



courser

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- [테스트: Recurrent Neural Networks](#)
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- **Programming Assignments**

테스트테스트 • 30 min30 minutes

Recurrent Neural Networks



과제 제출
기한년 8월 23일 오후 3:59 KST년 8월 23일 오후 3:59 KST
시도하기8 hours당 3회

계속하기



성적 받기
통과 점수:80% 이상
성적
100%

피드백 보기

최고 점수가 유지됩니다.



탐색 확인

이 페이지에서 나가시겠습니까?

이 페이지에 머물기

이 페이지에서 나가기



Recurrent Neural Networks
성적 평가 퀴즈 • 30 min

만료 년 8월 23일 오후 3:59 KST



축하합니다! 통과하셨습니다!

통과 점수: 80% 이상

학습 계속하기

성적
100%

Recurrent Neural Networks

최신 제출물 성적
100%

1.
질문 1

Suppose your training examples are sentences (sequences of words). Which of the following refers to the j^{th} word in the i^{th} training example?

1 / 1점

☒ ☐

$x^{(i)} < j > \mathbf{x(i)} < \mathbf{j} >$

☐ ☐

$x < i > (j) \mathbf{x} < \mathbf{i} > (\mathbf{j})$

☐ ☐

$x^{(j)} < i > \mathbf{x(j)} < \mathbf{i} >$

☐ ☐

$x < j > (i) \mathbf{x} < \mathbf{j} > (\mathbf{i})$



맞습니다

We index into the i^{th} row first to get the i^{th} training example (represented by parentheses), then the j^{th} column to get the j^{th} word (represented by the brackets).

2.
질문 2

Consider this RNN:



This specific type of architecture is appropriate when:

1 / 1점

☒ ☐

$T_x = T_y \mathbf{Tx} = \mathbf{T_y}$

☐ ☐

$T_x < T_y \mathbf{Tx} < \mathbf{T_y}$

☐ ☐

$T_x > T_y \mathbf{Tx} > \mathbf{T_y}$

☐ ☐

$T_x = 1 \mathbf{Tx} = 1$



맞습니다

It is appropriate when every input should be matched to an output.

3.
질문 3

To which of these tasks would you apply a many-to-one RNN architecture? (Check all that apply).



1 / 1점

☐☐

Speech recognition (input an audio clip and output a transcript)

☒☐

Sentiment classification (input a piece of text and output a 0/1 to denote positive or negative sentiment)



맞습니다

Correct!

☐☐

Image classification (input an image and output a label)

☒☐

Gender recognition from speech (input an audio clip and output a label indicating the speaker’s gender)



맞습니다

Correct!

4.
질문 4

You are training this RNN language model.



At the t^{th} time step, what is the RNN doing? Choose the best answer.

1 / 1점

☐☐

Estimating $P(y^{<1>}, y^{<2>}, ..., y^{<t-1>})P(y^{<1>}, y^{<2>}, ..., y^{<t-1>})$

☐☐

Estimating $P(y^{<t>})P(y^{<t>})$

☒☒

Estimating $P(y^{<t>} | y^{<1>}, y^{<2>}, ..., y^{<t-1>})P(y^{<t>} | y^{<1>}, y^{<2>}, ..., y^{<t-1>})$

☐☐

Estimating $P(y^{<t>} | y^{<1>}, y^{<2>}, ..., y^{<t>})P(y^{<t>} | y^{<1>}, y^{<2>}, ..., y^{<t>})$



맞습니다

Yes, in a language model we try to predict the next step based on the knowledge of all prior steps.

5.
질문 5

You have finished training a language model RNN and are using it to sample random sentences, as follows:



What are you doing at each time step t ?

1 / 1점

☐☐

(i) Use the probabilities output by the RNN to pick the highest probability word for that time-step as $\hat{y}^{<t>}$. (ii)

Then pass the ground-truth word from the training set to the next time-step.

☐ ☐

(i) Use the probabilities output by the RNN to randomly sample a chosen word for that time-step as $\hat{y}^{<t>}$ $y^{<t>}$.(ii)
Then pass the ground-truth word from the training set to the next time-step.

☐ ☐

(i) Use the probabilities output by the RNN to pick the highest probability word for that time-step as $\hat{y}^{<t>}$ $y^{<t>}$.(ii)
Then pass this selected word to the next time-step.

☒ ☐

(i) Use the probabilities output by the RNN to randomly sample a chosen word for that time-step as $\hat{y}^{<t>}$ $y^{<t>}$.(ii)
Then pass this selected word to the next time-step.



맞습니다

6.

