# 2019 Spring COM526000 Deep Learning - Homework 4

### Recurrent Neural Network

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## **Problems**

#### 1. Gated recurrent neural network

### (a) Embedding

Only encoding words into integer indices is not enough because can not learn the relation between words. We want to find someway that is capable of **capturing context of a word in a document**, **plus semantic and similarity**, **relation with other words**. That's why we need word embedding!

In word embedding, words are represented by dense vectors. Each vector represents the projection of the word into a continuous vector space. The position of a word within the vector space is learned from text and is based on the words that surround the word when it is used. Hence, this makes it possible to obtain meaningful results with arithmetic between vectors.

### (b) Idea and main difference between GRU and LSTM

🖶 Idea

Both LSTM cells and GRU cells have the ability to **keep memory/state of previous** activations rather than replacing the entire activation like a vanilla RNN.

Difference

The LSTM cells implement this idea via input, forget, and output gate.

- Input gate: regulates how much of the new cell state to keep
- Forget gate: regulates how much of the existing memory to forget
- Output gate: regulates how much of the cell state should be exposed to the next layers of the network

The GRU cells operates using a reset gate and an update gate.

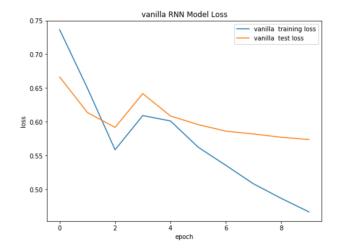
- Reset gate: sits between the previous activation and the next candidate activation to forget previous state
- Update gate: decides how much of the candidate activation to use in updating the cell

### (c) Vanilla RNN (hw4\_1\_105061210.py)

### Model structure

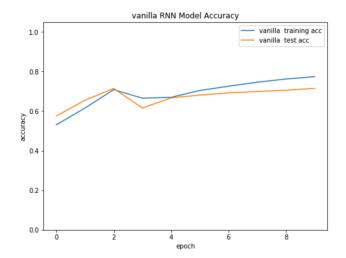
- Input (sequence length = 120 words)
- Embedding layer (size = 256)
- Stacked RNN cells with states (hidden size = 64, number of layers = 1)
- FC layer (on top of RNN output)
- Training parameters: learning rate = 0.00075, batch size = 125, epochs = 10

### Learning curve

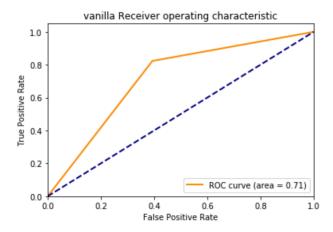


### Test accuracy = 0.79

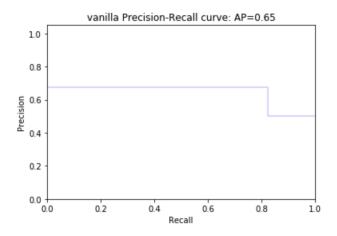
```
epoch: 10 train loss: 0.35261506
epoch: 10 train accuracy: 0.83343995
epoch: 10 test loss: 0.5353818
epoch: 10 test accuracy: 0.78976
```



## ROC curve



## PRC curve



## (d) ROC

X axis: False Positive Rate = 
$$\frac{False\ Positive}{False\ Positive\ + True\ Negative}$$
Y axis: True Positive Rate = 
$$\frac{True\ Positive}{True\ Positive}$$

A classifier with the random performance shows a straight line from (0, 0) to the top right corner (1, 1). The False Positive rate always equals to the True Positive rate; this means that this classifier is functionless.

True Positive + False Negative

## (e) PRC

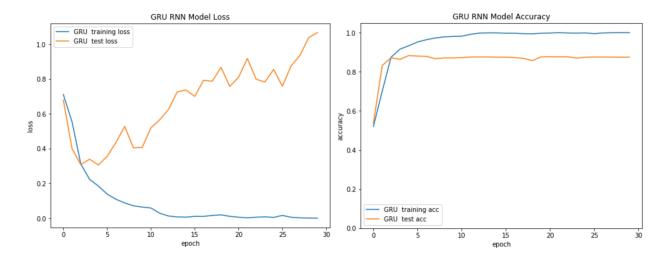
```
X axis: Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}
Y axis: True Positive Rate = 5
```

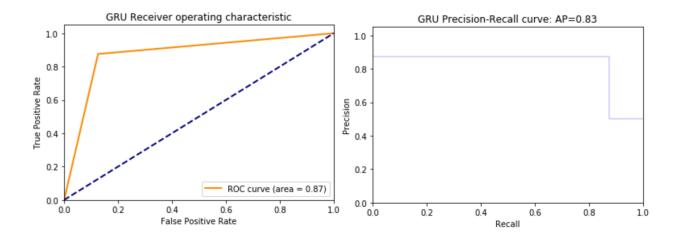
A classifier with the random performance shows a horizontal line in PRC. This line separates the precision-recall space into two areas. The separated area above the line is the area of good performance and the other area below the line is the area of poor performance.

