

Congratulations! You passed!

TO PASS 80% or higher

Keep Learning

GRADE
100%

Recurrent Neural Networks

LATEST SUBMISSION GRADE

100%

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

☒ $x^{(i)<j>}$

☐ $x^{<i>(j)}$

☐ $x^{(j)<i>}$

☐ $x^{<j>(i)}$

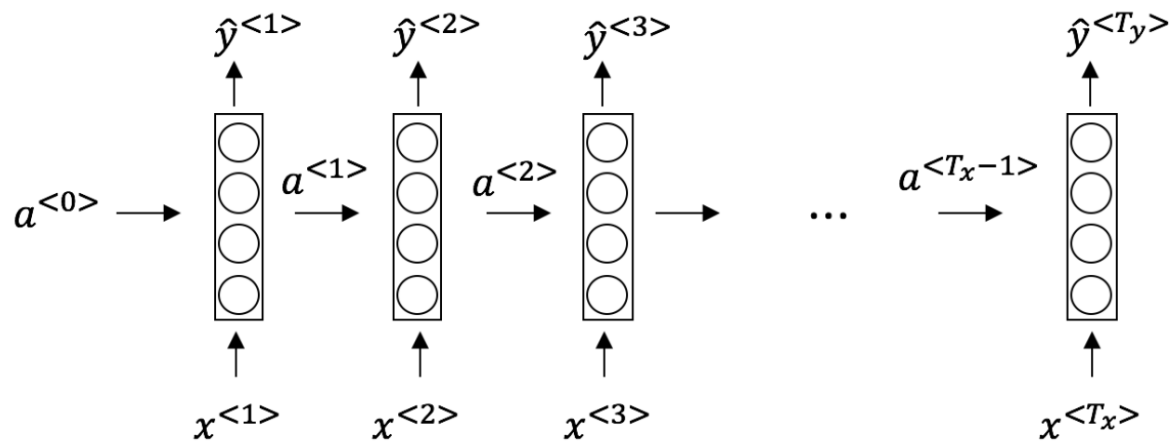
✓ **Correct**

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.

1 / 1 point

Consider this RNN:



This specific type of architecture is appropriate when:

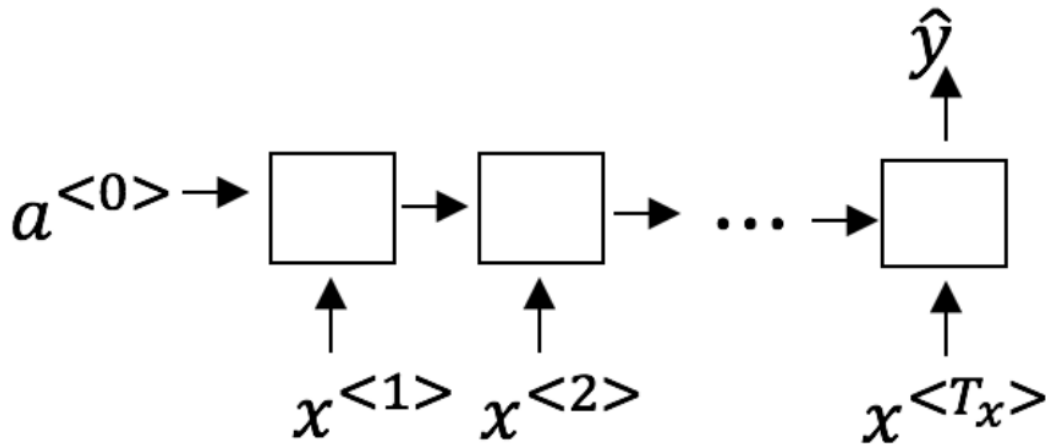
- ☒ $T_x = T_y$
- ☐ $T_x < T_y$
- ☐ $T_x > T_y$
- ☐ $T_x = 1$



