Recurrent Neural Network

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Recurrent Neural Networks

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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

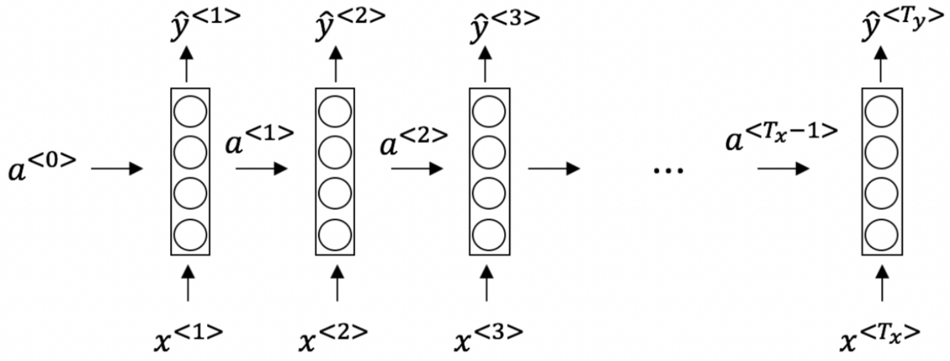
- ○ $x^{(s)<r>}$
- ○ $x^{<s>(r)}$
- ○ $x^{<r>(s)}$
- ◉ $x^{(r)<s>}$

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:

1 / 1 point



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

- False
- True

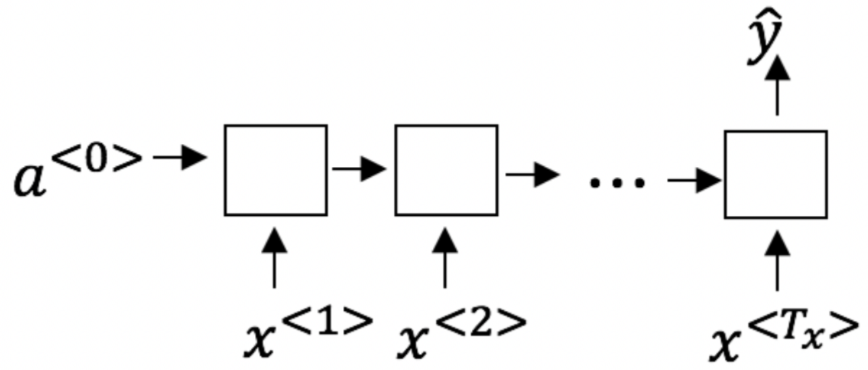
Expand

Correct

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)

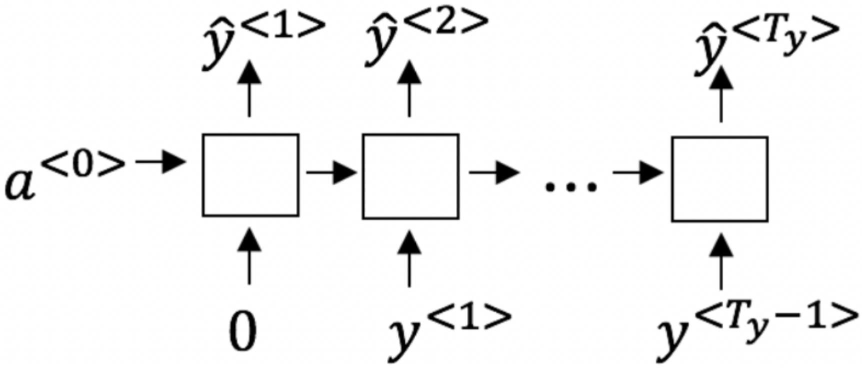
✓ **Correct**

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

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

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 $P(y^{<t>})$

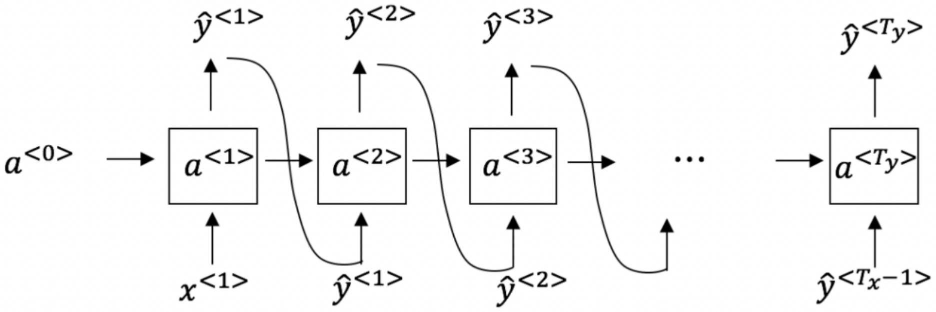
- False
- True

Expand

Correct
No, in a training model we try to predict the next steps 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 pick the highest probability word for that time-step. Then it passes the ground-truth word from the training set to the next time-step.

- (selected) False
- True

Expand

Correct
The probabilities output by the RNN are not used to pick the highest probability word and the ground-truth word from the training set is not the input to the next time-step.

6. You are training an RNN model, 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 / 1 point

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

Expand

Correct

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

- ○ 50000
- ◉ 500
- ○ 5
- ○ 200

Expand

Correct

Correct, Γ_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 $\Gamma_r \approx 1$ for a timestep, the gradient can propagate back through that timestep without much decay.
- ◉ Ashely's model (removing Γ_r), because if $\Gamma_u \approx 0$ 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 Γ_u), because if $\Gamma_r \approx 0$ 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 dependent on $c^{<t-1>}$.

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

1 / 1 point

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

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 blanks?

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

Expand

Correct
Yes, correct!

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!