Recurrent Neural Networks

Quiz, 10 questions

8/10 points (80%)

Congratulations! You passed!

Next Item

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points

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?

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

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).

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

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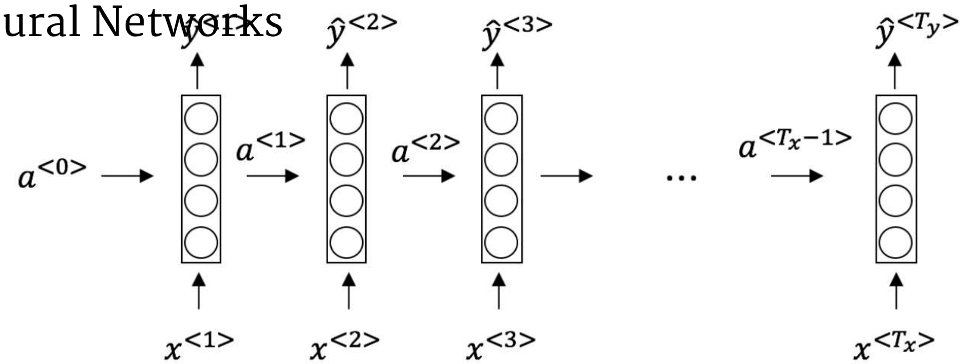
points

2.

Consider this RNN:



This specific type of architecture is appropriate when:

- ( ) $T_x = T_y$

Correct

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

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

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points

3.

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

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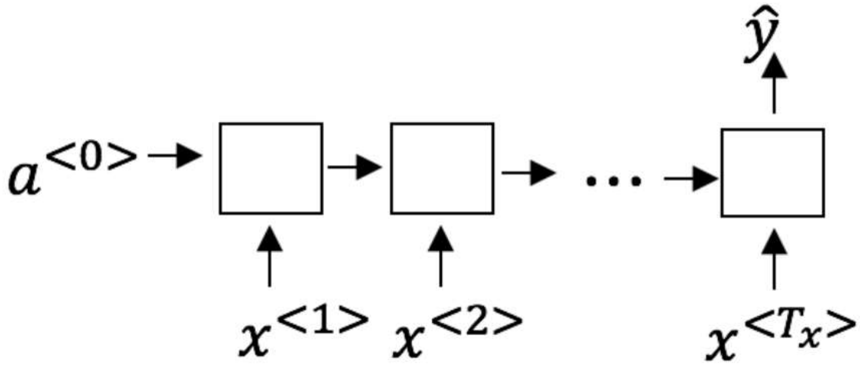

- [ ] Speech recognition (input an audio clip and output a transcript)

Un-selected is correct

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

Correct

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

Un-selected is correct

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

Correct

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1 / 1 points

4.

You are training this RNN language model.

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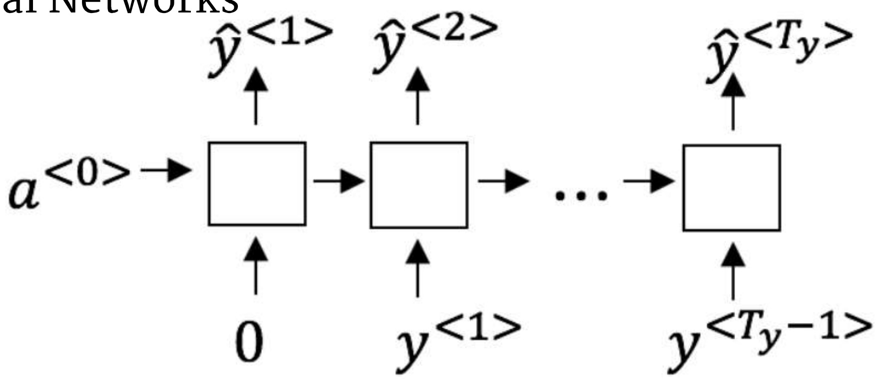


At the t^{th} time step, what is the RNN doing? Choose the best answer.

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

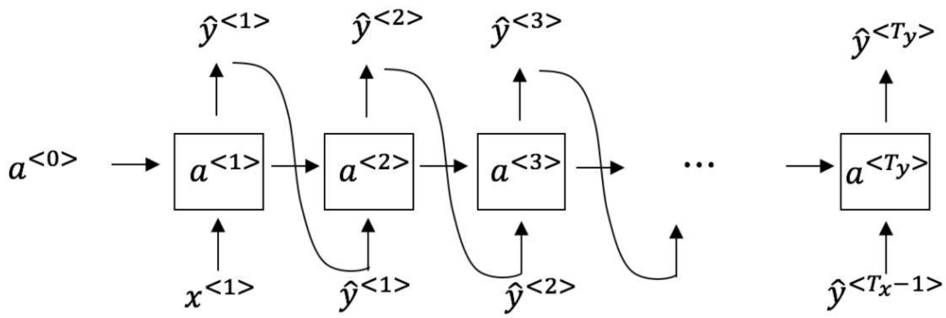
Correct

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

✖ 0 / 1 points

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.

This should not be selected
The ground-truth word from the training set is not the input 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.

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0 / 1
points

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.

This should not be selected

Vanishing and exploding gradients are common problems in training RNNs, but in the case of this problem, your weights and activations taking on the value of NaN implies one of the two.

- 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.

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1 / 1 points

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
- 100

Correct

- 300
- 10000

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1 / 1 points

8.

Here're the update equations for the GRU.

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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.
- 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

- 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.

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1 / 1
points

9.

Here are the equations for the GRU and the LSTM:

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

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

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

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

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

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

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

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?

- ◯ Γ_u and $1 - \Gamma_u$

Correct

- ◯ Γ_u and Γ_r
- ◯ $1 - \Gamma_u$ and Γ_u
- ◯ Γ_r and Γ_u

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1 / 1
points

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 $x \rightarrow y$. 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 $x^{<1>}, \ldots, x^{<t>}$, but not on $x^{<t+1>}, \ldots, x^{<365>}$

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Correct

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