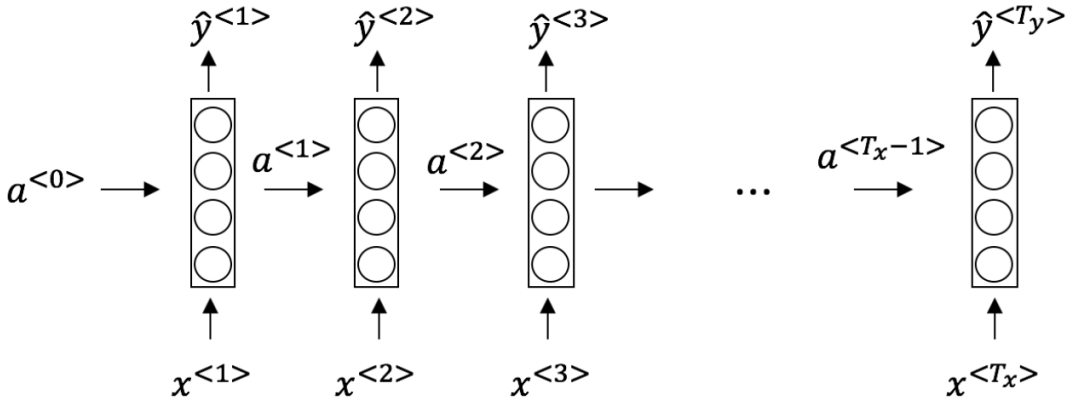
Recurrent Neural Networks

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)x(i)
   - [ ] x*(j)x(j)*
   - [ ] *x(j)x(j)*
   - [ ] *x(i)x(i)*

   > *We index into the ithith row first to get the ithith training example (represented by parentheses), then the jthjth column to get the jthjth word (represented by the brackets).*

2. *Consider this RNN:*

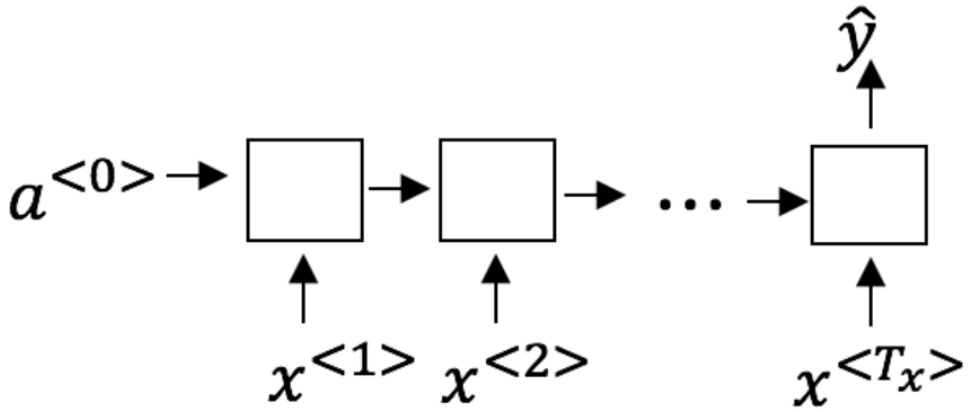


   This specific type of architecture is appropriate when:

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

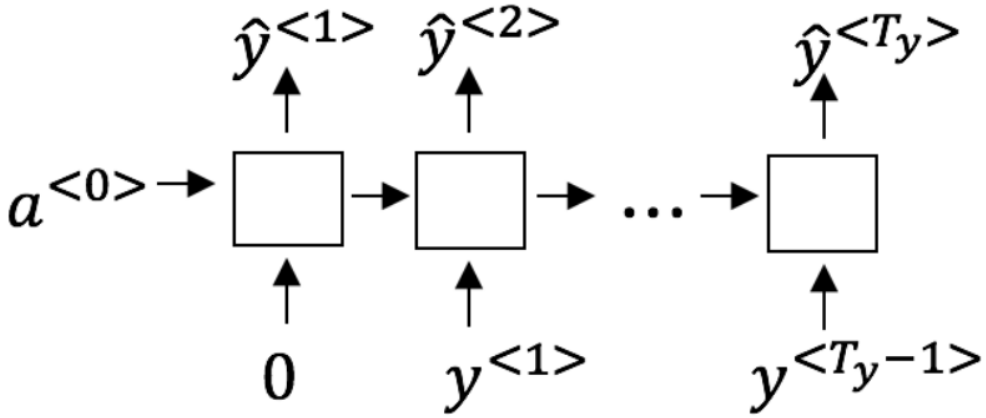
   > *It is appropriate when every input should be matched to an output.*

