CS224N Winter 2016 Homework [3]

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By turning in this assignment, I agree by the Stanford honor code and declare that all of this is my own work.

Problem 1: A window into NER

(a) i.
Yesterday, price of Apple increased 6.56 percent.
Here apply can be interpreted as Apple the company or apple the fruit.

Calvin Klein just released some nice designs for the winter season.
Here Calvin Klein can be interpreted as a name or a company.

ii.
Words alone can have ambiguity, therefore adding features other than the word itself can help reduce ambiguity.

iii.
First, the context of the word can help. The words around can imply the correct meaning of the center word. Second, dependence structure within the window could shed light on the function of the center word in the sentences, which helps interpreting its entity.

(b) i.
$e^{(t)}$ has dimension of $1 \times (2w+1)D$
W has dimension of $(2w+1)D \times H$
U has dimension of $H \times C$

ii.

$$\begin{aligned}
cost(ReLu) &= \mathcal{O}(H) + \mathcal{O}((2w+1)D \times H) \\
cost(softmax) &= \mathcal{O}(H \times C) + \mathcal{O}(C) \\
cost(CE) &= \mathcal{O}(C)
\end{aligned}$$

Given the sentences has length of T, the computation complexity is:

$$\begin{aligned}
cost &= T \times \mathcal{O}(\mathcal{O}(H) + \mathcal{O}((2w+1)D \times H) + \mathcal{O}(H \times C) + \mathcal{O}(C) + \mathcal{O}(C)) \\
&\approx \mathcal{O}((2w+1)D \times H \times T) \\
&\approx \mathcal{O}(wDHT)
\end{aligned}$$

(c) (code)

(d) i.
Entity level P/R/F1: 0.82/0.84/0.83
The confusion matrix shows that the model has a very low false positive rate of misclassifying null class into an entity. Among all the entities, ORG has the lowest accuracy.

Table 1: confusion matrix

Acutal \Predicted	PER	ORG	LOC	MISC	O
PER	2940.00	56.00	46.00	13.00	94.00
ORG	128.00	1676.00	92.00	63.00	133.00
LOC	54.00	119.00	1845.00	29.00	47.00
MISC	36.00	63.00	35.00	1018.00	116.00
O	37.00	42.00	12.00	31.00	42637.00

ii.
The first limitation is that the length of context is limited by the length of window size. For example the **Test and County Cricket Board** does not get right label, because the length has exceeded the window size.

The second limitation is that the model is too simplistic. The context is based solely on concatenating word vectors. The model can't decide which word in the context should it focus on. For example, **Grace Road** was not correctly classified in "at Grace Road". The word "at" is a very strong signal that the next word/phrases should be locations but the model fails to capture that. Currently the word "at" has the same effect anywhere within the window. With a more sophisticated model like LSTM or GRU, we should be able to put emphasis on words that are more relevant to the entity.

Problem 2:RNN for NER

(a) i.

The number of RNN parameters:

$$V \times D + H \times H + D \times H + H + H \times C + C$$

The number of window-based model parameters:

$$V \times D + (2w+1)D \times H + H + H \times C + C$$

Therefore, RNN has $(2wD - H)H$ more parameters than window-based model, assuming $2wD > H$

ii.

Cost for one time step:

$$cost(h) = \mathcal{O}(H \times H) + \mathcal{O}(D \times H) + \mathcal{O}(H)$$
$$cost(softmax) = \mathcal{O}(H \times C) + \mathcal{O}(C)$$
$$cost(CE) = \mathcal{O}(C)$$

Adding them up:

$$\mathcal{O}(H \times H) + \mathcal{O}(D \times H) + \mathcal{O}(H) + \mathcal{O}(H \times C) + \mathcal{O}(C) + \mathcal{O}(C) \approx \mathcal{O}(H \times H + D \times H)$$

Therefore the total cost for sentence of length T:

$$cost = \mathcal{O}((H \times H + D \times H)T)$$

(b) i.

