Attention in Seq2Seq Models

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Introduction to Large Language Models

NMT: The First Big Success Story of NLP Deep Learning

Neural Machine Translation went from a fringe research attempt in 2014 to the leading standard method in 2016

- 2014: First seq2seq paper published [Sutskever et al. 2014]
- 2016: Google Translate switches from SMT to NMT – and by 2018 everyone had
  - https://www.nytimes.com/2016/12/14/magazine/the-great-ai-awakening.html

- This was amazing!
  - SMT systems, built by hundreds of engineers over many years, were outperformed by NMT systems trained by small groups of engineers in a few months
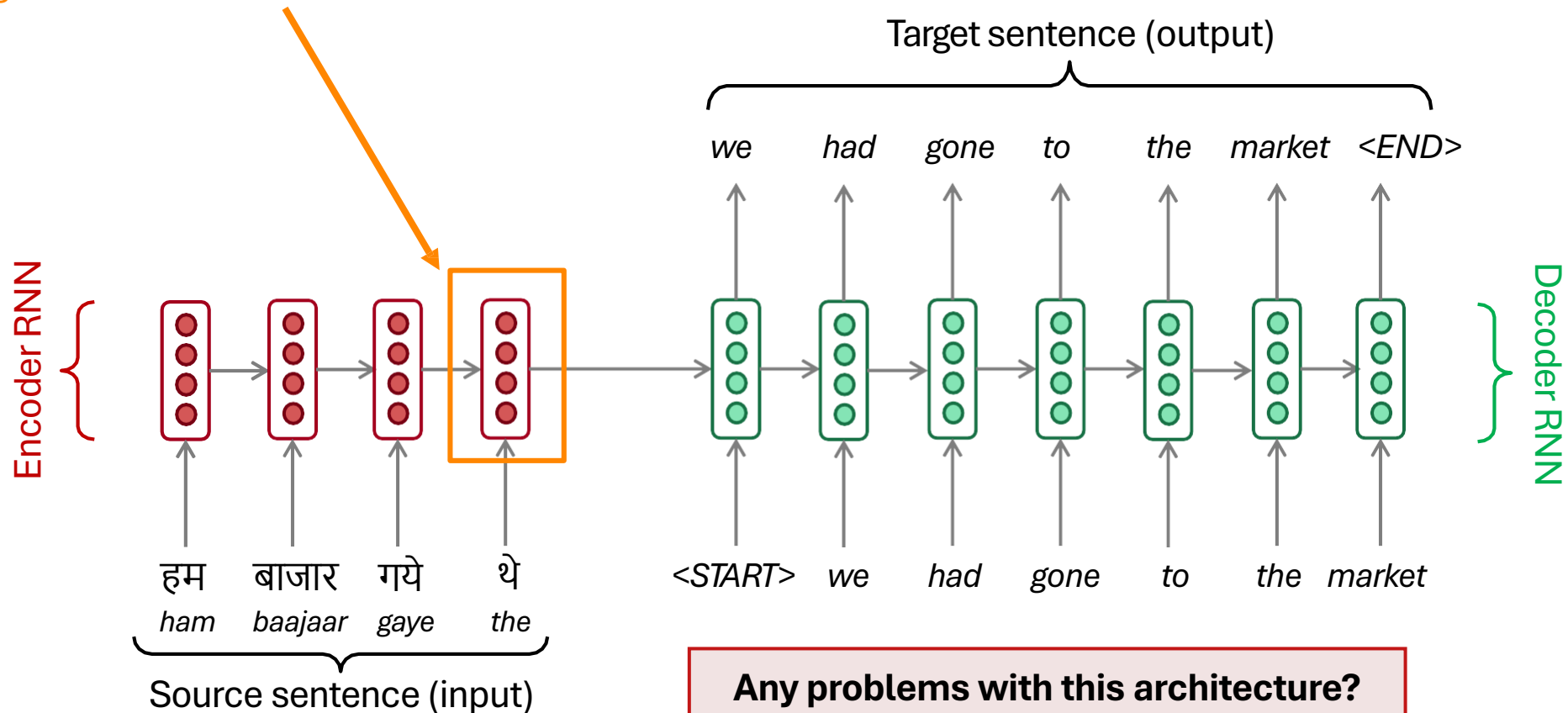
Issues With RNN

