Sentence-level Sentiment Classification with RNN

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Abstract

在这次作业中，我使用了 RNN + Self-Attention 来对句子进行情感分类。实验证明 RNN 等模型能够较好的完成这个任务。

1. Introduction

句子的情感分类问题指的是给出一个句子，要求判断这个句子表达的情感是正面的、负面的、中性的。因为句子的长度不固定，因此我使用了 RNN 这种可以处理不定长输入的结构。另外，我还加入了 Self-Attention 机制，并且与 CNN 进行了对比。

2. Related Work

TextCNN(Yoon Kim, 2014)：对于一个输入 $x_{1\dots n}$ ，添加多个不同的卷积核 w 和偏置 b，在该通道上的输出为 $c = [c_1, c_2, \dots, c_{n-h+1}]$，其中 $c_i = f(w \cdot x_{i\dots i+h-1} + b)$，然后取 $k\_max(c_i)$ 作为该通道上的输出（即每一个通道上最大的 k 个数）。这里 h 为 window 的长度。我们可以添加不同长度的多个卷积核。最后再把全部通道上的输出连接一个全连接层进行分类。

3. Approach

3.1 Basic Structure

Basic RNN

对于一组输入 $(x_1, x_2, \dots, x_n)$，中间状态为 $y'_i = h_i = f(W_x x_i + W_h h_{i-1} + b)$，输出为 $y = Softmax(f(W(\frac{1}{n}\sum_{i=1}^{n} y'_i) + b))$。

这里对 x 和 y' 进行了 Dropout，下同。

LSTM

中间状态为

$$
\begin{aligned}
i_i &= Sigmoid(W_1 x_i + W_2 h_{i-1} + b_1) \\
o_i &= Sigmoid(W_3 x_i + W_4 h_{i-1} + b_2) \\
u_i &= Sigmoid(W_5 x_i + W_6 h_{i-1} + b_3) \\
f_i &= tanh(W_7 x_i + W_8 h_{i-1} + b_4) \\
c_i &= f_i \otimes c_{i-1} + i_i \otimes u_i \\
h_i &= o_i \otimes tanh(c_i) \\
y'_i &= h_i
\end{aligned}
$$

GRU

中间状态为

$$
\begin{aligned}
r_i &= Sigmoid(W_1 x_i + W_2 h_{i-1} + b_1) \\
u_i &= Sigmoid(W_3 x_i + W_4 h_{i-1} + b_2) \\
c_i &= tanh(W_5 x_i + W_6 (r_i \otimes h_{i-1}) + b_3) \\
h_i &= (1 - u_i) \otimes h_{i-1} + u_i \otimes c_i \\
y'_i &= h_i
\end{aligned}
$$

3.2 Self Attention

对于一组 RNN 的输出 $Y' = \{y'_1, y'_2, \dots, y'_n\}$，计算

$$
\begin{aligned}
A &= Softmax(W_2 tanh(W_1 Y'^T)) \\
M &= AY'
\end{aligned}
$$

其中 W_1 是一个 $d_a \times u$ 的矩阵，W_2 是一个 $r \times d_a$ 的矩阵，u 为中间状态的长度，r 为特征数。

最后把 M 这个矩阵连上全连接层进行分类。

另外，我们还会把 $10^{-3} \times ||(AA^T - I)||_F^2$ 加到 Loss 上以训练 W_1 和 W_2。

4. Experiments

4.1 Datasets

使用了给出的数据集和词向量。

4.2 Implementation Details

使用了 GD 优化方法。学习率为 0.005。

mini batch size 为 16。

CNN 的 filter 包含长度为 $[2, 3, 4, 5]$ 的各 1000 个 filter。Drop Rate 为 0.5。$k = 5$。

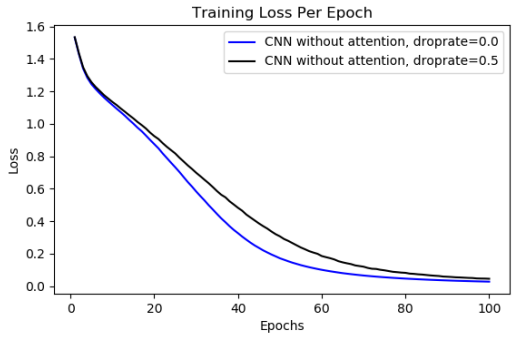
RNN cell 内部的隐藏状态大小为 512。还应用了梯度裁剪，最大梯度为 5。Drop Rate 为 0.3。

