Quiz: Recurrent Neural Networks

✓ Congratulations! You passed! Grade Latest Submission received 90% Grade 90%

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 s^{th} words
	in the r^{th} training example?

1/1 point

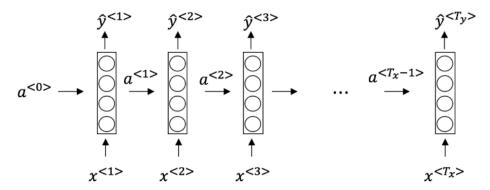
- $\bigcirc x^{< r > (s)}$
- x(r)<s>
- $\bigcirc x^{(s) < r >}$
- $\bigcirc x^{< s > (r)}$



We index into the r^{th} row first to get to the r^{th} training example (represented by parentheses), then the s^{th} column to get to the s^{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

- False
- True

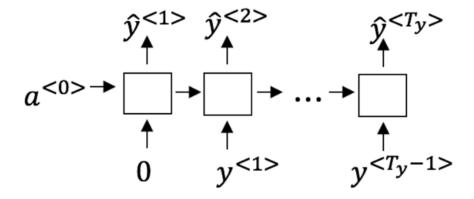


 $\label{lem:correct:this type of architecture is for applications where the input and output sequence length is the same.$

3.	Select the two tasks combination that could be addressed by a many-to-one RNN model architecture from the following:		
	Task 1: Gender recognition from audio. Task 2: Image classification.		
	Task 1: Gender recognition from audio. Task 2: Movie review (positive/negative) classification.		
Task 1: Speech recognition. Task 2: Gender recognition from audio.			
	Task 1: Image classification. Task 2: Sentiment classification.		
	∠ [™] Expand		
	 Correct Gender recognition from audio and movie review classification are two examples of many-to-one RNN architecture 		

4. Using this as the training model below, answer the following:

1/1 point



True/False: At the t^{th} time step the RNN is estimating $P(y^{< t>})$

- False
- True

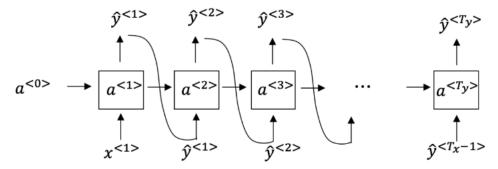
∠ Expand

⊘ Correct

No, in a training model we try to predict the next steps 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:

1/1 point



What are you doing at each time step t?

- (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 $\hat{y}^{<t>}$.(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 $\hat{y}^{< t>}$.(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 $\hat{y}^{< t>}$.(ii) Then pass this selected word to the next time-step.



⊘ Correct

6.	You are training an RNN model, 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?	1/1 point
	Vanishing gradient problem.	
	Exploding gradient problem.	
	The model used the ReLU activation function to compute g(z), where z is too large.	
	The model used the Sigmoid activation function to compute g(z), where z is too large.	
	∠ [≯] Expand	
	⊘ Correct	
7.	Suppose you are training an LSTM. You have an 80000 word vocabulary, and are using an LSTM with 800-dimensional activations $a^{< t>}$. What is the dimension of Γ_u at each time step? $ 8 $ 800 $ 8000 $	1/1 point
	○ 100	
	\bigcirc Correct Correct, Γ_u is a vector of dimension equal to the number of hidden units in the LSTM.	

8.	True/False: In order to simplify the GRU without vanishing gradient problems even when training on very long
	sequences you should remove the Γ_r i.e., setting $\Gamma_r=1$ always.

0/1 point

○ True

False



⊗ Incorrect

No, if Γ upprox0 for a timestep, the gradient can propagate back through that timestep without much decay. 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

LSTM

GRU

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

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

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

$$c^{< t>} = \Gamma_u * \tilde{c}^{< t>} + (1 - \Gamma_u) * c^{< t-1>} \qquad \qquad \Gamma_o = \sigma(W_o[a^{< t-1>}, x^{< t>}] + b_o)$$

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

$$a^{< t>} = \Gamma_o * c^{< t>}$$

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?

- $igotimes \Gamma_u$ and $1-\Gamma_u$
- \bigcap Γ_u and Γ_r
- $\bigcirc \quad 1 \Gamma_u \text{ and } \Gamma_u$
- \bigcap Γ_r and Γ_u



✓ Correct Yes, correct!

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

1/1 point

•	Unidirectional RN on $x^{<1>},\dots,x^{<3}$	N, because the value	e of $y^{< t>}$ dep	ends only on a	$x^{<1>},\ldots,x^{< t}$	>, but not
0	Bidirectional RNN gradients.	l, because this allows	backpropag	ation to comp	ute more accur	ate
0	Unidirectional RN weather.	N, because the value	e of $y^{< t>}$ dep	ends only on a	$x^{< t>}$, and not c	other days'
0	Bidirectional RNN more information	l, because this allows	the prediction	on of mood on	day t to take i	nto account
	∠ ⁿ Expand					

⊘ Correct