Machine Translation

COMP90042

Natural Language Processing

Lecture 17

Semester 1 2022 Week 9

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Introduction

- **Machine translation (MT)** is the task of translating text from one **source language** to another **target language**

虽然北风呼啸，但天空依然十分清澈

However, the sky remained clear under the strong north wind

Why?

- Removes language barrier
- Makes information in any languages accessible to anyone
- But translation is a classic “AI-hard” challenge
  - Difficult to preserve the meaning and the fluency of the text after translation

How good do you find machine translation (e.g. Google Translate)?

- I've never used it before
- Bad, it's not really usable
- Usable, but it needs a lot of manual correction
- Quite good, I use it quite often
- Perfect, machine translation is a solved task

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MT is Difficult

- Not just simple word for word translation
- Structural changes, e.g., syntax and semantics
- Multiple word translations, idioms
- Inflections for gender, case etc
- Missing information (e.g., determiners)

虽然	北	风	呼啸	，	但	天空	依然	十分	清澈
although	*north*	*wind*	*howls*	*,*	*but*	*sky*	*still*	*extremely*	*limpid*

Outline

- Statistical Machine Translation
- Neural Machine Translation
- Attention Mechanism
- Evaluation

Statistical MT

Early Machine Translation

- Started in early 1950s
- Motivated by the Cold War to translate Russian to English
- Rule-based system
  - Use bilingual dictionary to map Russian words to English words
- Goal: translate 1-2 million words an hour within 5 years

Statistical MT

- Given French sentence *f*, aim is to find the best English sentence *e*
  - $\text{argmax}_e \, P(e \mid f)$
- Use Baye's rule to decompose into two components
  - $\text{argmax}_e \, P(f \mid e) P(e)$

Language vs Translation Model

- $\text{argmax}_e \, P(f \mid e) P(e)$
- $P(e)$: **language model**
  - learns how to write fluent English text
- $P(f \mid e)$: **translation model**
  - learns how to translate words and phrases from English to French

How to Learn LM and TM?

- Language model:
  - Text statistics in large **monolingual corpora**
- Translation model:
  - Word co-occurrences in **parallel corpora**
  - i.e. English-French sentence pairs

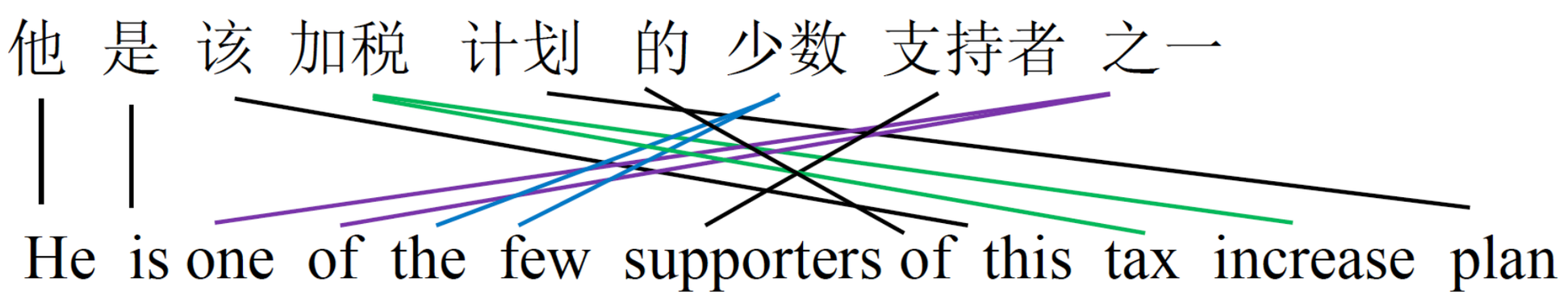
Parallel Corpora

- One text in multiple languages
- Produced by human translation
  - Bible, news articles, legal transcripts, literature, subtitles
  - Open parallel corpus: http://opus.nlpl.eu/

The Rosetta Stone

Models of Translation

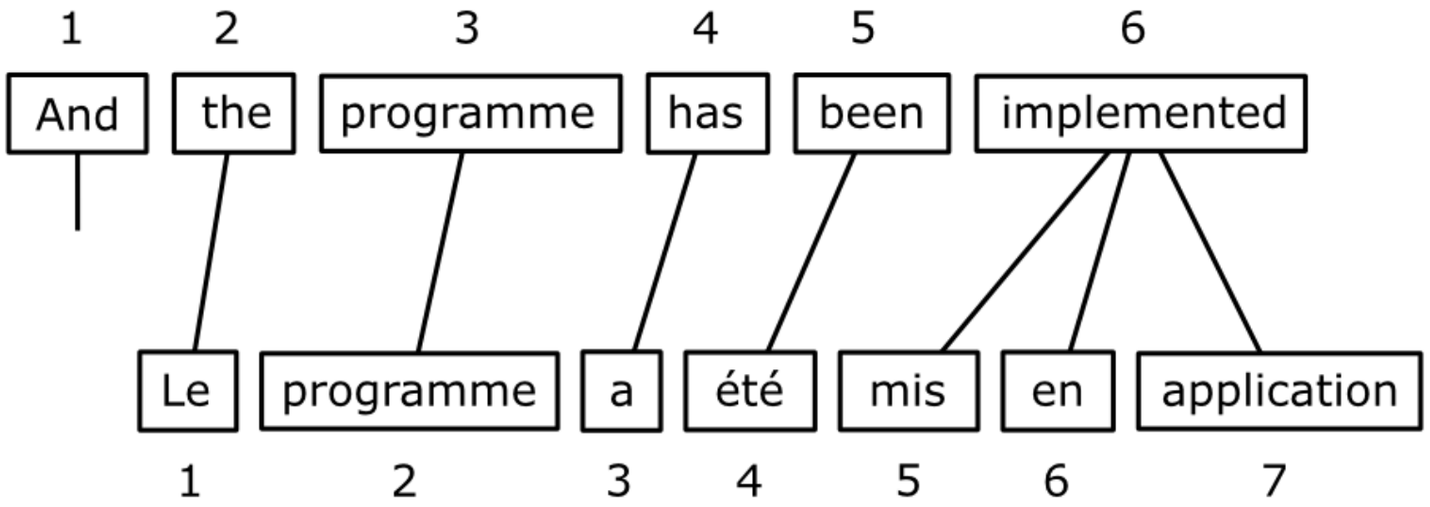
- How to learn $P(f \mid e)$ from parallel text?
- We only have sentence pairs; **words are not aligned** in the parallel text
- I.e. we don't have word to word translation



Zhang, Liu, Li, Zhou, Zong (2016)

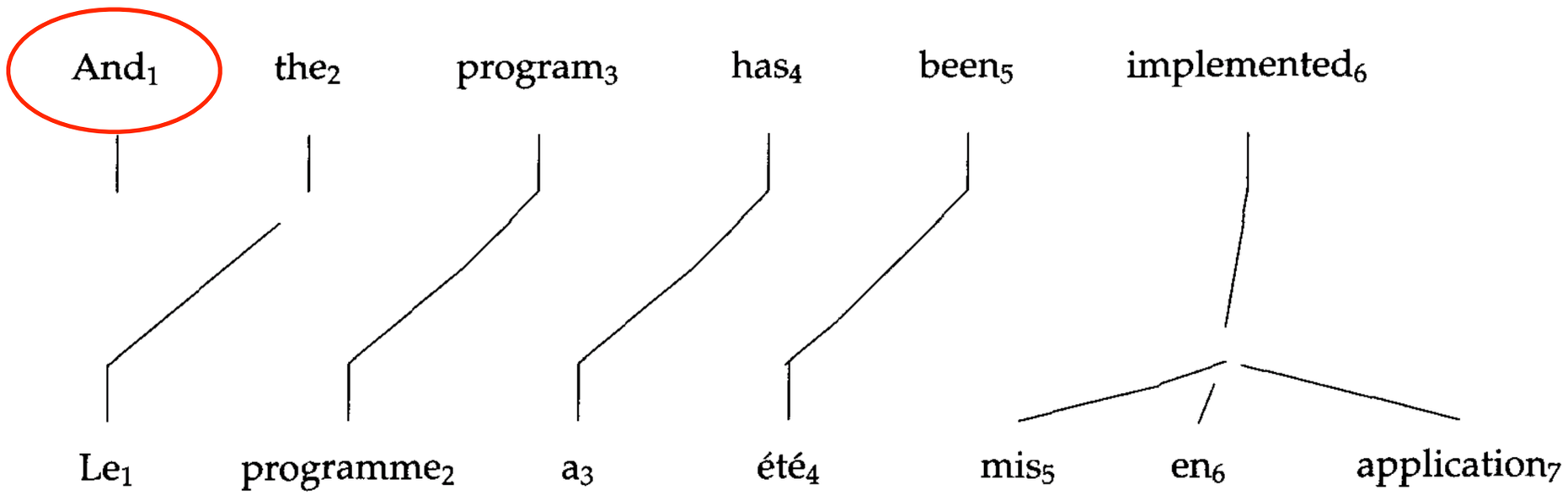
Alignment

- Idea: introduce **word alignment** as a latent variable into the model
  - $P(f, a \mid e)$
- Use algorithms such as expectation maximisation (EM) to learn (e.g. GIZA++)



Complexity of Alignment

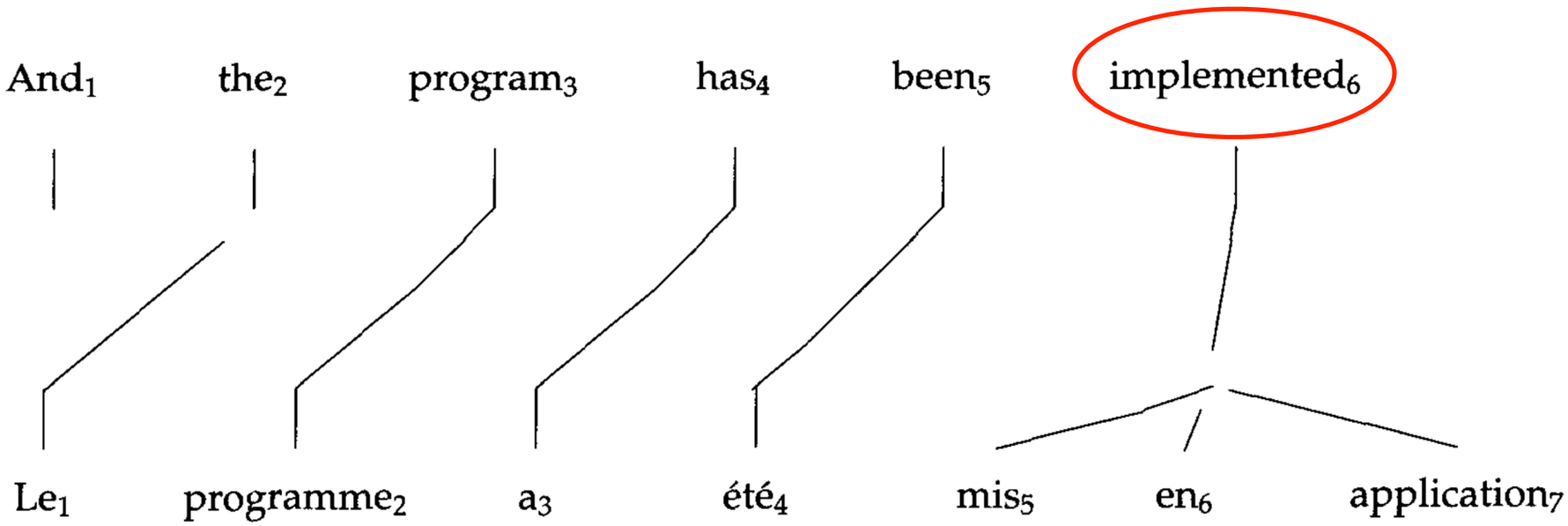
- Some words are dropped and have no alignment