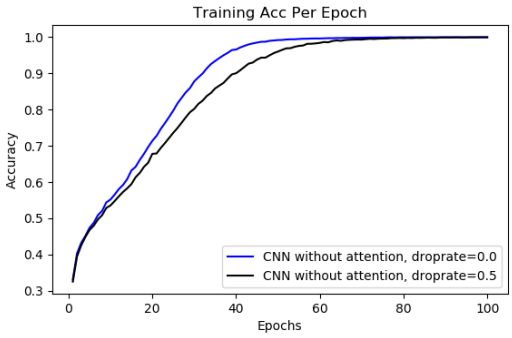
LSTM cell 的 b_4 和 GRU cell 的 b_1, b_2 初始化为全 1。其他超参数与 RNN 相同。

Self-Attention 的中间节点个数为 150，特征个数为 10。

将所有模型训练到收敛，取最大的 validation accuracy 作为评价指标。

4.3 Quantitative Results


Training Loss Per Epoch
CNN without attention, droprate=0.0
CNN without attention, droprate=0.5
Loss
Epochs


Training Acc Per Epoch
CNN without attention, droprate=0.0
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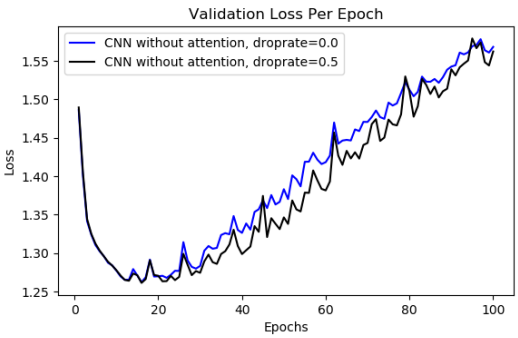
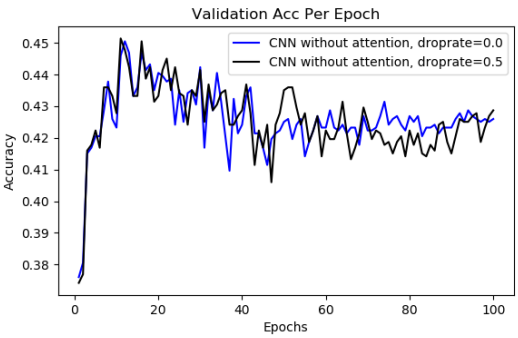
Accuracy
Epochs


Validation Loss Per Epoch
CNN without attention, droprate=0.0
CNN without attention, droprate=0.5
Loss
Epochs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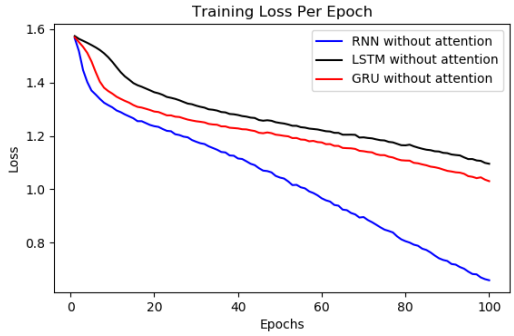
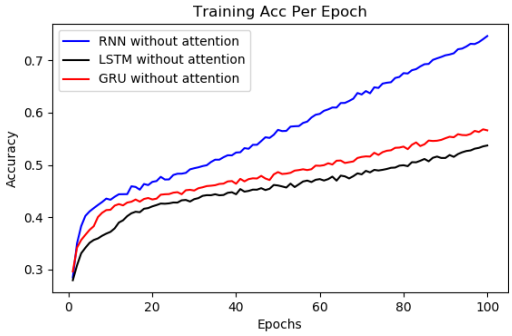
Accuracy
Epochs


