_non)
```

```
747
4827
```

```
In [3]: # Part 1 (c)
        # Advantage: RNN will also learn specific names
        # Disadvantage: computing power and time are spent learning words instead of
        # how words are connected (often more important)
```

```
In [4]: # Part 1 (d)
        import torchtext

        text_field = torchtext.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.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.data.TabularDataset("SMSSpamCollection", # name of the file
                                                "tsv",               # fields are separated by
                                                fields)
        # dataset[0].sms
        # dataset[0].label

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

In [5]: len(train)

Out[5]: 3343

In [6]: len(valid)

Out[6]: 1115

In [7]: len(test)

Out[7]: 1114

In [8]: # Part 1 (e)
        # A balanced training set will not lead to overfitting to the most popular
        # label. For example, if a dataset contains 90% label A, just by outputing A,
        # a model can get 90% accuracy.

        # 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
```

```
In [9]: # Part 1 (f)
        # text_field.vocab.stoi is a string-to-integer dictionary of existing
        # characters to their assigned integer values.
        # text_field.vocab.itos is an integer-to-string dictionary-like list of
        # integer values (represented by the index position) to their characters.

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

```
In [11]: text_field.vocab.stoi
```

```
Out[11]: defaultdict(<function torchtext.vocab._default_unk_index()>,
                     {'<unk>': 0,
                      '<pad>': 1,
                      ' ': 2,
                      'e': 3,
                      'o': 4,
                      't': 5,
                      'a': 6,
                      'n': 7,
                      'r': 8,
                      'i': 9,
                      's': 10,
                      'l': 11,
                      'u': 12,
                      'h': 13,
                      '0': 14,
                      'd': 15,
                      'c': 16,
                      '.': 17,
                      'm': 18,
                      'y': 19,
                      'w': 20,
                      'p': 21,
                      'g': 22,
                      '1': 23,
                      'f': 24,
                      'b': 25,
                      '2': 26,
                      'T': 27,
                      '8': 28,
                      'E': 29,
                      'k': 30,
                      'v': 31,
                      '5': 32,
                      'S': 33,
                      'C': 34,
```

```
'O': 35,
'I': 36,
'4': 37,
'N': 38,
'A': 39,
'x': 40,
'7': 41,
'6': 42,
'R': 43,
'3': 44,
',': 45,
'!': 46,
'9': 47,
'P': 48,
'L': 49,
'M': 50,
'U': 51,
'W': 52,
'H': 53,
'D': 54,
'F': 55,
'B': 56,
'Y': 57,
'G': 58,
'/': 59,
'?': 60,
"'": 61,
'č': 62,
'&': 63,
'-': 64,
':': 65,
'X': 66,
'V': 67,
'z': 68,
'*': 69,
'j': 70,
'K': 71,
')': 72,
'J': 73,
';': 74,
'+': 75,
'(': 76,
'Q': 77,
'q': 78,
'"': 79,
'#': 80,
'>': 81,
'=': 82,
```

```
                 '@': 83,
                 'Z': 84,
                 'ü': 85,
                 '<': 86,
                 '$': 87,
                 '': 88,
                 'Ü': 89,
                 '%': 90,
                 '\x92': 91,
                 '[': 92,
                 ']': 93,
                 '|': 94,
                 '\x93': 95,
                 'ą': 96,
                 '_': 97,
                 '': 98,
                 '': 99,
                 '': 100,
                 'ú': 101,
                 '\t': 102,
                 '\n': 103,
                 '\x91': 104,
                 '\x96': 105,
                 '\\': 106,
                 '^': 107,
                 '~': 108,
                 'ż': 109,
                 '': 110,
                 '': 111,
                 '': 112})
```

In [10]:
```
# Part 1 (g)
# <unk> represents an unknown, rare word. Used when dealing at word-level.
# <pad> is padding used to make batches of equal length.
```

In [33]:
```
# Part 1 (h)

train_iter = torchtext.data.BucketIterator(train,
                                           batch_size=32,
                                           sort_key=lambda x: len(x.sms), # to minimi
                                           sort_within_batch=True,        # sort with
                                           repeat=False)                  # repeat th

num_pad = []

print('Max length in each batch is the following:')
for i, batch in enumerate(train_iter):
    if i >= 10:
```

```
                break

            print(batch.sms[1][0].item())

            num_pad_batch = 0
            for j in batch.sms[0]:
                for k in j:
                    if k.item() == 1:
                        num_pad_batch += 1
            num_pad.append(num_pad_batch)

        print('The number of <pad>s in each batch is the following:')
        print(num_pad)
```

```
Max length in each batch is the following:
93
28
160
36
138
146
148
161
41
158
The number of <pad>s in each batch is the following:
[76, 27, 0, 20, 19, 30, 13, 20, 27, 0]
```

```
In [13]: # Part 2
         import torch
         import numpy

         # You mind find this code helpful for obtaining
         # pytorch one-hot vectors.

         ident = torch.eye(10, dtype = torch.float32)
         #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 [14]: import torch.nn as nn

         class RNN(nn.Module):
             def __init__(self, input_size, hidden_size, num_classes):
                 super(RNN, self).__init__()
                 self.emb = nn.Embedding(len(text_field.vocab.stoi), hidden_size)
                 self.hidden_size = hidden_size
                 self.rnn = nn.RNN(input_size, hidden_size, batch_first=True)
                 self.fc = nn.Linear(hidden_size, num_classes)

             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, :])
                 out = self.fc(torch.max(out, dim=1)[0])
                 return out

         # This code is here to help you test your model.
         # You may beed to change this depending on how your forward
         # function is set up.

         model = RNN(10, 10, 2)
         sample_batch = next(iter(train_iter))
         sms = sample_batch.sms[0]
         length = sample_batch.sms[1]
         y = model(sms)
         print(y.shape)
```

```
torch.Size([32, 2])
```

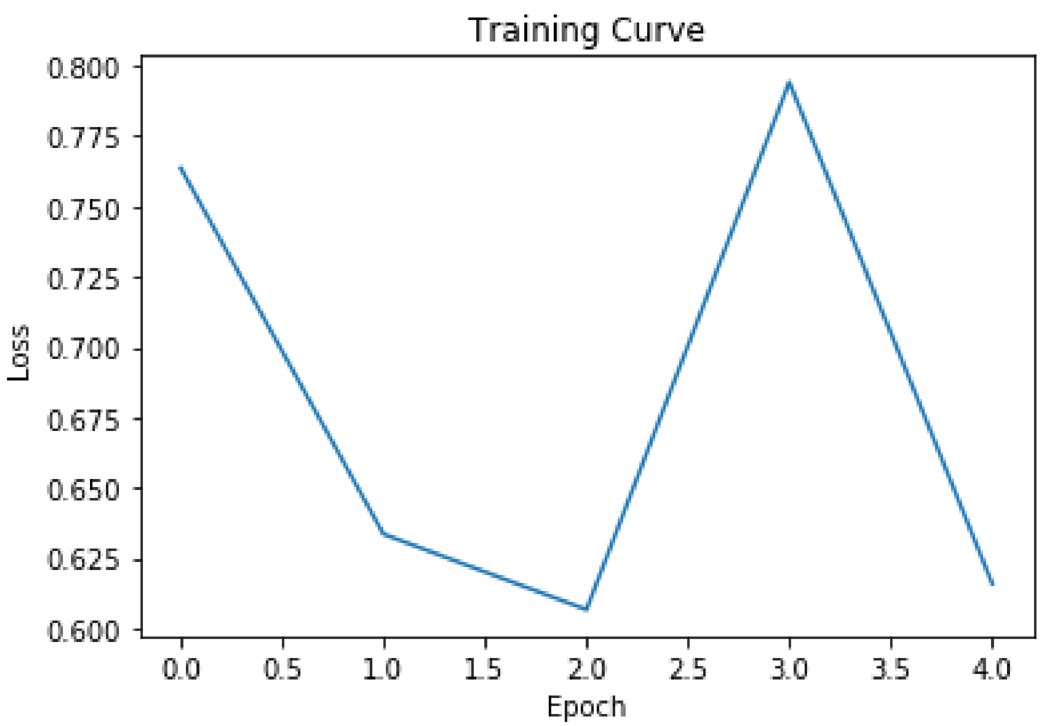
```
In [28]: # Part 3 (a)
         import matplotlib.pyplot as plt
         %matplotlib inline

         def get_accuracy(model, data):
             data_iter = torchtext.data.BucketIterator(data,
                                                       batch_size=64,
                                                       sort_key=lambda x: len(x.sms),
                                                       repeat=False)
             correct, total = 0, 0
             for i, batch in enumerate(data_iter):
                 output = model(batch.sms[0]) # You may need to modify this, depending on your
```