- Linear interaction distance
- Bottleneck problem
- Lack of parallelizability

ATTENTION

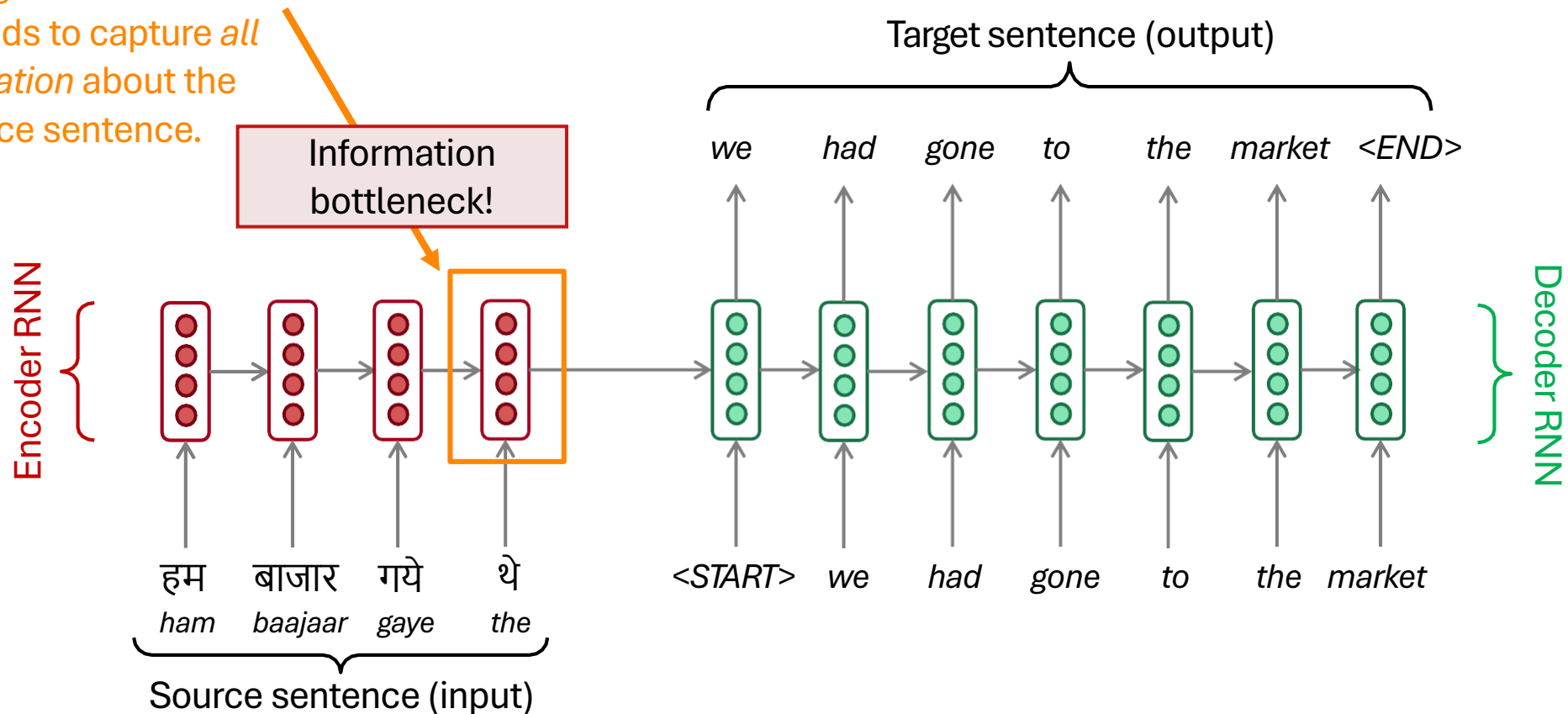# Attention

Sequence-to-Sequence: The Bottleneck Problem

Encoding of the source sentence

Target sentence (output)

Encoder RNN

Decoder RNN

we   had   gone   to   the   market   <END>

हम   बाजार   गये   थे
ham   baajaar   gaye   the

Source sentence (input)

<START>   we   had   gone   to   the   market

Any problems with this architecture?

Sequence-to-Sequence: The Bottleneck Problem

Encoding of the source sentence
This needs to capture *all information* about the source sentence.

Information bottleneck!

Target sentence (output)

Encoder RNN

Decoder RNN

we   had   gone   to   the   market   <END>

हम   बाजार   गये   थे
ham   *baajaar*   *gaye*   *the*

<START>   we   had   gone   to   the   market
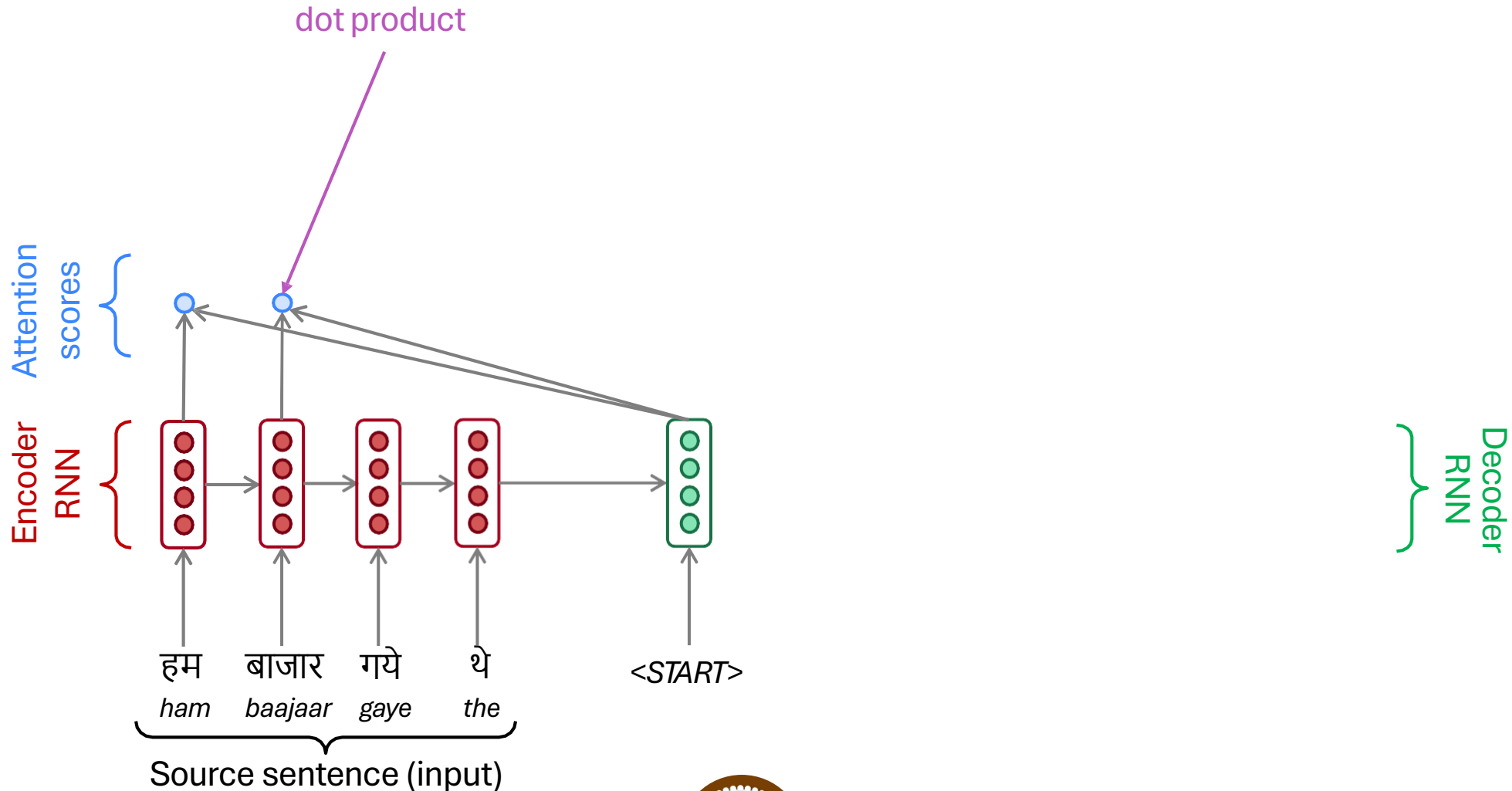
Source sentence (input)

NPTEL

LCS

Attention

- **Attention** provides a solution to the bottleneck problem.

- **Core idea**: on each step of the decoder, use direct connection to the encoder to focus on a particular part of the source sequence

- Let's start with the visualization of the attention mechanism.

