Recurrent Neural Networks
Graded Quiz • 20 min

**Due** August 4, 11:59 PM PDT

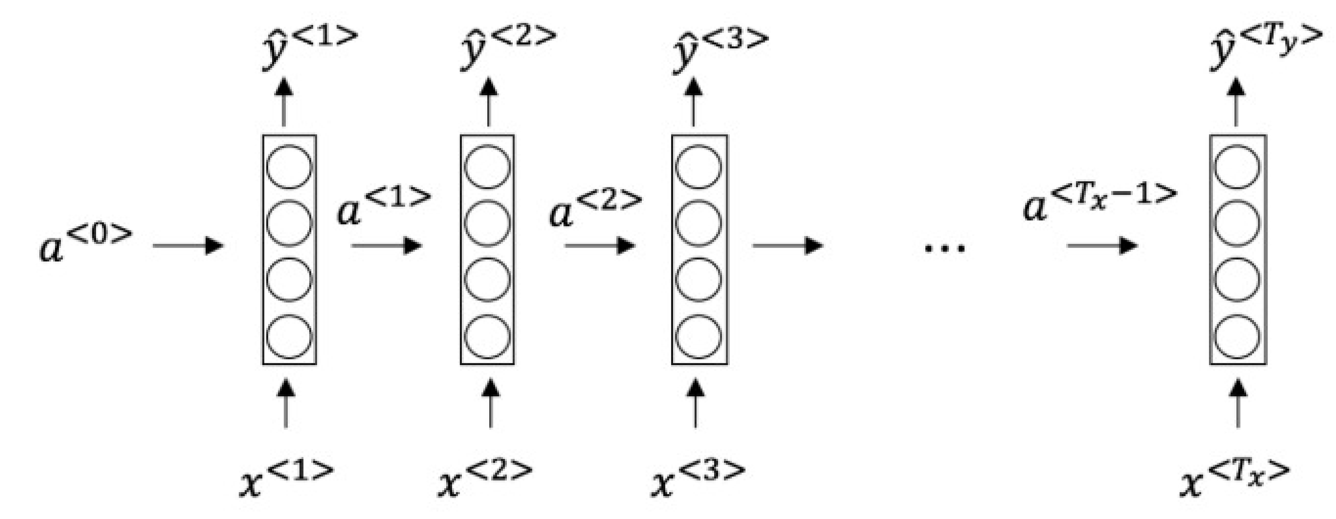
# Recurrent Neural Networks

TOTAL POINTS 10

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 point)

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

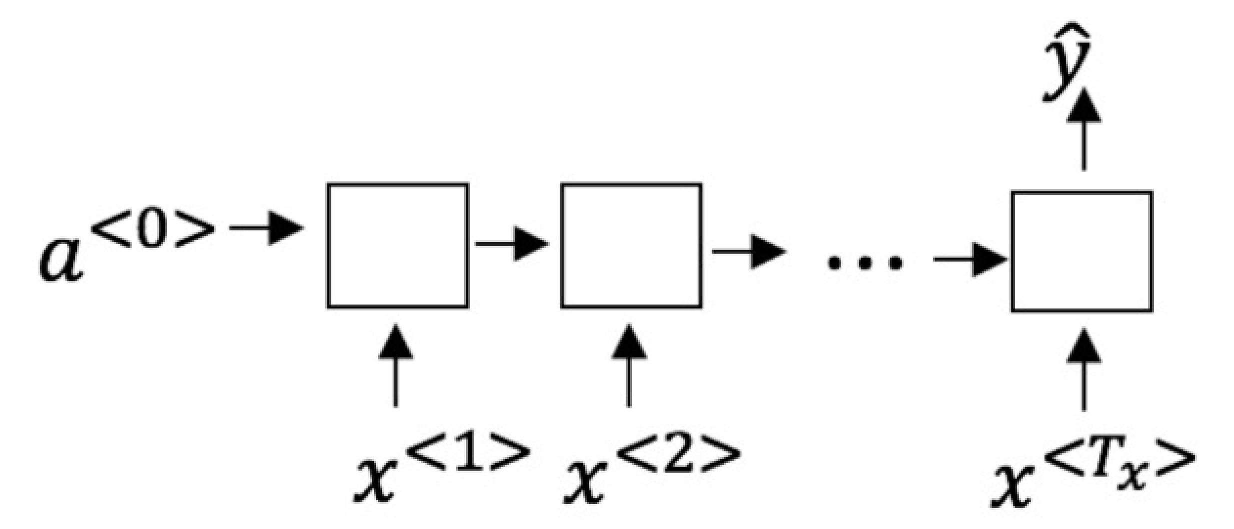
2. **Consider this RNN:** (1 point)




This specific type of architecture is appropriate when:

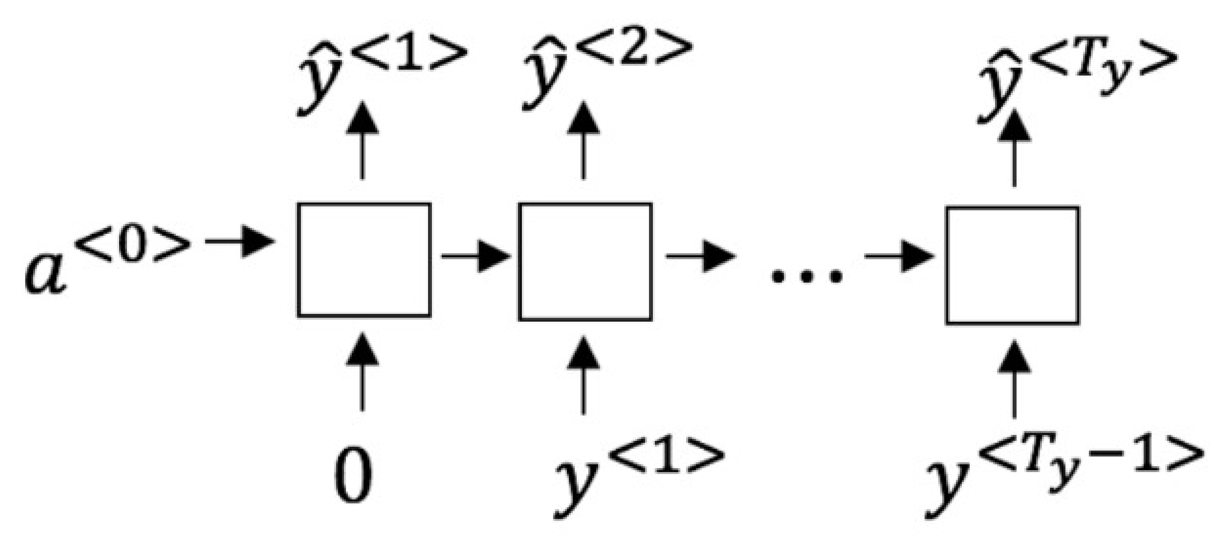
- ( ) $T_x < T_y$
- ( ) $T_x > T_y$
- ( ) $T_x = 1$

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

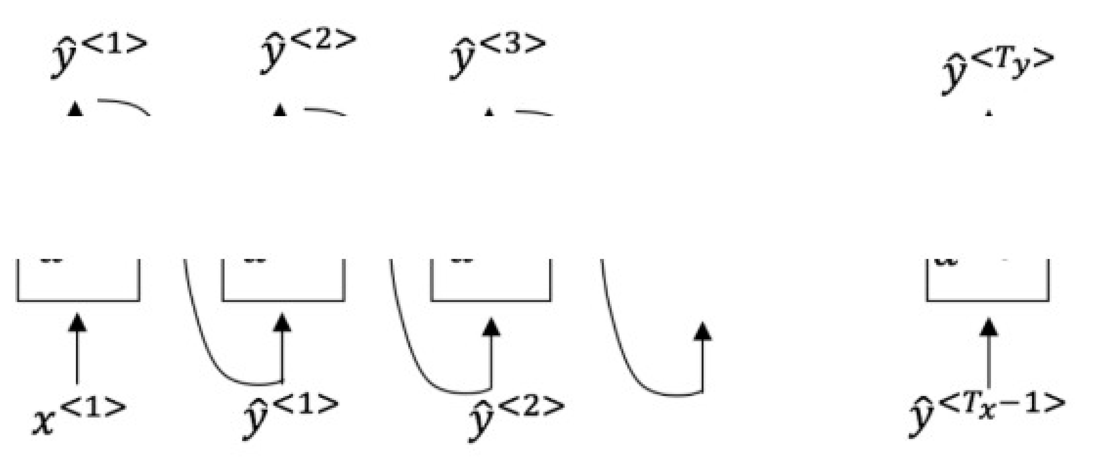
4. **You are training this RNN language model.** (1 point)




**At the $t^{th}$ time step, what is the RNN doing? Choose the best answer.**

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

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

6. **You are training an RNN, 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 point)

- ( ) Vanishing gradient problem.
- (●) Exploding gradient problem.
- ( ) ReLU activation function g(.) used to compute g(z), where z is too large.
- ( ) Sigmoid activation function g(.) used to compute g(z), where z is too large.

7. **Suppose you are training a LSTM. You have a 10000 word vocabulary, and are using an LSTM with 100-dimensional activations $a^{<t>}$. What is the dimension of $\Gamma_u$ at each time step?** (1 point)

- ( ) 300
- ( ) 10000

8. **Here're the update equations for the GRU.** (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 $\Gamma_u$. I.e., setting $\Gamma_u$ = 1. Betty proposes to simplify the GRU by removing the $\Gamma_r$. I. e., setting $\Gamma_r$ = 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 $\Gamma_u$), because if $\Gamma_r \approx 0$ for a timestep, the gradient can propagate back through that timestep without much decay.
- ( ) Alice's model (removing $\Gamma_u$), because if $\Gamma_r \approx 1$ for a timestep, the gradient can propagate back through that timestep without much decay.
- (●) Betty's model (removing $\Gamma_r$), because if $\Gamma_u \approx 0$ for a timestep, the gradient can propagate back through that timestep without much decay.
- ( ) Betty's model (removing $\Gamma_r$), because if $\Gamma_u \approx 1$ for a timestep, the gradient can propagate back through that timestep without much decay.

9. **Here are the equations for the GRU and the LSTM:** (1 point)

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

**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 the blanks?**

- (●) $\Gamma_u$ and $1 - \Gamma_u$
- ( ) $\Gamma_u$ and $\Gamma_r$
- ( ) $1 - \Gamma_u$ and $\Gamma_u$
- ( ) $\Gamma_r$ and $\Gamma_u$

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 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.