Training Loss Per Epoch
RNN without attention
LSTM without attention
GRU without attention
Loss
Epochs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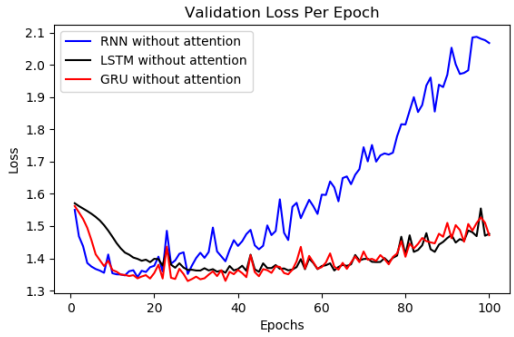
Accuracy
Epochs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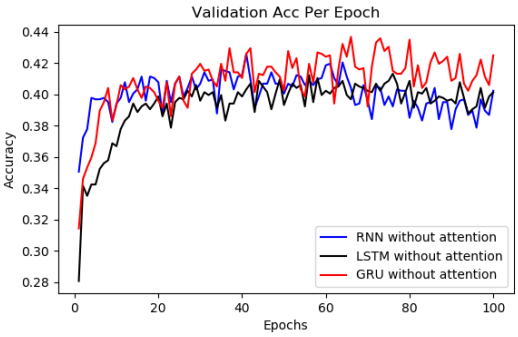
GRU without attention
Loss
Epochs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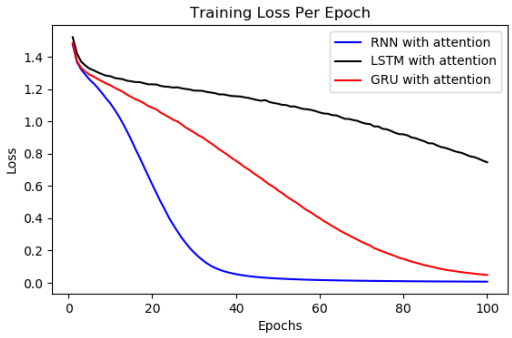
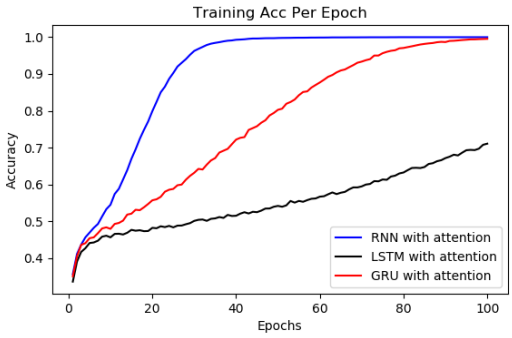
Accuracy
Epochs


Training Loss Per Epoch
RNN with attention
LSTM with attention
GRU with attention
Loss
Epochs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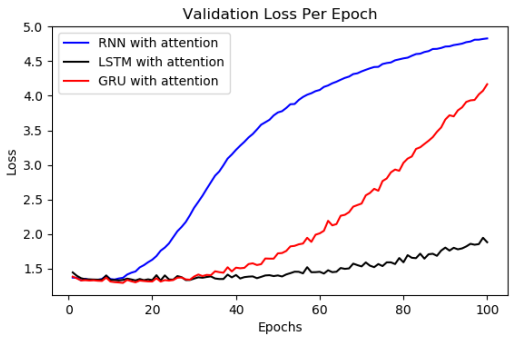
LSTM with attention
GRU with attention
Accuracy
Epochs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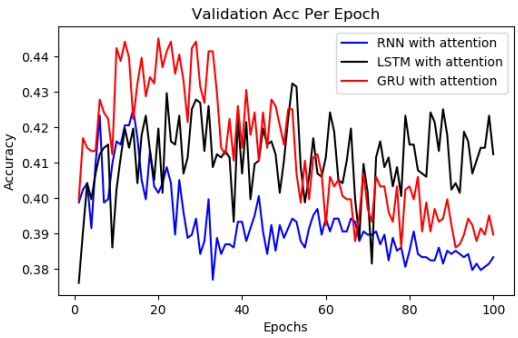
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Accuracy
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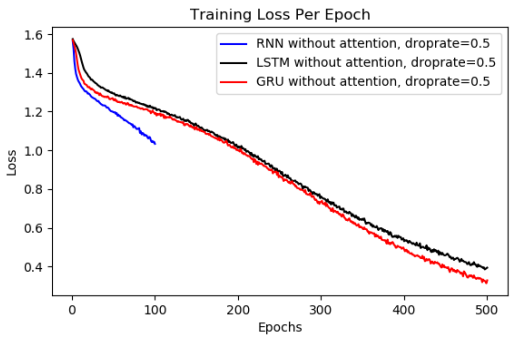
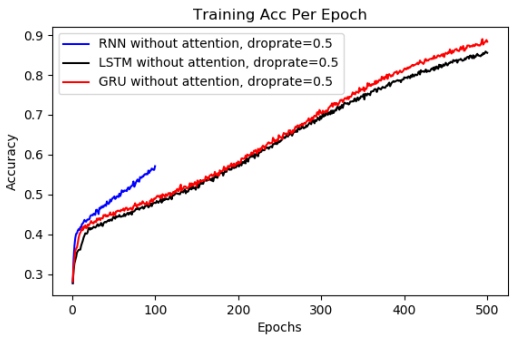

