Recurrent Neural Networks

Quiz, 10 questions

Congratulations! You passed!

Next Item

0 / 1 point

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?

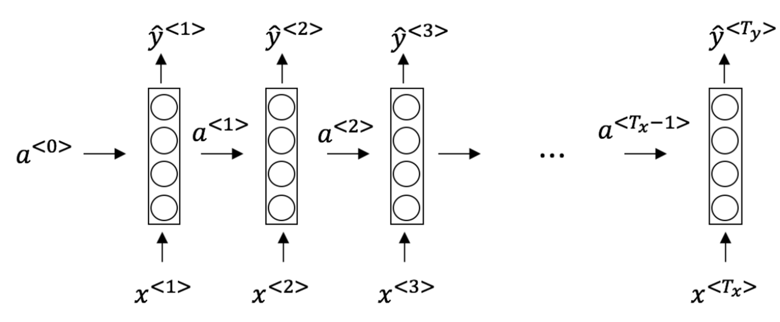
- ( ) $x^{(i)<j>}$
- ( ) $x^{<i>(j)}$
- (x) $x^{(j)<i>}$

This should not be selected
The parentheses represent the training example and the brackets represent the word. You should choose the training example and then the word.

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

1 / 1 point

2. Consider this RNN:



This specific type of architecture is appropriate when:

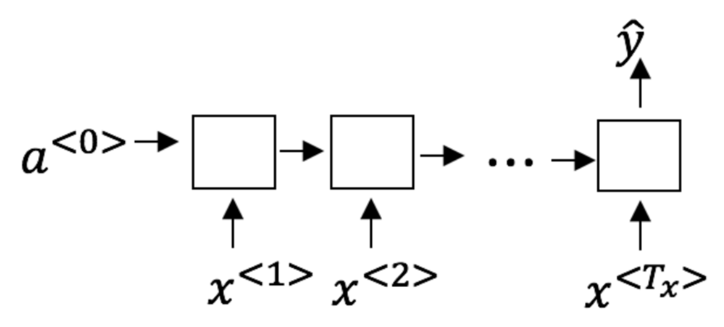
- (x) $T_x = T_y$

Correct
It is appropriate when every input should be matched to an output.

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

1 / 1 point

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



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

Un-selected is correct

- [x] Sentiment classification (input a piece of text and output a 0/1 to denote positive or negative sentiment)

Correct
Correct!

- [ ] Image classification (input an image and output a label)

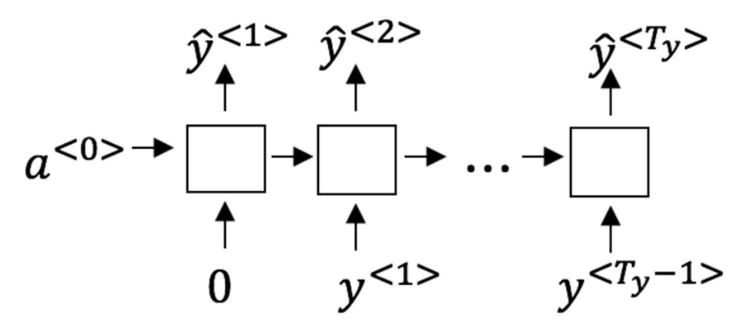
Un-selected is correct

- [x] Gender recognition from speech (input an audio clip and output a label indicating the speaker's gender)

Correct
Correct!

1 / 1 point

4. You are training this RNN language model.



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

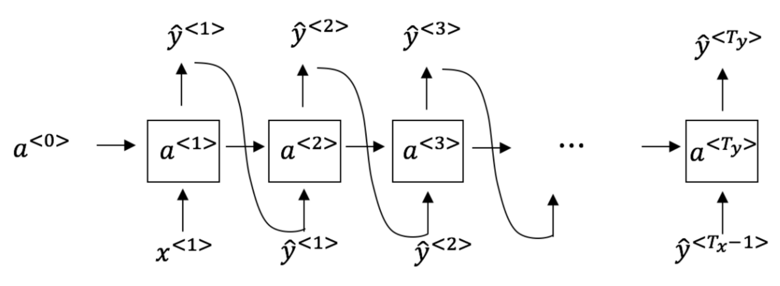
- ( ) Estimating $P(y^{<1>}, y^{<2>}, \dots, y^{<t-1>})$
- ( ) Estimating $P(y^{<t>})$
- (x) Estimating $P(y^{<t>} \mid y^{<1>}, y^{<2>}, \dots, y^{<t-1>})$

Correct
Yes, in a language model we try to predict the next step based on the knowledge of all prior steps.

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

1 / 1 point

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



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.
- (x) (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
Yes!

1 / 1 point

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?

- ( ) Vanishing gradient problem.
- (x) Exploding gradient problem.

Correct

- ( ) 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.

1 / 1 point

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 Γ_u at each time step?

- ( ) 1
- (x) 100

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

- ( ) 300
- ( ) 10000

1 / 1 point

8. Here're the update equations for the GRU.

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 = 1. 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.
- (x) 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.

Correct
Yes. For the signal to backpropagate without vanishing, we need $c^{<t>}$ to be highly dependant on $c^{<t-1>}$.

- ( ) 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.

1 / 1 point

9. Here are the equations for the GRU and the LSTM:

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

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?

- (x) Γ_u and $1 - \Gamma_u$

Correct
Yes, correct!

- ( ) Γ_u and Γ_r
- ( ) $1 - \Gamma_u$ and Γ_u
- ( ) Γ_r and Γ_u

1 / 1 point

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 $x^{<1>}, \dots, x^{<365>}$. You've also collected data on your dog's mood, which you represent as $y^{<1>}, \dots, y^{<365>}$. 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?

- ( ) 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.
- (x) Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<1>}, \dots, x^{<t>}$, but not on $x^{<t+1>}, \dots, x^{<365>}$

Correct
Yes!

- ( ) Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<t>}$, and not other days' weather.