Congratulations! You passed!

Grade received 100%

Latest Submission Grade 100%

To pass 80% or higher

Go to next item

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 / 1 point

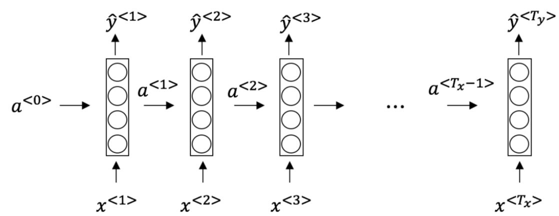
- (●) $x^{(i)<j>}$
- ( ) $x^{<i>(j)}$
- ( ) $x^{(j)<i>}$
- ( ) $x^{<j>(i)}$

Expand

Correct
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. Consider this RNN:

1 / 1 point



True/False: This specific type of architecture is appropriate when Tx=Ty

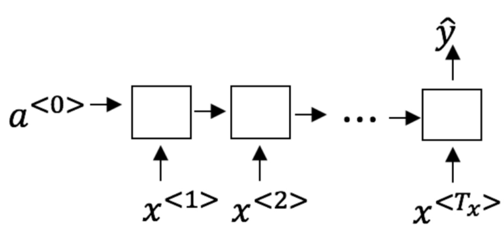
- (●) True
- ( ) False

Expand

Correct
It is appropriate when the input sequence and the output sequence have the same length or size.

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

1 / 1 point



- [ ] Speech recognition (input an audio clip and output a transcript)
- [x] Sentiment classification (input a piece of text and output a 0/1 to denote positive or negative sentiment)

  Correct
  Correct!

- [ ] Image classification (input an image and output a label)
- [x] Gender recognition from speech (input an audio clip and output a label indicating the speaker's gender)

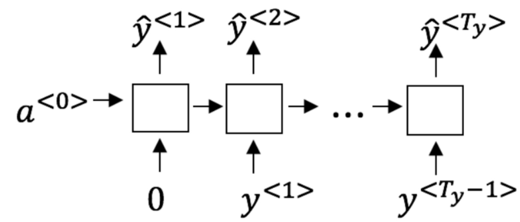
  Correct
  Correct!

Expand

Correct
Great, you got all the right answers.

4. You are training this RNN language model.

1 / 1 point



At the t^{th} time step, what is the RNN doing?

- Estimating $P(y^{<1>}, y^{<2>}, \ldots, y^{<t-1>})$
- Estimating $P(y^{<t>})$
- Typesetting math: 100% $^{<t>} \mid y^{<1>}, y^{<2>}, \ldots, y^{<t-1>})$

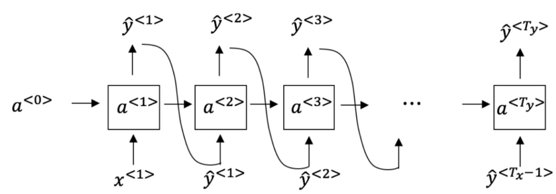
Expand

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

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

لقد انتهيت من تدريب نموذج اللغة RNN وتستخدمه لأخذ عينات من الجمل العشوائية ، على النحو التالي:

1 / 1 point



True/False: In this sample sentence, step t uses the probabilities output by the RNN to randomly sample a chosen word for that time-step. Then it passes this selected word to the next time-step.

صواب/خطأ: في هذه الجملة النموذجية، تستخدم الخطوة t الاحتمالات الناتجة بواسطة RNN لأخذ عينة عشوائية من كلمة مختارة لتلك الخطوة الزمنية. ثم يمرر هذه الكلمة المحددة إلى الخطوة الزمنية التالية.

- False
- True

Expand

Correct
Step t uses the probabilities output by the RNN to randomly sample a chosen word for that time-step. Then it passes this selected word to the next time-step.

6. True/False: If you are training an RNN model, and find that your weights and activations are all taking on the value of NaN (“Not a Number”) then you have an exploding gradient problem.

1 / 1 point

- False
- True

Expand

Correct
Correct! Exploding gradients happen when large error gradients accumulate and result in very large updates to the NN model weights during training. These weights can become too large and cause an overflow, identified as NaN.