Training Loss Per Epoch
RNN without attention, droprate=0.5
LSTM without attention, droprate=0.5
GRU without attention, droprate=0.5
Loss
Epochs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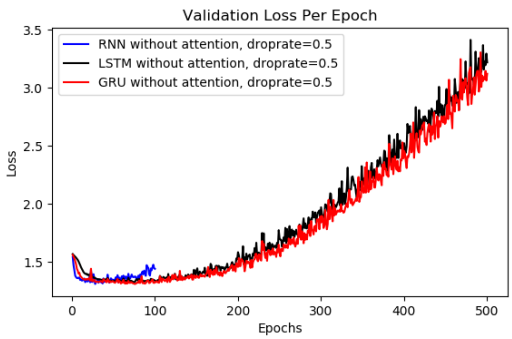
LSTM without attention, droprate=0.5
GRU without attention, droprate=0.5
Accuracy
Epochs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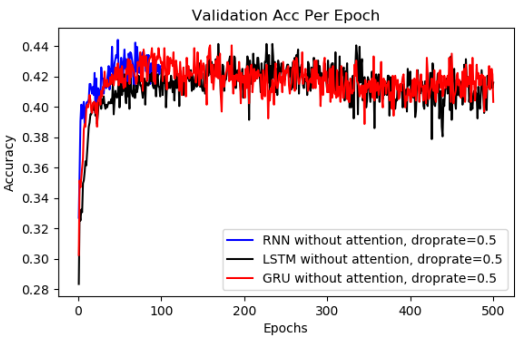
LSTM without attention, droprate=0.5
GRU without attention, droprate=0.5
Loss
Epochs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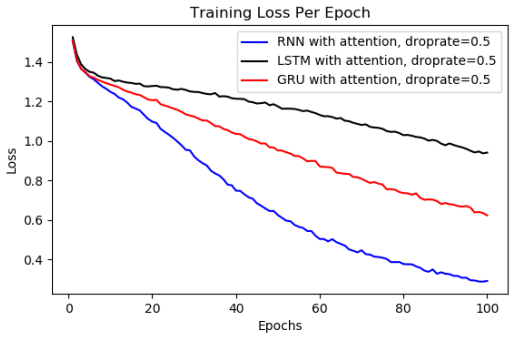
GRU without attention, droprate=0.5
Accuracy
