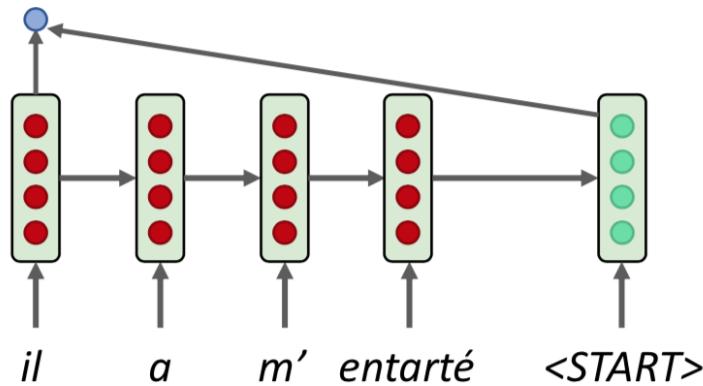

Deep Learning and Applications

Theja Tulabandhula

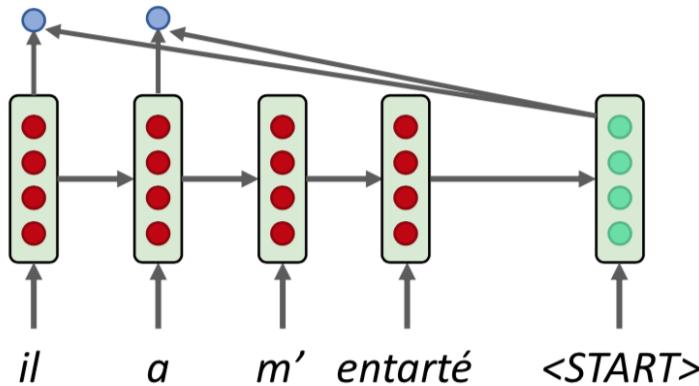
Attention

- Compute attention scores given some function α
 - Encoder hidden state h_1
 - Decoder hidden state s_1
- Attention score $a_{11} = f(h_1, s_1)$



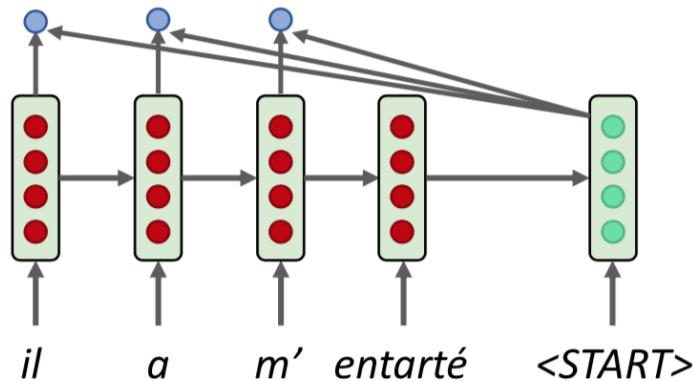
Attention

- Compute attention scores given some function α
 - Encoder hidden state h_2
 - Decoder hidden state s_1
- Attention score $a_{12} = f(h_2, s_1)$



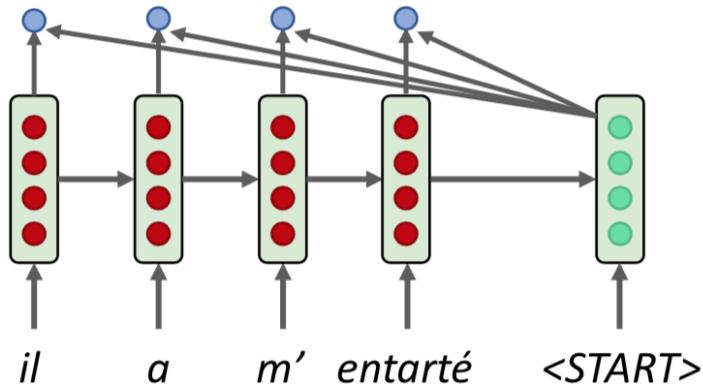
Attention

- Compute attention scores given some function α
 - Encoder hidden state h_3
 - Decoder hidden state s_1
- Attention score $a_{13} = f(h_3, s_1)$