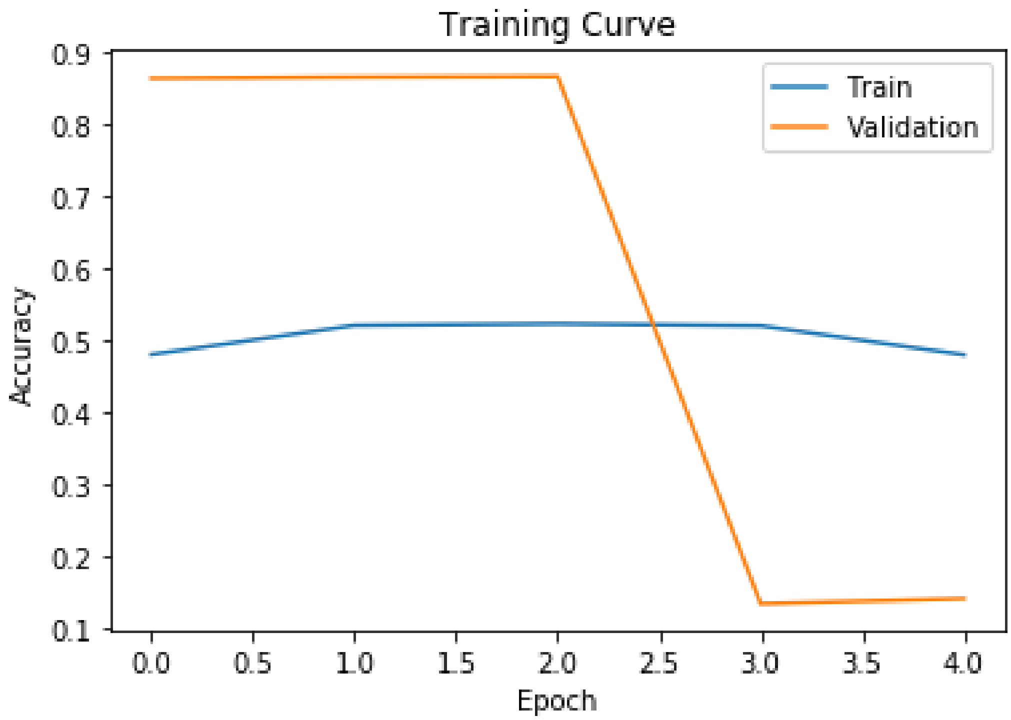
```python
            pred = output.max(1, keepdim=True)[1]
            correct += pred.eq(batch.label.view_as(pred)).sum().item()
            total += batch.sms[1].shape[0]
    return correct / total

def train_rnn_network(model, train, valid, num_epochs=5, learning_rate=1e-5, batch_si
    train_iter = torchtext.data.BucketIterator(train,
                                               batch_size=batch_size,
                                               sort_key=lambda x: len(x.sms), # to minimi
                                               sort_within_batch=True,        # sort with
                                               repeat=False)                   # repeat th

    criterion = nn.CrossEntropyLoss()
    optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
    losses, train_acc, valid_acc, loss = [], [], [], 0
    epochs = []
    for epoch in range(num_epochs):
        print(epoch)
        for j, batch in enumerate(train_iter):
            l = batch.label
            s = batch.sms

            optimizer.zero_grad()
            pred = model(s[0])
            loss = criterion(pred, l)

            loss.backward()
            optimizer.step()

        losses.append(float(loss))

        epochs.append(epoch)
        train_acc.append(get_accuracy(RNN(10, 10, 2), train))
        valid_acc.append(get_accuracy(RNN(10, 10, 2), 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()
```

```
In [16]: train_rnn_network(RNN(10, 10, 2), train_iter, valid, num_epochs=5,
                           learning_rate=1e-5)
```

```
0
Epoch 1; Loss 0.763615; Train Acc 0.480020; Val Acc 0.862780
1
Epoch 2; Loss 0.633558; Train Acc 0.520478; Val Acc 0.864574
2
Epoch 3; Loss 0.606716; Train Acc 0.522799; Val Acc 0.865471
3
Epoch 4; Loss 0.794142; Train Acc 0.519980; Val Acc 0.134529
4
Epoch 5; Loss 0.615960; Train Acc 0.479688; Val Acc 0.141704
```