Brown, Della Pietra, Della Pietra, Mercer, 1993

Complexity of Alignment

- One-to-many alignment



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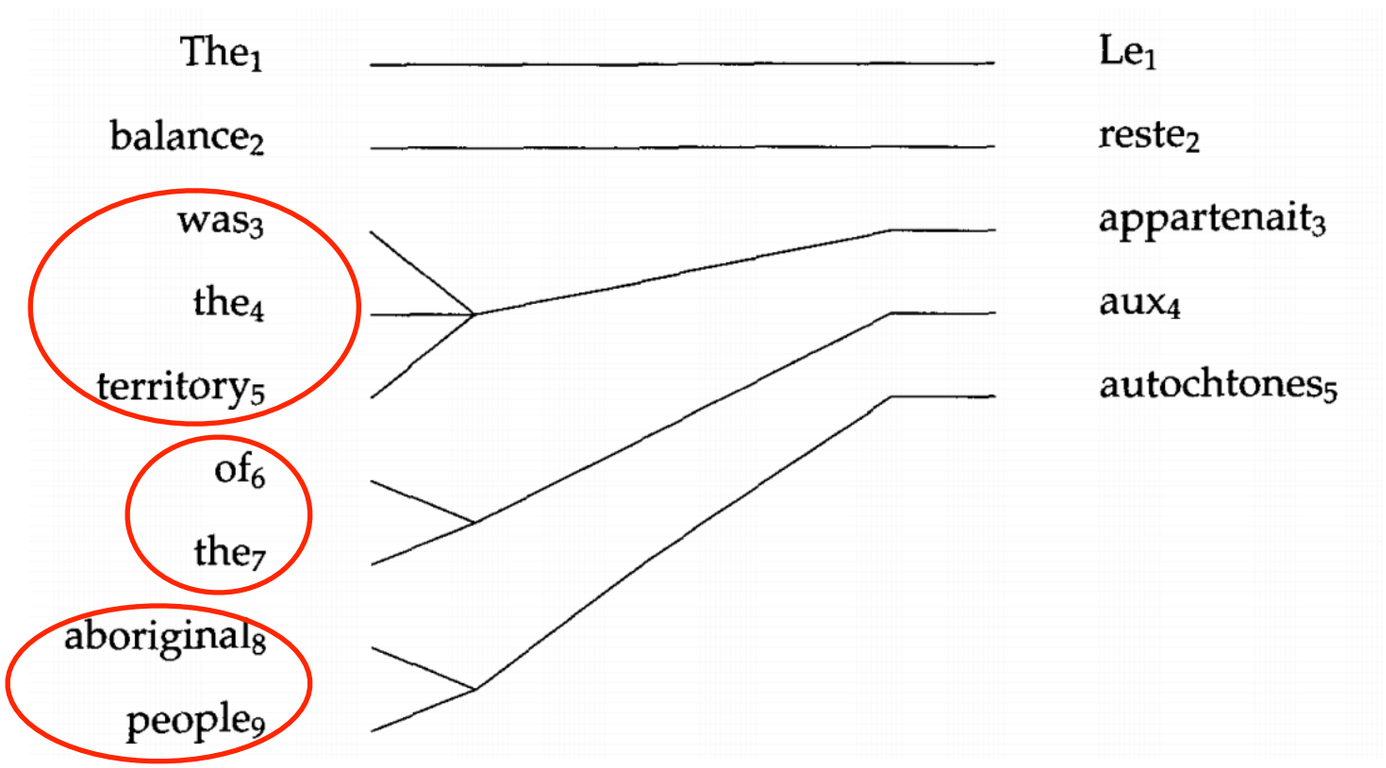
Complexity of Alignment

- Many-to-one alignment



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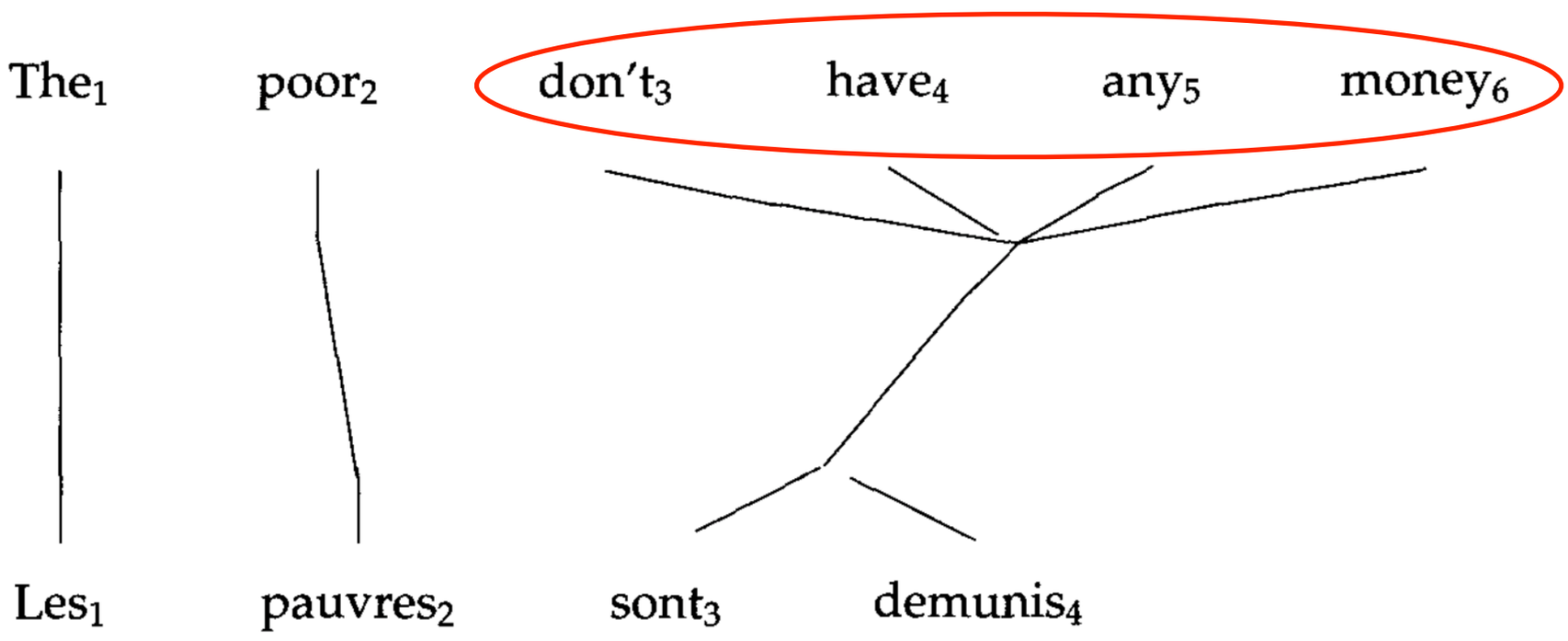
Complexity of Alignment

- Many-to-many alignment



Brown, Della Pietra, Della Pietra, Mercer, 1993

Statistical MT: Summary

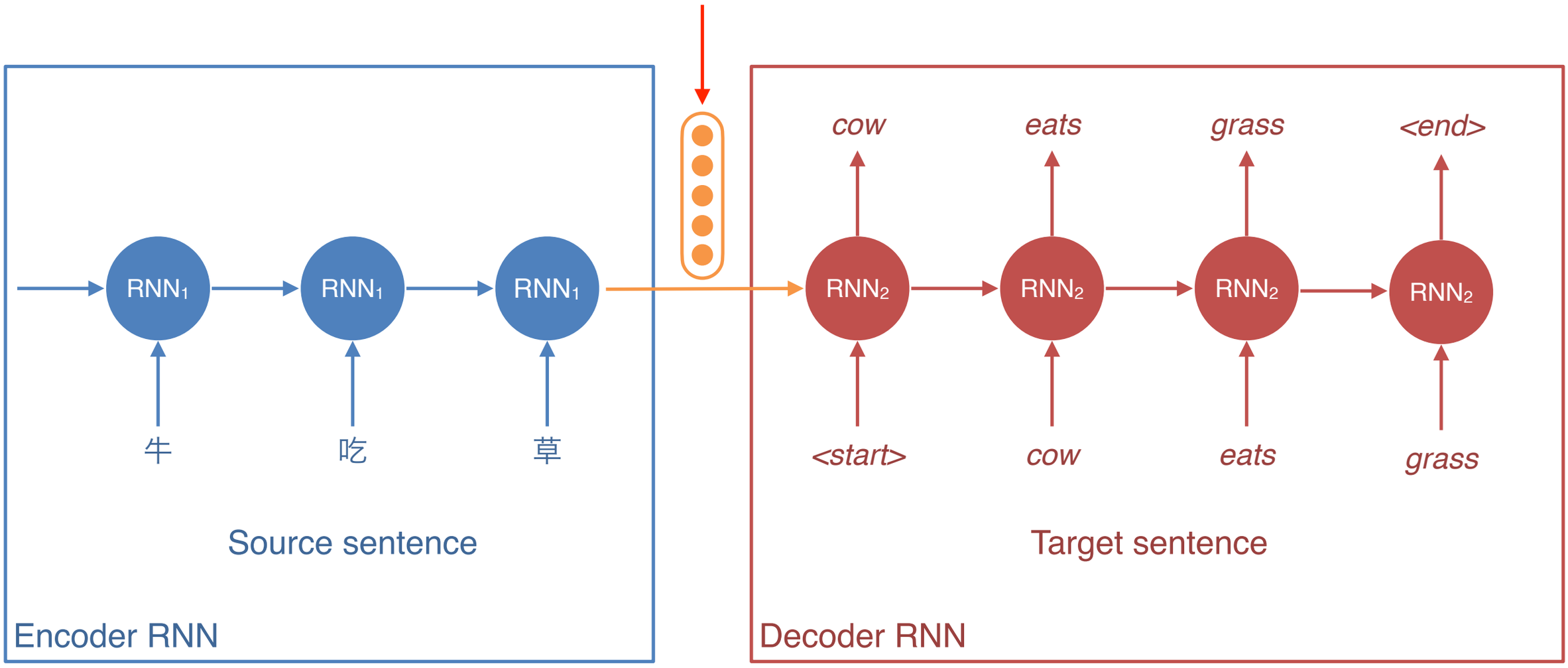
- A very popular field of research in NLP prior to 2010s
- Lots of feature engineering
- State-of-the-art systems are very complex
  - Difficult to maintain
  - Significant effort needed for new language pairs

