Your grade: 100%

Your latest: **100%** • Your highest: **100%** • To pass you need at least 80%. We keep your highest score.

Next item

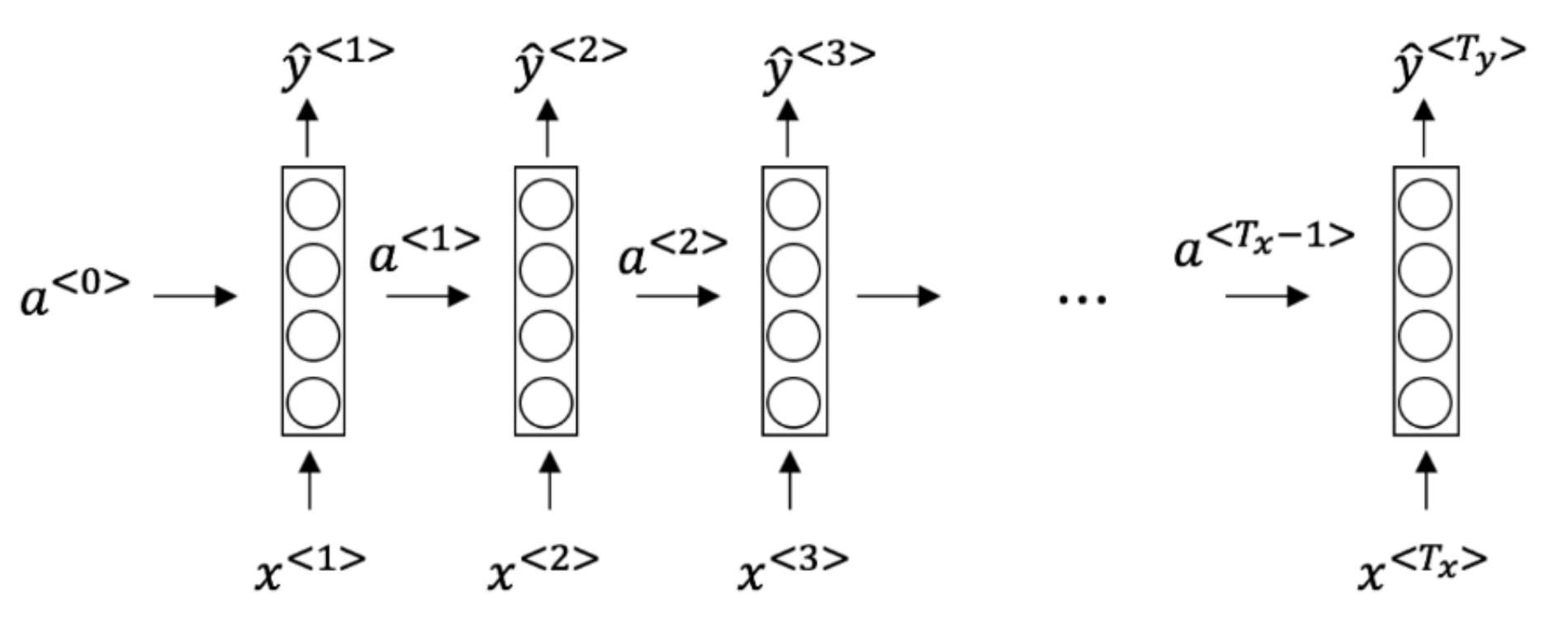
1. Suppose your training examples are sentences (sequences of words). Which of the following refers to the j^{th} word in the i^{th} training example? **1 / 1 point**

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

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

- False
- True

Expand

Correct
Correct! This type of architecture is for applications where the input and output sequence length is the same.

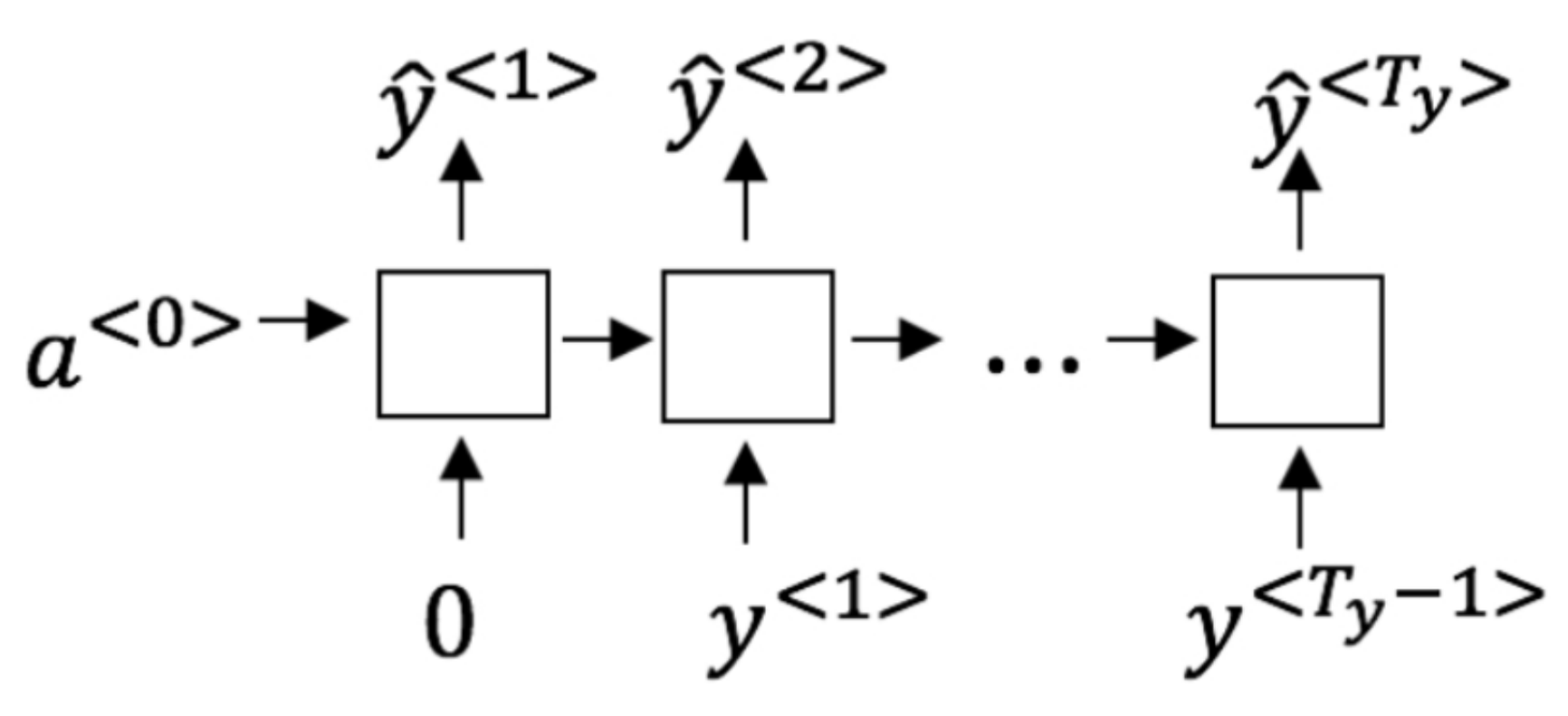
3. Select the two tasks combination that could be addressed by a many-to-one RNN model architecture from the following: **1 / 1 point**

