Congratulations! You passed!

Grade received 90% **Latest Submission Grade** 90% **To pass** 80% or higher

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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

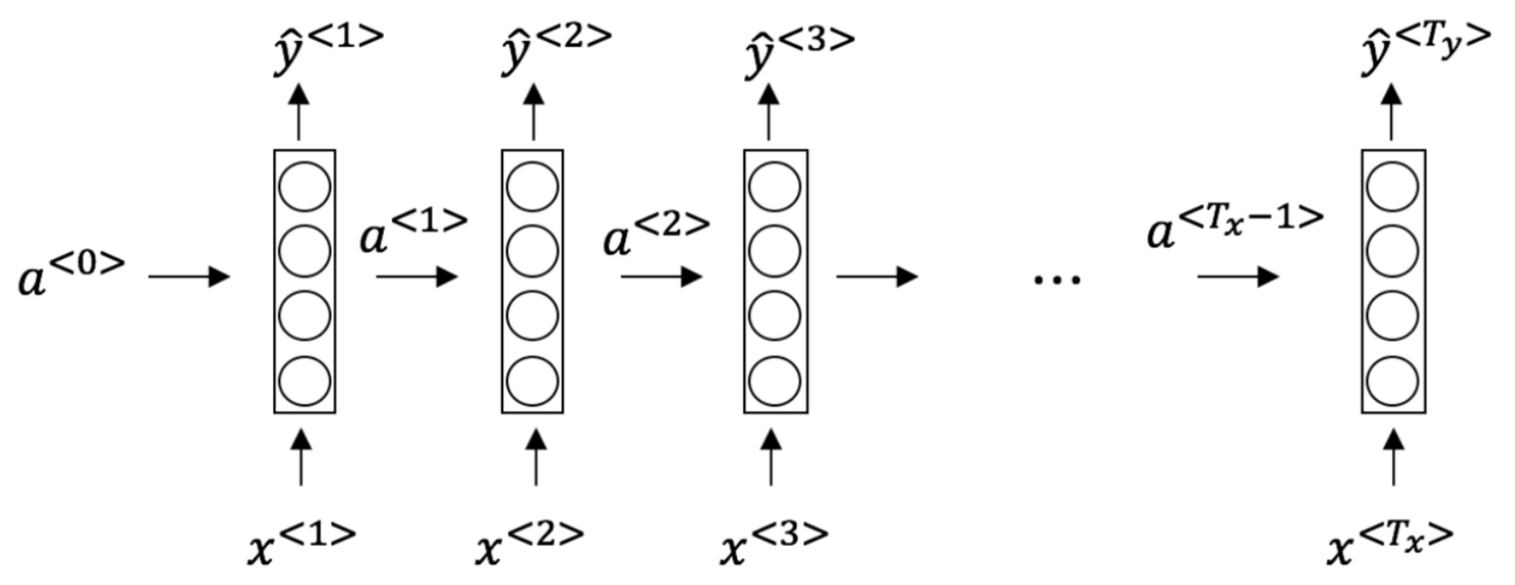
- (selected) $x^{(i)<j>}$
- $x^{<i>(j)}$
- $x^{(j)<i>}$
- $x^{<j>(i)}$

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

- False
- (selected) True

Expand

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

3. Select the two tasks combination that could be addressed by a many-to-one RNN model architecture from the following:

0 / 1 point

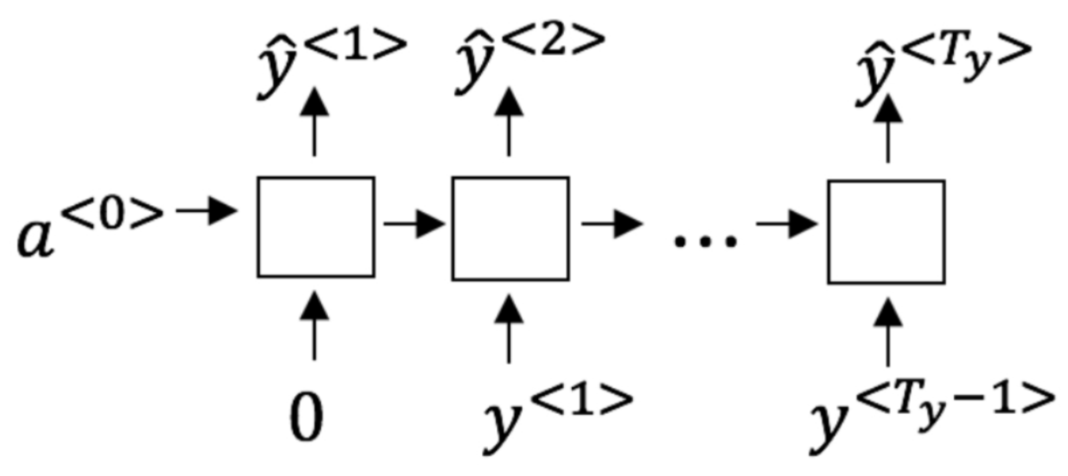
- **Task 1:** Image classification. **Task 2:** Sentiment classification.
- **Task 1:** Gender recognition from audio. **Task 2:** Image classification.
- (selected) **Task 1:** Speech recognition. **Task 2:** Gender recognition from audio.
- **Task 1:** Gender recognition from audio. **Task 2:** Movie review (positive/negative) classification.