Neural Machine Translation

Introduction

- Neural machine translation is a new approach to do machine translation
- Use a single neural model to directly translate from source to target
- Requires parallel text
- Architecture: encoder-decoder model
  - 1st RNN to encode the source sentence
  - 2nd RNN to decode the target sentence

This vector encodes the whole source sentence;
it is used as the initial state for decoder RNN



$$h_i = RNN_1(h_{i-1}, x_i)$$
$$s_t = RNN_2(s_{t-1}, y_t)$$
$$s_1 = h_{|x|}$$

Neural MT

- The decoder RNN can be interpreted as a **conditional language model**
  - Language model: predicts the next word given previous words in target sentence *y*
  - Conditional: prediction is also conditioned on the source sentence *x*
- $P(y|x) = P(y_1|x)P(y_2|y_1, x)\ldots P(y_t|y_1, \ldots, y_{t-1}, x)$

Training Neural MT

- Requires parallel corpus just like statistical MT
- Trains with next word prediction, just like a language model!

Language Model Training Loss

negative logprob of *cow*

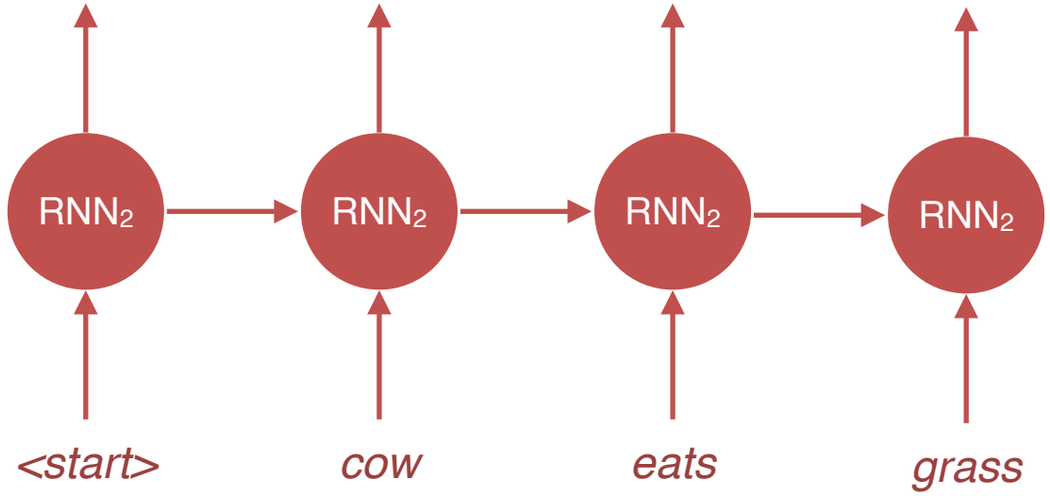
negative logprob of *eats*

negative logprob of *grass*

negative logprob of *<end>*

$$L_1 + L_2 + L_3 + L_4 = L_{total}$$

cow *eats* *grass* *<end>*



Neural MT Training Loss

negative logprob of *cow*

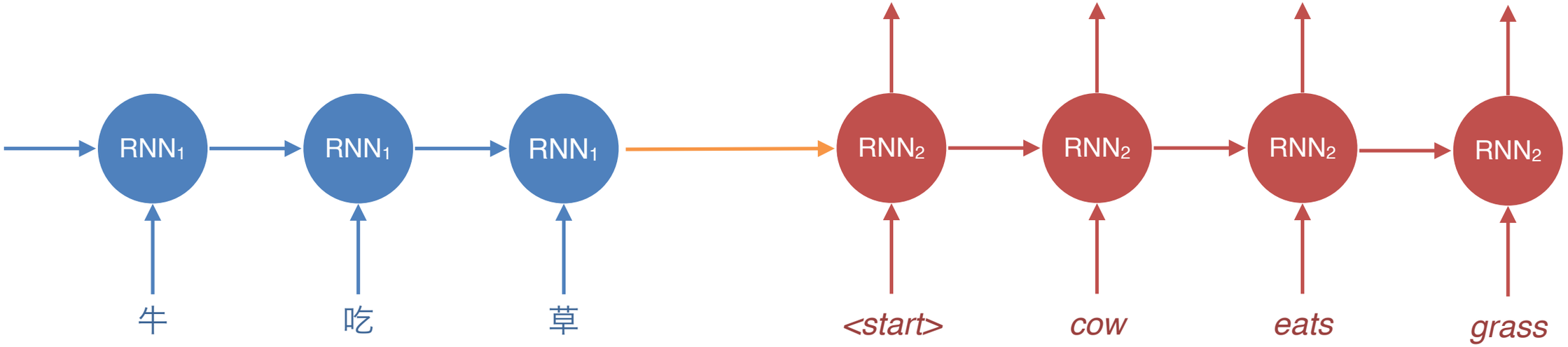
negative logprob of *eats*

negative logprob of *grass*

negative logprob of *<end>*

$$L_1 + L_2 + L_3 + L_4 = L_{total}$$

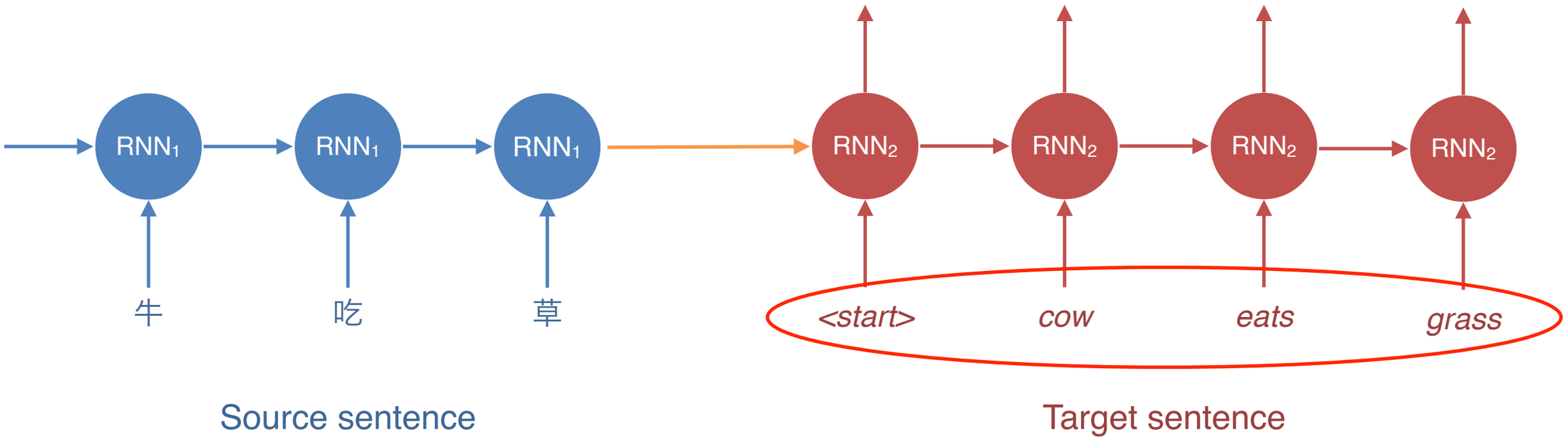
cow *eats* *grass* *<end>*



Source sentence

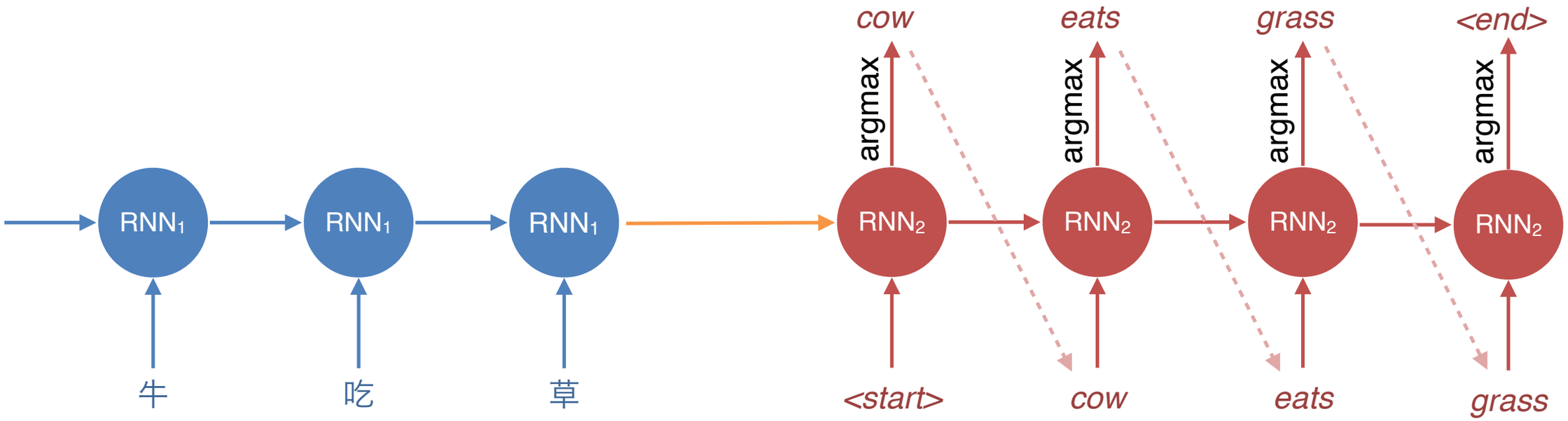
Target sentence

Training



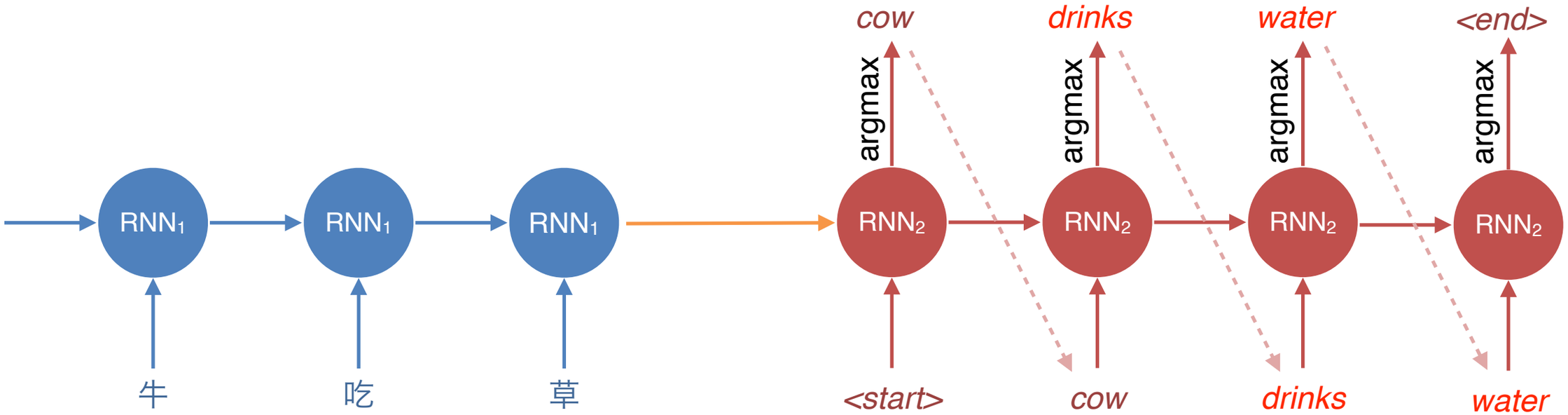
- During training, we have the target sentence
- We can therefore feed the right word from target sentence, one step at a time