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



- [ ] *peech 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.*



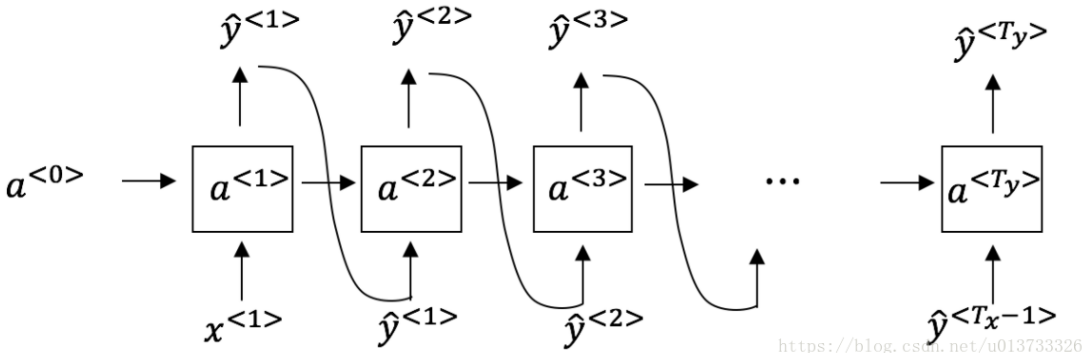
At the tthtth time step, what is the RNN doing? Choose the best answer.

- [ ] *Estimating P(y<1>,y<2>,...,y<t−1>)P(y<1>,y<2>,...,y<t−1>)*
- [ ] *Estimating P(y)P(y)*
- [x] *Estimating P(y |y<1>,y<2>,...,y<t−1>)P(y |y<1>,y<2>,...,y<t−1>)*
- [ ]

Estimating P(y |y<1>,y<2>,...,y)P(y |y<1>,y<2>,...,y)

> *Yes,in a language model we try to predict the next step based on the knowledge of all prior steps.*

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 $y^{<t>y}$. (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 $y^{<t>y}$. (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 $y^{<t>y}$. (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 $y^{<t>y}$. (ii) Then pass this selected word to the next time-step.*

> *题目说的是随机取样，因此不选AC。又因为这是取样过程不是训练过程，所以不选B。B实际上是训练过程在做的事*

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. What is the dimension of Γu at each time step?*

- [ ] *1*
- [x] *100*
- [ ] *300*
- [ ] *10000*

> *Γu的向量维度等于LSTM中隐藏单元的数量。*

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 ΓuΓu. I.e., setting ΓuΓu = 1. Betty proposes to simplify the GRU by removing the ΓrΓr. I. e., setting ΓrΓr = 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 ΓrΓr≈0 for a timestep, the gradient can propagate back through that timestep without much decay.*
- [ ] *Alice's model (removing Γu), because if ΓrΓr≈1 for a timestep, the gradient can propagate back through that timestep without much decay.*
- [x] *Betty's model (removing Γr), because if ΓuΓu≈0 for a timestep, the gradient can propagate back through that timestep without much decay.*
- [ ] *Betty's model (removing Γr), because if ΓuΓu≈1 for a timestep, the gradient can propagate back through that timestep without much decay.*