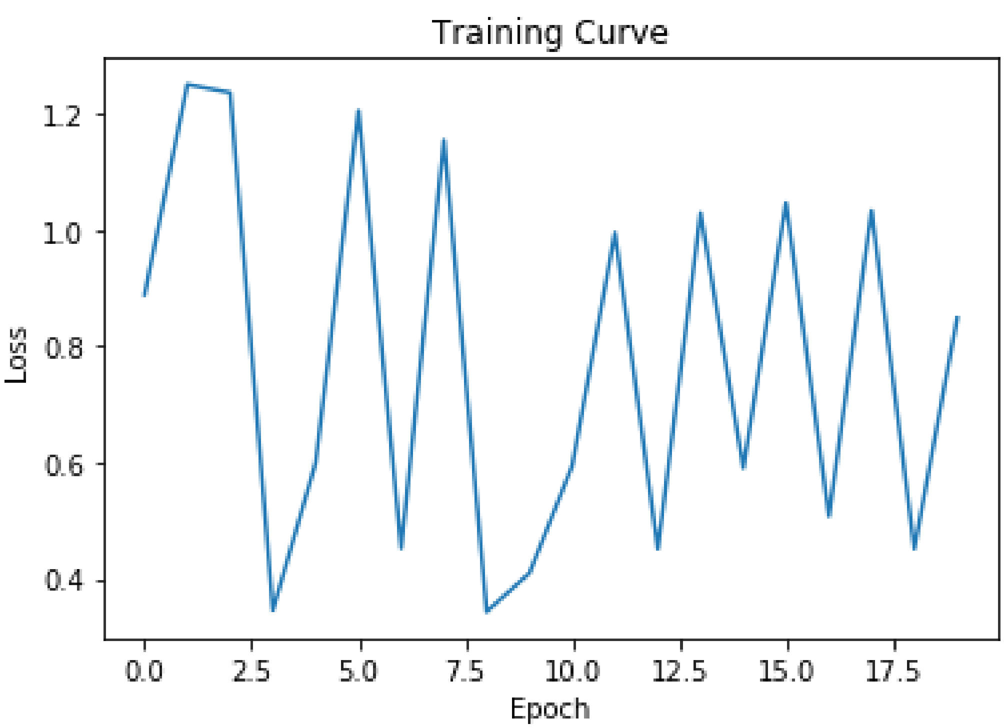


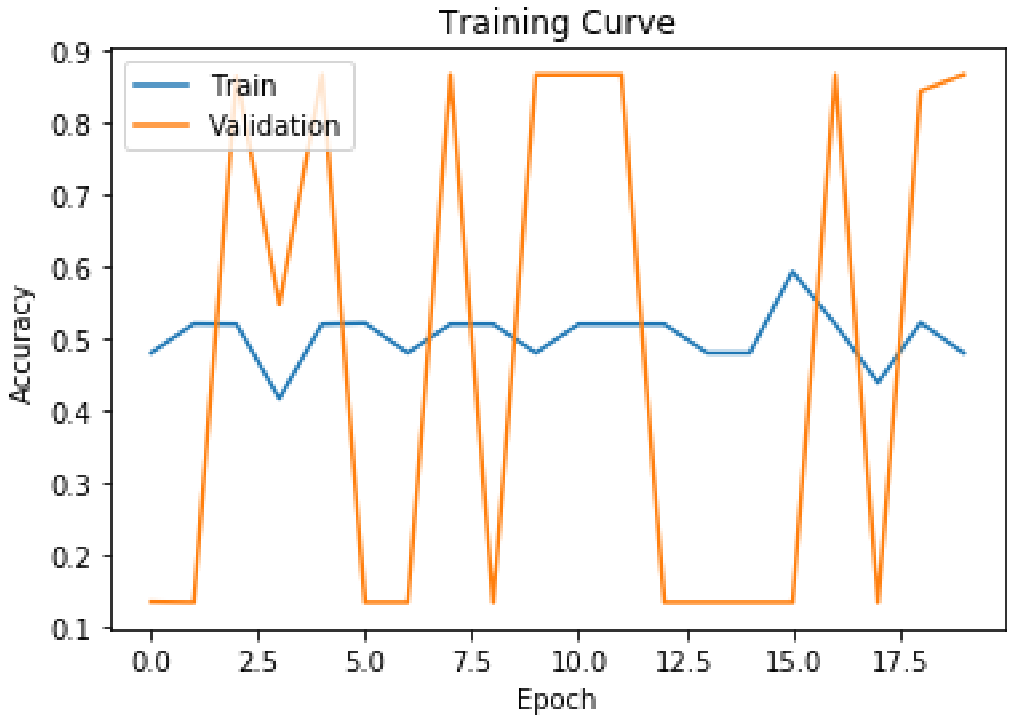


In [24]:
```
# Part 3 (b)
# Trial #1
# Previous num_epochs is 5. Could not see the overall trend well.
# Increased num_epochs to 20
# Valid acc is 85% (with consistency problems)

train_rnn_network(RNN(10, 10, 2), train_iter, valid, num_epochs=20,
                  learning_rate=1e-5)
```

```
0
Epoch 1; Loss 0.888866; Train Acc 0.480020; Val Acc 0.135426
1
Epoch 2; Loss 1.250517; Train Acc 0.520478; Val Acc 0.134529
2
Epoch 3; Loss 1.236499; Train Acc 0.519980; Val Acc 0.863677
3
Epoch 4; Loss 0.345989; Train Acc 0.416846; Val Acc 0.547085
4
Epoch 5; Loss 0.599730; Train Acc 0.519980; Val Acc 0.865471
5
Epoch 6; Loss 1.205293; Train Acc 0.521472; Val Acc 0.134529
6
Epoch 7; Loss 0.452605; Train Acc 0.480020; Val Acc 0.134529
7
```

```
Epoch 8; Loss 1.155143; Train Acc 0.519980; Val Acc 0.865471
8
Epoch 9; Loss 0.343446; Train Acc 0.519980; Val Acc 0.134529
9
Epoch 10; Loss 0.410172; Train Acc 0.480020; Val Acc 0.865471
10
Epoch 11; Loss 0.595016; Train Acc 0.519980; Val Acc 0.865471
11
Epoch 12; Loss 0.995447; Train Acc 0.519980; Val Acc 0.865471
12
Epoch 13; Loss 0.451761; Train Acc 0.519980; Val Acc 0.134529
13
Epoch 14; Loss 1.029853; Train Acc 0.480020; Val Acc 0.134529
14
Epoch 15; Loss 0.591017; Train Acc 0.480020; Val Acc 0.134529
15
Epoch 16; Loss 1.046984; Train Acc 0.592936; Val Acc 0.134529
16
Epoch 17; Loss 0.508067; Train Acc 0.519980; Val Acc 0.865471
17
Epoch 18; Loss 1.033620; Train Acc 0.438899; Val Acc 0.134529
18
Epoch 19; Loss 0.451655; Train Acc 0.521970; Val Acc 0.843049
19
Epoch 20; Loss 0.848682; Train Acc 0.480020; Val Acc 0.865471
```