Decoding at Test Time



- But at test time, we don’t have the target sentence (that’s what we’re trying to predict!)
- **argmax**: take the word with the highest probability at every step

Exposure Bias



- Describes the discrepancy between training and testing
- Training: always have the ground truth tokens at each step
- Test: uses its own prediction at each step
- Outcome: model is unable to recover from its own error

Greedy Decoding

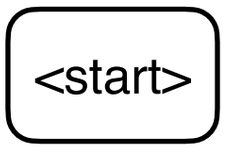
- argmax decoding is also called greedy decoding
- Issue: does not guarantee optimal probability $P(y \mid x)$

Exhaustive Search Decoding

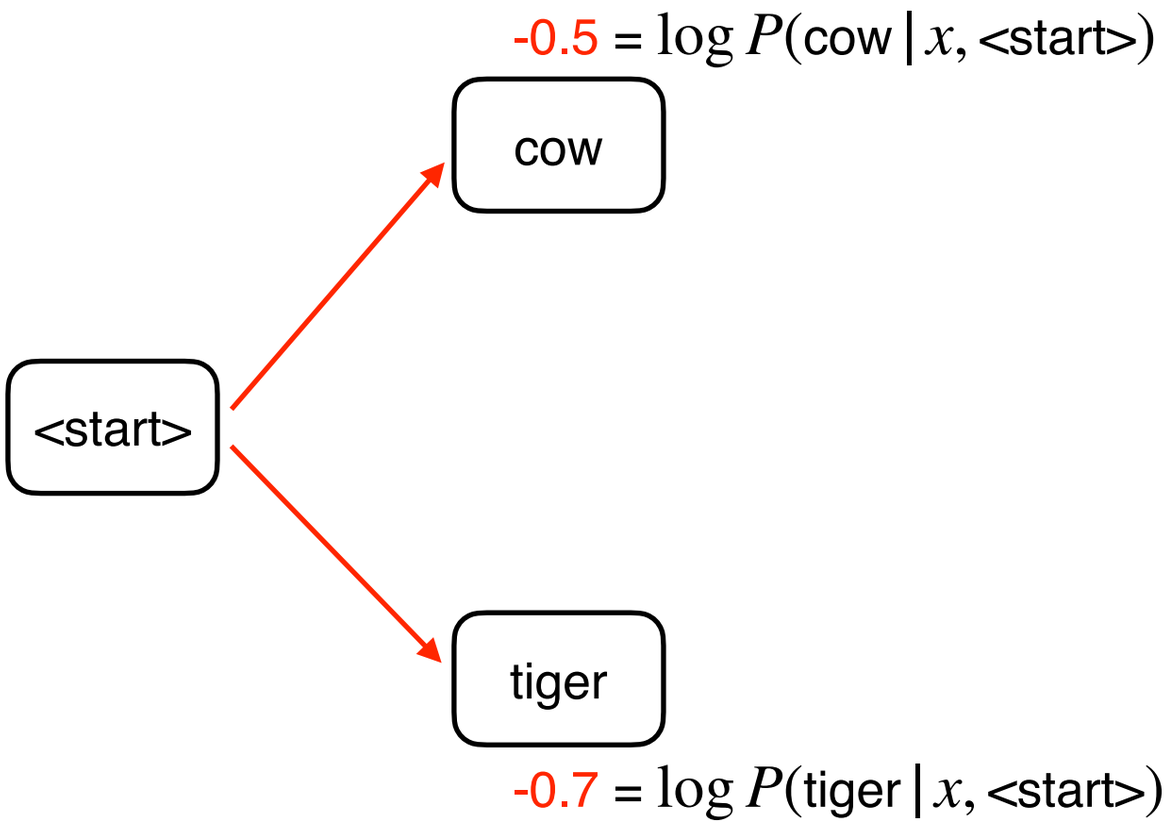
- To find optimal $P(y \mid x)$, we need to consider every word at every step to compute the probability of all possible sequences
- $O(V^n)$; V = vocab size; n = sentence length
- Far too expensive to be feasible

Beam Search Decoding

- Instead of considering all possible words at every step, consider **k best words**
- That is, we keep track of the top-k words that produce the best partial translations **(hypotheses)** thus far
- k = beam width (typically 5 to 10)
- k = 1 = greedy decoding
- k = V = exhaustive search decoding



Beam search decoding with k=2



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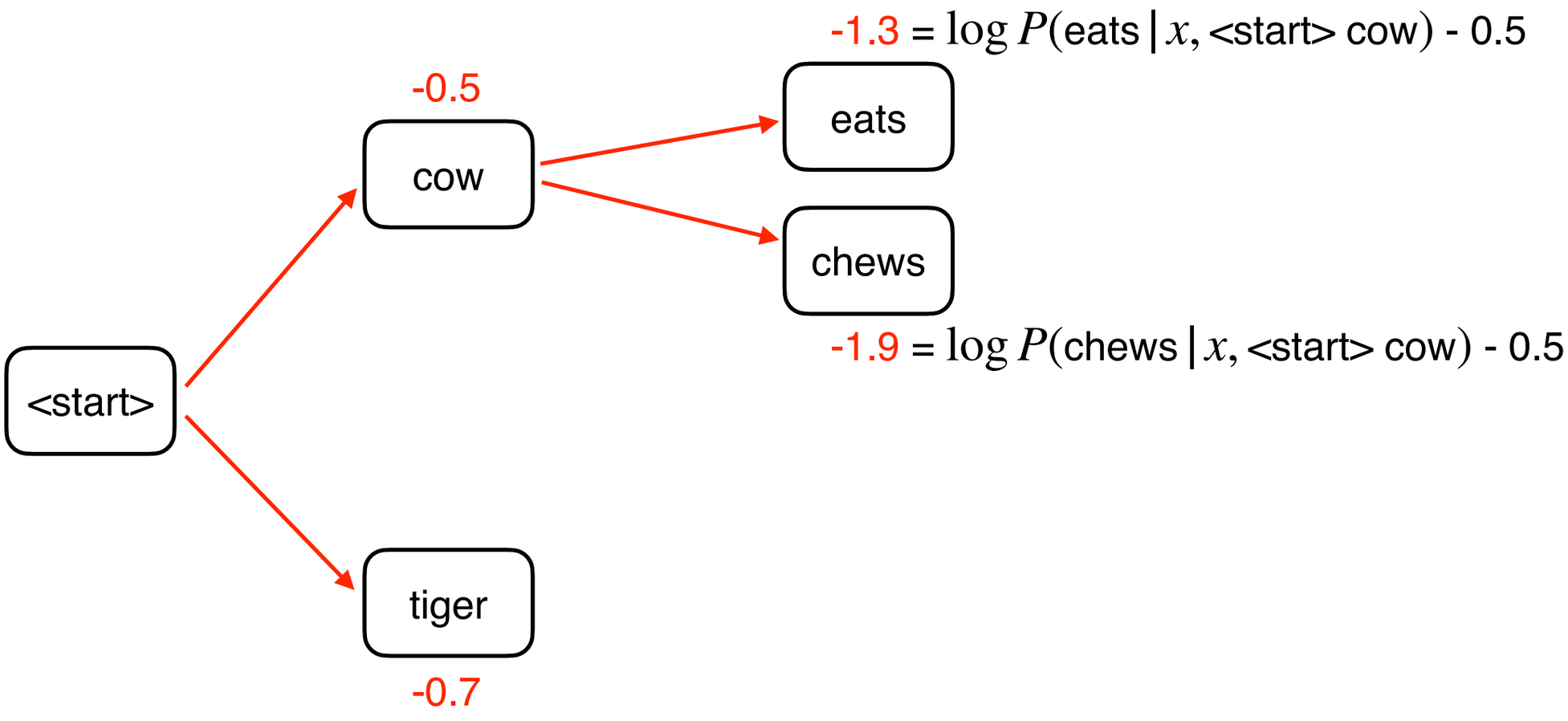

