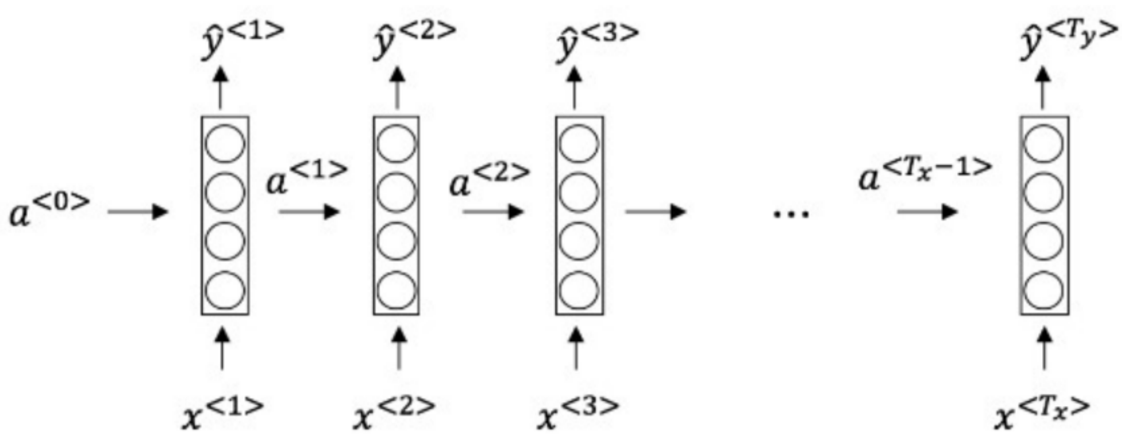
Week 1 Quiz - Recurrent Neural Networks

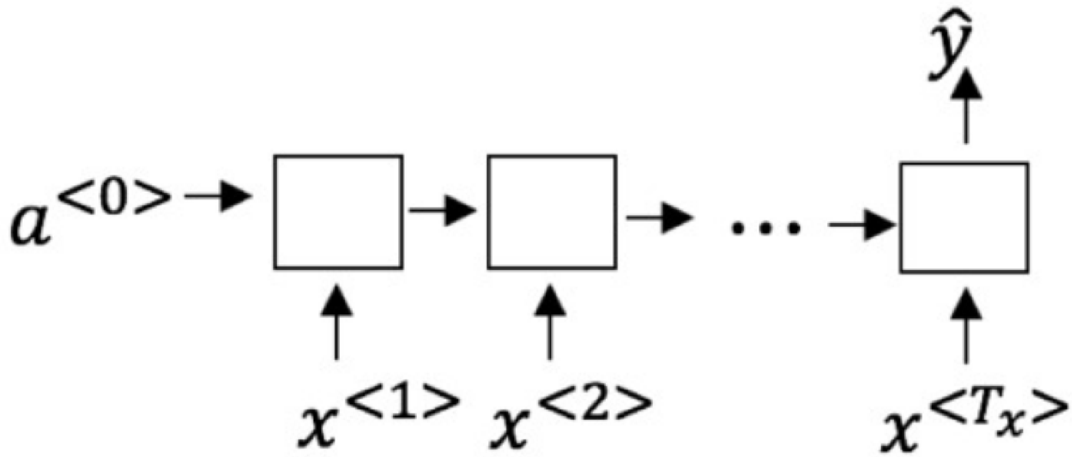
1. Suppose your training examples are sentences (sequences of words). Which of the following refers to the j^{th} word in the i^{th} training example?
   - [x] $x^{(i)<j>}$

   > We index into the i-th row first to get the ith training example (represented by parentheses), then the j-th column to get the jth word (represented by the brackets).

   - [ ] $x^{<i>(j)}$
   - [ ] $x^{(j)<i>}$
   - [ ] $x^{<j>(i)}$
2. Consider this RNN:

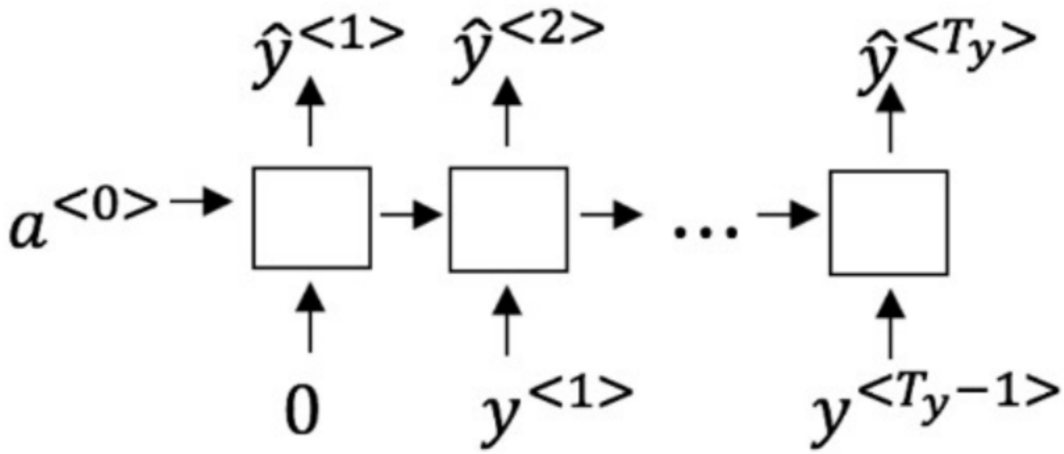


   This specific type of architecture is appropriate when:
   - [x] $T_x = T_y$
   - [ ] $T_x < T_y$
   - [ ] $T_x > T_y$
   - [ ] $T_x = 1$
3. To which of these tasks would you apply a many-to-one RNN architecture? (Check all that apply).



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

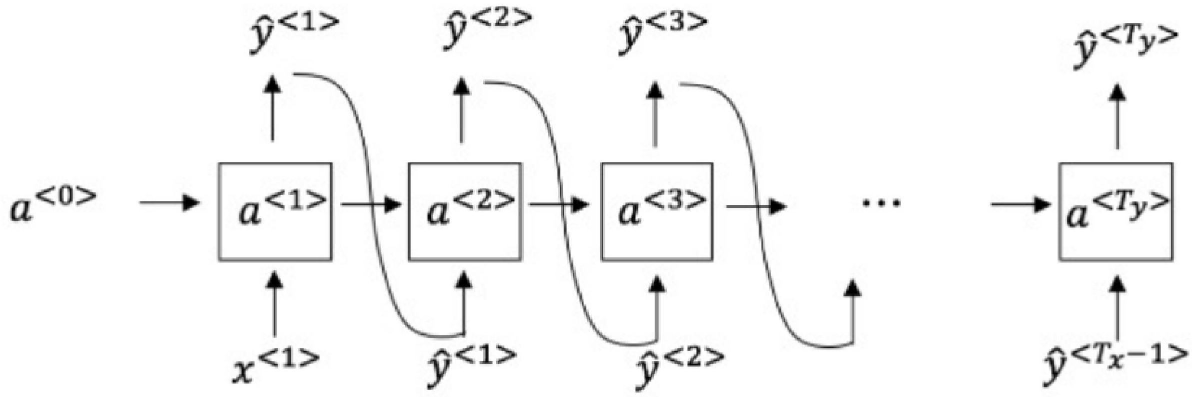
4. You are training this RNN language model.



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

- [ ] Estimating $P(y^{<1>}, y^{<2>}, \ldots, y^{<t-1>})$
- [x] Estimating $P(y^{<t>} \mid y^{<1>}, y^{<2>}, \ldots, y^{<t-1>})$
- [ ] Estimating $P(y^{<t>})$
- [ ] 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:



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?
   - ☐ Vanishing grdient 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 Γ_u at each time step?
   - ☐ 1
   - ☑ 100
   - ☐ 300
   - ☐ 10000
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 Γu. I.e., setting Γu = 1. Betty 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?

- [ ] Alice's model (removing Γu), because if $\Gamma r \approx 0$ for a timestep, the gradient can propagate back through that timestep without much decay.
- [ ] Alice's model (removing Γu), 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 Γr), because if $\Gamma u \approx 0$ for a timestep, the gradient can propagate back through that timestep without much decay.
- [ ] Betty's model (removing Γr), 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:

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?

- [x] Γu and $1-\Gamma u$
- [ ] Γu and Γr
- [ ] $1-\Gamma u$ and Γu
- [ ] Γr and $1-\Gamma u$

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→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 $x^{<t+1>}, \ldots, x^{<365>}$
    - [ ] Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<t>}$, and not other day's weather.