7. Suppose you are training an LSTM. You have a 50000 word vocabulary, and are using an LSTM with 500-dimensional activations $a^{<t>}$

لنفترض أنك تقوم بتدريب LSTM. لديك مفردات 50000 كلمة ، وتستخدم LSTM مع عمليات تنشيط 500 الأبعاد a. What is the dimension of Γ_u at each time step?

1 / 1 point

- 500
- 200

- 50000
- 5

Expand

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

8. Here are the update equations for the GRU. 1 / 1 point

GRU

$$\tilde{c}^{<t>} = \tanh(W_c[\Gamma_r * c^{<t-1>}, x^{<t>}] + b_c)$$

$$\Gamma_u = \sigma(W_u[\, c^{<t-1>}, x^{<t>}] + b_u)$$

$$\Gamma_r = \sigma(W_r[\, c^{<t-1>}, x^{<t>}] + b_r)$$

$$c^{<t>} = \Gamma_u * \tilde{c}^{<t>} + (1 - \Gamma_u) * c^{<t-1>}$$

$$a^{<t>} = c^{<t>}$$

Alice proposes to simplify the GRU by always removing the Γ_u. I.e., setting Γ_u = 0. Betty proposes to simplify the GRU by removing the Γ_r. I. e., setting Γ_r = 1 always. Which of these models is more likely to work without vanishing gradient problems even when trained on very long input sequences?

- Alice's model (removing Γ_u), because if $\Gamma_r \approx 0$ for a timestep, the gradient can propagate back through that timestep without much decay.
- Alice's model (removing Γ_u), because if $\Gamma_r \approx 1$ for a timestep, the gradient can propagate back through that timestep without much decay.
- Betty's model (removing Γ_r), because if $\Gamma_u \approx 0$ for a timestep, the gradient can propagate back through that timestep without much decay.
- Betty's model (removing Γ_r), because if $\Gamma_u \approx 1$ for a timestep, the gradient can propagate back through that timestep without much decay.

Expand

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

9. Here are the equations for the GRU and the LSTM: 1 / 1 point

GRU	LSTM
$\tilde{c}^{<t>} = \tanh(W_c[\Gamma_r * c^{<t-1>}, x^{<t>}] + b_c)$	$\tilde{c}^{<t>} = \tanh(W_c[a^{<t-1>}, x^{<t>}] + b_c)$
$\Gamma_u = \sigma(W_u[\, c^{<t-1>}, x^{<t>}] + b_u)$	$\Gamma_u = \sigma(W_u[\, a^{<t-1>}, x^{<t>}] + b_u)$
$\Gamma_r = \sigma(W_r[\, c^{<t-1>}, x^{<t>}] + b_r)$	$\Gamma_f = \sigma(W_f[\, a^{<t-1>}, x^{<t>}] + b_f)$
$c^{<t>} = \Gamma_u * \tilde{c}^{<t>} + (1 - \Gamma_u) * c^{<t-1>}$	$\Gamma_o = \sigma(W_o[\, a^{<t-1>}, x^{<t>}] + b_o)$
$a^{<t>} = c^{<t>}$	$c^{<t>} = \Gamma_u * \tilde{c}^{<t>} + \Gamma_f * c^{<t-1>}$
	$a^{<t>} = \Gamma_o * \tanh c^{<t>}$

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?

- Γ_u and $1 - \Gamma_u$
- Γ_u and Γ_r
- $1 - \Gamma_u$ and Γ_u
- Γ_r and Γ_u

Expand

Correct
Yes, correct!

10. Your 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 $x^{<1>}, \ldots, x^{<365>}$ 1 / 1 point

يعتمد مزاجك بشكل كبير على الطقس الحالي والأيام القليلة الماضية. لقد جمعت بيانات عن آخر 365 يوما عن الطقس، والتي تمثلها كتسلسل ك x. You've also collected data on your mood, which you represent as $y^{<1>}, \ldots, y^{<365>}$. You'd like to build a model to map from x→y. Should you use a Unidirectional RNN or Bidirectional RNN for this problem?

- Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<1>}, \ldots, x^{<t>}$, but not on $x^{<1>}, \ldots, x^{<365>}$.
- Bidirectional RNN, because this allows the prediction of mood on day t to take into account more information.
- Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<t>}$, and not other days' weather.
- Bidirectional RNN, because this allows backpropagation to compute more accurate gradients.

Expand

Correct