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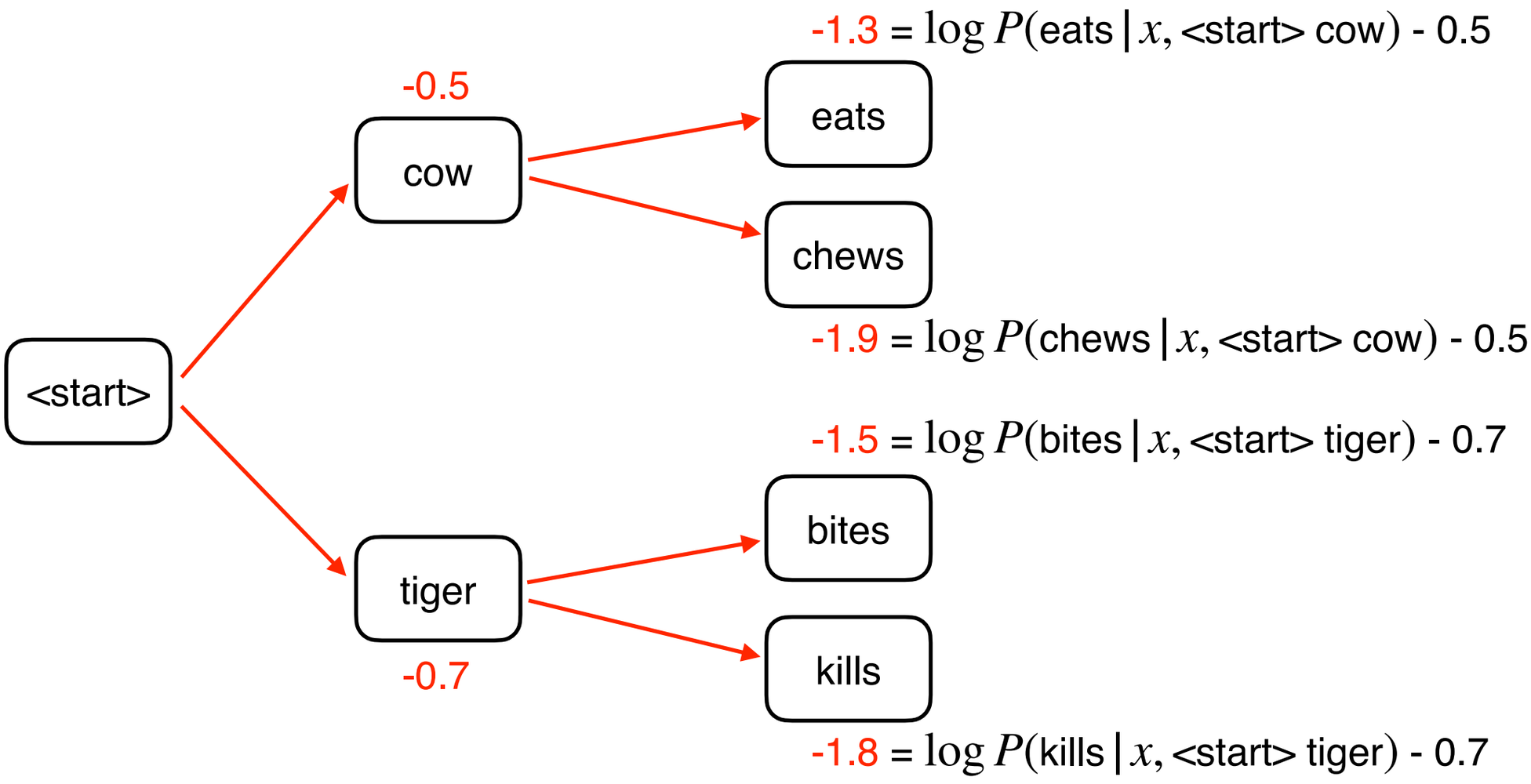
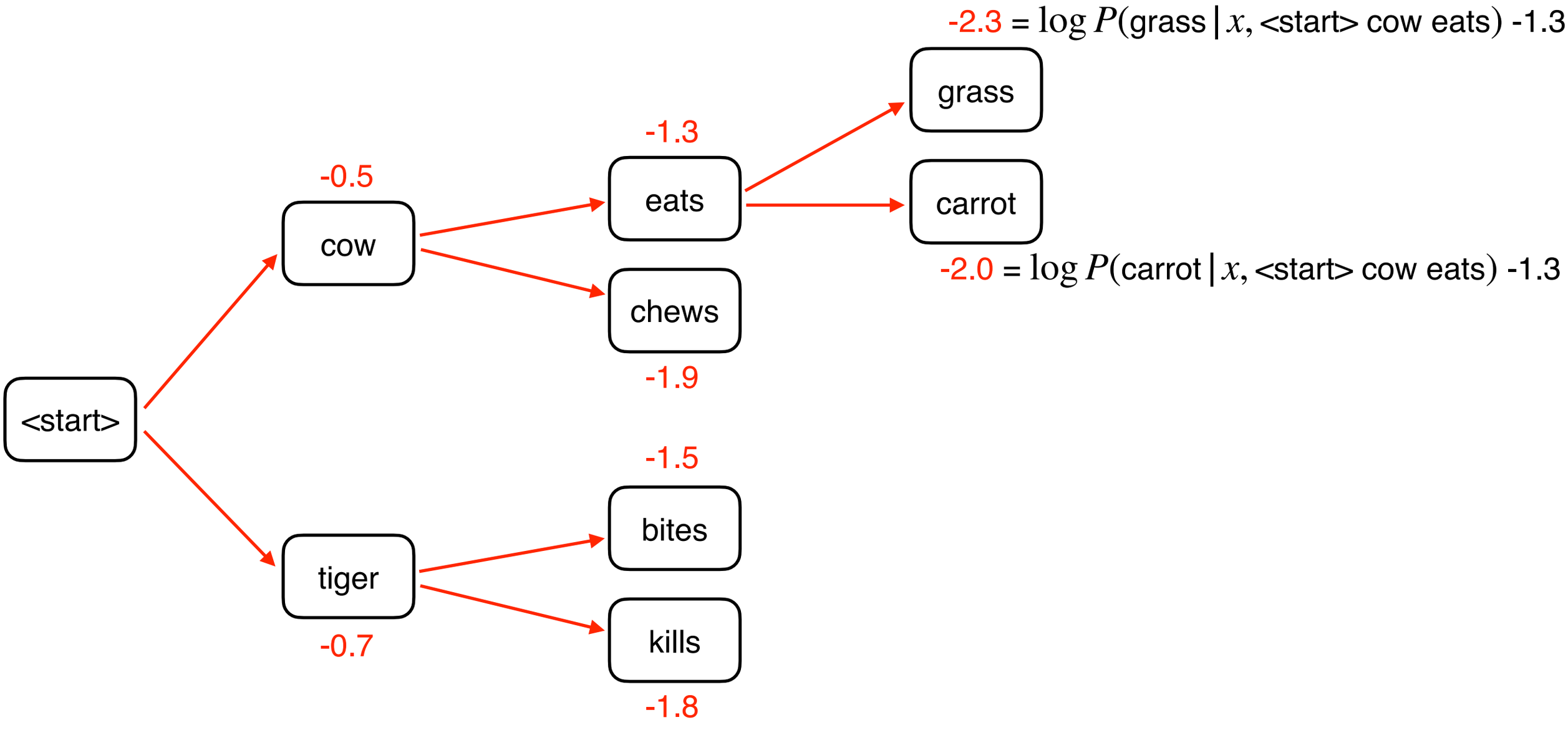
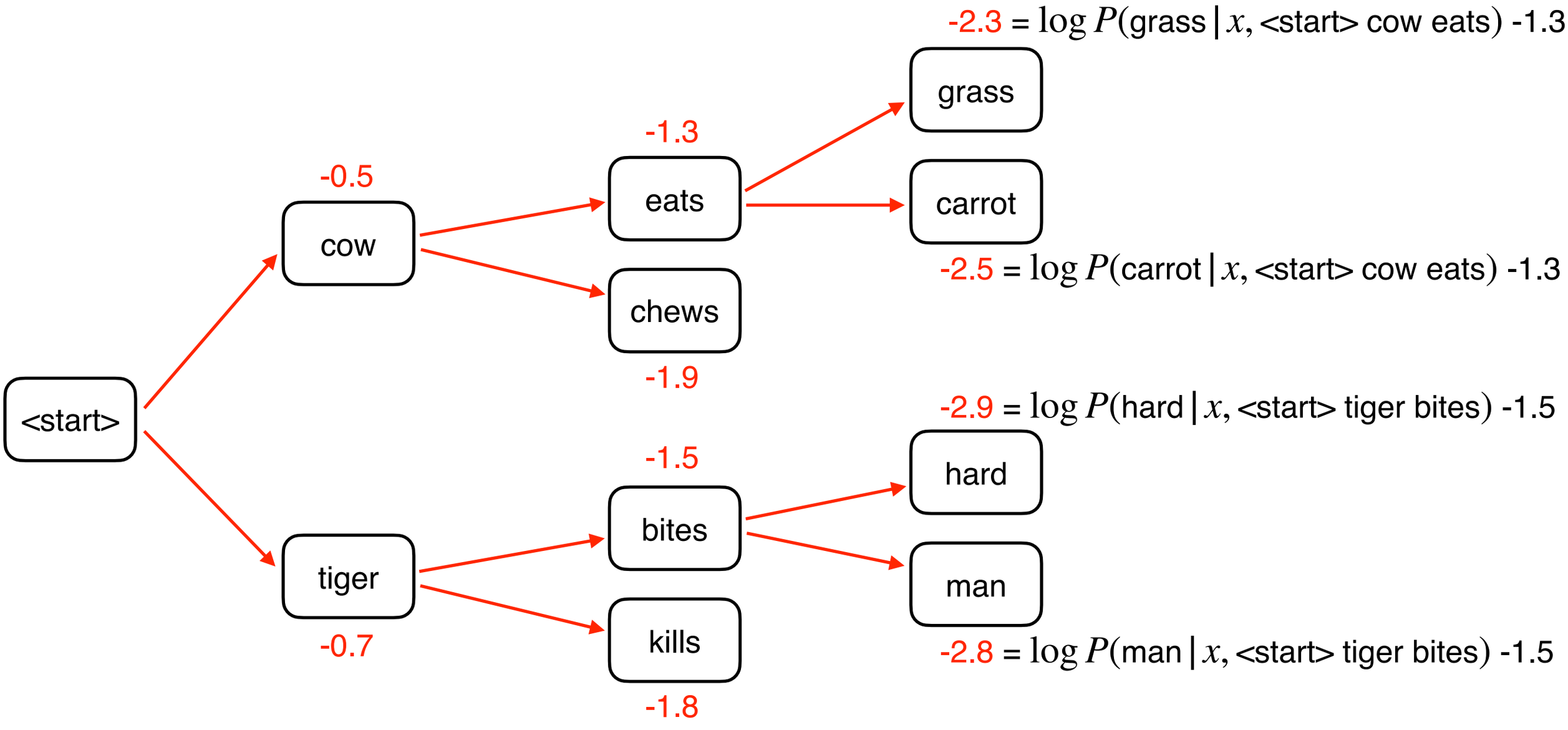