> *Yes, For the signal to backpropagate without vanishing, we need c<t> to be highly dependant on c<t−1>*
>
> *如果让Γu=1，那ct就与c<t-1>无关了，c这个变量就没有多大意义了*

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?*

- [x] *ΓuΓu and 1−ΓuΓu*
- [ ] *ΓuΓu and ΓrΓr*
- [ ] *1−ΓuΓu and ΓuΓu*
- [ ] *ΓrΓr and ΓuΓu*

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>x<1>,...,x<365>. You've also collected data on your dog's mood, which you represent as y<1>,...,y<365>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.*
- [x] *Unidirectional RNN, because the value of yy depends only on x<1>,...,xx<1>,...,x, but not on x<t+1>,...,x<365>x<t+1>,...,x<365>*
- [ ] *Unidirectional RNN, because the value of yy depends only on xx, and not other days' weather.*

Natural Language Processing & Word Embeddings

1. *Suppose you learn a word embedding for a vocabulary of 10000 words. Then the embedding vectors should be 10000 dimensional, so as to capture the full range of variation and meaning in those words.*
    - *True*
    - ***False***

---

1. *What is t-SNE?*
    - ***A non-linear dimensionality reduction technique.***
    - *A linear transformation that allows us to solve analogies on word vectors.*
    - *A supervised learning algorithm for learning word embeddings.*
    - *An open-source sequence modeling library.*

---

1. *Suppose you download a pre-trained word embedding which has been trained on a huge corpus of text. You then use this word embedding to train an RNN for a language task of recognizing if someone is happy from a short snippet of text, using a small training set.*

x(input text)	**y (happy?)**
I'm feeling wonderful today!	1
I'm bummed my cat is ill.	0
Really enjoying this!	1
Then even if the word "ecstatic" does not appear in your small training set, your RNN might reasonably be expected to recognize "I'm ecstatic" as deserving a label $y = 1$.	

Then even if the word “ecstatic” does not appear in your small training set, your RNN might reasonably be expected to recognize “I’m ecstatic” as deserving a label y=1y = 1y=1.
- [x] True
- [ ] False

---

1. *Which of these equations do you think should hold for a good word embedding? (Check all that apply)* ***AC***
    - *eboy−egirl≈ebrother−esister*
    - *eboy−egirl≈esister−ebrother*
    - $e_{boy} - e_{brother} \approx e_{girl} - e_{sister}$
    - $e_{boy} - e_{brother} \approx e_{sister} - e_{girl}$

---

1. *Let EEE be an embedding matrix, and let e1234e{1234}e1234 be a one-hot vector corresponding to word 1234. Then to get the embedding of word 1234, why don’t we call E∗e1234E∗e{1234}E∗e1234 in Python?*
    - ***It is computationally wasteful.***
    - *The correct formula is ET∗e1234E^T∗e_{1234}E**T∗e1234.*
    - *This doesn’t handle unknown words ().*

- *None of the above: Calling the Python snippet as described above is fine.*

---

1. *When learning word embeddings, we create an artificial task of estimating P(target∣context)P(target \mid context)P(target∣context)P(t**a**r**g**e**t∣c**o**n**t**e**x**t). It is okay if we do poorly on this artificial prediction task; the more important by-product of this task is that we learn a useful set of word embeddings.*

   - *True*
   - ***False***

   > *做得不好的话得到的词嵌入也会是错的*

---

1. *In the word2vec algorithm, you estimate P(t∣c)P(t \mid c)P(t∣c), where ttt is the target word and ccc is a context word. How are ttt and ccc chosen from the training set? Pick the best answer.*

   - ***c and t are chosen to be nearby words.***
   - *c is the one word that comes immediately before ttt.*
   - *c is the sequence of all the words in the sentence before ttt.*
   - *c is a sequence of several words immediately before ttt.*

---

1. *Suppose you have a 10000 word vocabulary, and are learning 500-dimensional word embeddings. The word2vec model uses the following softmax function:*

   *P(t∣c)=eθTtec∑10000t'=1eθTt'ecP(t \mid c)=\frac{e^{\theta_t^T e_c}}{\sum_{t'=1}^{10000} e^{\theta_{t'}^T e_c}}P(t∣c)=∑t'=110000eθt'Teceθ**t**T**e**c*

   Which of these statements are correct? Check all that apply.