## (f) Repeat (c) with GRU and LSTM (hw4\_1\_105061210.py)

### **GRU**

```
train loss: 3.7521193e-05
epoch:
        30
epoch:
        30
               train accuracy: 1.0
               test loss: 1.4814671
epoch:
       30
epoch:
       30
               test accuracy: 0.85011995
```

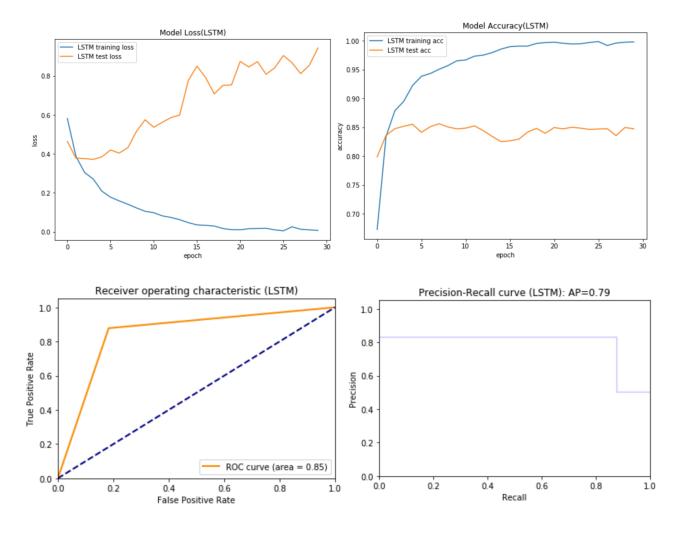




### ♣ LSTM

epoch: 30 train loss: 0.006879263 epoch: 30 train accuracy: 0.99824005

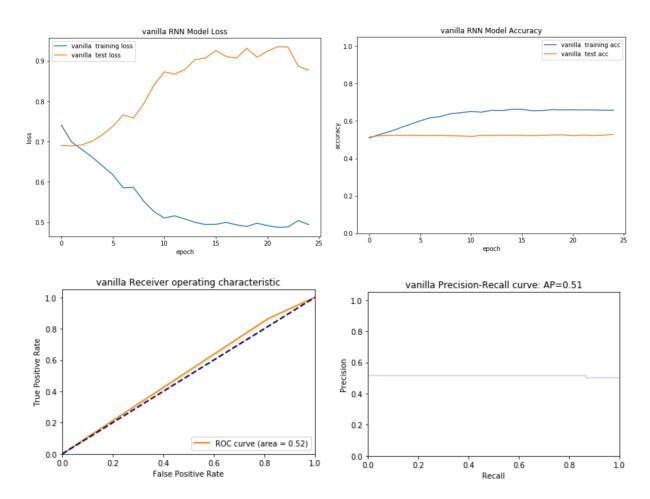
epoch: 30 test loss: 0.9433879 epoch: 30 test accuracy: 0.84748



### (g) Sequence length from 120 to 256 (hw4\_1\_105061210\_g.py)

#### Vanilla RNN

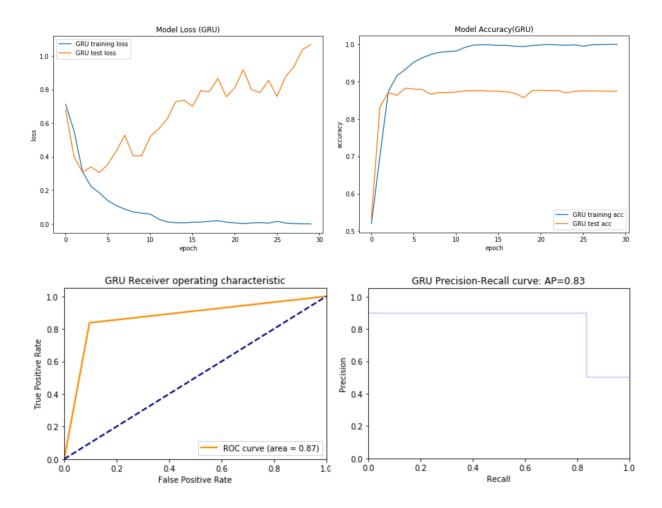
epoch: 25 train loss: 0.49406826 epoch: 25 train accuracy: 0.65752 epoch: 25 test loss: 0.8771144 epoch: 25 test accuracy: 0.52872



I try many different parameters, however, the performance of vanilla RNN becomes worse when change the maximum length of each review from 120 to 256.