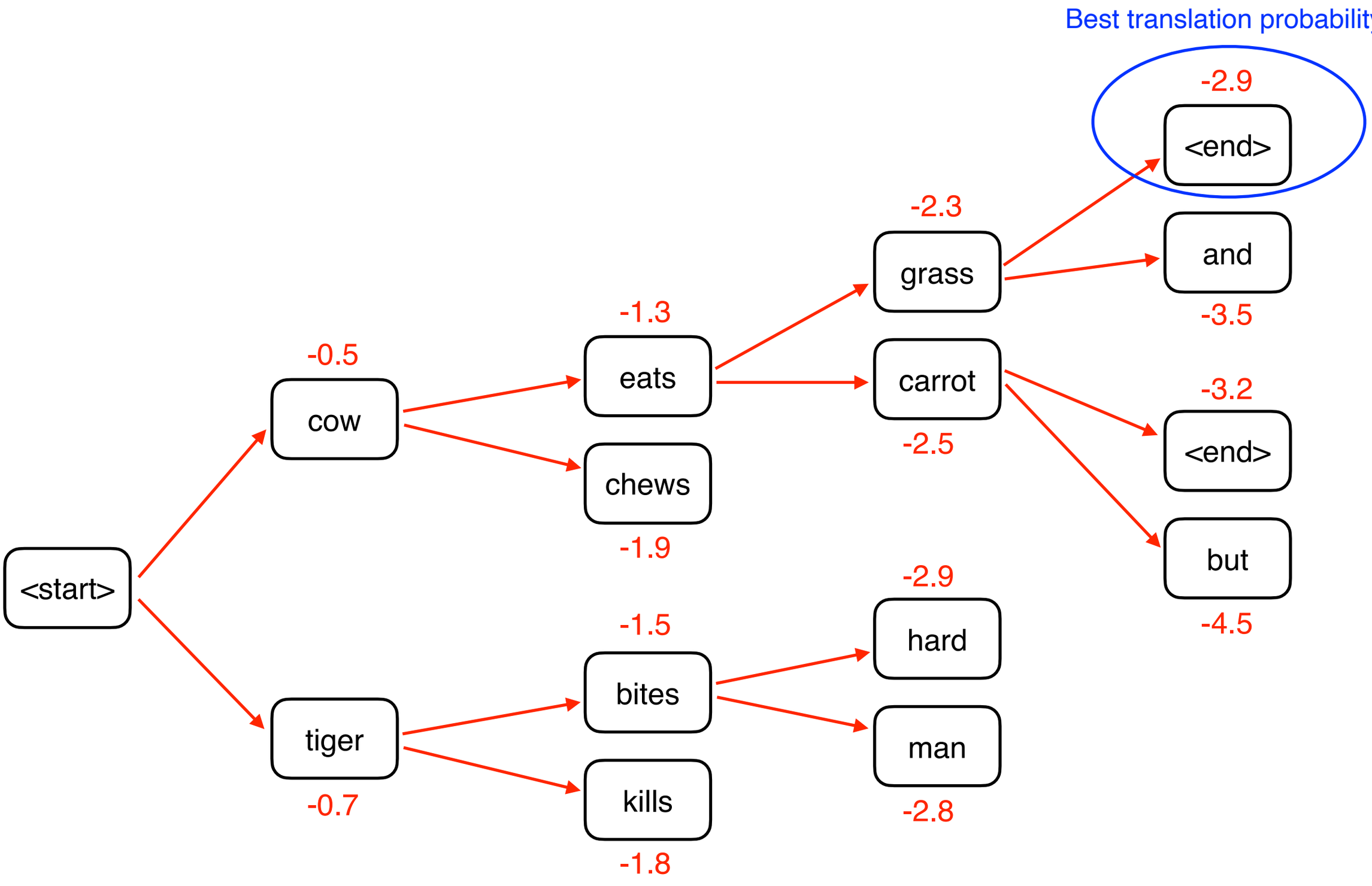
Beam search decoding with k=2



Beam search decoding with k=2

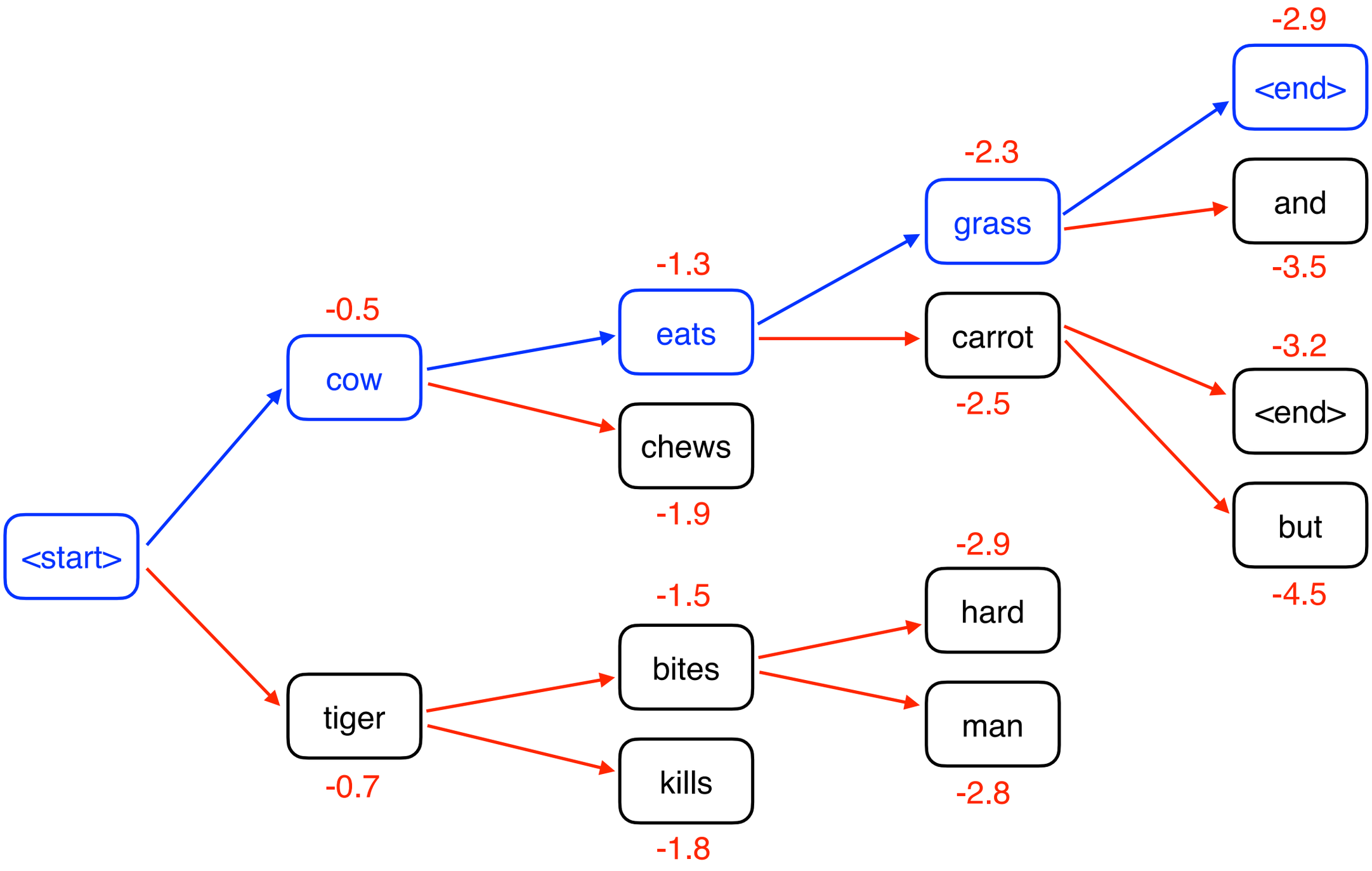


Beam search decoding with k=2



Beam search decoding with k=2

Follow pointers to get the target sentence



Beam search decoding with k=2

When to Stop?

- When decoding, we stop when we generate <end> token
- But multiple hypotheses may terminate their sentence at different time steps
- We store hypotheses that have terminated, and continue explore those that haven’t
- Typically we also set a maximum sentence length that can be generated (e.g. 50 words)

What are some issues of NMT?

- Information of the whole source sentence is represented by a single vector
- NMT can generate new details not in source sentence
- NMT tend to generate not very fluent sentences
- Black-box model; difficult to explain when it doesn't work

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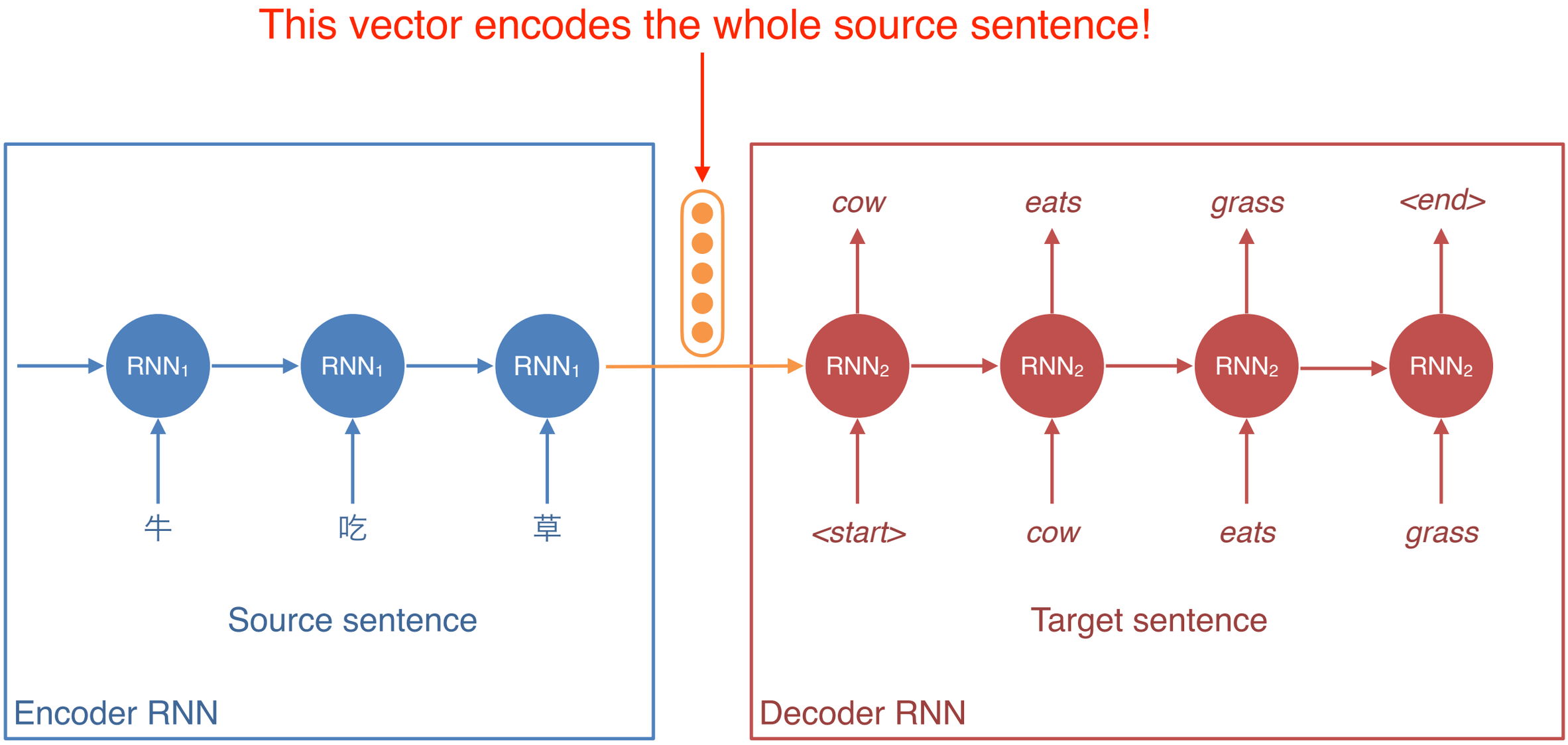
Neural MT: Summary