Sijun's answer

The problem with cross entropy loss is that is maximize the softmax probability of the correct label instead of just classify the labels correctly. Consider a 2 token batch with 2 class, the labels are

$$y^1 = [1, 0] \quad y^2 = [0, 1]$$

Case 1: $\hat{y}^1 = [0.6, 0.4]$ $\hat{y}^2 = [0.4, 0.6]$.
The model gets both labels correct. $J = -2\log 0.6 = 0.44$

Case 2: $\hat{y}^1 = [0.99, 0.01]$ $\hat{y}^2 = [0.51, 0.49]$.
The model gets only 1 label correct. $J = -\log 0.99 - \log 0.49 = 0.31$

While case 2 has a smaller cross entropy loss, it only correctly classified one label and has a smaller F_1 score.

Jiajun's answer

Consider a dataset that most of (over 90%) the entity is person, if the model label all the entity as person the cross entropy error should be smaller. However, by doing this the F_1 score should drop, because the prediction is biased and recall value will drop.

ii.

Sijun's answer

1. The F_1 score cannot be broken into token-level or batch-level terms and thus is impossible to do mini-batch optimization. It requires looking through the entire training set, which is unrealistic in terms of memory.
2. There's no gradient of F_1 w.r.t. the parameters. Optimizing F_1 will be ver hard since we need to reply on some variant of gradient descent for optimization.

Jiajun's answer

Optimizing F_1 score requires looking through the entire training set. The cost and memory requirement is huge.

(c) (code)

(d) **Sijun's answer**

The padded 0-vectors are at the end of the sentence. When the model unroll to the padded 0-vectors, it will make predictions based solely on the past memory (current word input is all zeros). Regardless of what the model predicts, it will add to the loss function. Since the loss of these tokens are not zero, it will produce a gradient and affect the batch gradient. With masking, we neglect the loss terms of the padded 0-vectors. They no longer have any effect on the loss and thus no effect on the gradient.

Jiajun's answer

The padded label y will be transform into a one-hot vector. When $y = 0$, the corresponding one-hot vector is $[1, 0, 0, 0, 0]$. Therefore, the padded label will be considered as label o. The cross entropy loss is not always zero for the padded part.

(e) (code)

(f) result:

(g) explanation:

Problem 3:Grooving with GRUs

(a) i.
$U_h = 1$, $W_h = 1$ and $b_h = 0$ will allow the RNN to replicate this behavior.

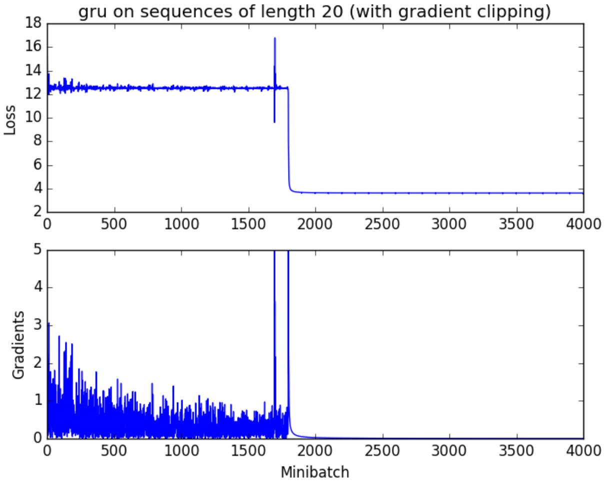
ii.
$U_z = 0$, $W_z = 1$, $U_h = 1$ and W_h can be any value.
When $x = 0$, $z_t = 0$ and $\tilde{h_t} = 0$ thus the hidden state will always be $h_t = 0$. Whenever $x = 1$, $z_t = 0$ and the hidden state will keep to be $h_t = h_{t-1} = 1$.

(b) i.
It is impossible for RNN to have togging behavior. U_t has to be a positive number in order to let h_t switch to 1. Therefore for the second time when $x = 1$ it is impossible to let h_t switch back to 0.

ii.
$b_r = 1$, $U_z = -1$, $W_z = 1$, $U_h = 1$ and $W_h = -1$. When $x = 0$, $z_t = 0$ and $\tilde{h_t} = 0$ thus the hidden state will always be $h_t = 0$. When $x = 1$ for the first time, $z_t = 0$ but $\tilde{h_t} = 1$ thus the hidden state will switch to $h_t = 1$. If $h_t = 1$ and $x = 0$, $z_t = 1$ and hidden state $h_t = h_{t-1} = 1$. But if $x = 1$, $z_t = 0$ and hidden state $h_t = \tilde{h_t} = 0$.