#### 🕌 GRU

epoch: 30 train loss: 0.00044441235 epoch: 30 train accuracy: 0.99996 epoch: 30 test loss: 1.0667396 epoch: 30 test accuracy: 0.87484

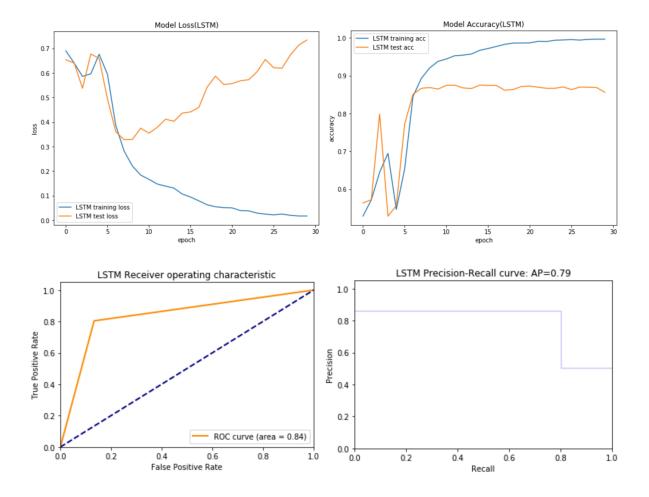


The test accuracy of GRU RNN becomes better when changing the maximum length of each review from 120 to 256. And the ROC, PRC seem to be unchanged.

### ♣ LSTM

epoch: 25 train loss: 0.024770021 epoch: 25 train accuracy: 0.99455994

epoch: 25 test loss: 0.6548944 epoch: 25 test accuracy: 0.8702



The test accuracy of LSTM RNN becomes better when changing the maximum length of each review from 120 to 256. And there are just a bit differences between the ROC, PRC.

## 2. Sequence to sequence learning

- ✓ Preprocessing data (please run hw4\_2\_105061210\_pre.py)
  - Read both source and target texts and split them into sentences
  - Create word-to-integer tables (including 4 special tokens: <PAD>, <EOS>, <UNK>, <GO>)
    for both source (English) and target (French)
  - Also create integer-to-word tables for both source (English) and target (French)
  - Transfer the source and target text, then save them and the tables as 'preprocess.p' for later usage

### ✓ Model structure

- # Embedding layer for encoder (size = 200)
- Encoder using LSTM cells (layers = 3, hidden size = 128)
- ♣ Embedding layer for decoder (size = 200)
  - Before embedding, add special token <GO> in front of all target sentences (for train)
- Decoder using LSTM cells (layers = 3, hidden size = 128)
  - The training and inference process share the same architecture and parameters

### ✓ Training process

- Learning rate = 0.001, batch size = 128
- Pad every sentence in the same batch to the max. sentence length in that batch
- Cost computed using 'Weighted cross-entropy loss for a sequence of logits'
- Using Adam optimizer

### ✓ Accuracy

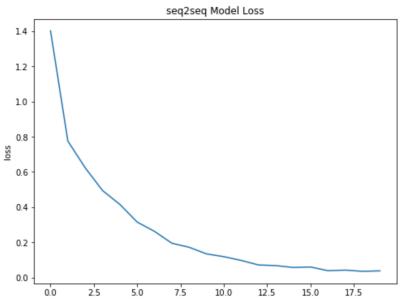
- Padding (so the target and the logit have the same length)
- Calculate the average of where the targets and the logits have the same value

### ✓ Performance enhancement

- ♣ Dropout (training dropout keep rate = 0.5, testing dropout keep rate = 1.0)
- Gradient clipping (keep the gradients in the boundary of (-1, 1))
  - Gradient clipping is believed to improve the performance of RNNs by solving the problems of gradient vanishing or exploding.