Sequence-to-Sequence With Attention

dot product

Attention scores

Encoder RNN

Decoder RNN

हम
ham

बाजार
baajaar

गये
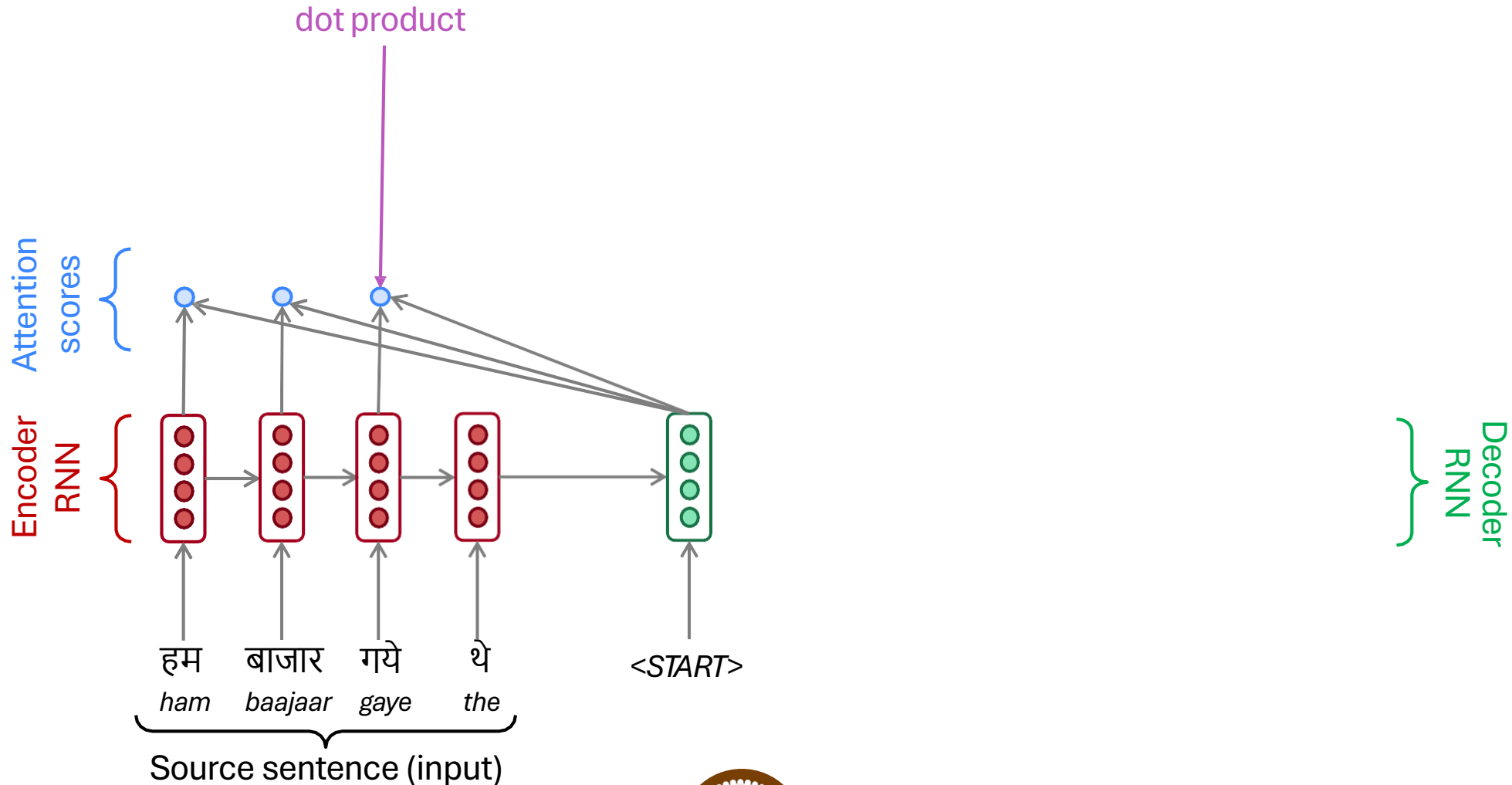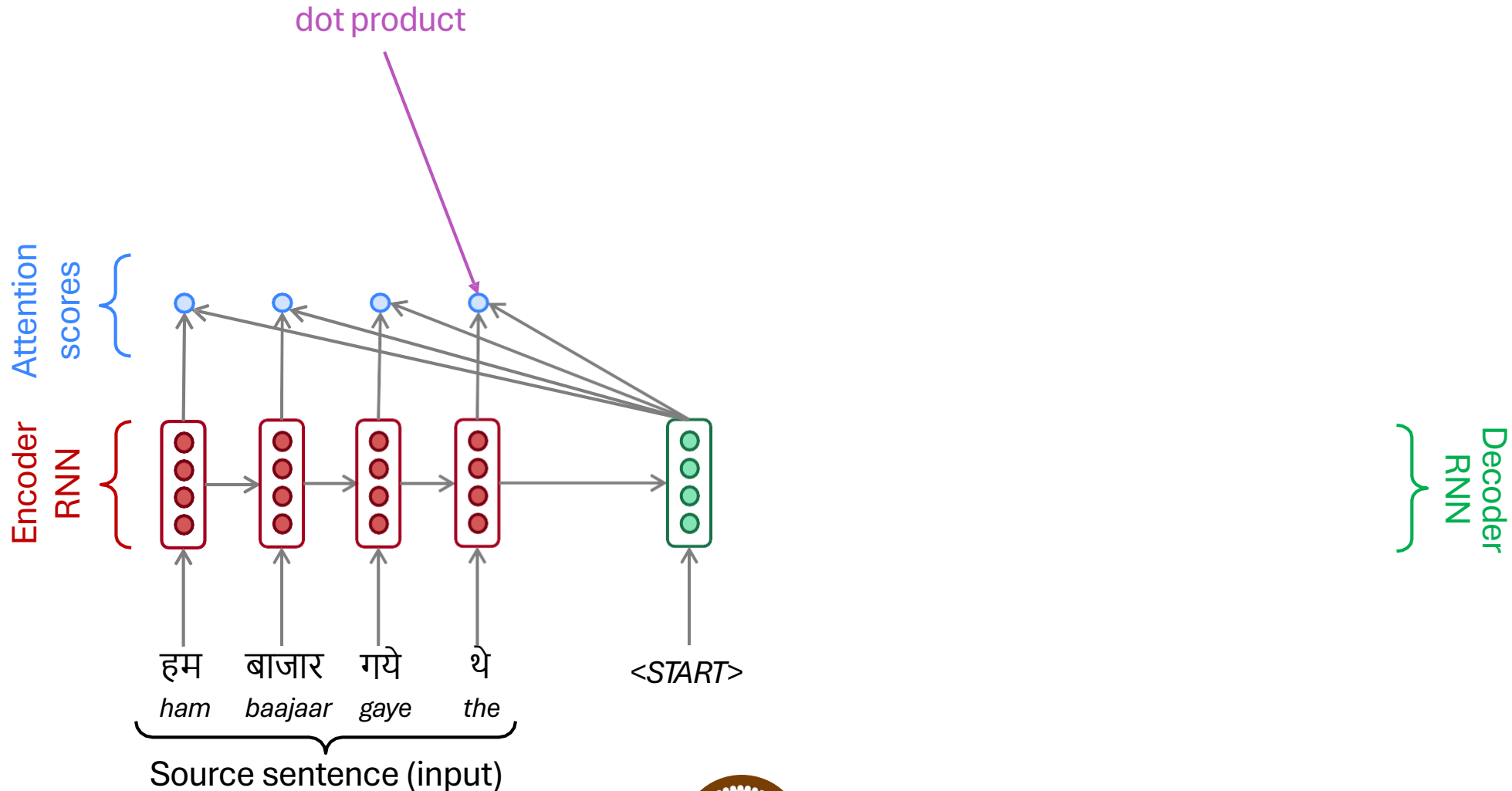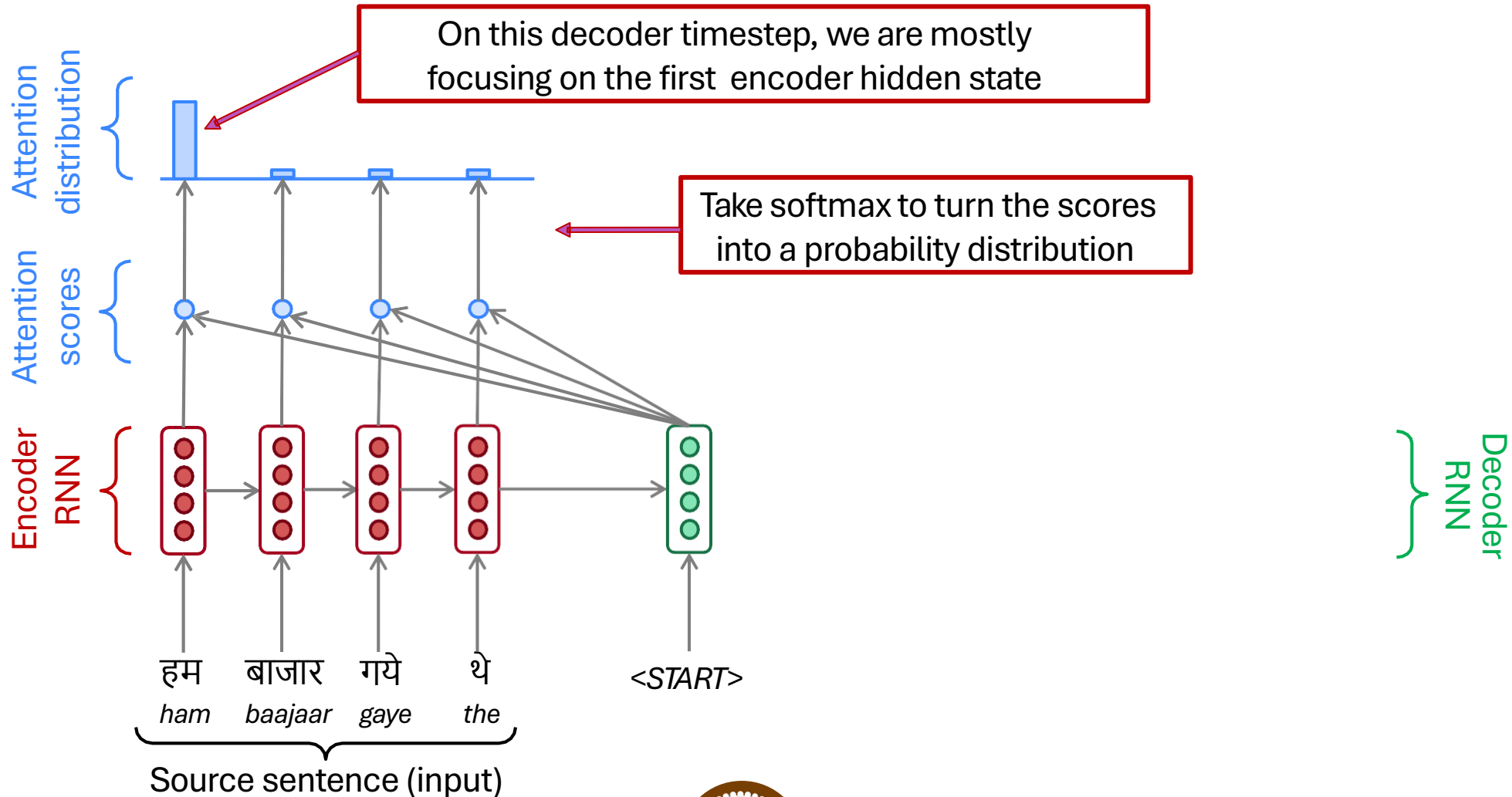*gaye*