   - ***θt and ec are both 500 dimensional vectors.***
   - *θt and ec are both 10000 dimensional vectors.*
   - ***θt and ec are both trained with an optimization algorithm such as Adam or gradient descent.***
   - *After training, we should expect θt to be very close to ec when ttt and ccc are the same word.*

---

1. *Suppose you have a 10000 word vocabulary, and are learning 500-dimensional word embeddings.The GloVe model minimizes this objective:*

$$\min \sum_{i=1}^{10,000} \sum_{j=1}^{10,000} f(X_{ij})(\theta_i^T e_j + b_i + b\prime_j - logX_{ij})^2$$

   Which of these statements are correct? Check all that apply.

   - *θi and ej hould be initialized to 0 at the beginning of training.*
   - ***θi and ej hould be initialized randomly at the beginning of training.***
   - ***Xij is the number of times word i appears in the context of word j.***
   - ***The weighting function f(.) must satisfy f(0)=0.***

     > *The weighting function helps prevent learning only from extremely common word pairs. It is not necessary that it satisfies this function.*

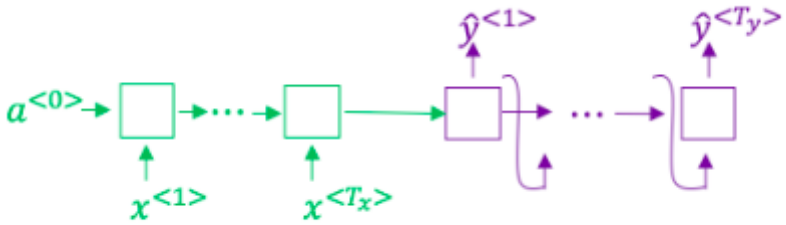
---

1. *You have trained word embeddings using a text dataset of m1m_1m1 words. You are considering using these word embeddings for a language task, for which you have a separate labeled dataset of m2m_2m2 words. Keeping in mind that using word embeddings is a form of transfer learning, under which of these circumstance would you expect the word embeddings to be helpful?*

- ***m1>>m2***
- *m1<<m2*

Sequence models & Attention mechanism

1. *Consider using this encoder-decoder model for machine translation.*



This model is a "conditional language model" in the sense that the encoder portion (shown in green) is modeling the probability of the input sentence xxx. - [x] True - [ ] False

1. *In beam search, if you increase the beam width BB, which of the following would you expect to be true? Check all that apply.*
    - ***Beam search will run more slowly.***
    - ***Beam search will use up more memory.***
    - ***Beam search will generally find better solutions (i.e. do a better job maximizing P(y \| x)***
    - *Beam search will converge after fewer steps.*

---

1. *In machine translation, if we carry out beam search without using sentence normalization, the algorithm will tend to output overly short translations.*
    - *True*
    - *False*

---

1. *Suppose you are building a speech recognition system, which uses an RNN model to map from audio clip x to a text transcript yyy. Your algorithm uses beam search to try to find the value of y that maximizes P(y \|x)*
   On a dev set example, given an input audio clip, your algorithm outputs the transcript yˆ=\hat{y} =y^= "I'm building an A Eye system in Silly con Valley.", whereas a human gives a much superior transcript y∗ "I'm building an AI system in Silicon Valley.".
   According to your model,

$$P(\hat{y} \mid x) = 1.09 * 10^{-7}$$

$$P(y^* \mid x) = 7.21 * 10^{-8}$$

   Would you expect increasing the beam width B to help correct this example?