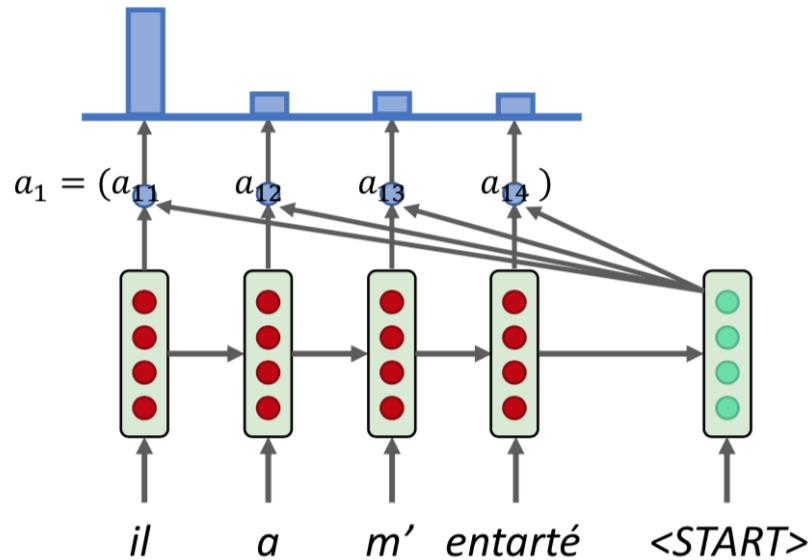
Attention

- Compute attention scores given some function α
 - Encoder hidden state h_4
 - Decoder hidden state s_1
- Attention score $a_{14} = f(h_4, s_1)$



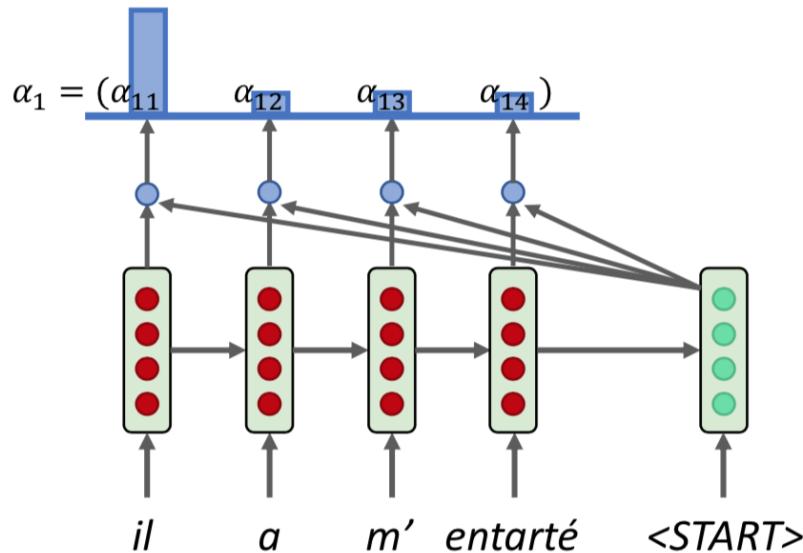
Attention

- Convert attention scores into a distribution by softmax.