थे
the

<START>

Source sentence (input)

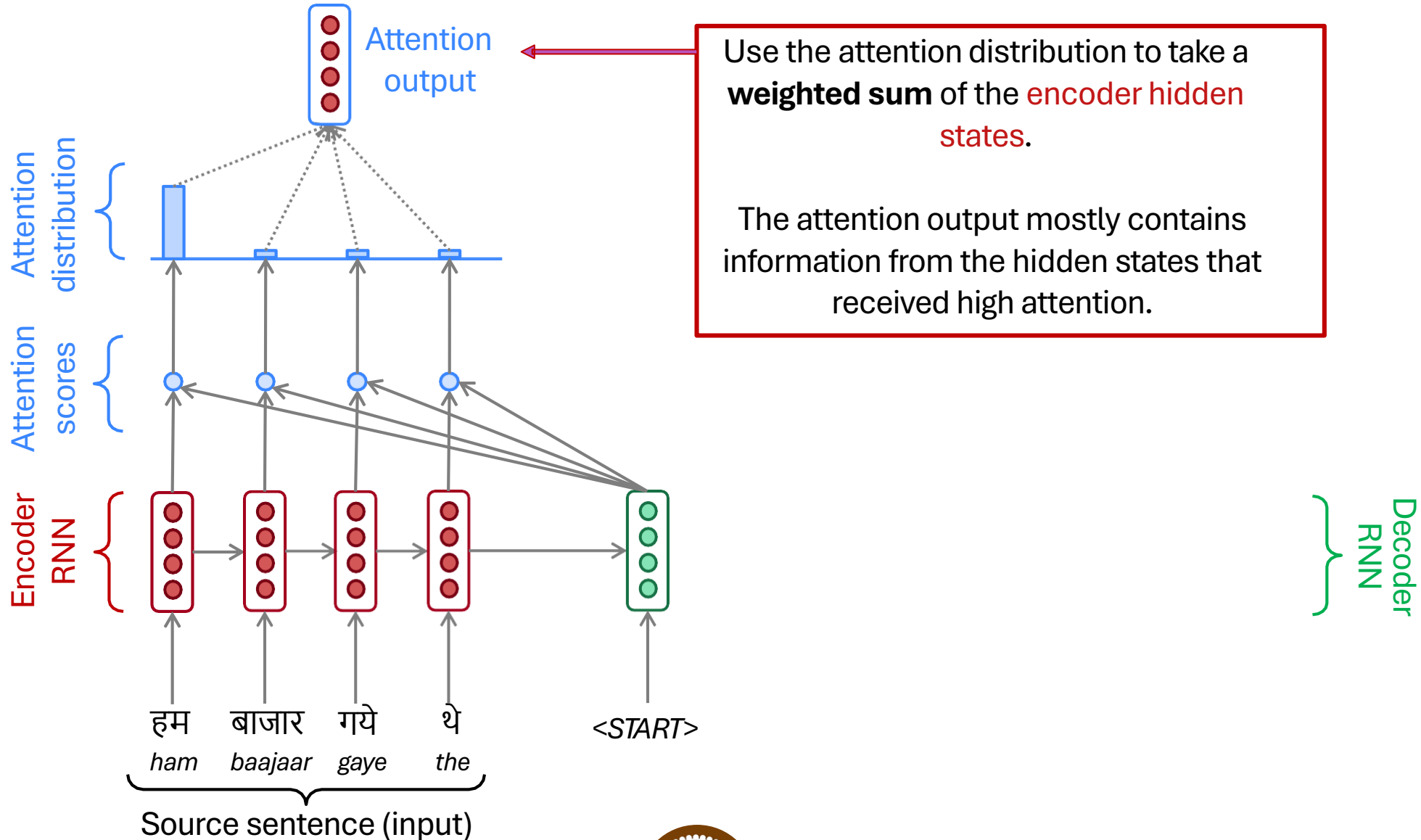# Sequence-to-Sequence With Attention

Sequence-to-Sequence With Attention

dot product

Attention scores

Encoder RNN

Decoder RNN

हम
ham

बाजार
baajaar

गये
gaye

थे
the

<START>

Source sentence (input)

Sequence-to-Sequence With Attention

dot product

Attention scores

Encoder RNN

Decoder RNN

हम *ham*   बाजार *baajaar*   गये *gaye*   थे *the*   <START>

Source sentence (input)

Sequence-to-Sequence With Attention

On this decoder timestep, we are mostly focusing on the first encoder hidden state

Take softmax to turn the scores into a probability distribution

Attention distribution

Attention scores

Encoder RNN

Decoder RNN

हम
ham

बाजार
baajaar

गये
gaye

थे
the

<START>

Source sentence (input)

Sequence-to-Sequence With Attention

Attention output

Attention distribution

Attention scores

Encoder RNN

Decoder RNN

