Congratulations! You passed!

Grade received 90% **Latest Submission 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} word in the r^{th} training example?

1 / 1 point

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

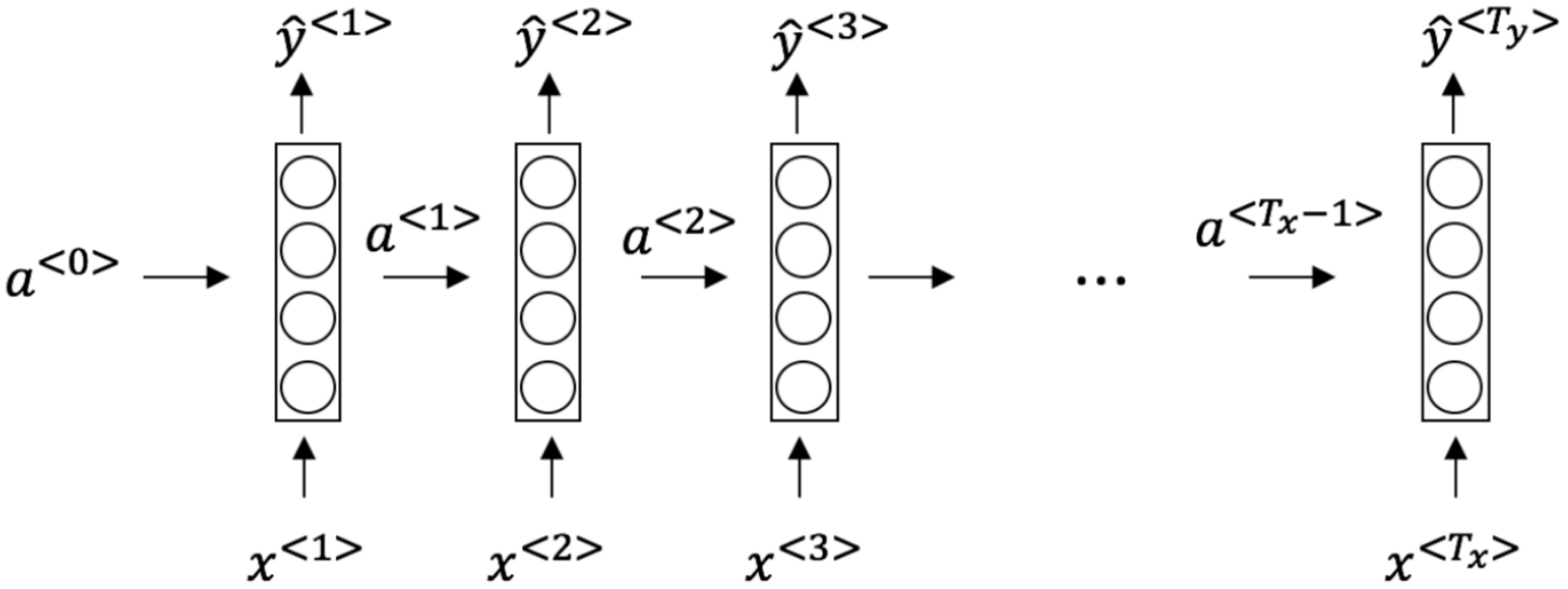
Expand

Correct

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:

0 / 1 point



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

- [x] False
- [ ] True

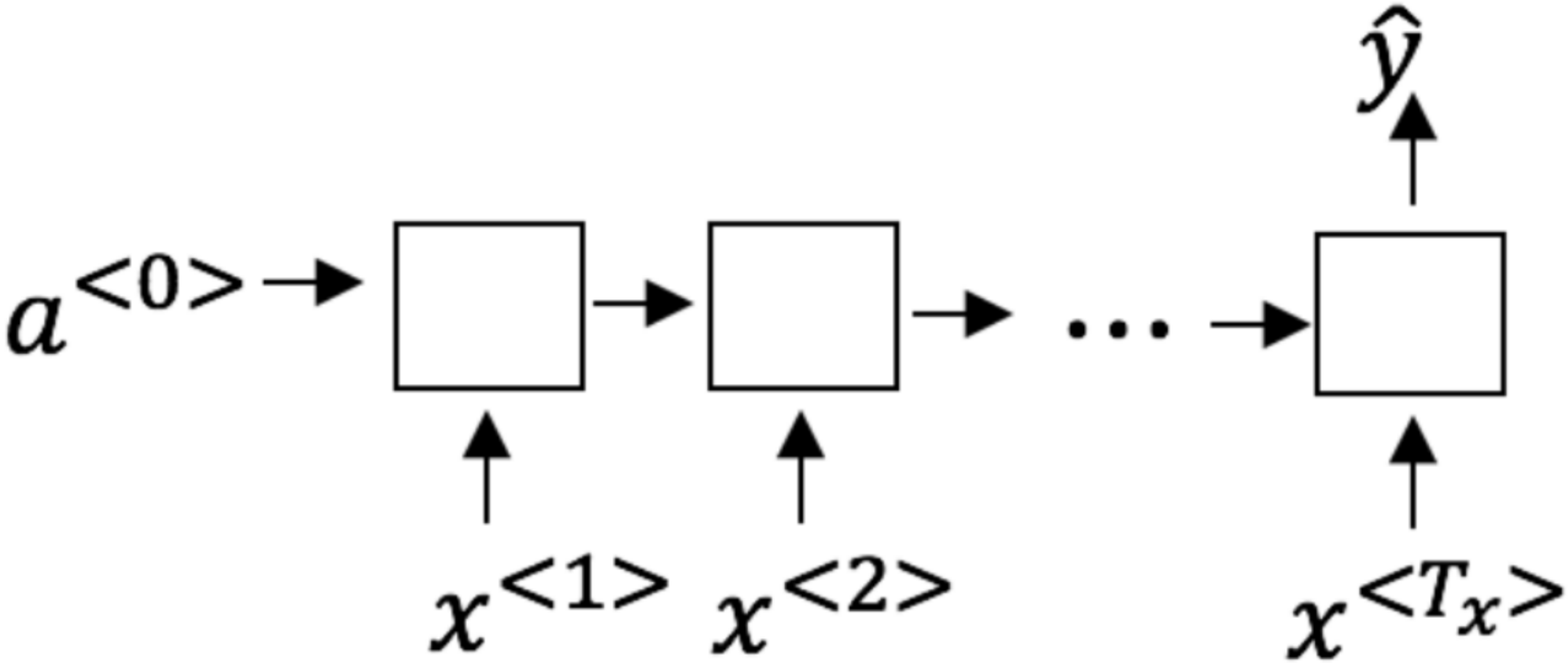
Expand

Incorrect

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?

1 / 1 point



- [ ] Image classification (input an image and output a label)
- [x] Music genre recognition

Correct

This is an example of many-to-one architecture.

- [x] Language recognition from speech (input an audio clip and output a label indicating the language being spoken)

Correct

This is an example of many-to-one architecture.