Correct

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

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



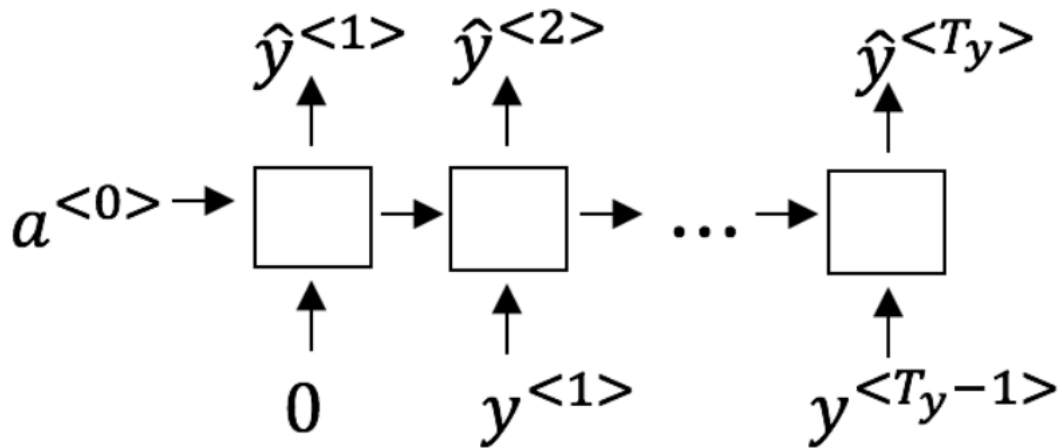
- ☐ Speech recognition (input an audio clip and output a transcript)
- ☒ Sentiment classification (input a piece of text and output a 0/1 to denote positive or negative sentiment)

✓ **Correct**
Correct!

- ☐ Image classification (input an image and output a label)
- ☒ Gender recognition from speech (input an audio clip and output a label indicating the speaker's gender)

✓ **Correct**
Correct!

You are training this RNN language model.



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

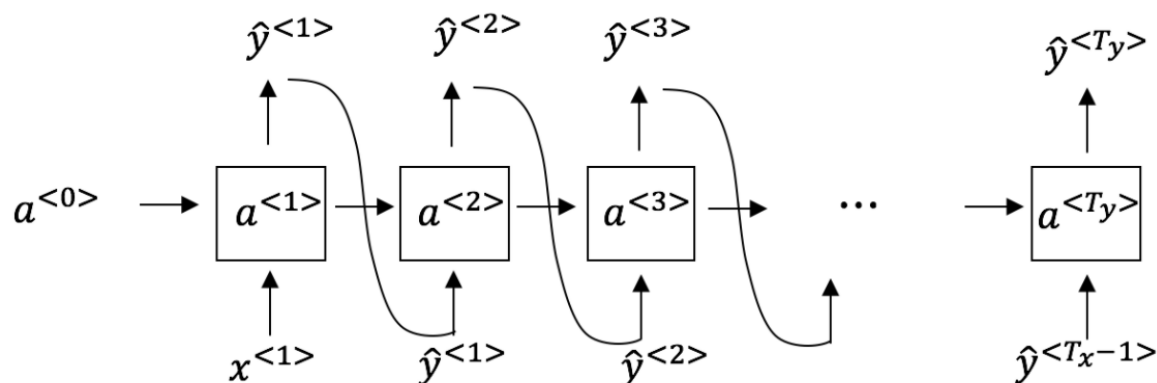
- ☐ Estimating $P(y^{<1>}, y^{<2>}, \dots, y^{<t-1>})$
- ☐ Estimating $P(y^{<t>})$
- ☒ Estimating $P(y^{<t>} \mid y^{<1>}, y^{<2>}, \dots, y^{<t-1>})$
- ☐ Estimating $P(y^{<t>} \mid y^{<1>}, y^{<2>}, \dots, y^{<t>})$



Correct

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

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.
- ☒ (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!

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 / 1 point

- ☐ Vanishing gradient problem.
- ☒ Exploding gradient problem.
- ☐ ReLU activation function $g(\cdot)$ used to compute $g(z)$, where z is too large.
- ☐ Sigmoid activation function $g(\cdot)$ used to compute $g(z)$, where z is too large.

✓ **Correct**

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 / 1 point

- ☐ 1
- ☒ 100
- ☐ 300
- ☐ 10000



Correct

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

8. Here're 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 $\Gamma_u = 1$. Betty proposes to simplify the GRU by removing the Γ_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 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.

 **Correct**

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

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

1 / 1 point

GRU

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

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

$$\Gamma_r = \sigma(W_r[c^{<t-1>}, x^{<t>}] + b_r)$$

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

$$a^{<t>} = c^{<t>}$$

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

 **Correct**

Yes, correct!

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 $x \rightarrow y$. 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.
- ☒ Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<1>}, \dots, x^{<t>}$, but not on $x^{<t+1>}, \dots, x^{<365>}$
- ☐ Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<t>}$, and not other days' weather.

✓ **Correct**
Yes!