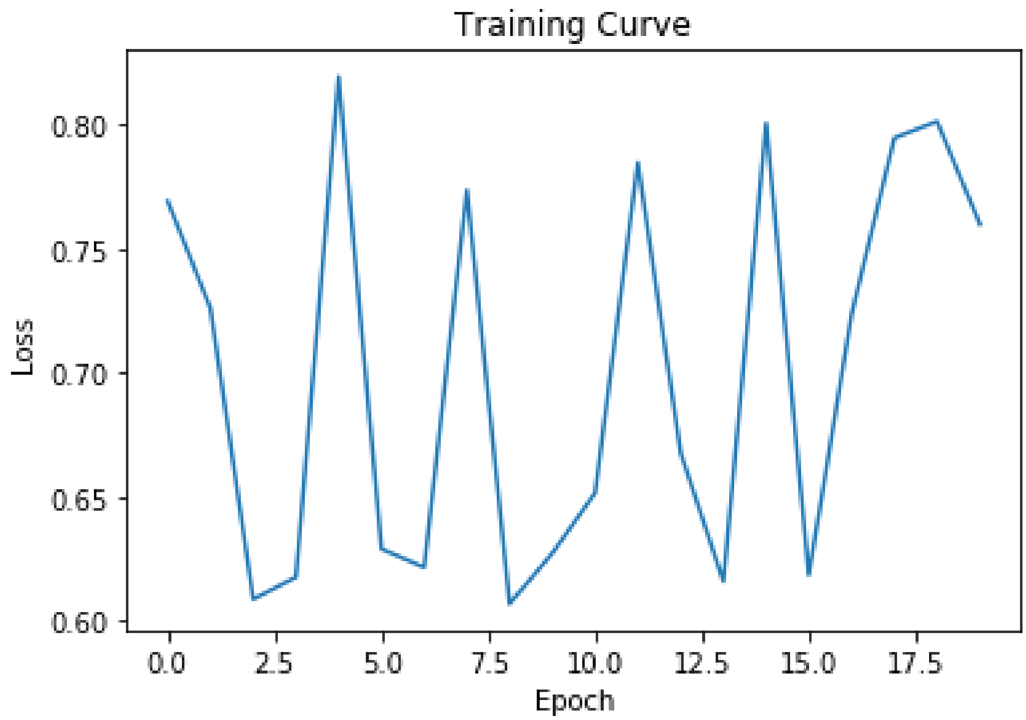




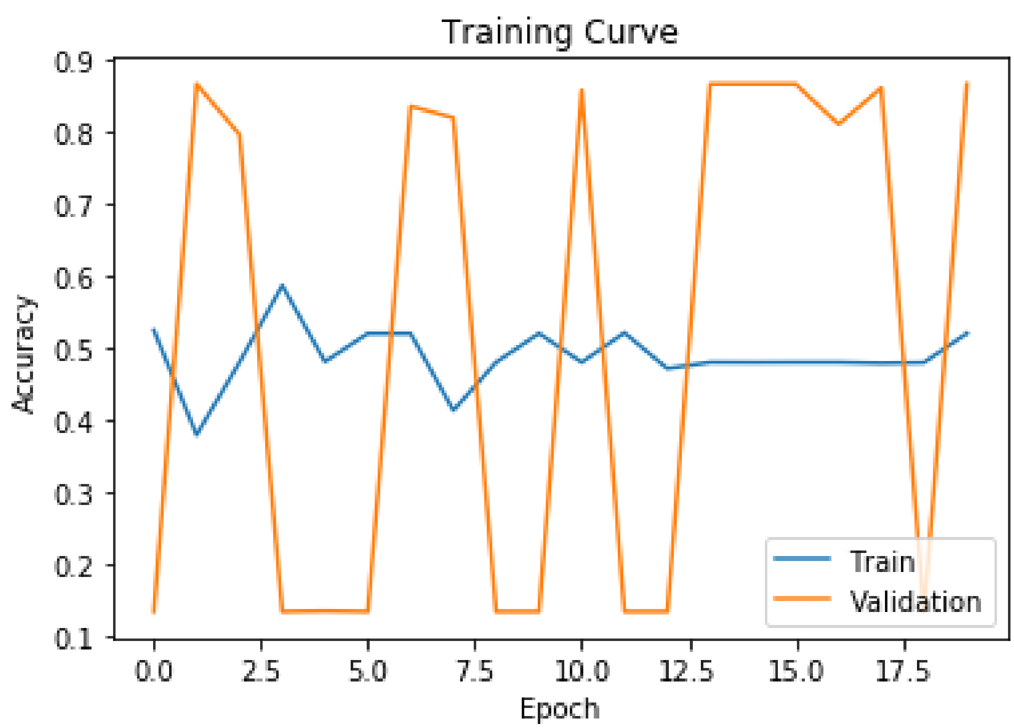

```
In [25]: # Trial #2
         # Previous loss and valid plots very jittery, thought decreasing learning_rate
         # would stablized. It did not.
         # Decreased learning_rate to 1e-6
         # Valid acc is still 85% (with consistency problems)

         train_rnn_network(RNN(10, 10, 2), train_iter, valid, num_epochs=20,
                           learning_rate=1e-6)
```

```
0
Epoch 1; Loss 0.769215; Train Acc 0.524623; Val Acc 0.134529
1
Epoch 2; Loss 0.726124; Train Acc 0.379373; Val Acc 0.865471
2
Epoch 3; Loss 0.608583; Train Acc 0.480020; Val Acc 0.795516
3
Epoch 4; Loss 0.617511; Train Acc 0.586470; Val Acc 0.134529
4
Epoch 5; Loss 0.819547; Train Acc 0.480849; Val Acc 0.135426
5
Epoch 6; Loss 0.628893; Train Acc 0.519980; Val Acc 0.134529
```

```
6
Epoch 7; Loss 0.621459; Train Acc 0.519980; Val Acc 0.834978
7
Epoch 8; Loss 0.773693; Train Acc 0.413198; Val Acc 0.818834
8
Epoch 9; Loss 0.606781; Train Acc 0.480020; Val Acc 0.134529
9
Epoch 10; Loss 0.627239; Train Acc 0.520146; Val Acc 0.134529
10
Epoch 11; Loss 0.651540; Train Acc 0.480020; Val Acc 0.856502
11
Epoch 12; Loss 0.784925; Train Acc 0.520975; Val Acc 0.134529
12
Epoch 13; Loss 0.667630; Train Acc 0.471398; Val Acc 0.134529
13
Epoch 14; Loss 0.615776; Train Acc 0.480020; Val Acc 0.865471
14
Epoch 15; Loss 0.800693; Train Acc 0.479854; Val Acc 0.865471
15
Epoch 16; Loss 0.618387; Train Acc 0.480020; Val Acc 0.865471
16
Epoch 17; Loss 0.723727; Train Acc 0.480020; Val Acc 0.809865
17
Epoch 18; Loss 0.794773; Train Acc 0.478859; Val Acc 0.860090
18
Epoch 19; Loss 0.801456; Train Acc 0.479688; Val Acc 0.134529
19
Epoch 20; Loss 0.759925; Train Acc 0.519980; Val Acc 0.865471
```



Training Curve
0.80
0.75
0.70
0.65
0.60
Loss
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Epoch

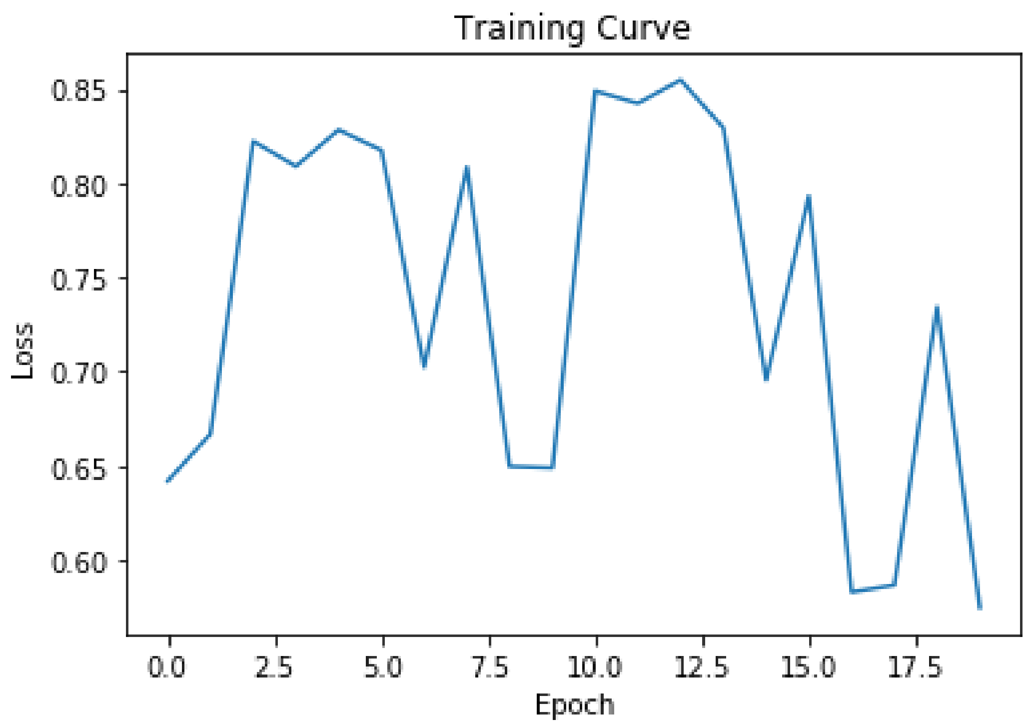


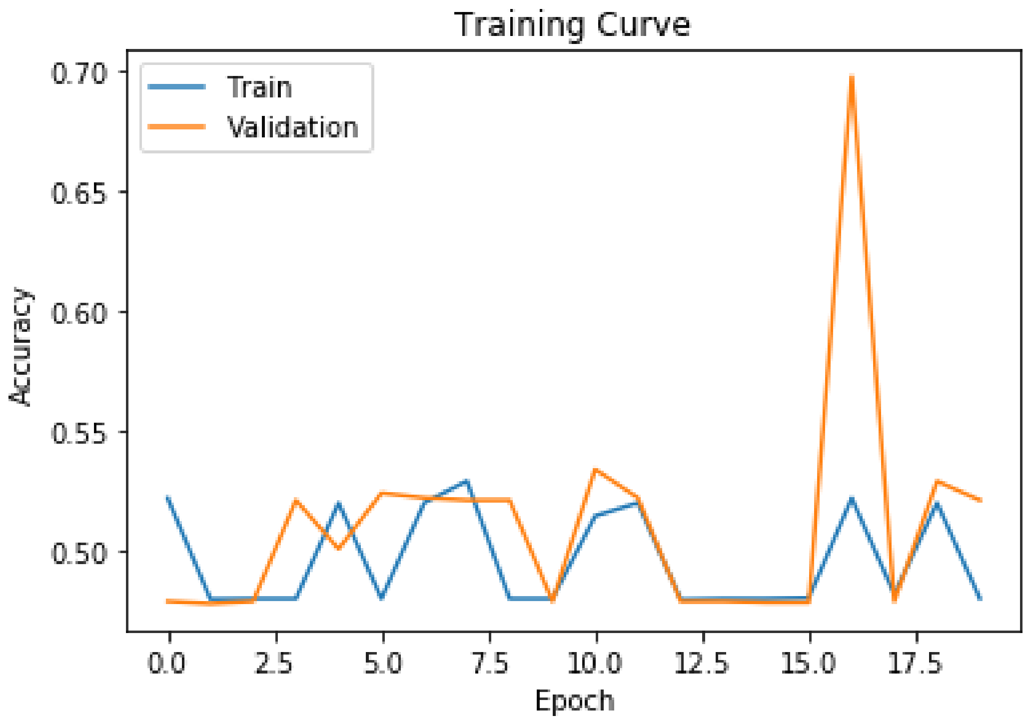
Training Curve
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
Accuracy
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Epoch
Train
Validation