हम
ham

बाजार
baajaar

गये
gaye

थे
the

<START>

Source sentence (input)

Use the attention distribution to take a **weighted sum** of the encoder hidden states.

The attention output mostly contains information from the hidden states that received high attention.

Sequence-to-Sequence With Attention

Concatenate attention output with decoder hidden state, then use to compute $\hat{y}_1$ as before

Sequence-to-Sequence With Attention

Attention output

had

$\hat{y}_2$

Attention distribution

Attention scores

Encoder RNN

Decoder RNN

हम
ham

बाजार
baajaar

गये
gaye

थे
the

<START>

we

Source sentence (input)

Sometimes we take the attention output from the previous step, and also feed it into the decoder (along with the usual decoder input).

Sequence-to-Sequence With Attention

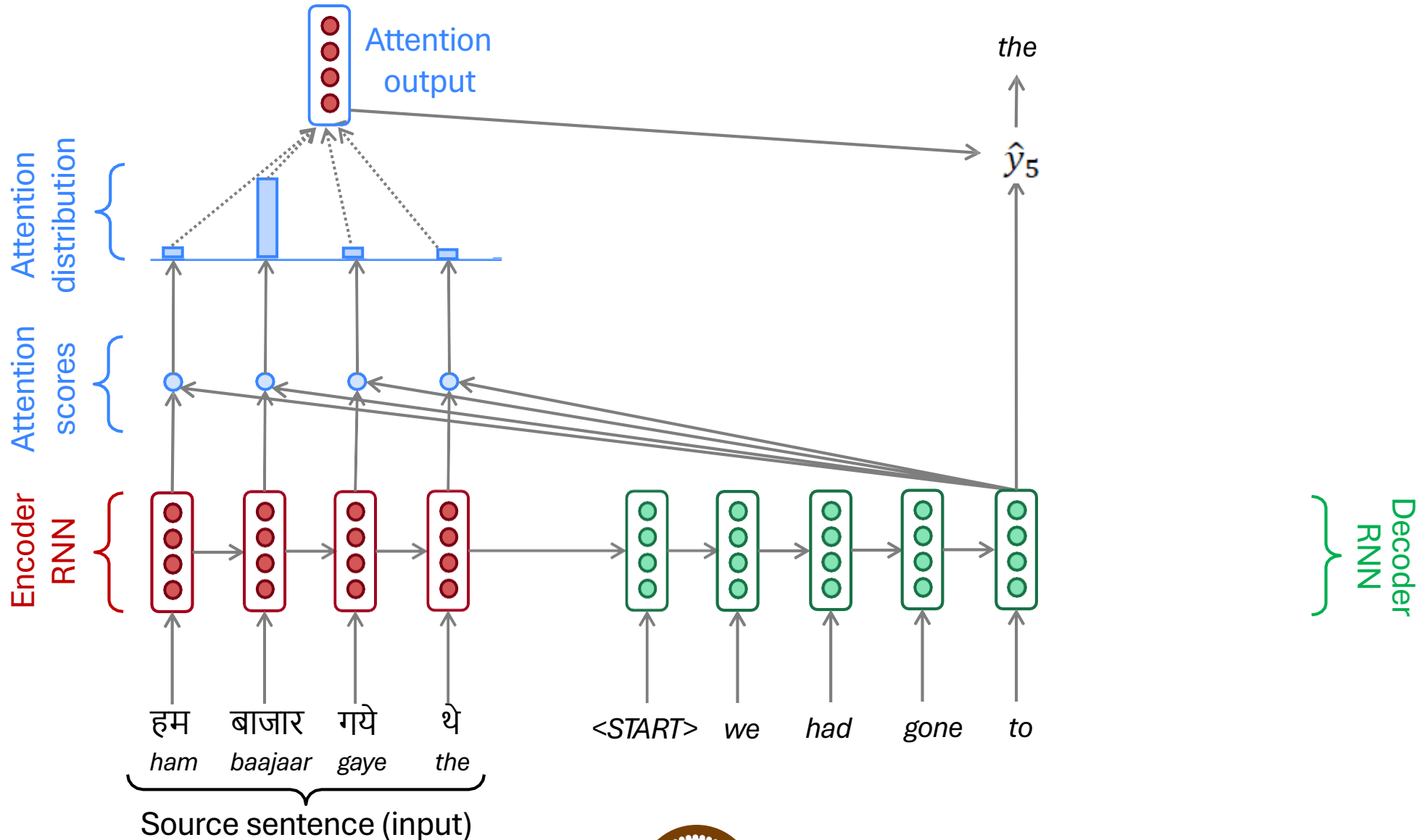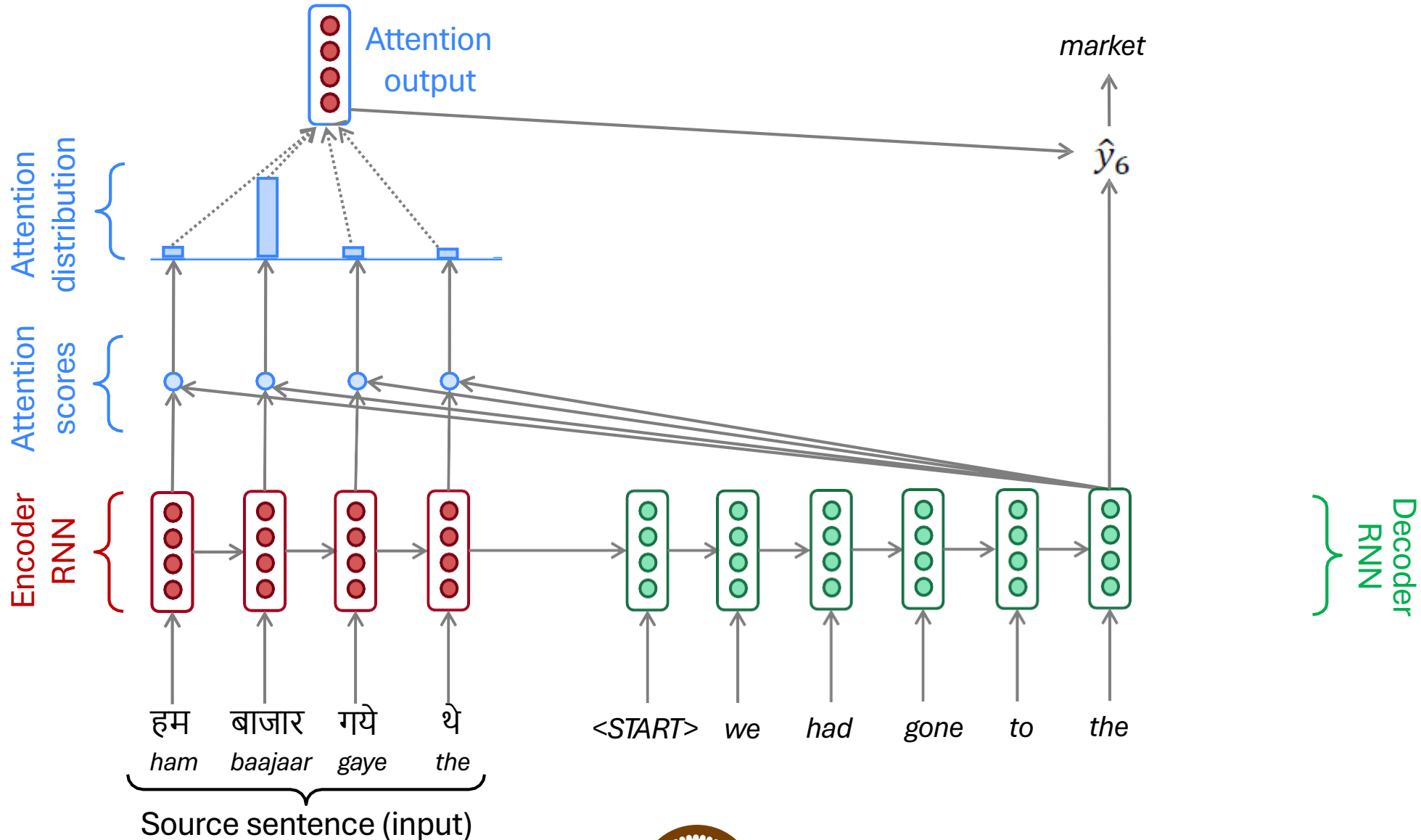# Sequence-to-Sequence With Attention