- ***No, because P(y∗ |x)≤P(yˆ |x) indicates the error should be attributed to the RNN rather than to the search algorithm.***
- *No, because P(y∗ |x)≤P(yˆ |x) indicates the error should be attributed to the search algorithm rather than to the RNN.*
- *Yes, because P(y∗ |x)≤P(yˆ |x) indicates the error should be attributed to the RNN rather than to the search algorithm.*
- *Yes, because P(y∗ |x)≤P(yˆ |x) indicates the error should be attributed to the search algorithm rather than to the RNN.*

---

1. *Continuing the example from Q4, suppose you work on your algorithm for a few more weeks, and now find that for the vast majority of examples on which your algorithm makes a mistake,*

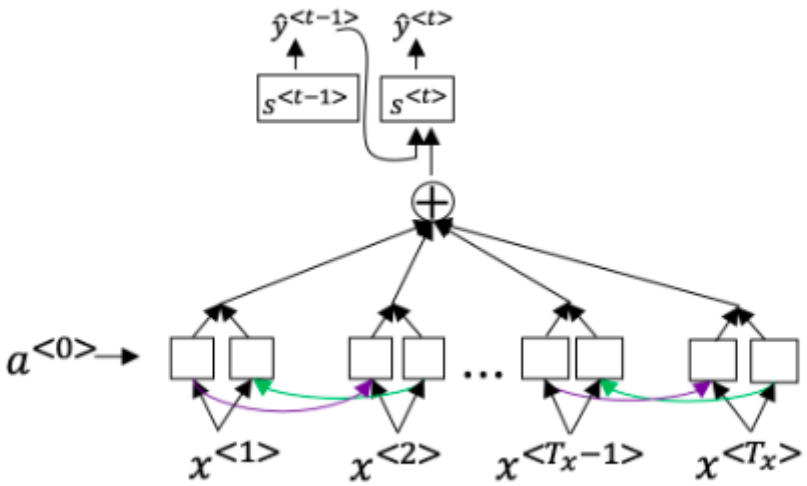
   P(y∗ |x)>P(yˆ |x)

   . This suggest you should focus your attention on improving the search algorithm.

   - ***True***
   - *False*

---

1. *Consider the attention model for machine translation.*



Further, here is the formula for $a^{<t,t'>} = \frac{\exp(e^{<t,t'>})}{\sum_{t'=1}^{T_x} \exp(e^{<t,t'>})}$

Which of the following statements about α<t,t'> are true? Check all that apply.

- ***We expect α<t,t'> to be generally larger for values of a<t'> that are highly relevant to the value the network should output for y<t>. (Note the indices in the superscripts.)***
- *We expect α<t,t'> to be generally larger for values of a<t> that are highly relevant to the value the network should output for y<t'>. (Note the indices in the superscripts.)*
- *∑tα<t,t'>=1 (Note the summation is over t)*
- ***∑t'α<t,t'>=1 (Note the summation is over t'.)***

1. *The network learns where to "pay attention" by learning the values e<t,t'>, which are computed using a small neural network:*
   We can't replace s<t−1> with s<t> as an input to this neural network. This is because s<t> depends on α<t,t'> which in turn depends on e<t,t'>; so at the time we need to evalute this network, we

haven't computed s<t>yet.

- *True*
- *False*

---

1. *Compared to the encoder-decoder model shown in Question 1 of this quiz (which does not use an attention mechanism), we expect the attention model to have the greatest advantage when:*
    - *The input sequence length Tx is large.*
    - *The input sequence length Tx is small.*

---

1. *Under the CTC model, identical repeated characters not separated by the "blank" character () are collapsed. Under the CTC model, what does the following string collapse to?*
   __c_oo_o_kk_b_ooooo_oo__kkk
    - *cokbok*
    - ***cookbook***
    - *cook book*
    - *coookkbooooooookkk*

---

1. *In trigger word detection,*

x<t>

is:

- ***Features of the audio (such as spectrogram features) at time t.***
- *The t-th input word, represented as either a one-hot vector or a word embedding.*
- *Whether the trigger word is being said at time t.*
- *Whether someone has just finished saying the trigger word at time t.*