In [26]:
```
# Trial #3
# Thought a model trained with a balanced dataset would not do well during
# validation with an imbalanced dataset.
# Duplicated spam in valid dataset by a factor of 6 also
# Valid acc is 70% at peek

old_valid_examples = valid.examples
valid_spam = []
for item in valid.examples:
    if item.label == 1:
        valid_spam.append(item)

valid.examples = old_valid_examples + valid_spam * 6

train_rnn_network(RNN(10, 10, 2), train_iter, valid, num_epochs=20,
                  learning_rate=1e-6)
```

```
0
Epoch 1; Loss 0.641894; Train Acc 0.521970; Val Acc 0.478908
1
Epoch 2; Loss 0.666710; Train Acc 0.479854; Val Acc 0.477916
2
Epoch 3; Loss 0.822245; Train Acc 0.480020; Val Acc 0.478908
3
Epoch 4; Loss 0.808926; Train Acc 0.480020; Val Acc 0.521092
4
Epoch 5; Loss 0.828313; Train Acc 0.519980; Val Acc 0.500744
5
Epoch 6; Loss 0.817445; Train Acc 0.480020; Val Acc 0.524069
6
Epoch 7; Loss 0.702273; Train Acc 0.519980; Val Acc 0.522084
7
Epoch 8; Loss 0.808636; Train Acc 0.529100; Val Acc 0.521092
8
Epoch 9; Loss 0.649615; Train Acc 0.480020; Val Acc 0.521092
9
Epoch 10; Loss 0.648863; Train Acc 0.480020; Val Acc 0.478908
10
Epoch 11; Loss 0.848926; Train Acc 0.514508; Val Acc 0.533995
11
Epoch 12; Loss 0.842385; Train Acc 0.519980; Val Acc 0.522084
12
Epoch 13; Loss 0.854700; Train Acc 0.479688; Val Acc 0.478908
13
Epoch 14; Loss 0.829356; Train Acc 0.480020; Val Acc 0.478908
14
Epoch 15; Loss 0.695435; Train Acc 0.480020; Val Acc 0.478412
15
```

```
Epoch 16; Loss 0.793028; Train Acc 0.480352; Val Acc 0.478412
16
Epoch 17; Loss 0.582858; Train Acc 0.521970; Val Acc 0.697767
17
Epoch 18; Loss 0.586601; Train Acc 0.481844; Val Acc 0.478908
18
Epoch 19; Loss 0.734364; Train Acc 0.519980; Val Acc 0.529032
19
Epoch 20; Loss 0.574606; Train Acc 0.480020; Val Acc 0.521092
```