Epochs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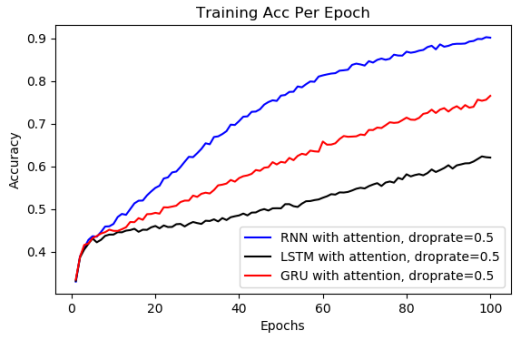
Epochs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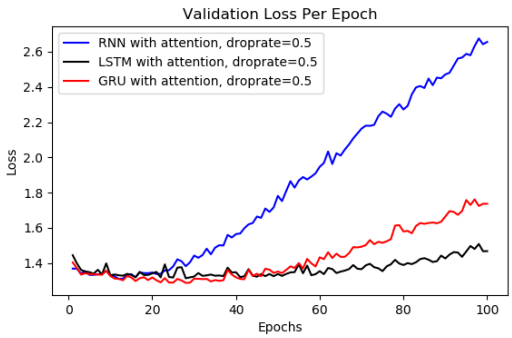
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LSTM with attention, droprate=0.5
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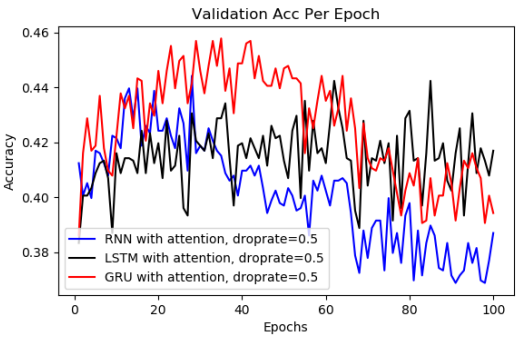
Loss
Epochs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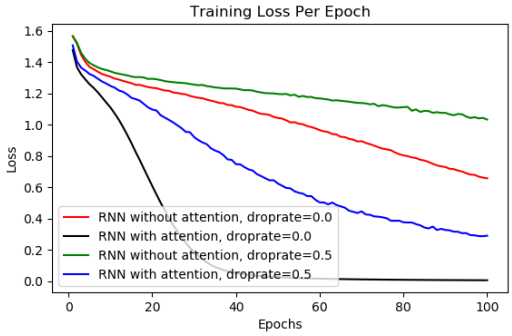
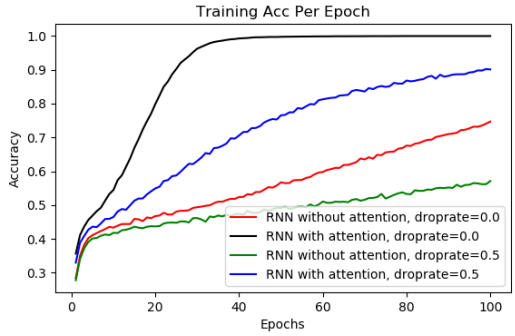
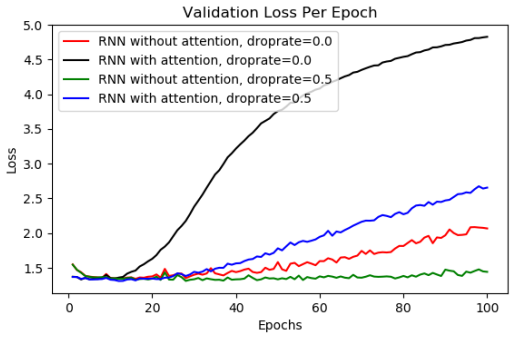
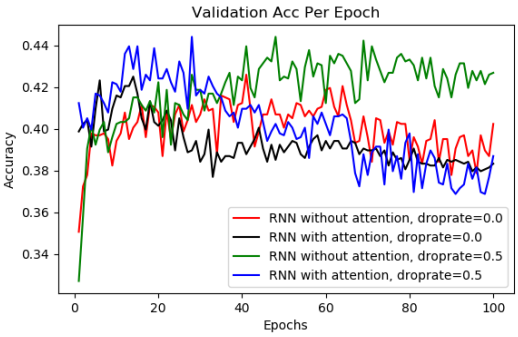
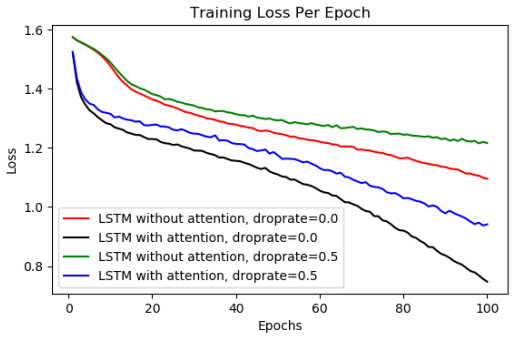
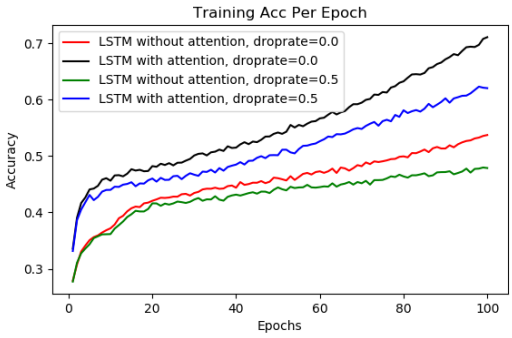

