# Recurrent Neural Networks

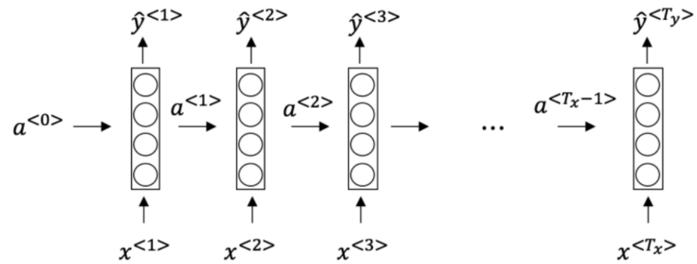
1. Suppose your training examples are sentences (sequences of words). Which of the following refers to the $j^{th}$ word in the $i^{th}$ training example?

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

   1 point

2. Consider this RNN:

   1 point



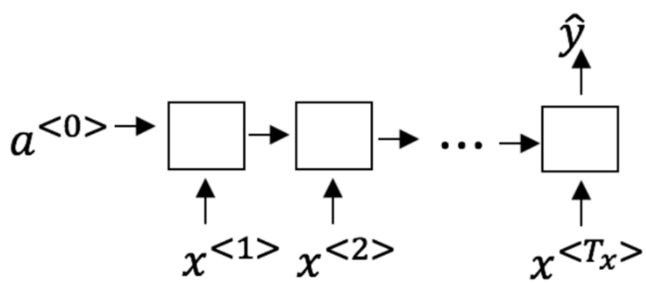

   This specific type of architecture is appropriate when:

   - ○ $T_x = T_y$
   - ○ $T_x < T_y$
   - ○ $T_x > T_y$
   - ○ $T_x = 1$



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

   1 point

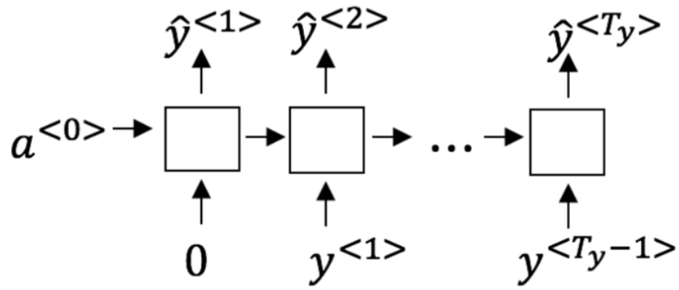



   - ☐ Speech recognition (input an audio clip and output a transcript)
   - ☐ Sentiment classification (input a piece of text and output a 0/1 to denote positive or negative sentiment)

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

4. You are training this RNN language model.

1 point



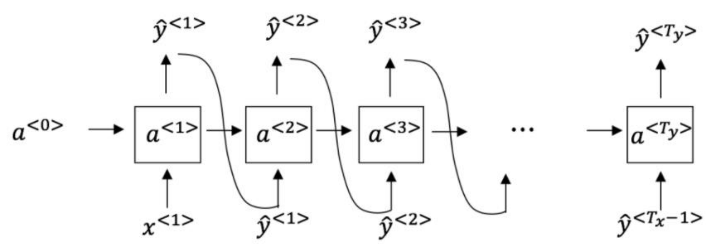

At the $t^{th}$ time step, what is the RNN doing? Choose the best answer.

- ◯ 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

- 1
- 100
- 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 |
| --- | --- |
| $\tilde{c}^{<t>} = \tanh(W_c[\Gamma_r * c^{<t-1>}, x^{<t>}] + b_c)$ | $\tilde{c}^{<t>} = \tanh(W_c[a^{<t-1>}, x^{<t>}] + b_c)$ |
| $\Gamma_u = \sigma(W_u[\, c^{<t-1>}, x^{<t>}] + b_u)$ | $\Gamma_u = \sigma(W_u[\, a^{<t-1>}, x^{<t>}] + b_u)$ |

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

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

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

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

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

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

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

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?

- $\Gamma_u$ 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.



1. $x^{(i)<j>}$
2. $T_x = T_y$
3. 
   a. Sentiment classification(input a piece of text and output 0/1 to denote positive or negative sentiment)
   b. Gender recognition from speech(input an audio clip and output a label indicating the speaker's gender)
4. Estimating P($y^{<t>} \mid y^{<1>}, \ldots, y^{<t-1>}$)
5. (i) Use the probabilties 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. Exploding gradient problem
7. 100
8. 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.
9. $\Gamma_u$ and $\Gamma_{1-u}$
10. Unidierectional RNN, because the value of $y^{<t>}$ depends only on $x^{<1>}, \ldots, x^{<t>}$, but not $x^{<t+1>}, \ldots, x^{<365>}$