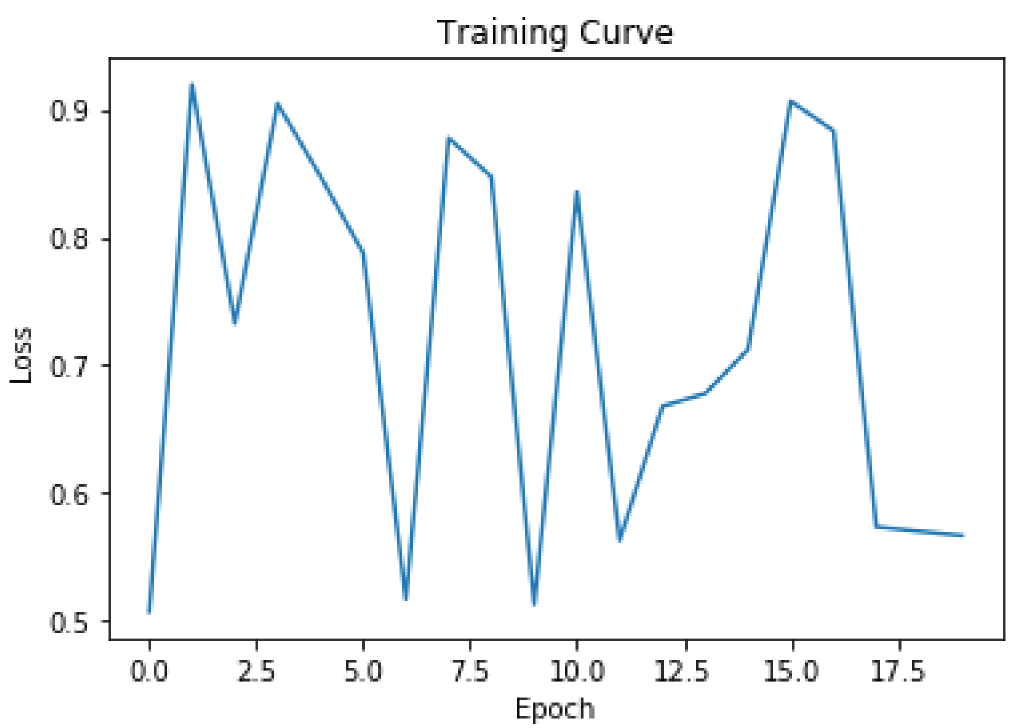


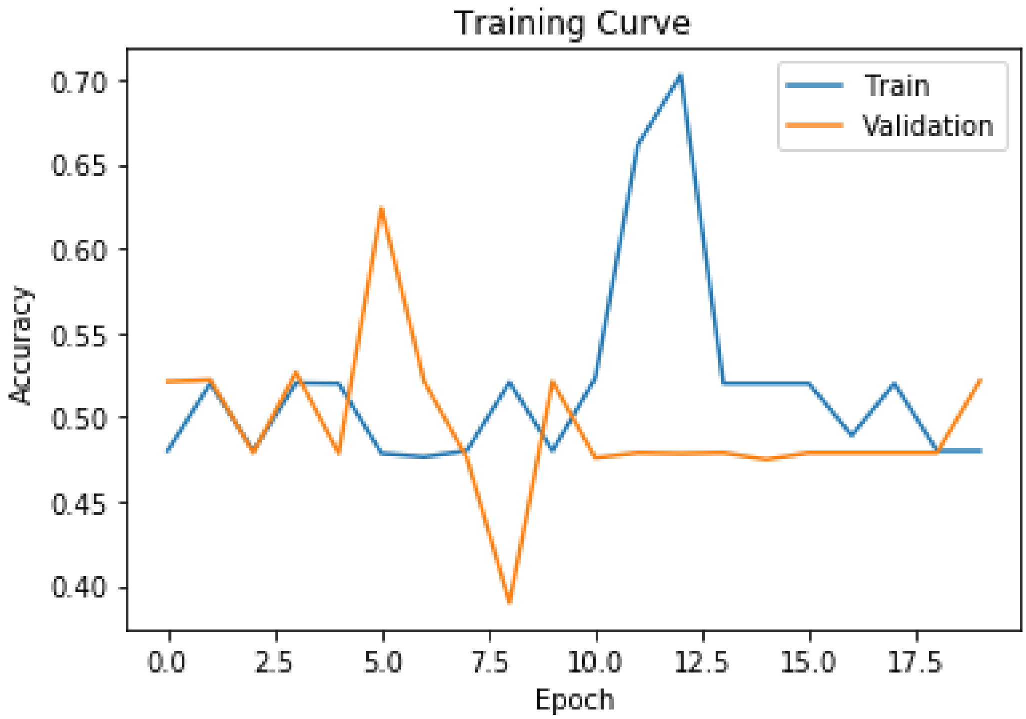


In [29]:
```
# Trial #4
# Thought previous plot was too stable, decreasing batch_size may bring more
# improvement.
# Decreased batch_size to 8
# Valid acc is 63% at peek

train_rnn_network(RNN(10, 10, 2), train, valid, num_epochs=20,
                  learning_rate=1e-6, batch_size=8)
```

```
0
Epoch 1; Loss 0.506941; Train Acc 0.480020; Val Acc 0.521092
1
Epoch 2; Loss 0.919603; Train Acc 0.519980; Val Acc 0.522084
2
Epoch 3; Loss 0.732741; Train Acc 0.480020; Val Acc 0.478908
3
Epoch 4; Loss 0.904622; Train Acc 0.520312; Val Acc 0.526551
4
Epoch 5; Loss 0.847900; Train Acc 0.519980; Val Acc 0.478412
5
Epoch 6; Loss 0.787778; Train Acc 0.478528; Val Acc 0.623821
6
Epoch 7; Loss 0.516550; Train Acc 0.476538; Val Acc 0.521092
7
```

```
Epoch 8; Loss 0.877684; Train Acc 0.480020; Val Acc 0.475931
8
Epoch 9; Loss 0.847396; Train Acc 0.520643; Val Acc 0.390074
9
Epoch 10; Loss 0.512623; Train Acc 0.480020; Val Acc 0.521092
10
Epoch 11; Loss 0.835399; Train Acc 0.523130; Val Acc 0.475931
11
Epoch 12; Loss 0.562757; Train Acc 0.661416; Val Acc 0.478908
12
Epoch 13; Loss 0.667825; Train Acc 0.702703; Val Acc 0.478412
13
Epoch 14; Loss 0.677824; Train Acc 0.519980; Val Acc 0.478908
14
Epoch 15; Loss 0.712267; Train Acc 0.519980; Val Acc 0.474938
15
Epoch 16; Loss 0.906640; Train Acc 0.519980; Val Acc 0.478908
16
Epoch 17; Loss 0.883359; Train Acc 0.489139; Val Acc 0.478908
17
Epoch 18; Loss 0.573429; Train Acc 0.519980; Val Acc 0.478908
18
Epoch 19; Loss 0.569902; Train Acc 0.480020; Val Acc 0.478908
19
Epoch 20; Loss 0.566561; Train Acc 0.480020; Val Acc 0.521588
```

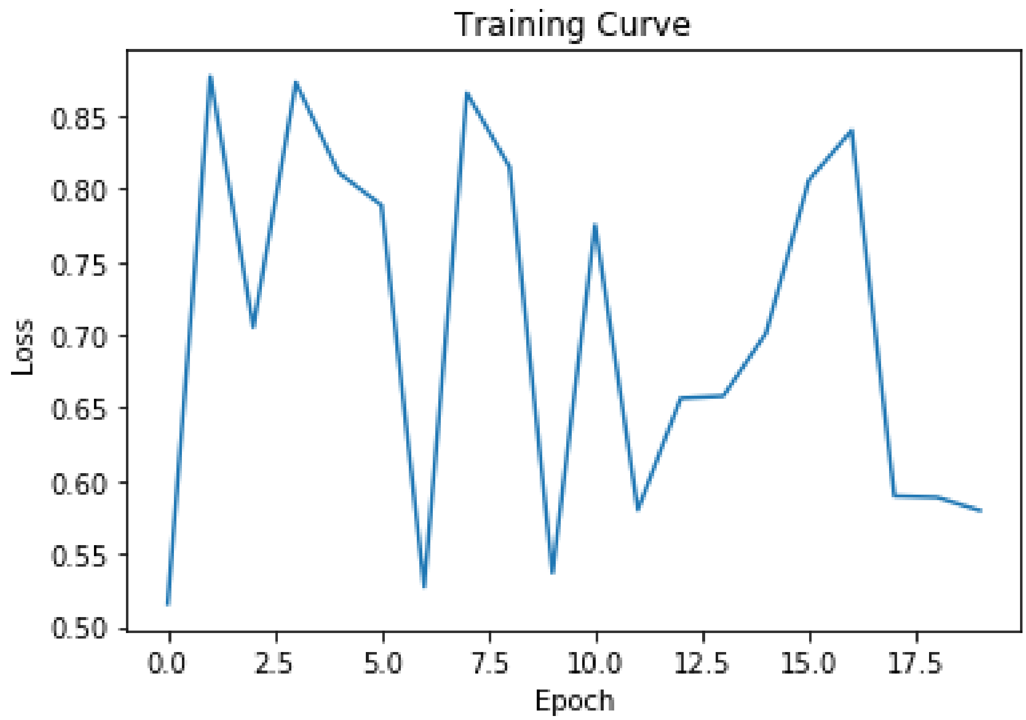


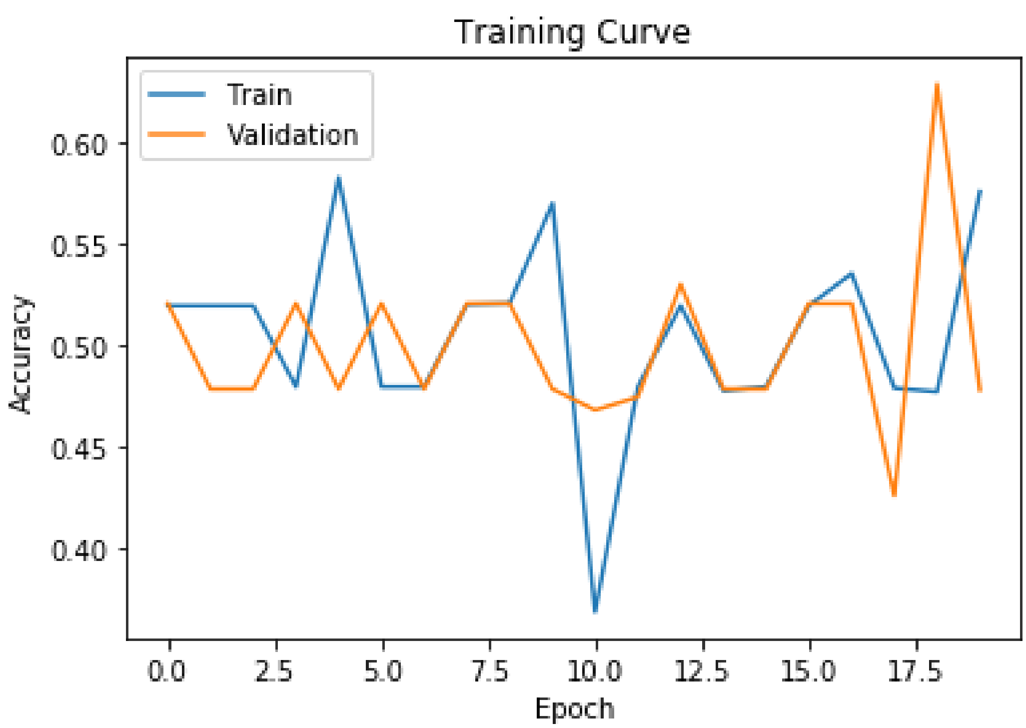


In [30]:
```
# Trial #5
# Previous hyper-parameters ran reasonably quick, thought increasing layer
# sizes could improve accuracy.
# Increased input and hidden layer sizes to 20
# Valid acc is 63% at peek

train_rnn_network(RNN(20, 20, 2), train, valid, num_epochs=20,
                  learning_rate=1e-6, batch_size=8)
```

```
0
Epoch 1; Loss 0.515827; Train Acc 0.519980; Val Acc 0.521092
1
Epoch 2; Loss 0.877051; Train Acc 0.519980; Val Acc 0.478908
2
Epoch 3; Loss 0.705355; Train Acc 0.519980; Val Acc 0.478908
3
Epoch 4; Loss 0.872909; Train Acc 0.480020; Val Acc 0.521092
4
Epoch 5; Loss 0.811247; Train Acc 0.583320; Val Acc 0.478908
5
Epoch 6; Loss 0.788810; Train Acc 0.480020; Val Acc 0.521092
```

```
6
Epoch 7; Loss 0.527461; Train Acc 0.480020; Val Acc 0.478908
7
Epoch 8; Loss 0.865794; Train Acc 0.520643; Val Acc 0.521092
8
Epoch 9; Loss 0.815014; Train Acc 0.521141; Val Acc 0.521092
9
Epoch 10; Loss 0.537031; Train Acc 0.570552; Val Acc 0.478908
10
Epoch 11; Loss 0.775206; Train Acc 0.369093; Val Acc 0.468486
11
Epoch 12; Loss 0.580069; Train Acc 0.480020; Val Acc 0.474938
12
Epoch 13; Loss 0.656616; Train Acc 0.519980; Val Acc 0.530521
13
Epoch 14; Loss 0.658153; Train Acc 0.478030; Val Acc 0.478908
14
Epoch 15; Loss 0.701381; Train Acc 0.480020; Val Acc 0.478908
15
Epoch 16; Loss 0.805945; Train Acc 0.519980; Val Acc 0.521092
16
Epoch 17; Loss 0.840178; Train Acc 0.535898; Val Acc 0.521092
17
Epoch 18; Loss 0.589724; Train Acc 0.479357; Val Acc 0.426303
18
Epoch 19; Loss 0.588810; Train Acc 0.477533; Val Acc 0.629280
19
Epoch 20; Loss 0.579693; Train Acc 0.576190; Val Acc 0.478412
```