질문 6

You are training an RNN, and find that your weights and activations are all taking on the value of NaN ("Not a Number"). Which of these is the most likely cause of this problem?

1 / 1점

☐ ☐

Vanishing gradient problem.

☒ ☐

Exploding gradient problem.

☐ ☐

ReLU activation function $g(\cdot)$ used to compute $g(z)$, where z is too large.

☐ ☐

Sigmoid activation function $g(\cdot)$ used to compute $g(z)$, where z is too large.



맞습니다

7.

질문 7

Suppose you are training a LSTM. You have a 10000 word vocabulary, and are using an LSTM with 100-dimensional activations $a^{<t>}$ $a^{<t>}$. What is the dimension of $\Gamma_u \Gamma_u$ at each time step?

1 / 1점

☐ ☐

1

☒ ☐

100

☐ ☐

300

☐ ☐

10000



맞습니다

Correct, $\Gamma_u \Gamma_u$ is a vector of dimension equal to the number of hidden units in the LSTM.

8.

질문 8

Here're the update equations for the GRU.



Alice proposes to simplify the GRU by always removing the $\Gamma_u \Gamma_u$. I.e., setting $\Gamma_u \Gamma_u = 1$. Betty proposes to simplify the GRU by removing the $\Gamma_r \Gamma_r$. I. e., setting $\Gamma_r \Gamma_r = 1$ always. Which of these models is more likely to work without vanishing gradient problems even when trained on very long input sequences?

1 / 1점

☐ ☐

Alice's model (removing $\Gamma_u \Gamma_u$), because if $\Gamma_r \approx 0 \Gamma_r \approx 0$ for a timestep, the gradient can propagate back through that timestep without much decay.

☐ ☐

Alice's model (removing $\Gamma_u \Gamma_u$), because if $\Gamma_r \approx 1 \Gamma_r \approx 1$ for a timestep, the gradient can propagate back through that timestep without much decay.

☒ ☐

Betty's model (removing $\Gamma_r \Gamma_r$), because if $\Gamma_u \approx 0 \Gamma_u \approx 0$ for a timestep, the gradient can propagate back through that timestep without much decay.

☐ ☐

Betty's model (removing $\Gamma_r \Gamma_r$), because if $\Gamma_u \approx 1 \Gamma_u \approx 1$ for a timestep, the gradient can propagate back through that timestep without much decay.



맞습니다

Yes. For the signal to backpropagate without vanishing, we need $c^{<t>}$ $c^{<t>}$ to be highly dependent on $c^{<t-1>}$ $c^{<t-1>}$.

9.
질문 9

Here are the equations for the GRU and the LSTM:



From these, we can see that the Update Gate and Forget Gate in the LSTM play a role similar to _____ and _____ in the GRU. What should go in the blanks?

1 / 1점

☒ ☐

$\Gamma_u \Gamma_u$ and $1 - \Gamma_u 1 - \Gamma_u$

☐ ☐

$\Gamma_u \Gamma_u$ and $\Gamma_r \Gamma_r$

☐ ☐

$1 - \Gamma_u 1 - \Gamma_u$ and $\Gamma_u \Gamma_u$

☐ ☐

$\Gamma_r \Gamma_r$ and $\Gamma_u \Gamma_u$



맞습니다

Yes, correct!

10.
질문 10

You have a pet dog whose mood is heavily dependent on the current and past few days' weather. You've collected data for the past 365 days on the weather, which you represent as a sequence as $x^{<1>}, \dots, x^{<365>}$ $x^{<1>}, \dots, x^{<365>}$. You've

also collected data on your dog's mood, which you represent as $y^{<1>}, \dots, y^{<365>}$ $y^{<1>}, \dots, y^{<365>}$. You'd like to build a model to map from $x \rightarrow y$ $x \rightarrow y$. Should you use a Unidirectional RNN or Bidirectional RNN for this problem?

1 / 1점

☐

☐

Bidirectional RNN, because this allows the prediction of mood on day t to take into account more information.

☐

☐

Bidirectional RNN, because this allows backpropagation to compute more accurate gradients.

☒

☒

Unidirectional RNN, because the value of $y^{<t>}$ $y^{<t>}$ depends only on $x^{<1>}, \dots, x^{<t>}$ $x^{<1>}, \dots, x^{<t>}$, but not on $x^{<t+1>}, \dots, x^{<365>}$ $x^{<t+1>}, \dots, x^{<365>}$

☐

☐

Unidirectional RNN, because the value of $y^{<t>}$ $y^{<t>}$ depends only on $x^{<t>}$ $x^{<t>}$, and not other days' weather.



맞습니다

Yes!