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# **Applied Natural Language Processing**

**Dr. Jerome J. Braun**

## **This Lecture: Neural Attention for NLP I**

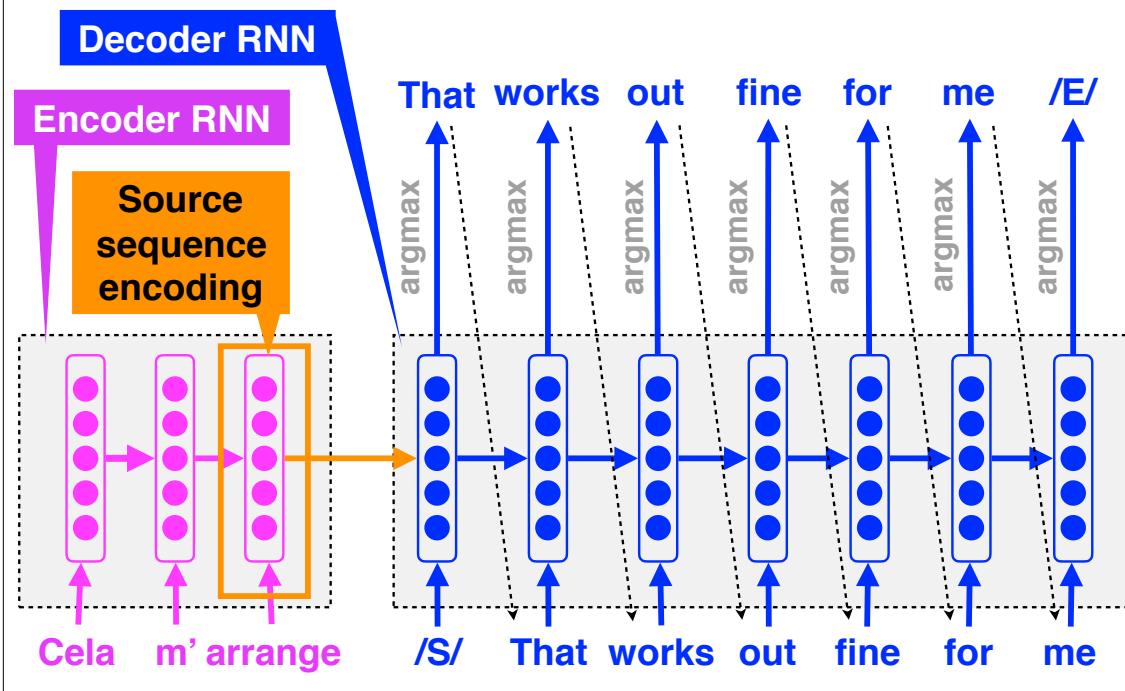
Course: Applied Natural Language Processing in Engineering  
IE 7500

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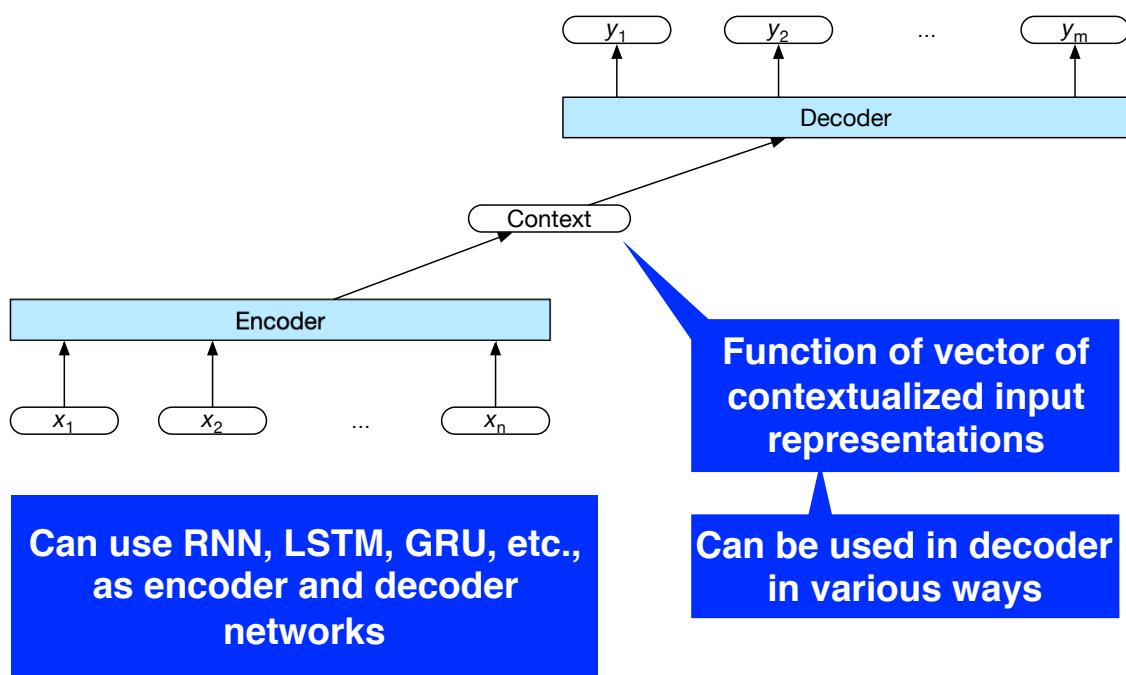
## NMT Seq2seq at Test-time (Recap)