- **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:** Gender recognition from audio. **Task 2:** Image classification.
- **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**



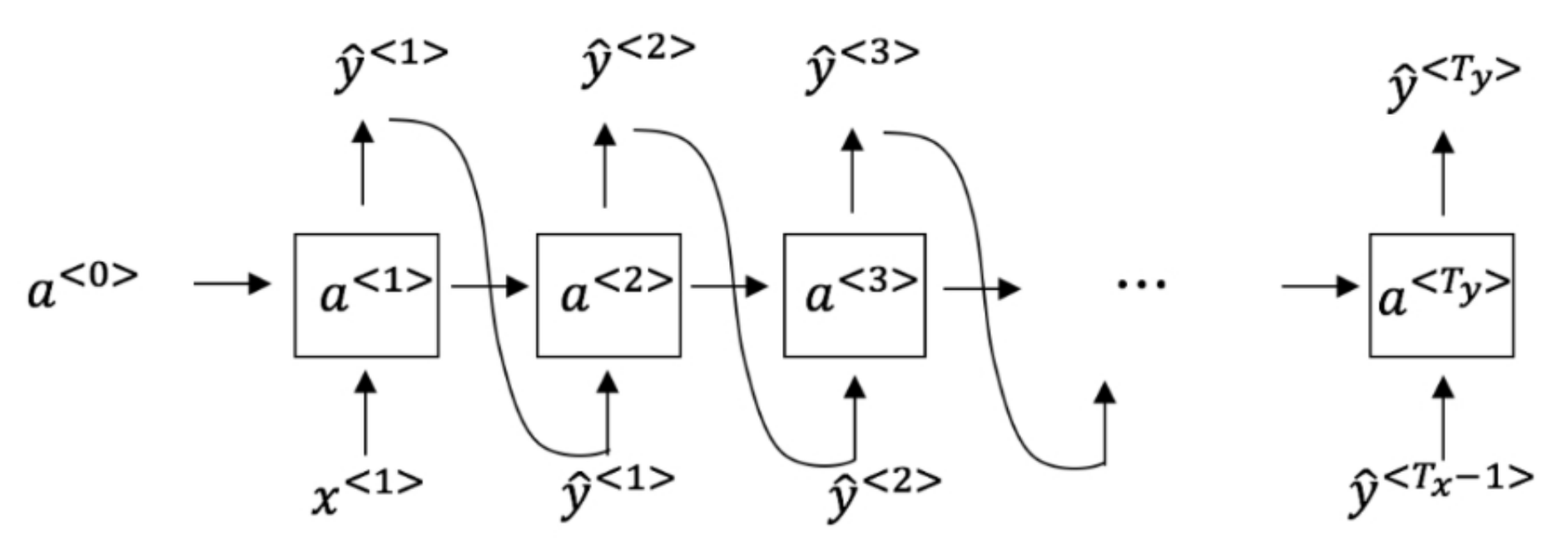
True/False: At the t^{th} time step the RNN is estimating $P(y^{<t>} \mid y^{<1>}, y^{<2>}, \ldots, y^{<t-1>})$

- True
- 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.

- 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 $a^{<t>}$. What is the dimension of Γ_u at each time step? **1 / 1 point**

- 5
- 500
- 200
- 50000

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

- True
- False

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. 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 $x^{<1>}, \ldots, x^{<365>}$. You've also collected data on your dog's mood, which you represent as $y^{<1>}, \ldots, y^{<365>}$. You'd like to build a model to map from $x \to y$. 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.
- Bidirectional RNN, because this allows backpropagation to compute more accurate gradients.
- Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<1>}, \ldots, x^{<t>}$, but not on $x^{<t+1>}, \ldots, x^{<365>}$
- Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<t>}$, and not other days' weather.

Expand

Correct
Yes!