**Recurrent Neural Networks**
Total points 10

**Question 1**

**Suppose your training examples are sentences (sequences of words). Which of the following refers to the jthj^{th}jth word in the ithi^{th}ith training example?**

**x^{(i)<j>}**

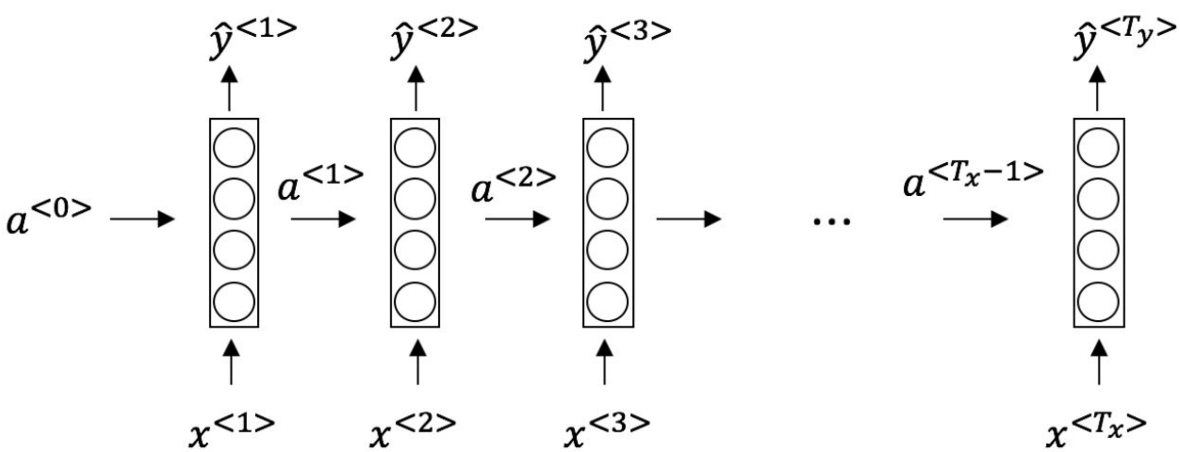
x^{<i>(j)}

x^{(j)<i>}

x^{<j>(i)}

**Question 2**

**Consider this RNN:**




**This specific type of architecture is appropriate when:**

**Tx=Ty**

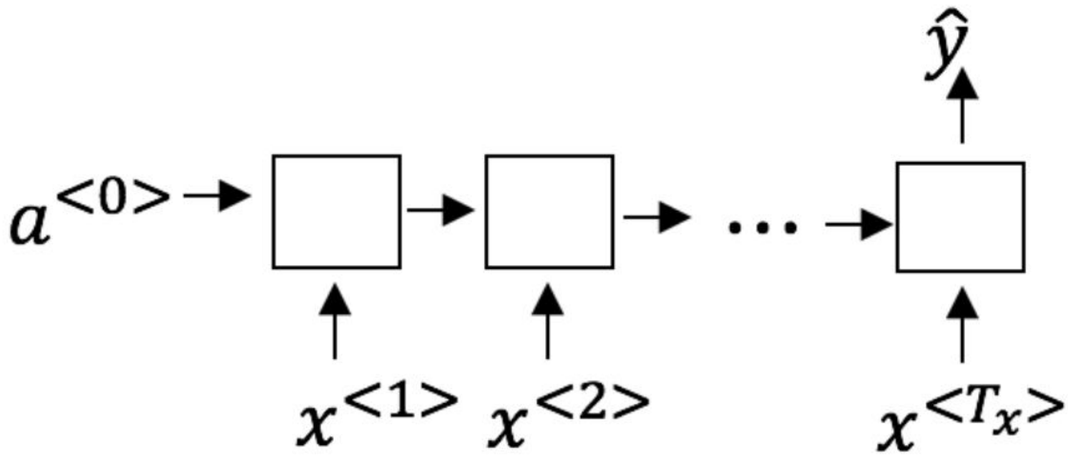
Tx<Ty

Tx>Ty

Tx=1

**Question 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)

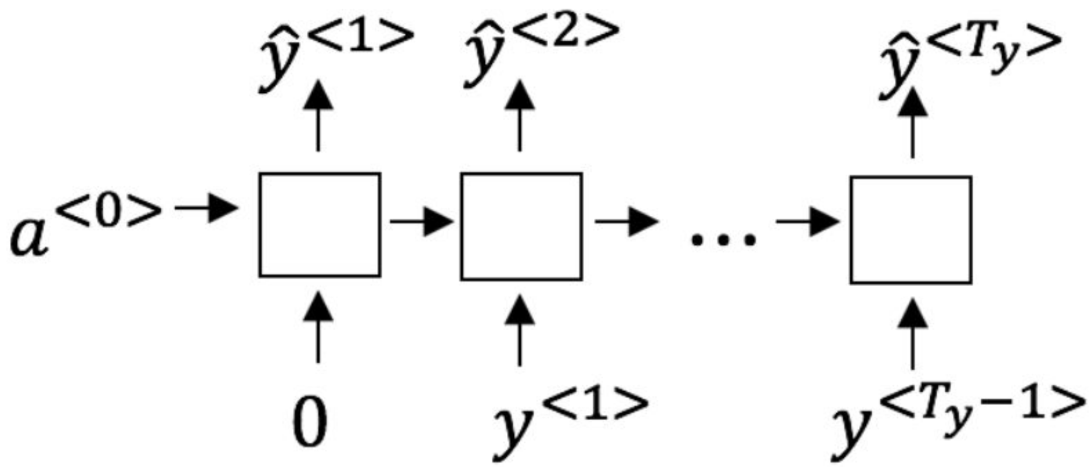
**Sentiment classification (input a piece of text and output a 0/1 to denote positive or negative sentiment)**

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)**

**Question 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>}, …, y^{<t-1>})

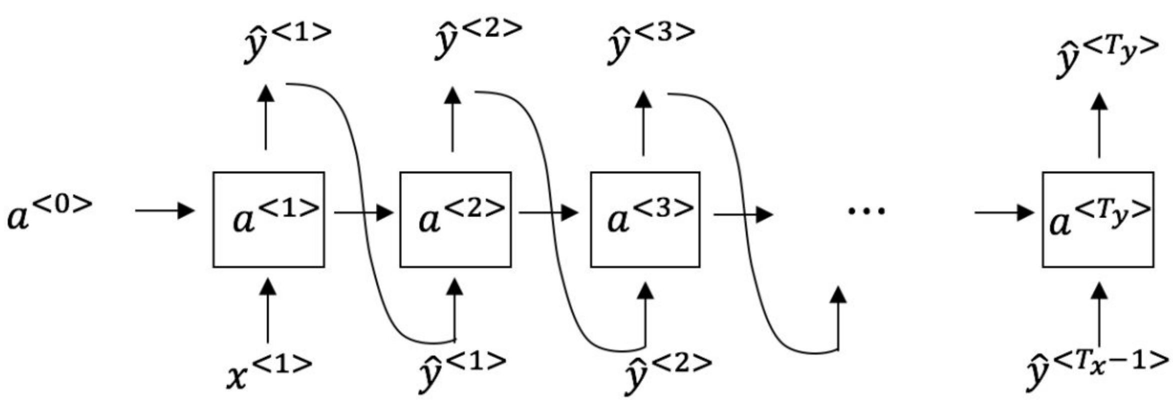
Estimating P(y^{<t>})

**Estimating P(y^{<t>} | y^{<1>}, y^{<2>}, …, y^{<t-1>})**

Estimating P(y^{<t>} | y^{<1>}, y^{<2>}, …, y^{<t>})

**Question 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.

**(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.**

**Question 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.**

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.

**Question 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 Γu\Gamma_uΓu at each time step?**

1

**100**

300

10000

**Question 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 Γr≈0 for a timestep, the gradient can propagate back through that timestep without much decay.

Alice's model (removing Γu), because if Γr≈1 for a timestep, the gradient can propagate back through that timestep without much decay.

**Betty's model (removing Γr), because if Γu≈0 for a timestep, the gradient can propagate back through that timestep without much decay.**

Betty's model (removing Γr), because if Γu≈1 for a timestep, the gradient can propagate back through that timestep without much decay.

**Question 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 the blanks?**

**Γu and 1−Γu**

Γu and Γr

1−Γu and Γu

Γr and Γu

**Question 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→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>y^{<t>}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>y^{<t>}y<t> depends only on x<t>x^{<t>}x<t>, and not other days’ weather.