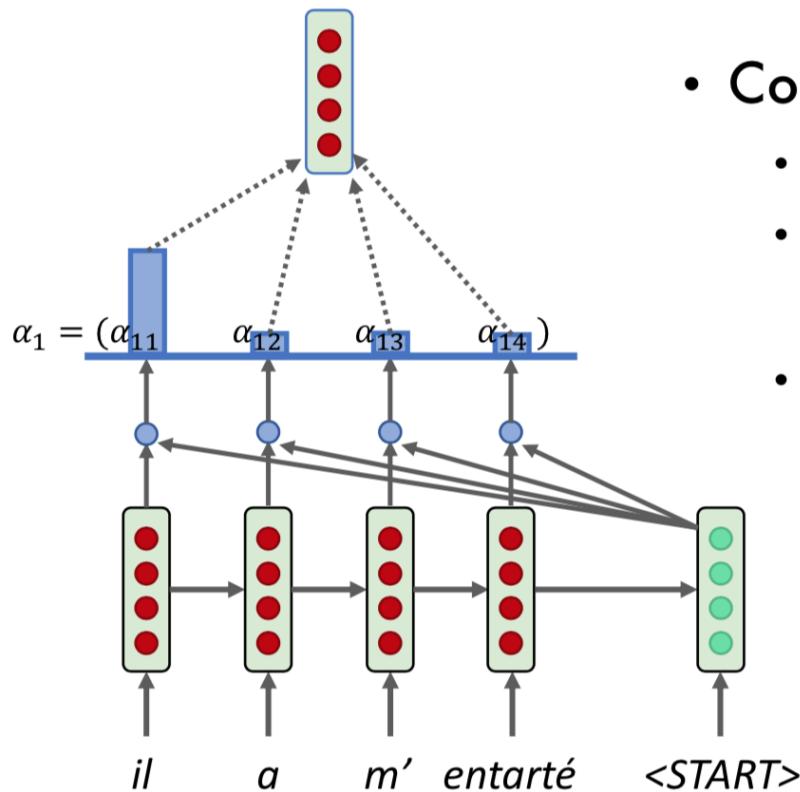


Attention

- Convert attention scores into a distribution by softmax.
 - $\alpha_1 = \text{softmax}(a_1)$
 - We are mostly focusing on the encoder's 1st hidden state h_1 .