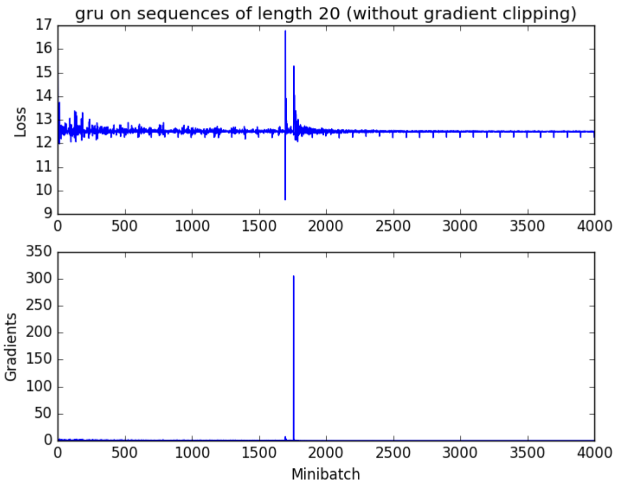
(c) (code)

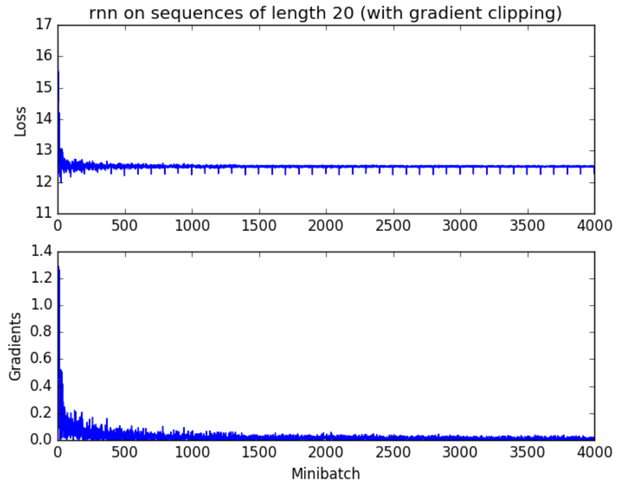
(d)

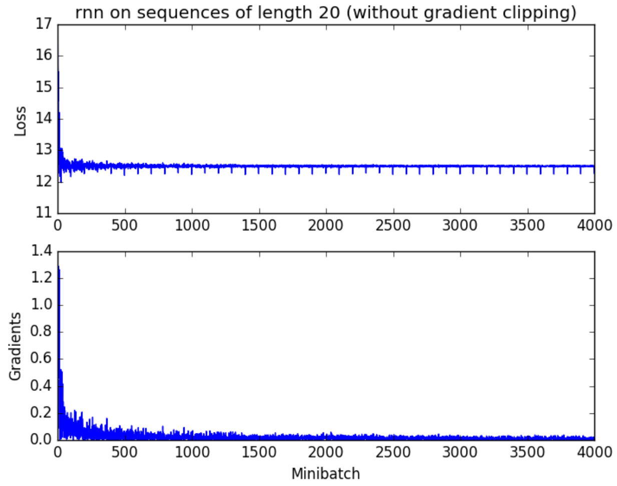


(e) explanation:

(f) waiting for the GPU then we can train this F1 score


gru on sequences of length 20 (without gradient clipping)
Loss
17
16
15
14
13
12
11
10
9
0
500
1000
1500
2000
2500
3000
3500
4000
Gradients
350
300
250
200
150
100
50
0
0
500
1000
1500
2000
2500
3000
3500
4000
Minibatch


rnn on sequences of length 20 (with gradient clipping)
Loss
17
16
15
14
13
12
11
0
500
1000
1500
2000
2500
3000
3500
4000
Gradients
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0
500
1000
1500
2000
2500
3000
3500
4000
Minibatch


rnn on sequences of length 20 (without gradient clipping)
Loss
17
16
15
14
13
12
11
0
500
1000
1500
2000
2500
3000
3500
4000
Gradients
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
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500
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Minibatch