J. Braun

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## Abstract Encoder-Decoder Network



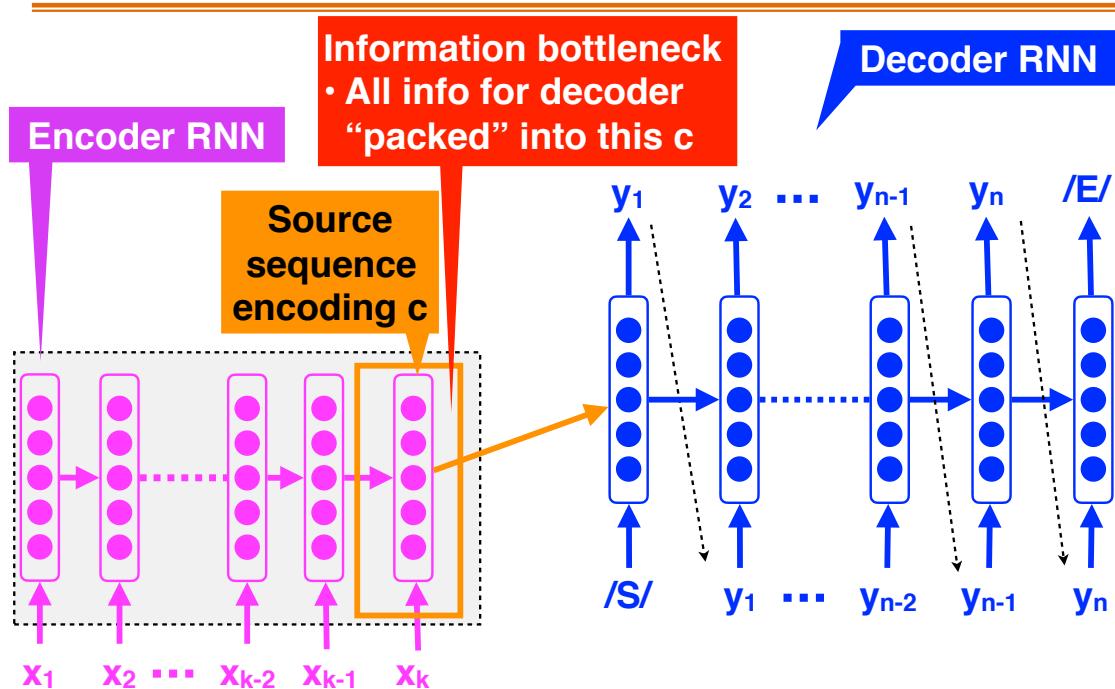
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# Context

- Context vector  $c$  should be function of encoder's hidden states, i.e.,  $c = f(h_1:h_n)$ 
  - But number of hidden states varies according to length of input
- Using encoder's final hidden state as context
  - Avoids issue of variable length of input
  - But introduces issue of excessive focus on latter parts of input sequence

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## Encoder-Decoder Information Bottleneck



# Context

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- **Addressing issue of excessive focus on latter parts of input sequence**
  - Bi-RNNs — context vector formed by concatenating final states of forward and backward passes
  - Produce context vector by summing (or averaging) encoder hidden states
    - ♦ Loses info about individual encoder states that might be useful in decoding

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# Attention Mechanism – Why

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Better representation of context, for following reasons:

- Take entire encoder context into account
- Update context dynamically during decoding
- Context remains fixed-size vector