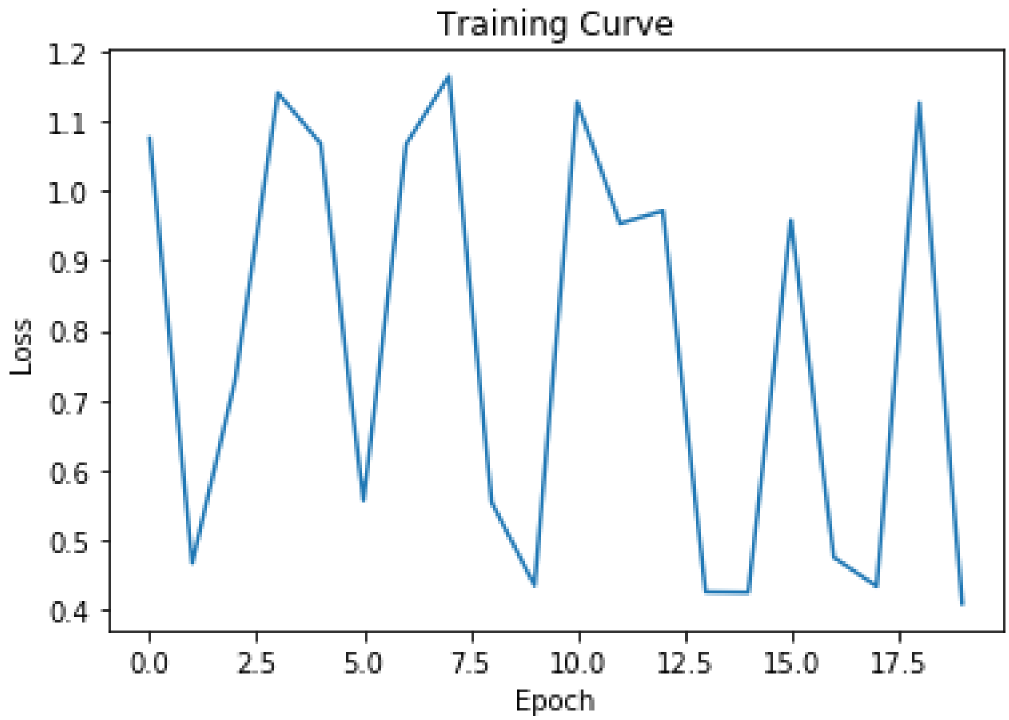

Training Curve
Loss
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Epoch

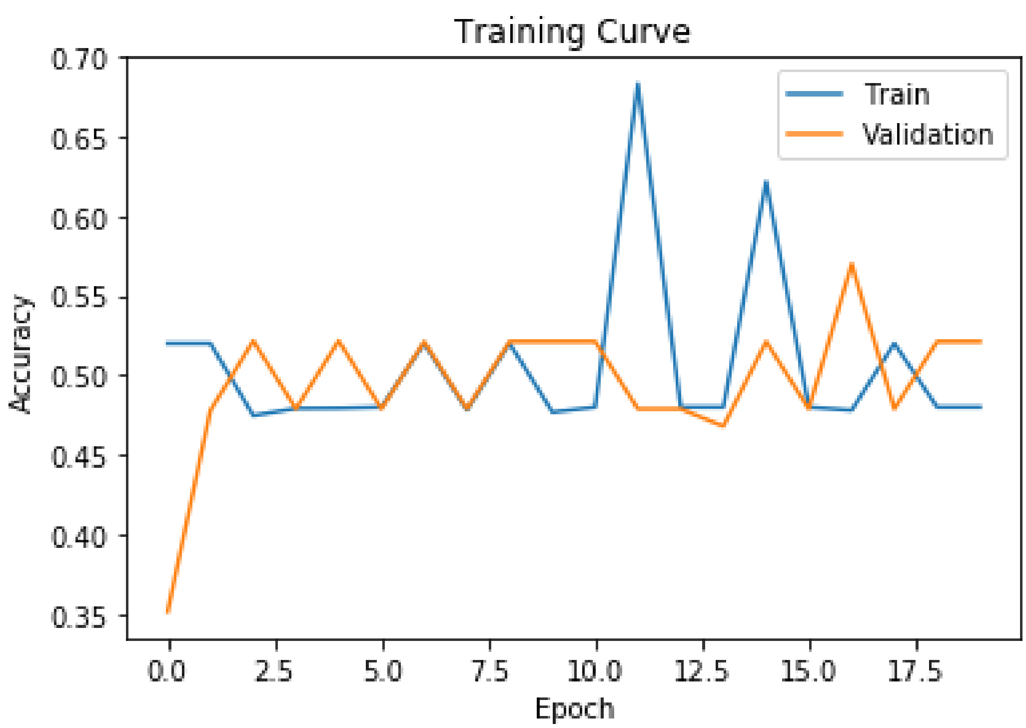

Training Curve
Train
Validation
Accuracy
0.40
0.45
0.50
0.55
0.60
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Epoch

```
In [31]: # Trial #6
         # Previous plots' shapes too unorthodox, thought increasing batch_size would
         # bring more stability and more traditional plot shape.
         # Increased batch_size to 256
         # Valid acc is 58% at peek

         train_rnn_network(RNN(20, 20, 2), train, valid, num_epochs=20,
                           learning_rate=1e-6, batch_size=256)
```

```
0
Epoch 1; Loss 1.076035; Train Acc 0.519980; Val Acc 0.351861
1
Epoch 2; Loss 0.466367; Train Acc 0.519980; Val Acc 0.477916
2
Epoch 3; Loss 0.728957; Train Acc 0.474714; Val Acc 0.521588
3
Epoch 4; Loss 1.140865; Train Acc 0.479191; Val Acc 0.478908
4
Epoch 5; Loss 1.068177; Train Acc 0.479357; Val Acc 0.521588
5
Epoch 6; Loss 0.556215; Train Acc 0.480020; Val Acc 0.478908
6
Epoch 7; Loss 1.067514; Train Acc 0.519980; Val Acc 0.521092
7
Epoch 8; Loss 1.164998; Train Acc 0.478196; Val Acc 0.478908
8
Epoch 9; Loss 0.553509; Train Acc 0.519980; Val Acc 0.521092
9
Epoch 10; Loss 0.433946; Train Acc 0.476870; Val Acc 0.521092
10
Epoch 11; Loss 1.127679; Train Acc 0.480020; Val Acc 0.521092
11
Epoch 12; Loss 0.953405; Train Acc 0.682806; Val Acc 0.478908
12
Epoch 13; Loss 0.971642; Train Acc 0.480020; Val Acc 0.478908
13
Epoch 14; Loss 0.424787; Train Acc 0.480020; Val Acc 0.467990
14
Epoch 15; Loss 0.424081; Train Acc 0.621290; Val Acc 0.521092
15
Epoch 16; Loss 0.958184; Train Acc 0.480020; Val Acc 0.478908
16
Epoch 17; Loss 0.474263; Train Acc 0.478030; Val Acc 0.569727
17
Epoch 18; Loss 0.432907; Train Acc 0.519980; Val Acc 0.478908
18
Epoch 19; Loss 1.126798; Train Acc 0.480020; Val Acc 0.521092
19
```

```
Epoch 20; Loss 0.407969; Train Acc 0.480020; Val Acc 0.521092
```

