EAI6080 Week 5 Assignment (Week 4 Supplement)

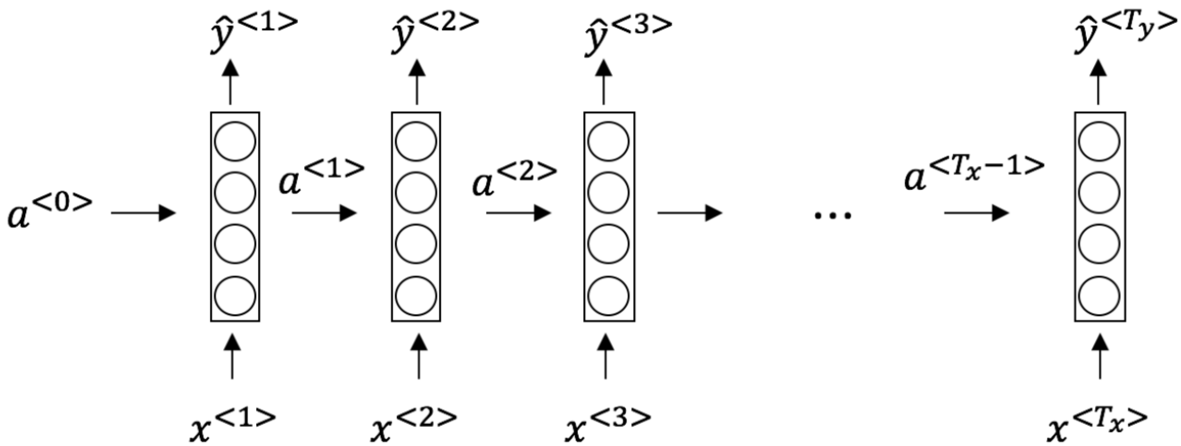
NAME:

Date:

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?

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

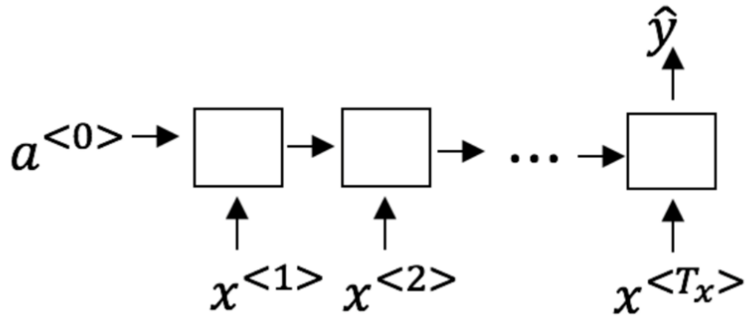
2. Consider this RNN:



This specific type of architecture is appropriate when:

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

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



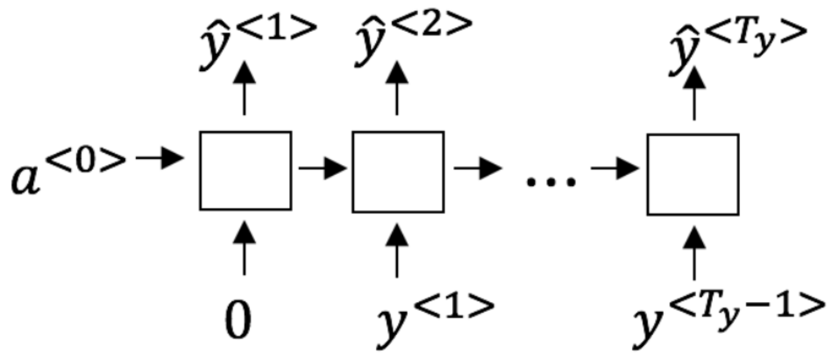
☐ Speech recognition (input an audio clip and output a transcript)

☑ 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.



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

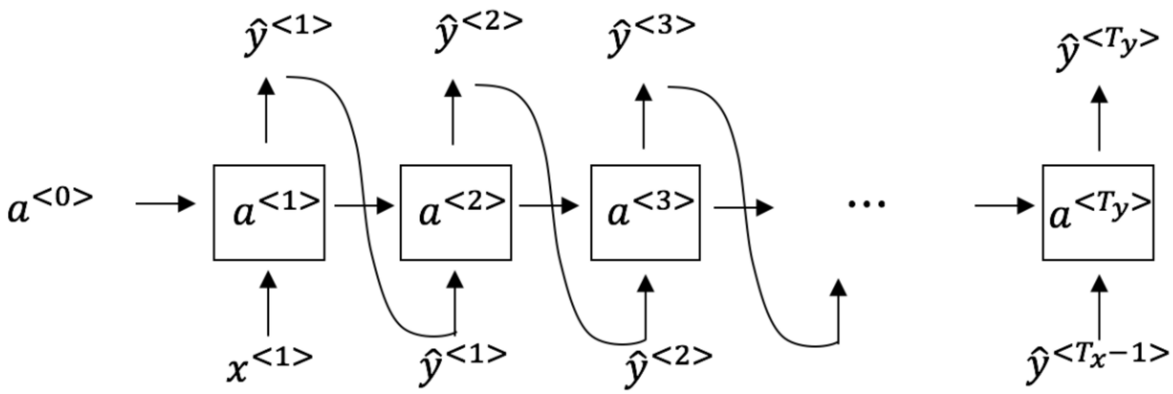
○ Estimating $P(y^{<1>},y^{<2>},\ldots,y^{<t-1>})$

○ Estimating $P(y^{<t>})$

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

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

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 tt?

- (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.
- **(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.** **TRUE**

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.
- **Exploding gradient problem.** **TRUE**
- 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. 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 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. TRUE**
- Betty’s model (removing \Gamma_rΓ_r), because if \Gamma_u \approx 1$\Gamma_u \approx 1$ for a timestep, the gradient can propagate back through that timestep without much decay.

8. 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 blanks?

- [x] **Γ_u and 1-1−Γ_u** **TRUE**
- [ ] Γ_u and Γ_r
- [ ] 1-Γ_u and Γ_u
- [ ] Γ_r and Γ_u

9. 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.
- [x] **Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<1>},\dots,x^{<t>}$, but not on $x^{<t+1>},\dots,x^{<365>}$** **TRUE**
- [ ] Unidirectional RNN, because the value of $y^{<t>}$ depends only on $x^{<t>}$, and not other days' weather.