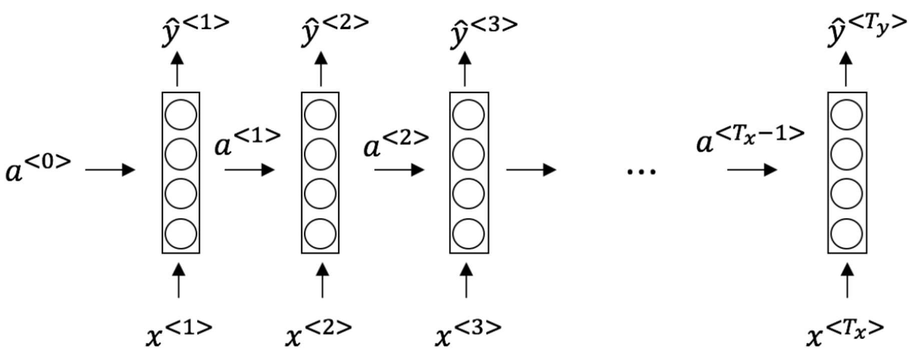
C5W1-Quiz-Recurrent-Neural-Networks

1. Suppose your training examples are sentences (sequences of words). Which of the following refers to the *jth* word in the *ith* training example?

   - [x] ~~*x(i)<j>*~~
   - [ ] ***x<i>(j)***
   - [ ] ***x(j)<i>***
   - [ ] ***x<j>(i)***

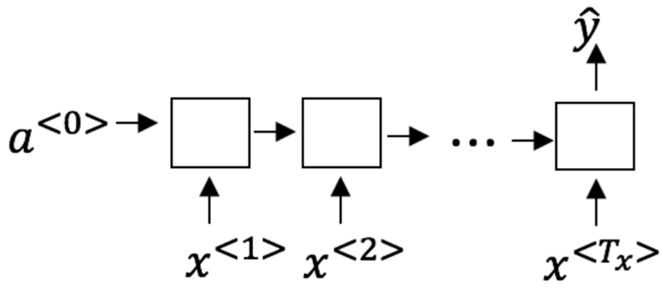
2. Consider this RNN:

   This specific type of architecture is appropriate when:

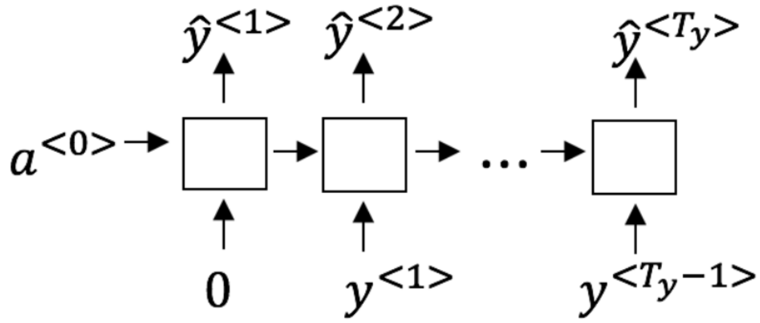
   - [x] ~~*Tx=Ty*~~
   - [ ] ***Tx<Ty***
   - [ ] ***Tx>Ty***
   - [ ] ***Tx=1***

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 output 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)**~~

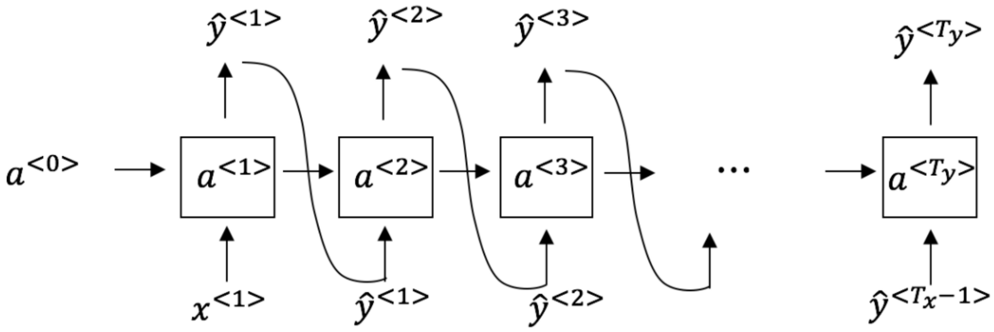
4. You are training this RNN language model.



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

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



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 *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 *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 *y*^<*t*>. (ii) Then pass this selected word to the next time-step.**
- [x] ~~**(i) Use the probabilities output by the RNN to randomly sample a chosen word for that time-step as *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 gradient problem.**
- [x] ~~**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**

- [x] ~~100~~
- [ ] **300**
- [ ] **10000**

8. Here're the update equations for the GRU.

$$\text{GRU}$$

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

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

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

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

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

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	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?

- [x] ~~Γ*u* and 1−Γ*u*~~
- [ ] **Γ*u* and Γ*r***
- [ ] **1−Γ*u* and Γ*u***
- [ ] **Γ*r* and Γ*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>,…,*x*<365>. You've also collected data on your dog's mood, which you represent as *y*<1>,…,*y*<365>. You'd like to build a model to map from x \rightarrow y*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>,…,*x*<*t*>, but not on *x*<*t*+1>,…,*x*<365>~~
- [ ] **Unidirectional RNN, because the value of *y*<*t*> depends only on x^{<t>}*x*<*t*>, and not other days' weather.**