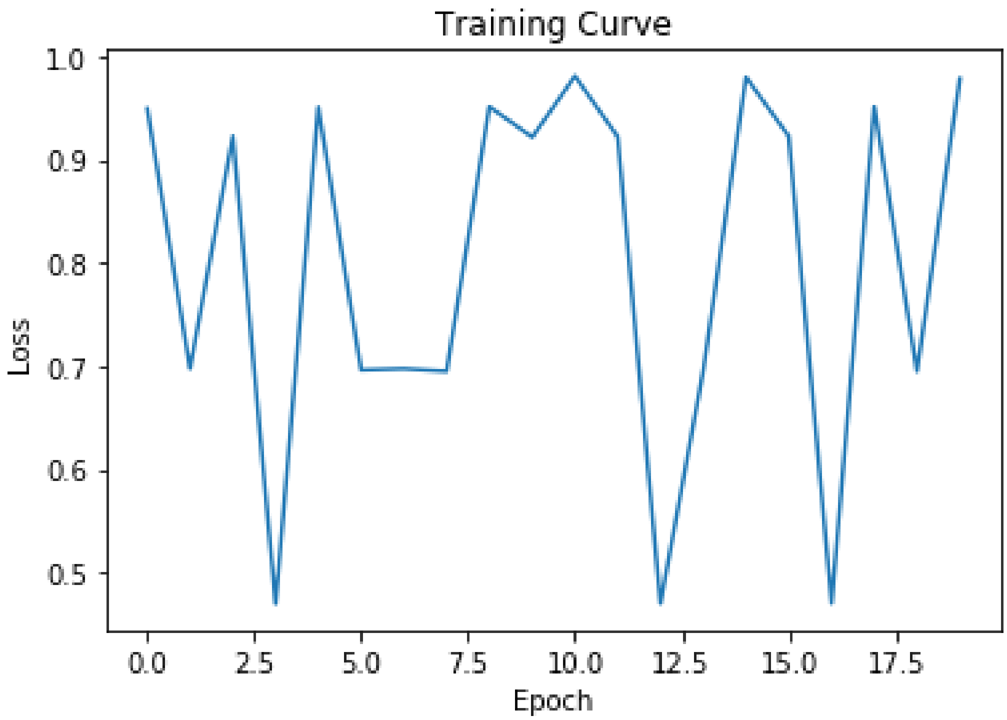


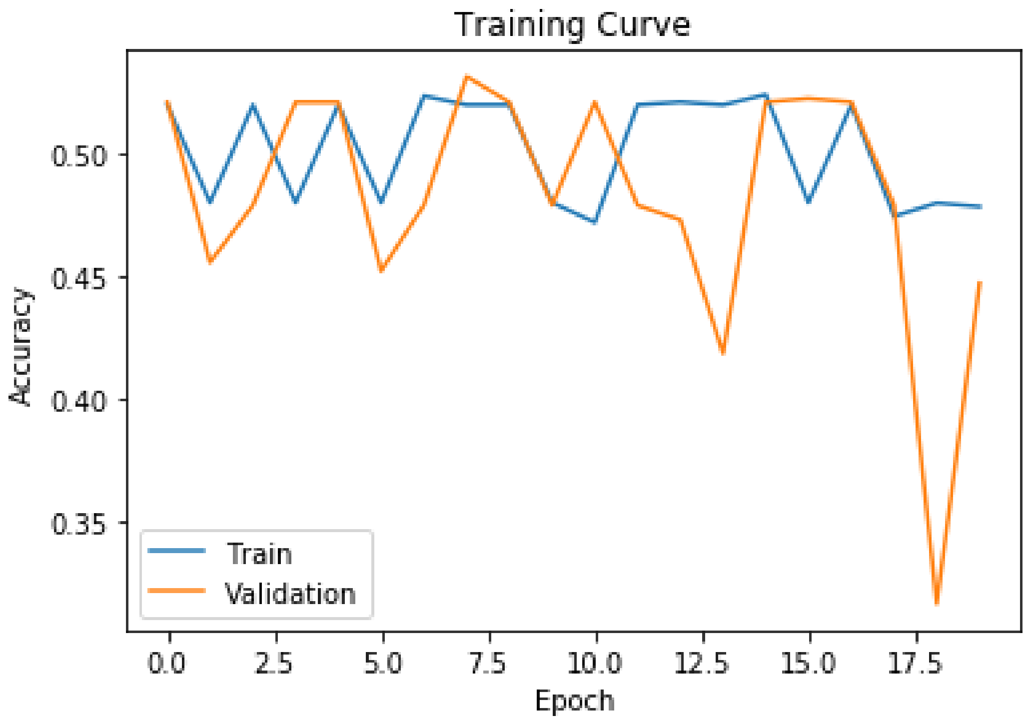


```
In [32]: # Trial #7
         # Previous change worked somewhat well, thought further increasing the
         # batch_size would improve result like last time. It did not work.
         # Increased batch_size to 1024
         # Valid acc is 53% at peek

         train_rnn_network(RNN(20, 20, 2), train, valid, num_epochs=20,
                           learning_rate=1e-6, batch_size=1024)
```

```
0
Epoch 1; Loss 0.949650; Train Acc 0.519980; Val Acc 0.521092
1
Epoch 2; Loss 0.697485; Train Acc 0.480020; Val Acc 0.455583
2
Epoch 3; Loss 0.922858; Train Acc 0.519980; Val Acc 0.478908
3
Epoch 4; Loss 0.469681; Train Acc 0.480020; Val Acc 0.521092
4
Epoch 5; Loss 0.951101; Train Acc 0.519980; Val Acc 0.521092
5
Epoch 6; Loss 0.696137; Train Acc 0.480020; Val Acc 0.452109
6
Epoch 7; Loss 0.697391; Train Acc 0.523628; Val Acc 0.478908
7
Epoch 8; Loss 0.694923; Train Acc 0.519980; Val Acc 0.531514
8
Epoch 9; Loss 0.951492; Train Acc 0.519980; Val Acc 0.521092
9
Epoch 10; Loss 0.921834; Train Acc 0.480020; Val Acc 0.478908
10
Epoch 11; Loss 0.981023; Train Acc 0.471895; Val Acc 0.521092
11
Epoch 12; Loss 0.922342; Train Acc 0.519980; Val Acc 0.478908
12
Epoch 13; Loss 0.470069; Train Acc 0.521141; Val Acc 0.472953
13
Epoch 14; Loss 0.695546; Train Acc 0.519980; Val Acc 0.418362
14
Epoch 15; Loss 0.980040; Train Acc 0.524125; Val Acc 0.521092
15
Epoch 16; Loss 0.922818; Train Acc 0.480020; Val Acc 0.522581
16
Epoch 17; Loss 0.470106; Train Acc 0.519980; Val Acc 0.521092
17
Epoch 18; Loss 0.951533; Train Acc 0.474382; Val Acc 0.478908
```

```
18
Epoch 19; Loss 0.694851; Train Acc 0.479854; Val Acc 0.316129
19
Epoch 20; Loss 0.978571; Train Acc 0.478362; Val Acc 0.447146
```






```
In [ ]: # Part 3 (c)
        # Best result is trial #5. Valid acc is 63% with decent overall shape.
        # More complex model likely will help accuracy. Current one quite simple.
```

```
In [ ]: # Part 4
        # Not too difficult task.
        # A baseline model could be a word-level RNN looking for keywords to detect spam.
        # In my experience, spam emails are not written creatively. Thus, detecting
        # a few keywords, such as "free", "lottery", "gift", "trial", is likely to
        # give a decent result.
```