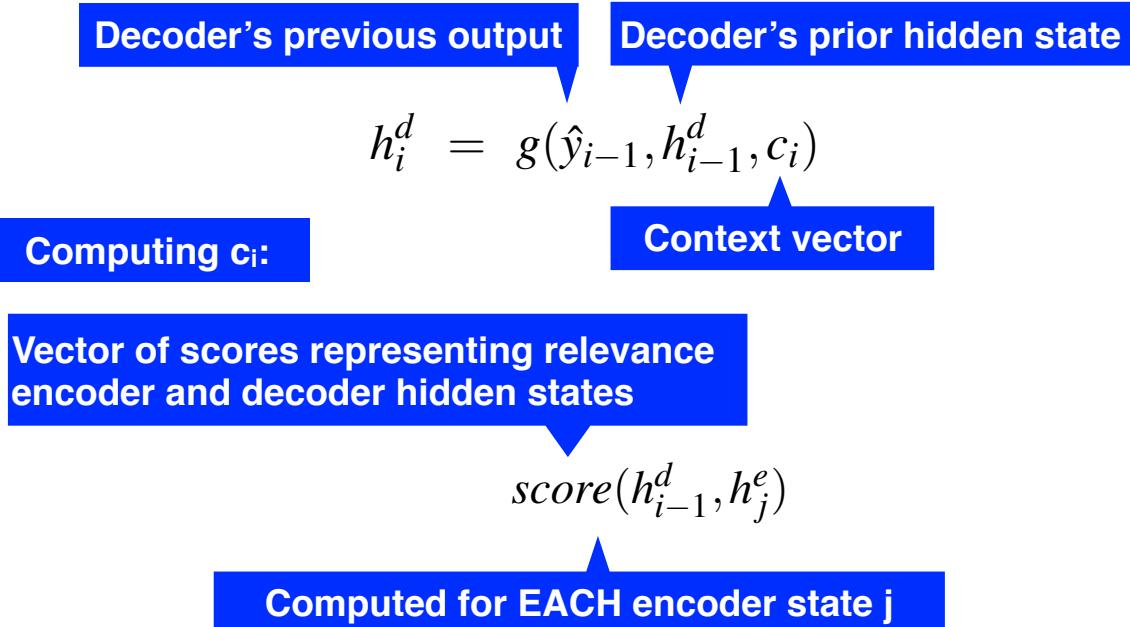
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# Attention Mechanism — How

- Static context vector replaced by dynamic construct  $c_i$ 
  - Derived from encoder hidden states
    - At each point during decoding
  - New  $c_i$  generated at each decoding step  $i$ 
    - This takes all hidden states of encoder into account
    - Context  $c_i$  made available during decoding
      - Current decoder state conditioned on all of the following
        - $c_i$
        - Prior hidden state
        - Previous output generated by decoder

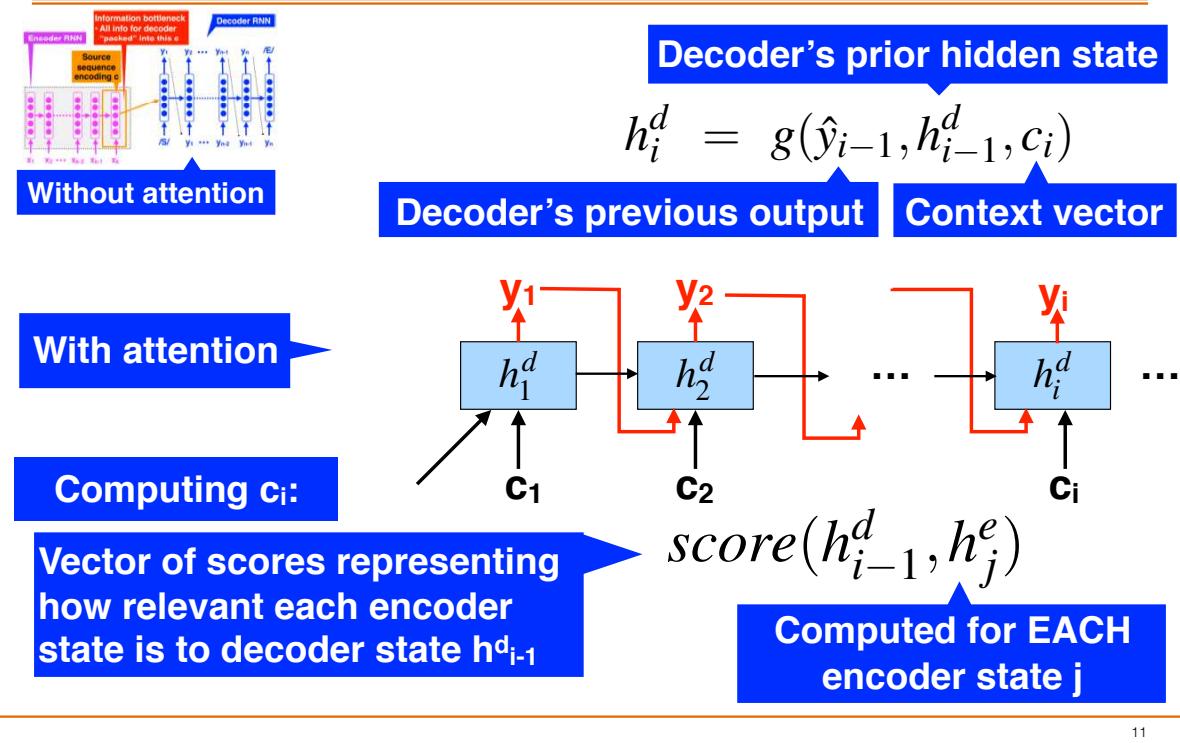
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# Attention Mechanism