Training Loss Per Epoch
RNN without attention, droprate=0.0
RNN with attention, droprate=0.0
RNN without attention, droprate=0.5
RNN with attention, droprate=0.5
Loss
Epochs

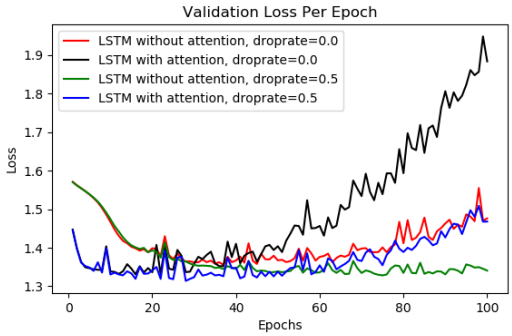

Training Acc Per Epoch
RNN without attention, droprate=0.0
RNN with attention, droprate=0.0
RNN without attention, droprate=0.5
RNN with attention, droprate=0.5
Accuracy
Epochs

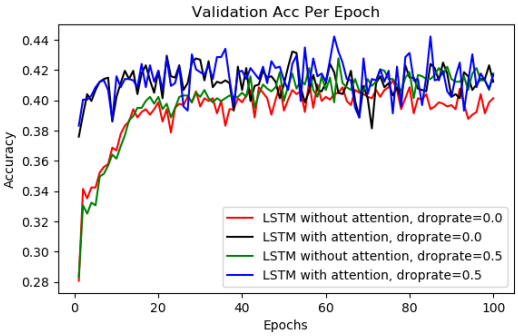

Validation Loss Per Epoch
RNN without attention, droprate=0.0
RNN with attention, droprate=0.0
RNN without attention, droprate=0.5
RNN with attention, droprate=0.5
Loss
Epochs

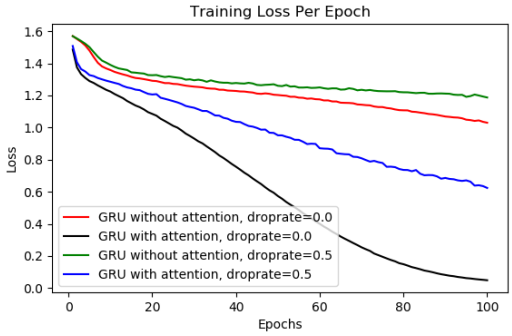

Validation Acc Per Epoch
RNN without attention, droprate=0.0
RNN with attention, droprate=0.0
RNN without attention, droprate=0.5
RNN with attention, droprate=0.5
Accuracy
Epochs

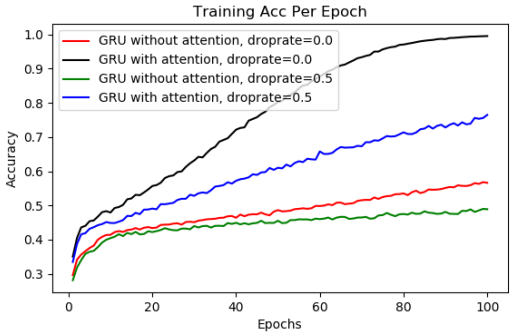

Training Loss Per Epoch
Loss
Epochs
LSTM without attention, droprate=0.0
LSTM with attention, droprate=0.0
LSTM without attention, droprate=0.5
LSTM with attention, droprate=0.5