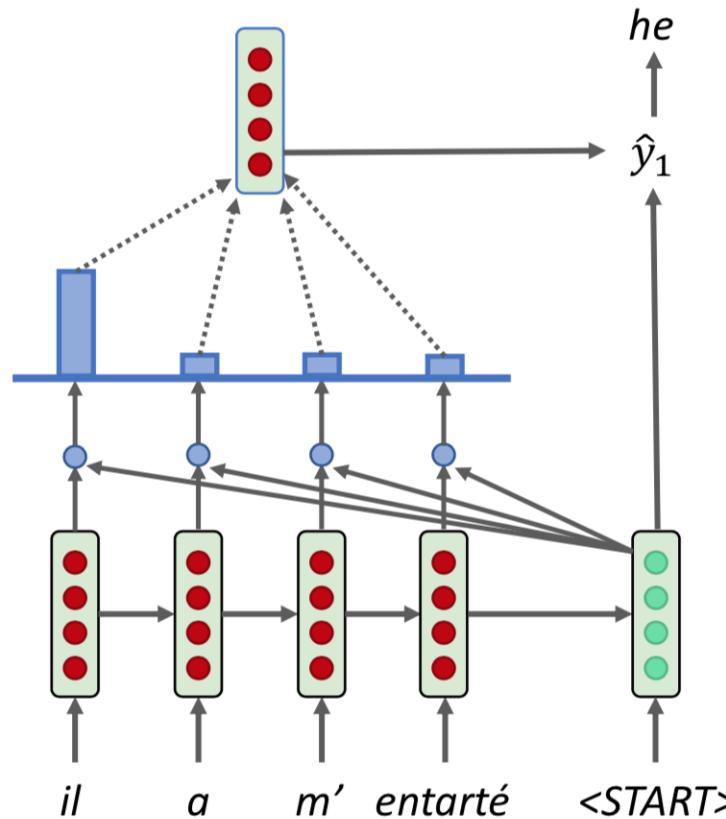


Attention



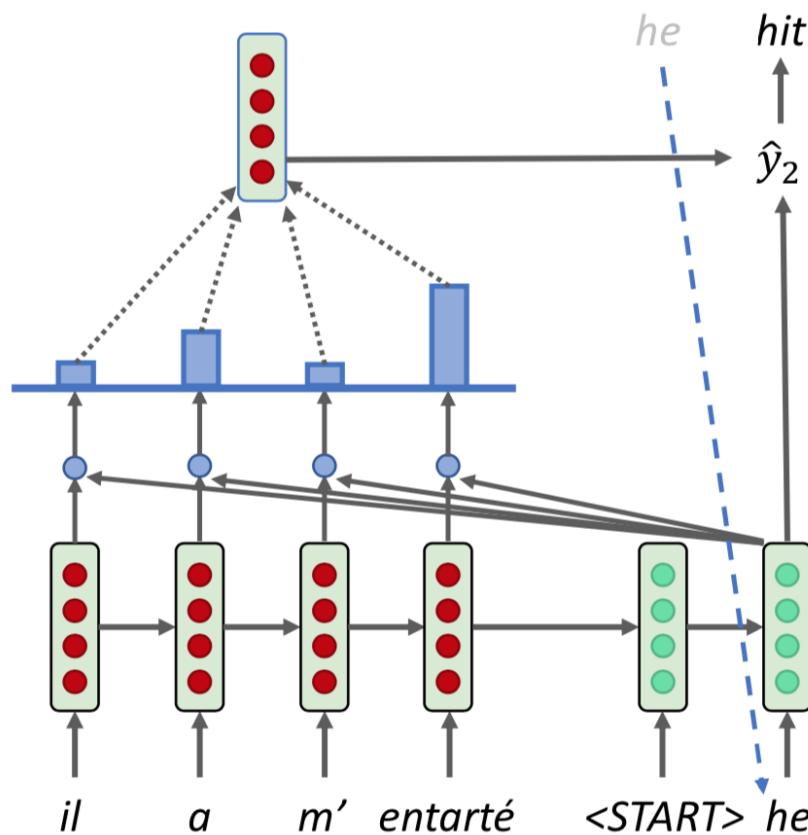
- Compute the attention output z_1 .
 - Weighted sum of hidden states.
 - $$z_1 = \sum_{t=1}^4 \alpha_{1t} h_t$$
- Attention output contains information of every hidden state proportionally to attention distribution α .

Attention

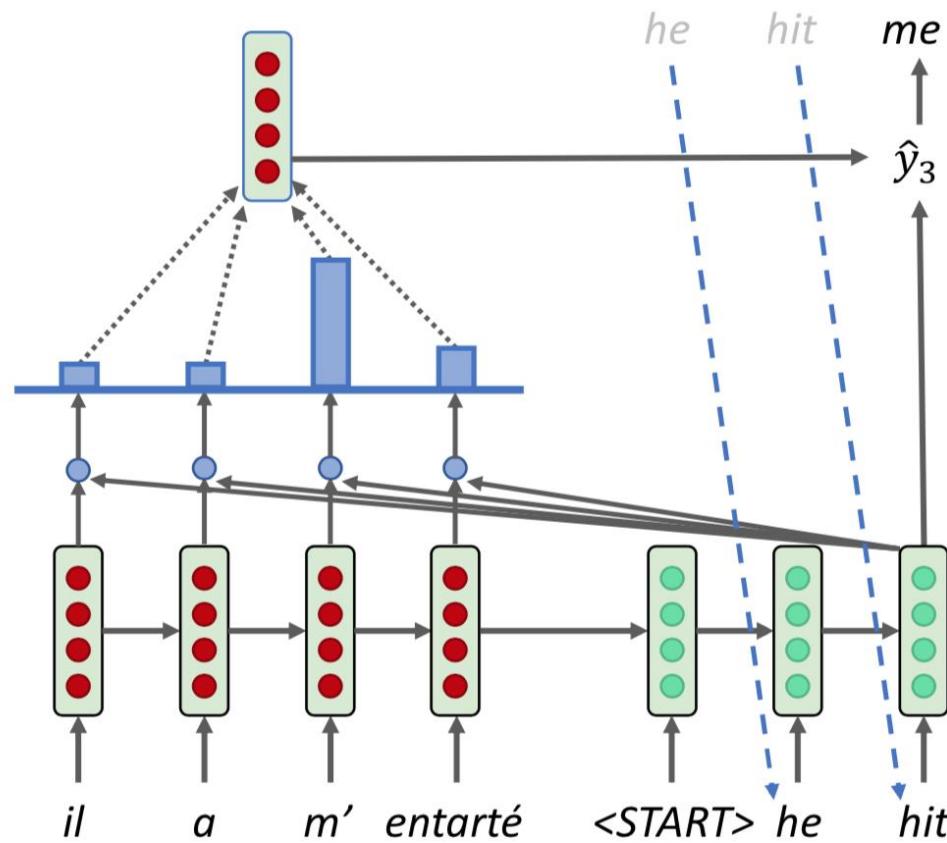


- **Concatenate then generate**
 - $[z_t; s_t] \in \mathbb{R}^{2d}$
 - $\hat{y}_t = \text{softmax}(g([z_t; s_t]))$