Sequence-to-Sequence With Attention

Sequence-to-Sequence With Attention

Attention: In Equations

- We have encoder hidden states $h_1, \ldots, h_N \in \mathbb{R}^h$

- On timestep t, we have decoder hidden state $s_t \in \mathbb{R}^h$

- We get the attention scores e^t for this step:

$$e^t = [s_t^T h_1, \ldots, s_t^T h_N] \in \mathbb{R}^N$$

- We take softmax to get the attention distribution α^t for this step (this is a probability distribution, sums to 1)

$$\alpha^t = \text{softmax}(e^t) \in \mathbb{R}^N$$

- We use α^t to take a weighted sum of the encoder hidden states to get the attention output a_t

$$a_t = \sum_{i=1}^{N} \alpha_i^t h_i \in \mathbb{R}^h$$

- Finally we concatenate the attention output a_t with the decoder hidden state s_t and proceed as in the non-attention seq2seq model
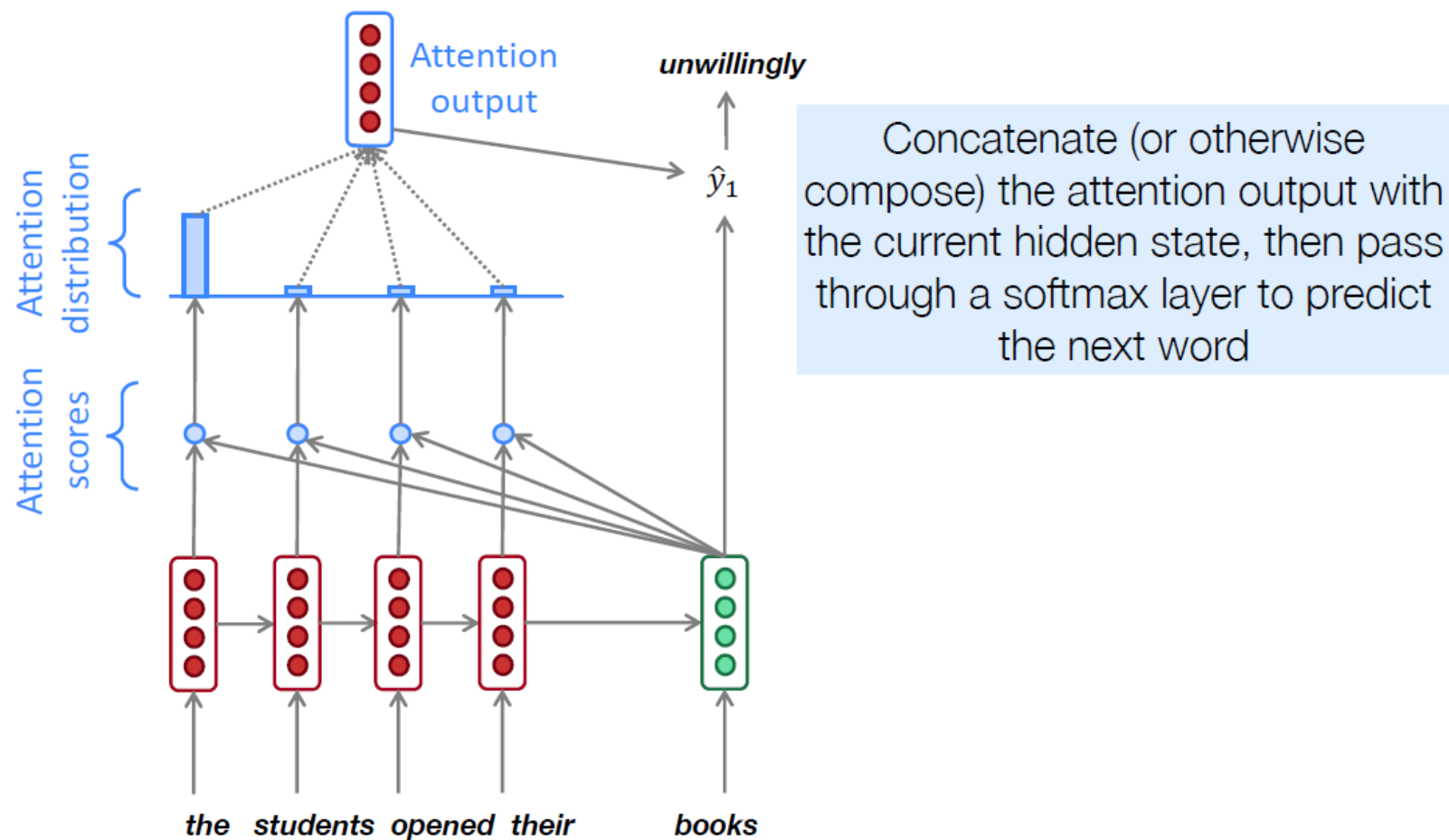
$$[a_t; s_t] \in \mathbb{R}^{2h}$$