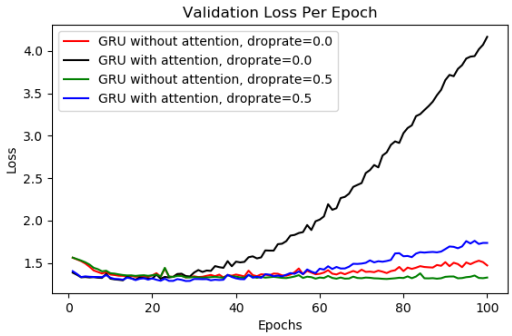

Training Acc Per Epoch
Accuracy
Epochs
LSTM without attention, droprate=0.0
LSTM with attention, droprate=0.0
LSTM without attention, droprate=0.5
LSTM with attention, droprate=0.5

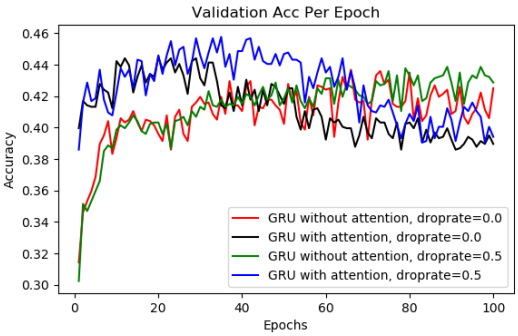

Validation Loss Per Epoch
Loss
Epochs
LSTM without attention, droprate=0.0
LSTM with attention, droprate=0.0
LSTM without attention, droprate=0.5
LSTM with attention, droprate=0.5


Validation Acc Per Epoch
Accuracy
Epochs
LSTM without attention, droprate=0.0
LSTM with attention, droprate=0.0
LSTM without attention, droprate=0.5
LSTM with attention, droprate=0.5


Training Loss Per Epoch
Loss
Epochs
GRU without attention, droprate=0.0
GRU with attention, droprate=0.0
GRU without attention, droprate=0.5
GRU with attention, droprate=0.5


Training Acc Per Epoch
Accuracy
Epochs
GRU without attention, droprate=0.0
GRU with attention, droprate=0.0
GRU without attention, droprate=0.5
GRU with attention, droprate=0.5


Validation Loss Per Epoch
Loss
Epochs
GRU without attention, droprate=0.0
GRU with attention, droprate=0.0
GRU without attention, droprate=0.5
GRU with attention, droprate=0.5


Validation Acc Per Epoch
Accuracy
Epochs
GRU without attention, droprate=0.0
GRU with attention, droprate=0.0
GRU without attention, droprate=0.5
GRU with attention, droprate=0.5

模型	正确率(with Self-Attention)	正确率(without Self-Attention)
CNN	----------	$45.05\%/45.14\%$
RNN	$42.51\%/44.41\%$	$42.60\%/44.41\%$
LSTM	$43.23\%/44.23\%$	$41.33\%/44.14\%$
GRU	$44.50\%/45.78\%$	$43.69\%/44.05\%$

（其中每一个中左边的数值是未加 Dropout 的结果，右边的数值是带 Dropout 的结果）

通过对比，可以得到结论：在没有 Self-Attention 时， RNN 的收敛速度较快，LSTM 和 GRU 的收敛速度差不多相同，在没有 Dropout 时，RNN 的正确率最高，有 Dropout 时 GRU 的正确率最高。在有 Self-Attention 时，RNN 的收敛速度最快，GRU 次之，LSTM 最慢。GRU 的正确率最高。无论是否有 Self-Attention，加入 Dropout 会给正确率带来一定的提升。Self-Attention 能提高模型的正确率（RNN 除外）和加快模型的收敛速度。最终，GRU+Self-Attention+Dropout 能够在正确率上超过 CNN 方法。

5. Conclusion

通过实验和对比，我发现 RNN、LSTM、GRU 三种模型都能比较好的完成这次任务，其中 GRU 的正确率最高并且能超过 CNN 方法。另外 Self-Attention 也能提高正确率和收敛速度。

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