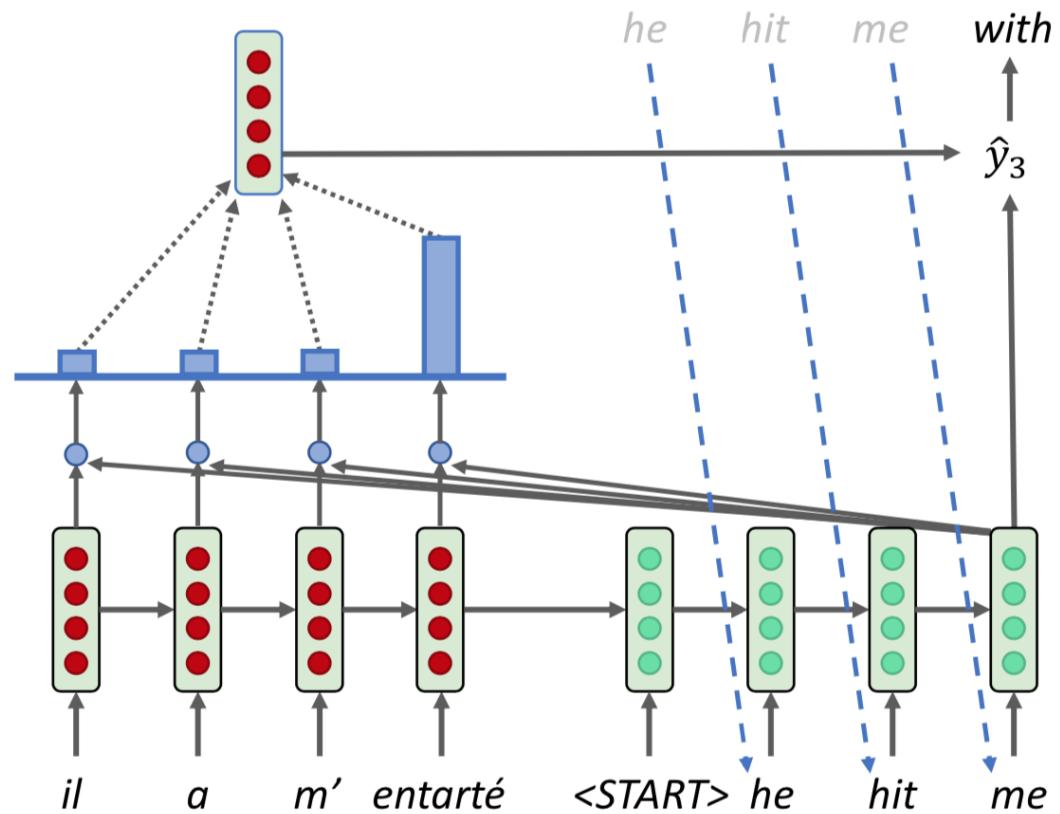
Attention



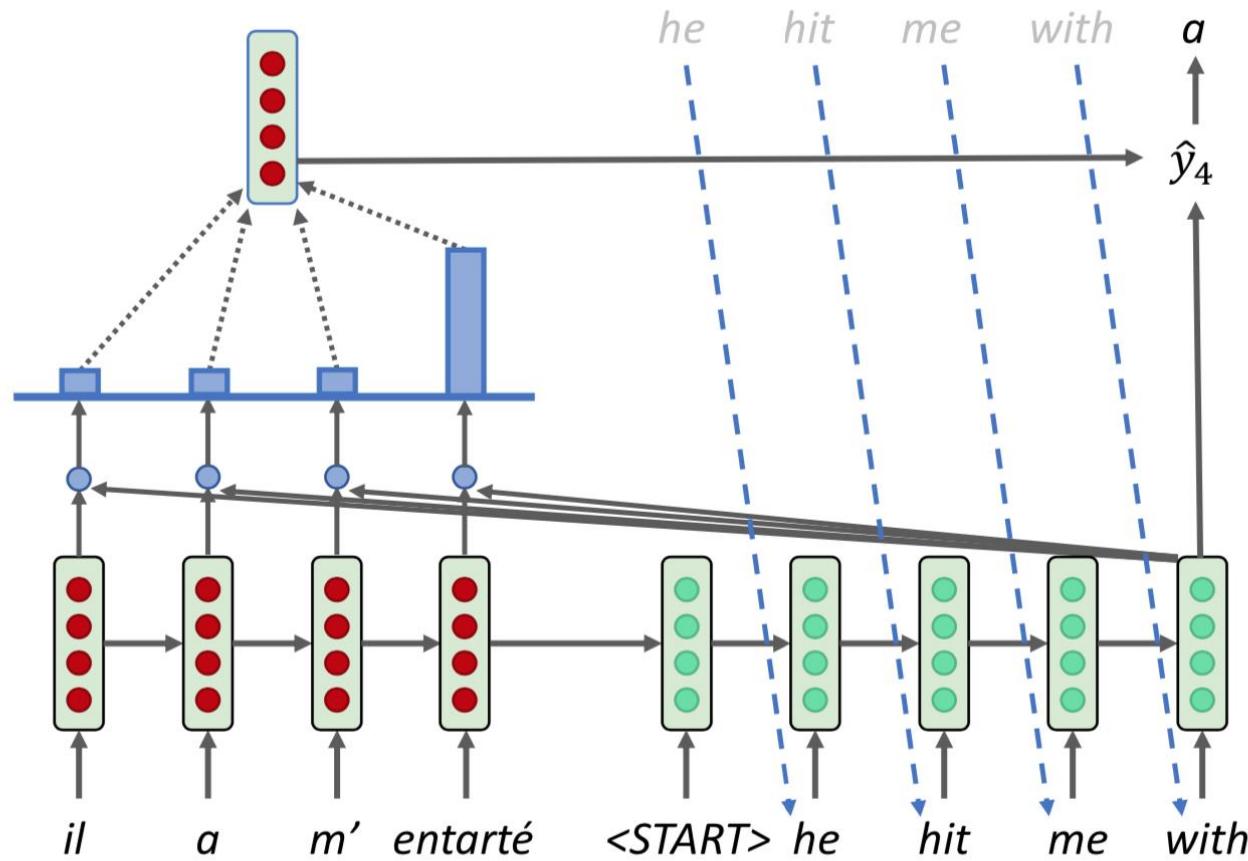
Attention



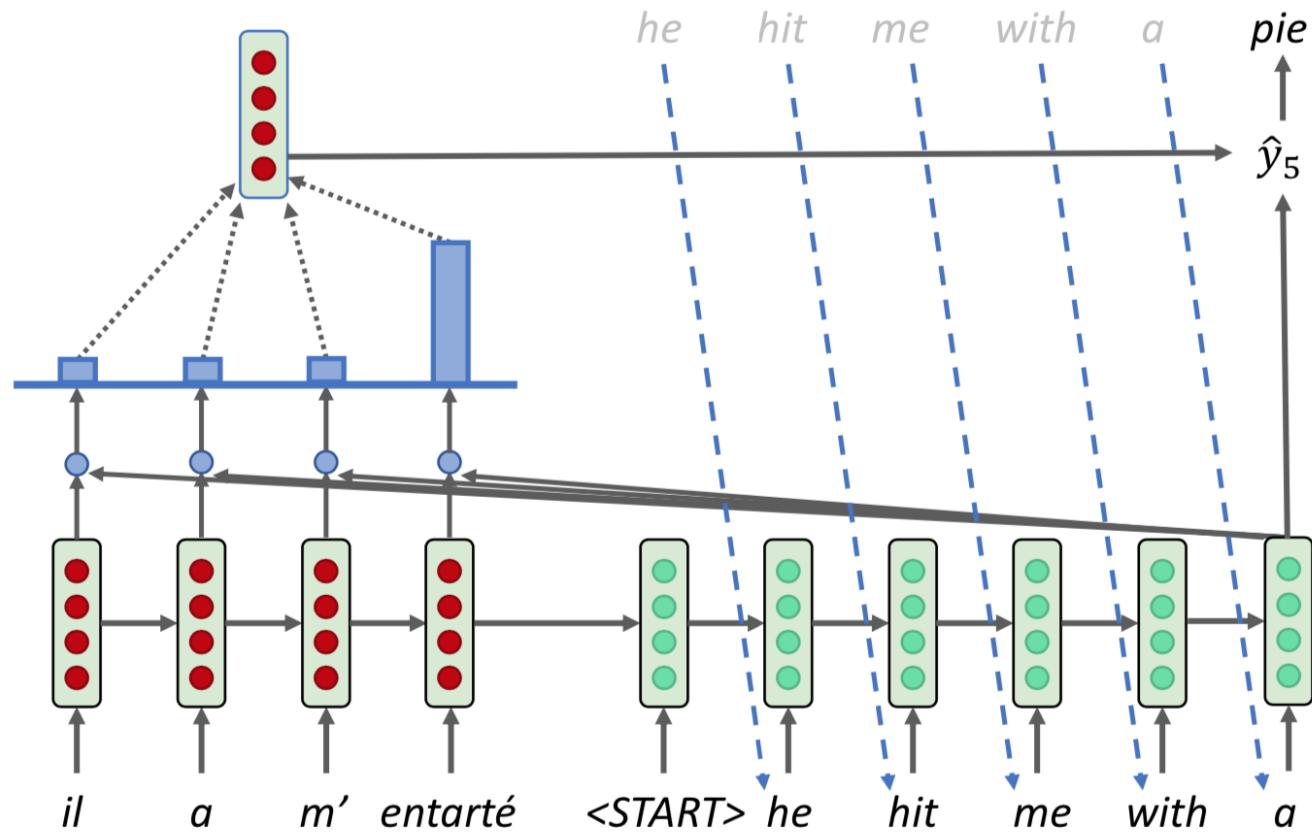
Attention



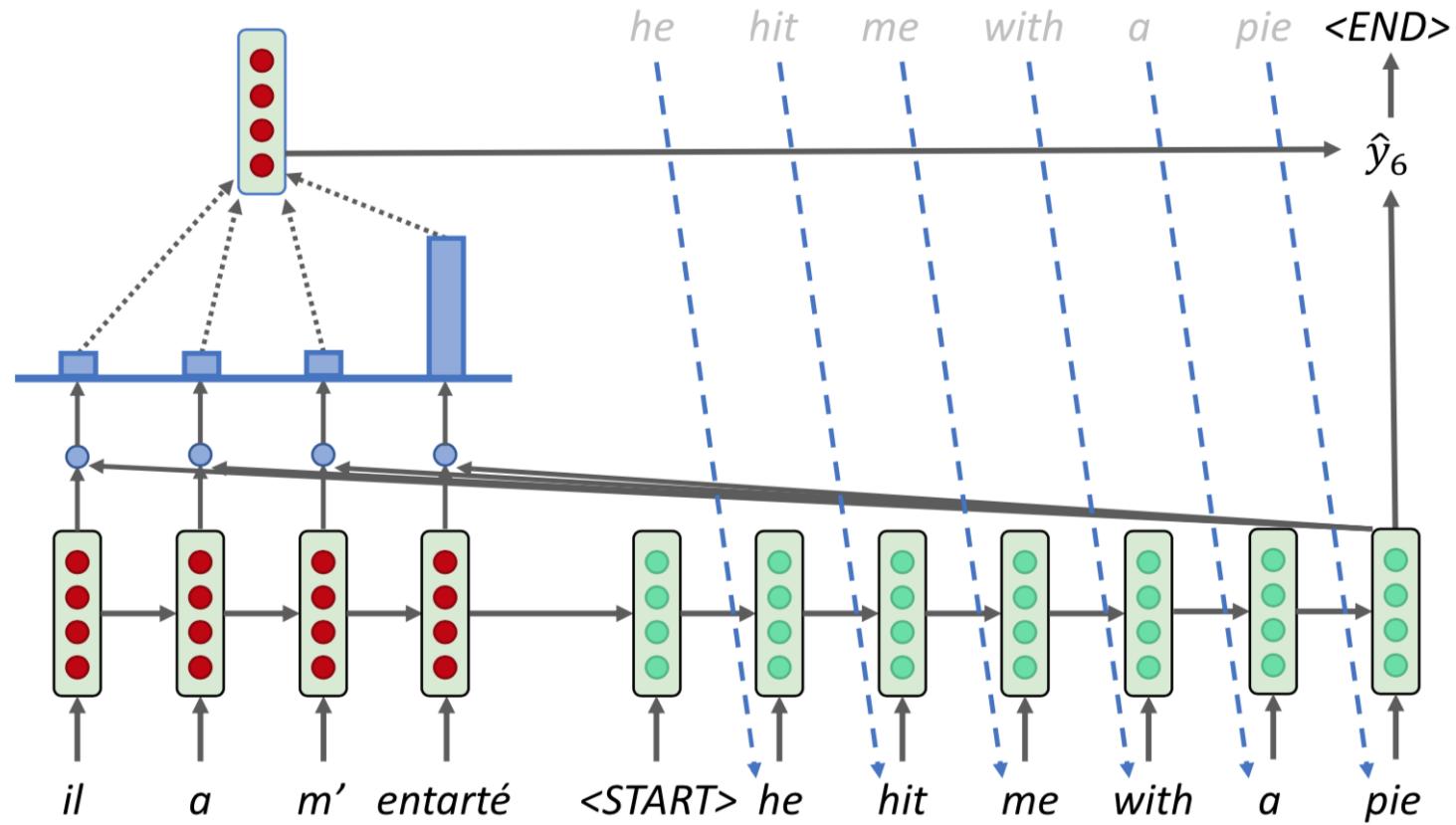
Attention



Attention



Attention



Attention

- For each time t ,
 - Decoder hidden state $s_t \in \mathbb{R}^d$.
 - For every encoder hidden state h_1, \dots, h_T ,

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Attention