Expand

Incorrect
Speech recognition is an example of many-to-many recognition.

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

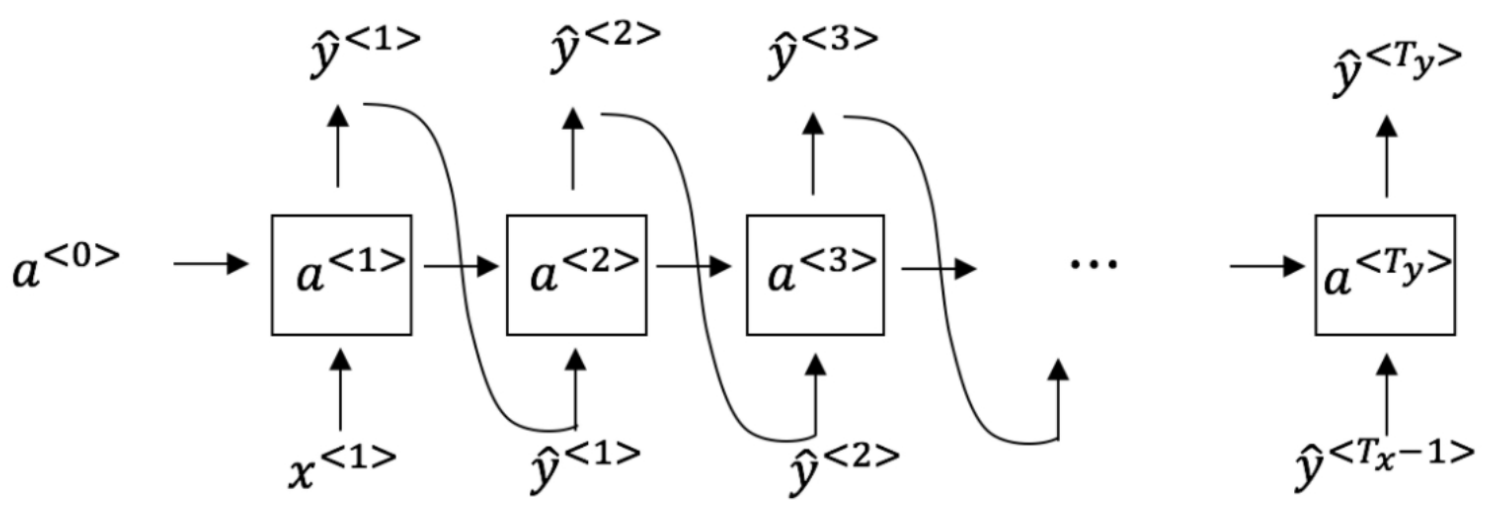
- False

Expand

Correct
Yes, in a training model we try to predict the next step based on 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.

- (selected) True
- False

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
- (selected) 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
- (selected) 100
- 300
- 10000

Expand

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

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

1 / 1 point

GRU

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

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

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

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

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

- Sarah'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.
- Ashely'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.
- Sarah's model (removing
- (selected) Ashely'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.

Expand

Correct
Yes. 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 different role to Γu and 1- Γu.

1 / 1 point

GRU

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

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

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

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

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

LSTM

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

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

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

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

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

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

- False
- (selected) True

Expand

Correct
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→y. Should you use a Unidirectional RNN or Bidirectional RNN for this problem?

1 / 1 point

- Bidirectional RNN, because this allows the prediction of mood on day t to take into account more information.
- (selected) Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<1>}, \ldots, x^{<t>}$, but not on $x^{<1>}, \ldots, x^{<365>}$.
- 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