#### ✓ Result

Epoch Batch 500/1076 Train Accuracy: 0.4656, Validation Accuracy: 0.4799, Loss: 1.4005 Batch 1000/1076 Epoch Train Accuracy: 0.5540, Validation Accuracy: 0.5532, Loss: 0.7753 Batch 500/1076 Epoch 1 Train Accuracy: 0.6223, Validation Accuracy: 0.6302, Loss: 0.6236 Epoch 1 Batch 1000/1076 Train Accuracy: 0.6577, Validation Accuracy: 0.6570, Loss: 0.4947 Epoch 2 Batch 500/1076 Train Accuracy: 0.6910, Validation Accuracy: 0.6562, Loss: 0.4158 Batch 1000/1076 Train Accuracy: 0.8221, Validation Accuracy: 0.7254, Loss: 0.3156 Batch 500/1076 Train Accuracy: 0.7922, Validation Accuracy: 0.7801, Loss: 0.2628 Batch 1000/1076 3 Train Accuracy: 0.8860, Validation Accuracy: 0.8237, Loss: 0.1957 4 Batch 500/1076 Train Accuracy: 0.8922, Validation Accuracy: 0.8519, Loss: 0.1726 4 Batch 1000/1076 Train Accuracy: 0.9165, Validation Accuracy: 0.8434, Loss: 0.1351 5 Batch 500/1076 Train Accuracy: 0.9273, Validation Accuracy: 0.8791, Loss: 0.1194 Epoch 5 Batch 1000/1076 Train Accuracy: 0.9428, Validation Accuracy: 0.8943, Loss: 0.0981 Epoch 6 Batch 500/1076 Train Accuracy: 0.9434, Validation Accuracy: 0.9010, Loss: 0.0723 Batch 1000/1076 Epoch 6 Train Accuracy: 0.9574, Validation Accuracy: 0.9200, Loss: 0.0688 Epoch 7 Batch 500/1076 Train Accuracy: 0.9543, Validation Accuracy: 0.9215, Loss: 0.0582 Epoch Batch 1000/1076 7 Train Accuracy: 0.9616, Validation Accuracy: 0.9286, Loss: 0.0609 Batch 500/1076 Epoch 8 Train Accuracy: 0.9605, Validation Accuracy: 0.9438, Loss: 0.0398 Epoch Batch 1000/1076 8 Train Accuracy: 0.9680, Validation Accuracy: 0.9435, Loss: 0.0431 Batch 500/1076 Epoch 9 Train Accuracy: 0.9867, Validation Accuracy: 0.9524, Loss: 0.0363 Batch 1000/1076 Epoch 9 Train Accuracy: 0.9730, Validation Accuracy: 0.9401, Loss: 0.0390



```
Source (English)
  Word Indices:
                      [197, 116, 40, 8, 202, 7, 55, 54, 24, 80, 40, 180, 79, 107, 161]
  English Words: ['new', 'jersey', 'is', 'sometimes', 'quiet', 'during', 'autumn', ',', 'and', 'it', 'is', 'snowy',
'in', 'april', '.']
Translation (French)
  Word Indices: [243, 200, 28, 72, 138, 199, 179, 106, 48, 133, 182, 172, 311, 28, 81, 150, 89, 125, 1] French Words: new jersey est parfois calme au cours de l'automne, et il est neigeux en avril . <EOS>
INFO:tensorflow:Restoring parameters from checkpoints/model
Source (English)
  Word Indices:
                      [209, 33, 30, 40, 172, 73, 7, 152, 54, 24, 80, 40, 172, 108, 79, 150, 161]
English Words: ['the', 'united', 'states', 'is', 'usually', 'chilly', 'during', 'july', ',', 'and', 'it', 'is', 'usually', 'freezing', 'in', 'november', '.']
Translation (French)
                      [221, 44, 28, 65, 254, 150, 248, 182, 172, 311, 205, 50, 150, 62, 125, 1]
  Word Indices:
  French Words: les états-unis est généralement froid en juillet , et il gèle habituellement en novembre . <EOS>
 ______
INFO:tensorflow:Restoring parameters from checkpoints/model
Source (English)
  Word Indices:
                      [38, 40, 172, 202, 7, 35, 54, 24, 80, 40, 172, 123, 79, 112, 161]
English Words: ['california', 'is', 'usually', 'quiet', 'during', 'march', ',', 'and', 'it', 'is', 'usually', 'hot', 'in', 'june', '.']
Translation (French)
                      [14, 28, 65, 138, 150, 60, 182, 172, 311, 28, 65, 309, 150, 161, 125, 1]
  Word Indices:
  French Words: california est généralement calme en mars , et il est généralement chaud en juin . <EOS>
INFO:tensorflow:Restoring parameters from checkpoints/model
Word Indices: [209, 33, 30, 40, 8, 115, 7, 112, 54, 24, 80, 40, 117, 79, 189, 161]
English Words: ['the', 'united', 'states', 'is', 'sometimes', 'mild', 'during', 'june', ',', 'and', 'it', 'is', 'c old', 'in', 'september', '.']
Translation (French)
                      [221, 44, 28, 72, 304, 150, 161, 182, 172, 311, 80, 254, 150, 256, 125, 1]
  Word Indices:
  French Words: les états-unis est parfois doux en juin , et il fait froid en septembre . <EOS>
```