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

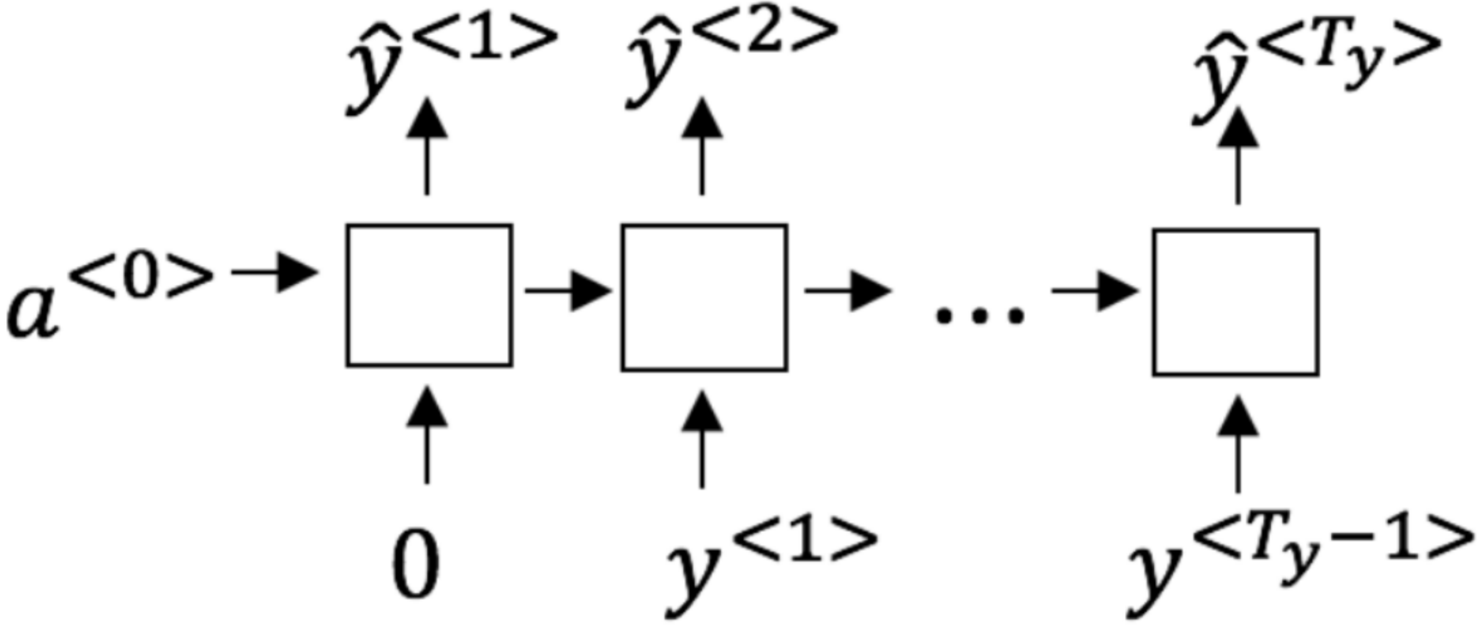
Expand

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 $P(y^{<t>})$
- (•) Estimating $P(y^{<t>} \mid y^{<1>}, y^{<2>}, \ldots, y^{<t-1>})$
- ( ) Estimating $P(y^{<t>} \mid y^{<1>}, y^{<2>}, \ldots, y^{<t>})$

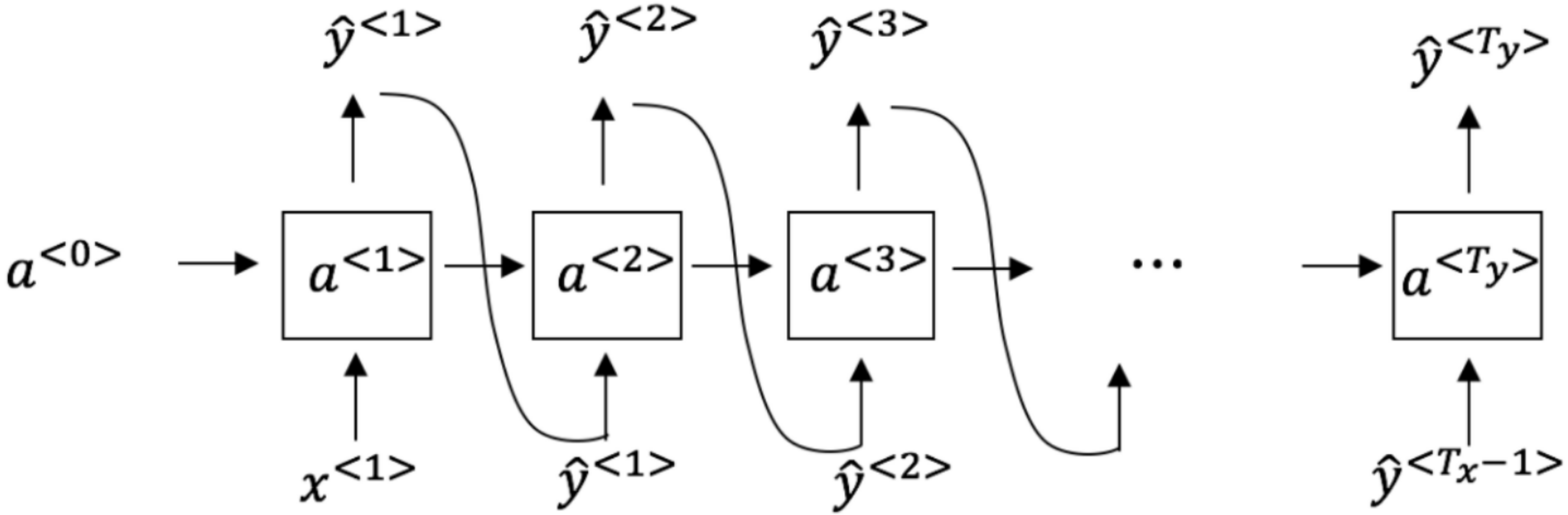
Expand

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:

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.

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

1 / 1 point

- 1
- 100
- 300
- 10000

Expand

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.

1 / 1 point

- [ ] False
- [x] True

Expand

Correct

If Γu≈0 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. True/False: Using the equations for the GRU and LSTM below the Update Gate and Forget Gate in the LSTM play a role similar to 1- Γu and Γu.

1 / 1 point

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

- [ ] True
- [x] False

Expand

Correct

Instead of using Γu to compute 1 - Γu, LSTM uses 2 gates (Γu and Γf) to compute the final value of the hidden state. So, Γf is used instead of 1 - Γu.

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 $x^{<1>}, \ldots, x^{<365>}$. 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 $x \rightarrow y$. Should you use a Unidirectional RNN or Bidirectional RNN for this problem?

1 / 1 point

- ○ Bidirectional RNN, because this allows backpropagation to compute more accurate gradients.
- ○ Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<t>}$, and not other days' weather.
- ◉ 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.

Expand

Correct