- Single end-to-end model
  - Statistical MT systems have multiple sub-components
- Less feature engineering
- Can produce new details that are not in the source sentence (*hallucination*)

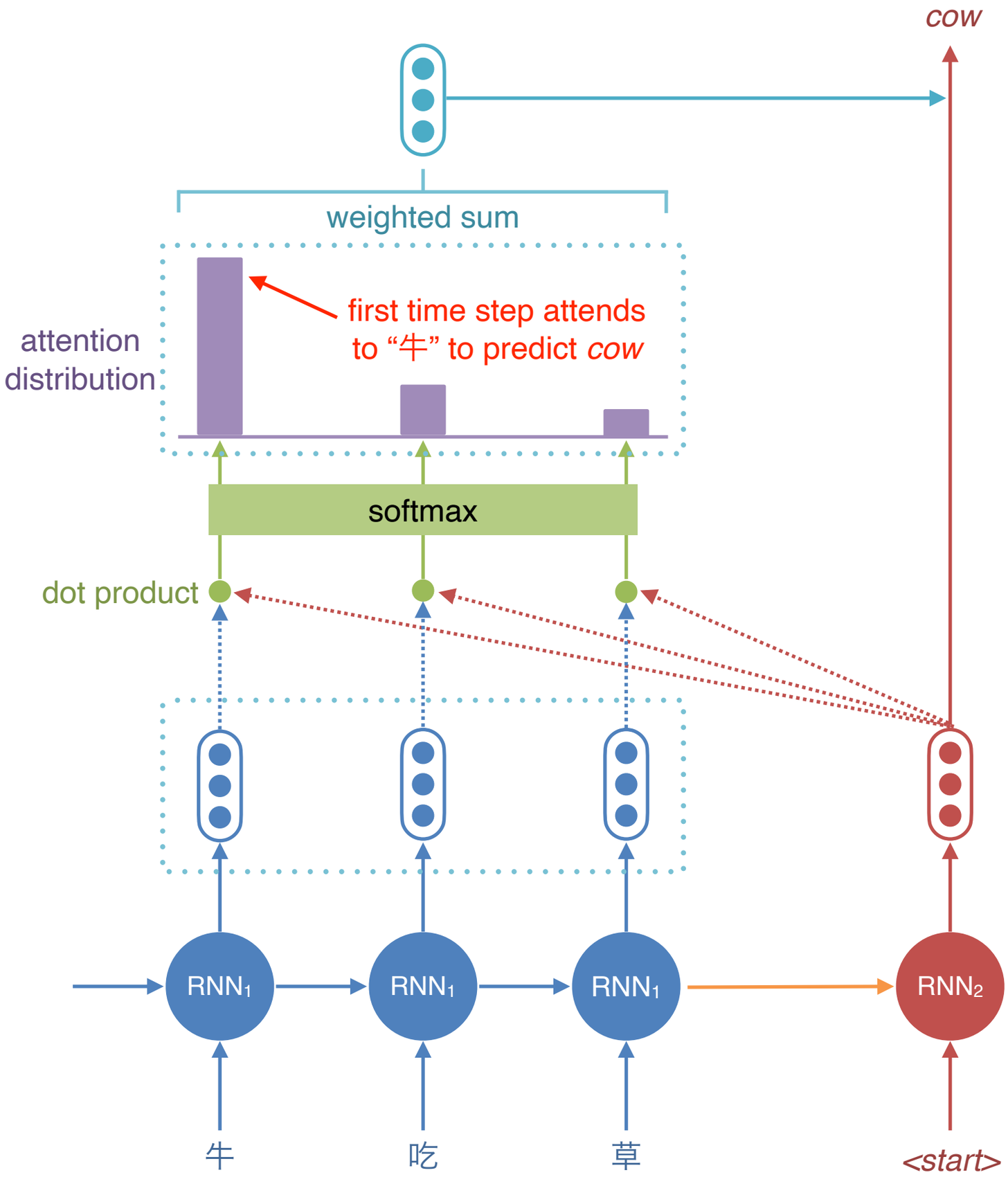
Attention Mechanism

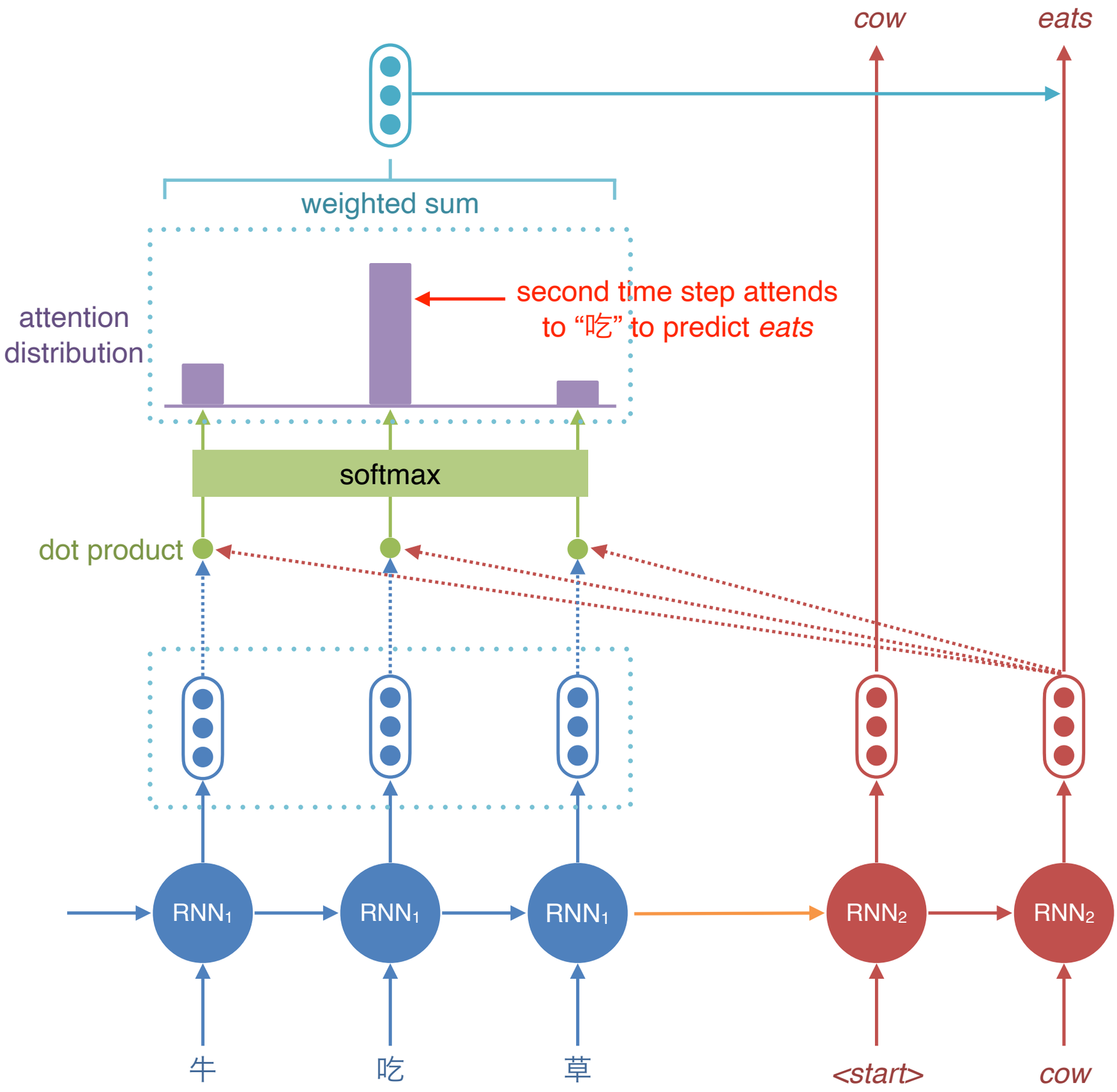


- With a long source sentence, the encoded vector is unlikely to capture all the information in the sentence
- This creates an **information bottleneck**

Attention

- For the decoder, at every time step allow it to '**attend**' to words in the source sentence


cow
weighted sum
attention distribution
first time step attends to “牛” to predict cow
softmax
dot product
RNN1
RNN1
RNN1
RNN2
牛
吃
草
<start>