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# Attention Mechanism



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## Context $c_i$ Computation

$$h_i^d = g(\hat{y}_{i-1}, h_{i-1}^d, c_i)$$

**Computing  $c_i$ :**

**Assume this score is:**

- Measure of similarity of (between):
  - Decoder hidden state
  - Each hidden state of encoder

**Use dot product as similarity measure**

$$score(h_{i-1}^d, h_j^e) = h_{i-1}^d \cdot h_j^e$$

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## More Robust Similarity Score (1)

- Dot product is static measure – does not adapt during training
- More robust similarity score

Parametrize score with dedicated set of weights ( $W_s$ )

$$score(h_{i-1}^d, h_j^e) = h_{i-1}^d W_s h_j^e$$

Allows network to learn WHICH ASPECTS of SIMILARITY between decoder and encoder states are important to current task

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## More Robust Similarity Score (2)

Normalize parametrized scores with softmax

$$\alpha_{ij} = \text{softmax}(score(h_{i-1}^d, h_j^e) \quad \forall j \in e)$$

$$= \frac{\exp(score(h_{i-1}^d, h_j^e))}{\sum_k \exp(score(h_{i-1}^d, h_k^e))}$$

Results in vector of weights  $\alpha_{ij}$  that express proportional relevance of each encoder hidden state  $j$  to current decoder state  $i$

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## More Robust Similarity Score (3)

Compute fixed-length context vector

$$\alpha_{ij} = \text{softmax(score}(h_{i-1}^d, h_j^e) \forall j \in e)$$

$$= \frac{\exp(score(h_{i-1}^d, h_j^e))}{\sum_k \exp(score(h_{i-1}^d, h_k^e))}$$

For *current* decoder state

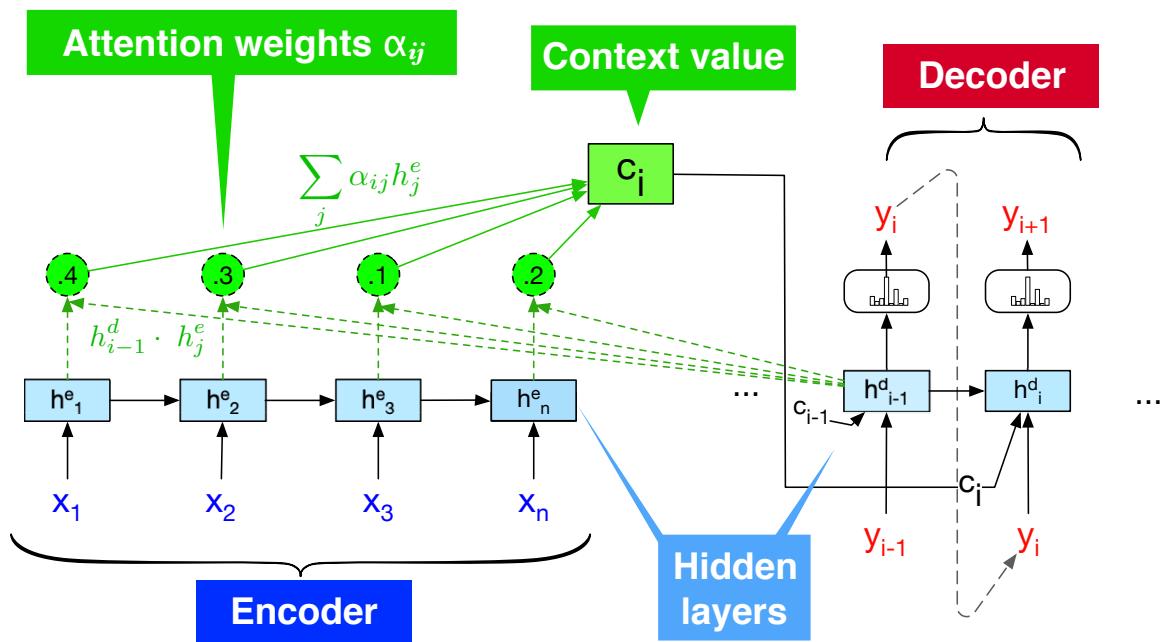
Computed as weighted average over all encoder hidden states

$$c_i = \sum_j \alpha_{ij} h_j^e$$

Results in vector of weights  $\alpha_{ij}$  that express proportional relevance of each encoder hidden state  $j$  to current decoder state  $i$

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## Encoder-Decoder with Attention



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- **Questions?**