Attention is Great

- **Attention significantly improves NMT performance**
  - It's very useful to allow decoder to focus on certain parts of the source
- **Attention solves the bottleneck problem**
  - Attention allows decoder to look directly at source; bypass bottleneck
- **Attention helps with vanishing gradient problem**
  - Provides shortcut to faraway states
- **Attention provides some interpretability**
  - By inspecting attention distribution, we can see what the decoder was focusing on
  - We get (soft) alignment for free!
  - This is cool because we never explicitly trained an alignment system
  - The network just learned alignment by itself

Seq2Seq+Attention for LM

Concatenate (or otherwise compose) the attention output with the current hidden state, then pass through a softmax layer to predict the next word

Attention is a *General* Deep Learning Technique

- We've seen that attention is a great way to improve the sequence-to-sequence model for Machine Translation.

- <u>However</u>: You can use attention in many architectures (not just seq2seq) and many tasks (not just MT)

- More general definition of attention:

  - Given a set of vector *values*, and a vector *query*, attention is a technique to compute a weighted sum of the values, dependent on the query.

- We sometimes say that the query *attends to* the values.

- For example, in the seq2seq + attention model, each decoder hidden state (query) *attends to* all the encoder hidden states (values).

- **Intuition**:

  - The weighted sum is a *selective summary* of the information contained in the values, where the query determines which values to focus on.

  - Attention is a way to obtain a *fixed-size representation of an arbitrary set of representations* (the values), dependent on some other representation (the query).
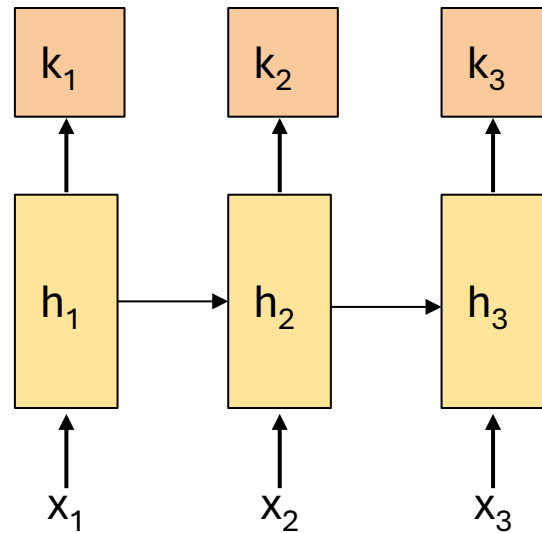
Attention

Encoding

h_1 → h_2 → h_3
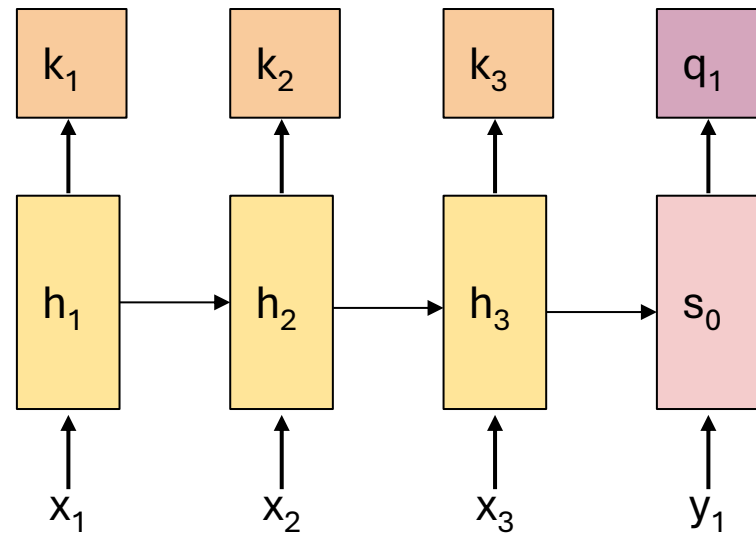
↑   ↑   ↑

x_1 x_2 x_3
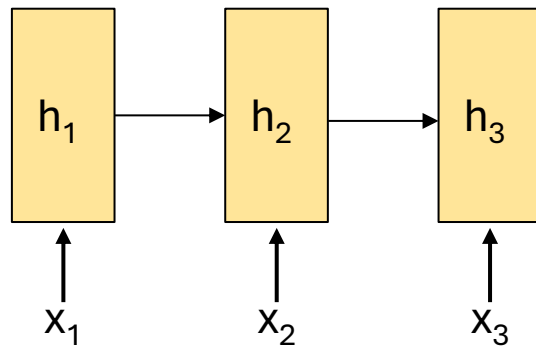
Input Sequence

Attention

Key vectors represent what information is encoded at each encoder time step.