- For each time t ,
 - Decoder hidden state $s_t \in \mathbb{R}^d$.
 - For every encoder hidden state h_1, \dots, h_T ,
 - Compute attention scores $a_t = (a_{t1}, \dots, a_{tT})$ where $a_{tu} = f(h_u, s_t)$.
 - Convert a_t to attention distribution $\alpha_t = (\alpha_{t1}, \dots, \alpha_{tT}) = \text{softmax}(a_t)$.
 - Get the weighted encoder state $z_t = \sum_{u=1}^T \alpha_{tu} h_u$
 - Vertically concatenate the states: $[z_t; s_t] \in \mathbb{R}^{2d}$
 - Predict an output (as a distribution): $\hat{y}_t = \text{softmax}(g([z_t; s_t]))$

Attention

- **Basic dot-product attention:** $\alpha_{tu} = f(h_u, s_t) = s_t^T h_u$
 - Assume $\dim(s_t) = \dim(h_u)$.
 - Nothing to learn for f
- **Multiplicative attention:** $\alpha_{tu} = f(h_u, s_t) = s_t^T W h_u$
 - Say $d_1 = \dim(h_u), d_2 = \dim(s_t)$.
 - Then we should learn $W \in \mathbb{R}^{d_2 \times d_1}$ from the training data.
- **Additive attention:** $\alpha_{tu} = f(h_u, s_t) = v^T \tanh(W_h h_u + W_s s_t)$.
 - Say $d_3 = \dim(v)$, which will be a new user hyper-parameter.
 - Then we should learn $W_h \in \mathbb{R}^{d_3 \times d_1}, W_s \in \mathbb{R}^{d_3 \times d_2}$, and $v \in \mathbb{R}^{d_3}$.

Example III (Extension): Auto-Reply

- Third version: Attention Mechanism
- Ideally output could consider ‘attention’ to parts of history