cow
eats
weighted sum
attention distribution
second time step attends to “吃” to predict eats
softmax
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RNN1
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RNN2
牛
吃
草
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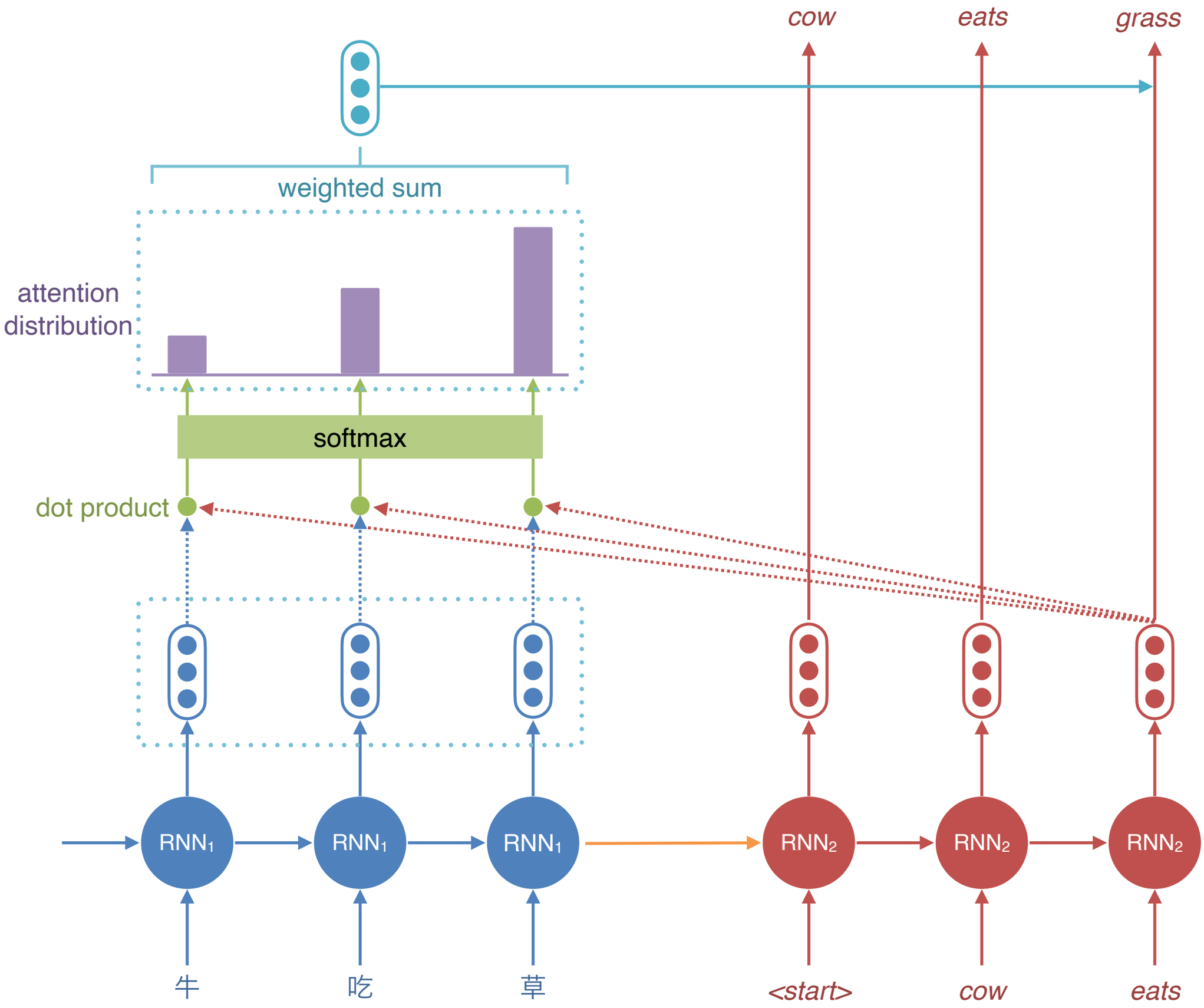
cow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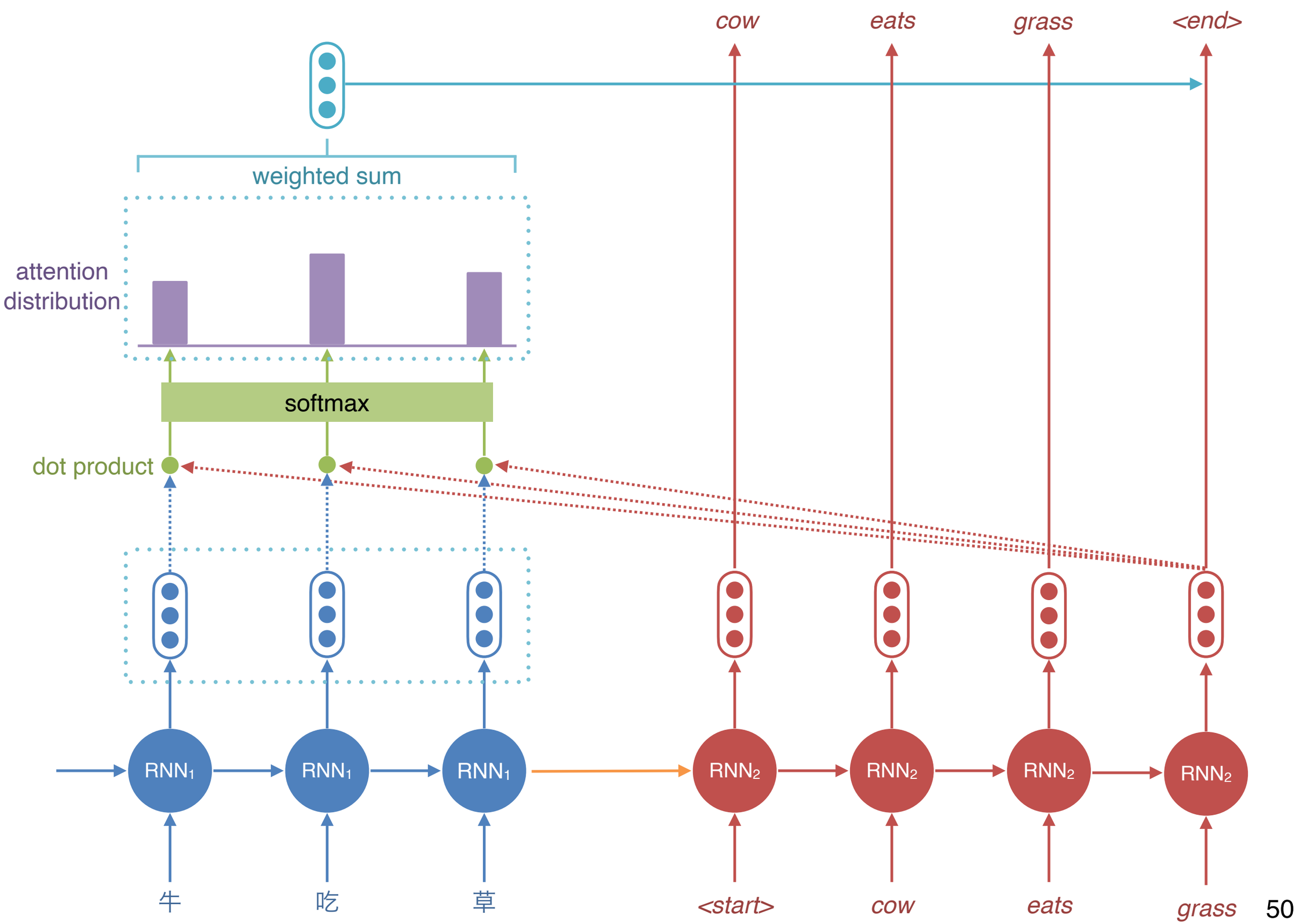
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cow
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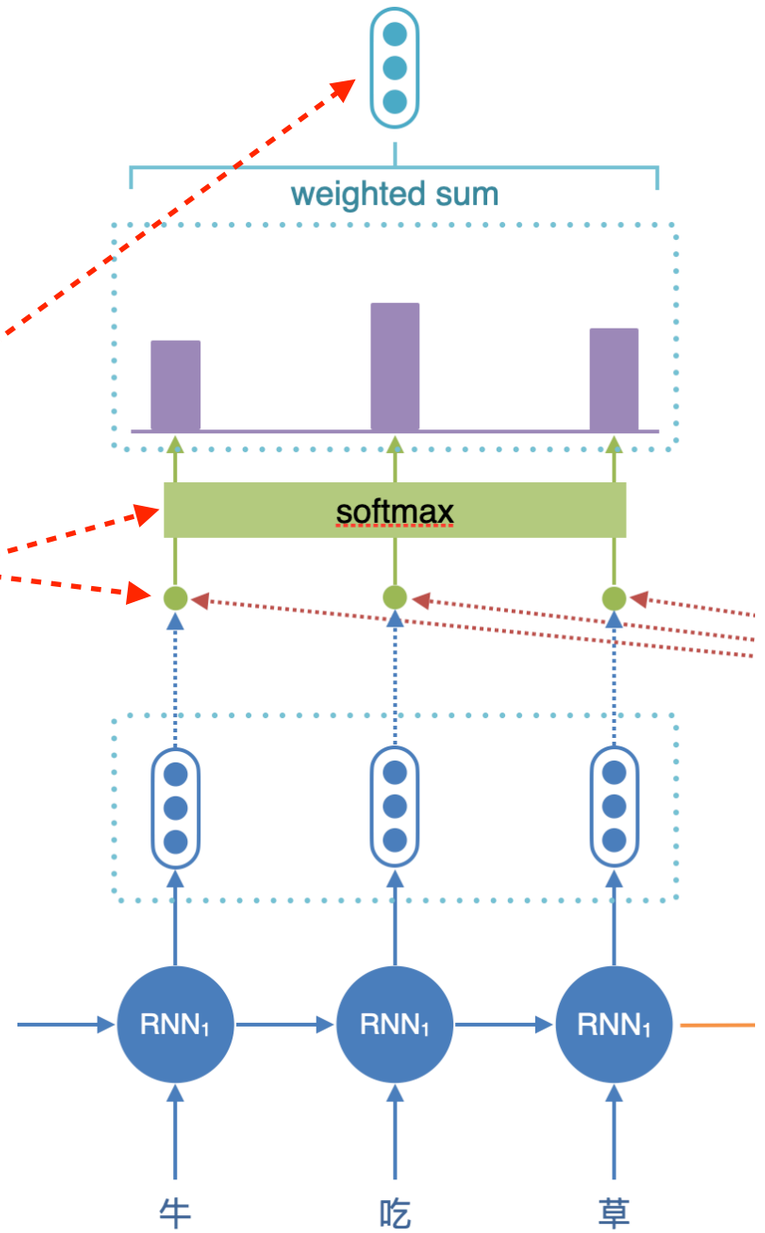
Encoder-Decoder with Attention

- Encoder hidden states: $h_i = RNN_1(h_{i-1}, x_i)$
- Decoder hidden states: $s_t = RNN_2(s_{t-1}, y_t)$
- For each time step in the decoder, attend to each of the hidden states to produce the attention weights:
  - $e_t = [s_t^\intercal h_1, s_t^\intercal h_2, \ldots, s_t^\intercal h_{|x|}]$
- Apply softmax to the attention weights to get a valid probability distribution:
  - $\alpha_t = \text{softmax}(e_t)$
- Compute weighted sum of the encoder hidden states:
  - $c_t = \sum_{i=1}^{|x|} \alpha_t^i h_i$
- Concatenate c_t and s_t to predict the next word



context vector

Variants

- Attention:
  - Dot product: $s_t^\intercal h_i$
  - Bilinear: $s_t^\intercal W h_i$
  - Additive: $v^\intercal \tanh(W_s s_t + W_h h_i)$
- c_t can be injected to the current state (s_t), or to the input word (y_t)

Attention: Summary

- Solves the information bottleneck issue by allowing decoder to have access to the source sentence words directly
- Provides some form of interpretability
  - Attention weights can be seen as word alignments
- Most state-of-the-art NMT systems use attention
  - Google Translate (https://slator.com/technology/google-facebook-amazon-neural-machine-translation-just-had-its-busiest-month-ever/)

Evaluation

MT Evaluation

- BLEU: compute n-gram overlap between "reference" translation and generated translation
- Typically computed for 1 to 4-gram

$$\text{BLEU} = \text{BP} \times \exp\left(\frac{1}{N}\sum_{n}^{N} \log p_n\right)$$

"Brevity Penalty" to penalise short outputs

$$p_n = \frac{\text{\# correct n-grams}}{\text{\# predicted n-grams}}$$

$$\text{BP} = \min\left(1, \frac{\text{output length}}{\text{reference length}}\right)$$

A Final Word

- Statistical MT
- Neural MT
  - Nowadays use Transformers rather than RNNs
- Encoder-decoder with attention architecture is a general architecture that can be used for other tasks
  - Summarisation (lecture 21)
  - Other generation tasks such as dialogue generation

Reading

- JM3 Ch. 10.2-10.5
- Optional: GIZA++ word alignment - https://www.aclweb.org/anthology/W08-0509.pdf