Encoding

k$_1$ k$_2$ k$_3$

h$_1$ → h$_2$ → h$_3$

x$_1$ x$_2$ x$_3$

Input Sequence

Attention

Query vectors represent what information we are **looking for** at each decoder time step.
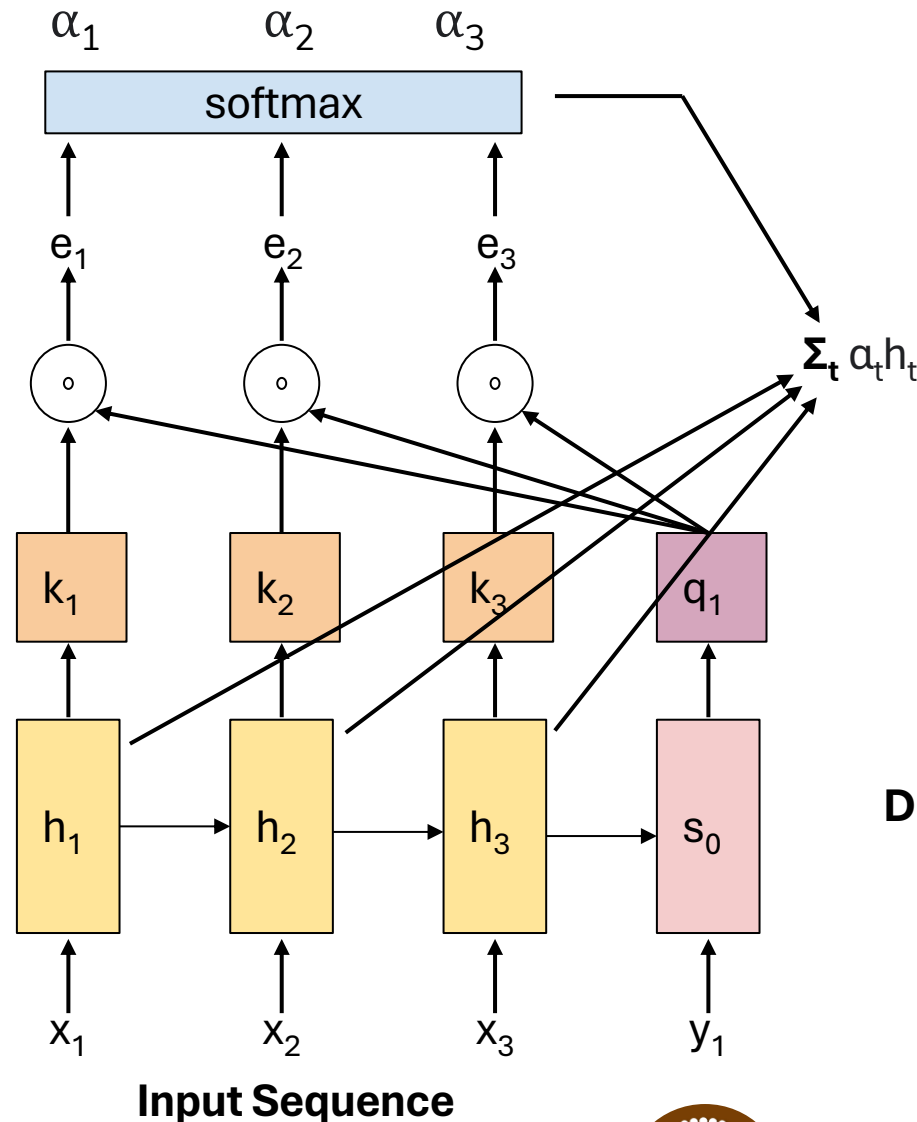
Decoding

Input Sequence
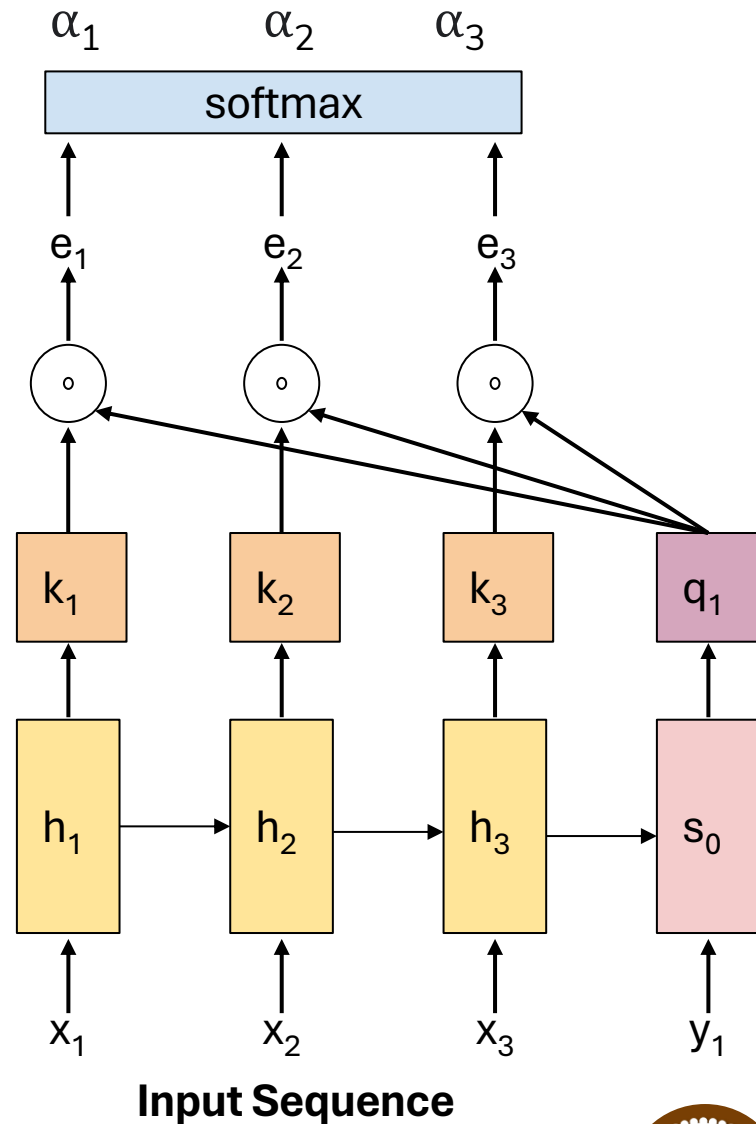
Attention

Softmax converts the similarity scores into a **probability distribution**.

Dot product between query vector and every key vector gives **similarity score**.

Decoding

Input Sequence

Attention

The output of attention mechanism is the **weighted sum** of hidden vectors.

Instead of simply summing up the hidden vectors, we can transform them using a learned function to generate **value vectors** and then compute a weighted sum.

Variants of Attention

- Original formulation: $a(\mathbf{q}, \mathbf{k}) = w_2^T \tanh(W_1[\mathbf{q}; \mathbf{k}])$

- Bilinear product: $a(\mathbf{q}, \mathbf{k}) = \mathbf{q}^T W \mathbf{k}$ Luong et al., 2015

- Dot product: $a(\mathbf{q}, \mathbf{k}) = \mathbf{q}^T \mathbf{k}$ Luong et al., 2015

- Scaled dot product: $a(\mathbf{q}, \mathbf{k}) = \dfrac{\mathbf{q}^T \mathbf{k}}{\sqrt{|\mathbf{k}|}}$ Vaswani et al., 2017

More information:
"Deep Learning for NLP Best Practices", Ruder, 2017. http://ruder.io/deep-learning-nlp-best-practices/index.html#attention
"Massive Exploration of Neural Machine Translation Architectures", Britz et al, 2017, https://arxiv.org/pdf/1703.03906.pdf

Self-Attention