Sequence to Sequence Models for Machine Translation (2)

CMSC 723 / LING 723 / INST 725

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Slides & figure credits: Graham Neubig

Introduction to Neural Machine Translation

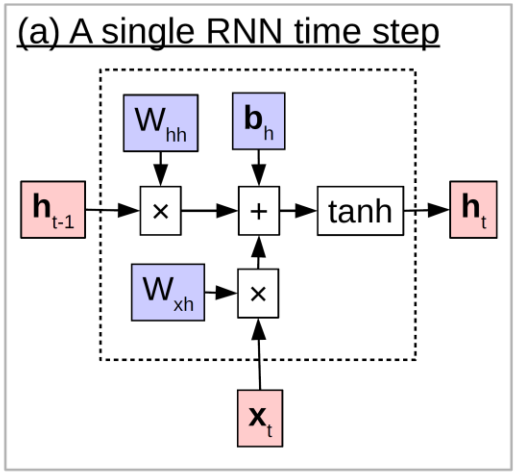
- Neural language models review

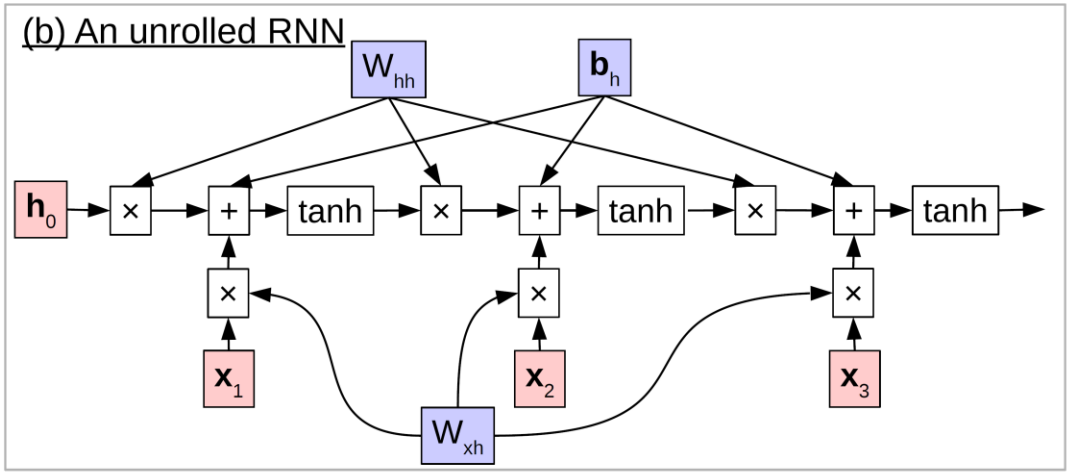
- Sequence to sequence models for MT
  - Encoder-Decoder
  - Sampling and search (greedy vs beam search)
  - **Practical tricks**

- **Sequence to sequence models for other NLP tasks**

- **Attention mechanism**

A recurrent language model



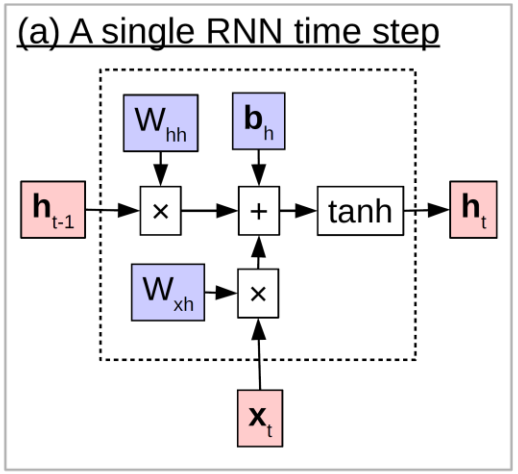


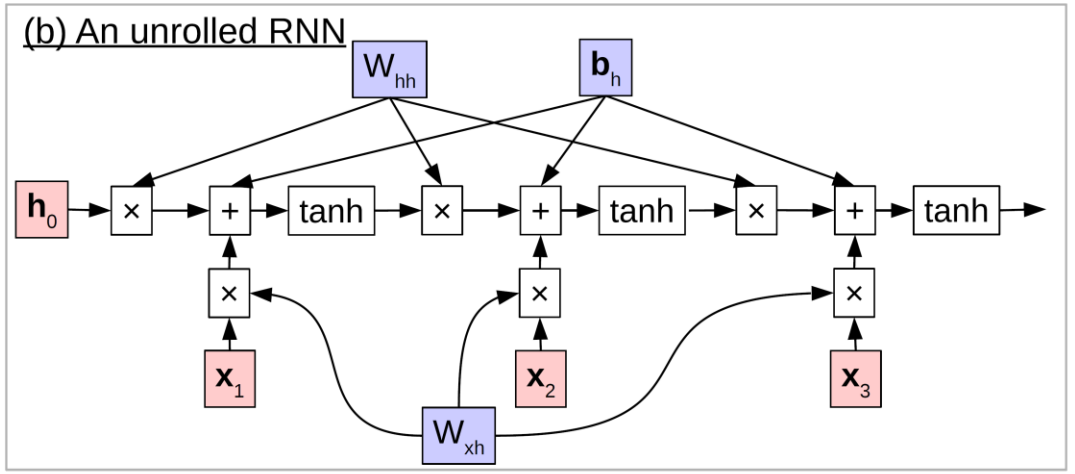
$$\boldsymbol{m}_t = M_{\cdot,e_{t-1}}$$

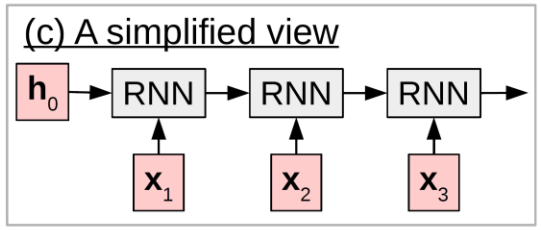
$$\boldsymbol{h}_t = \begin{cases} \tanh(W_{mh}\boldsymbol{m}_t + W_{hh}\boldsymbol{h}_{t-1} + \boldsymbol{b}_h) & t \geq 1, \\ \mathbf{0} & \text{otherwise.} \end{cases}$$

$$\boldsymbol{p}_t = \text{softmax}(W_{hs}\boldsymbol{h}_t + b_s).$$

A recurrent language model





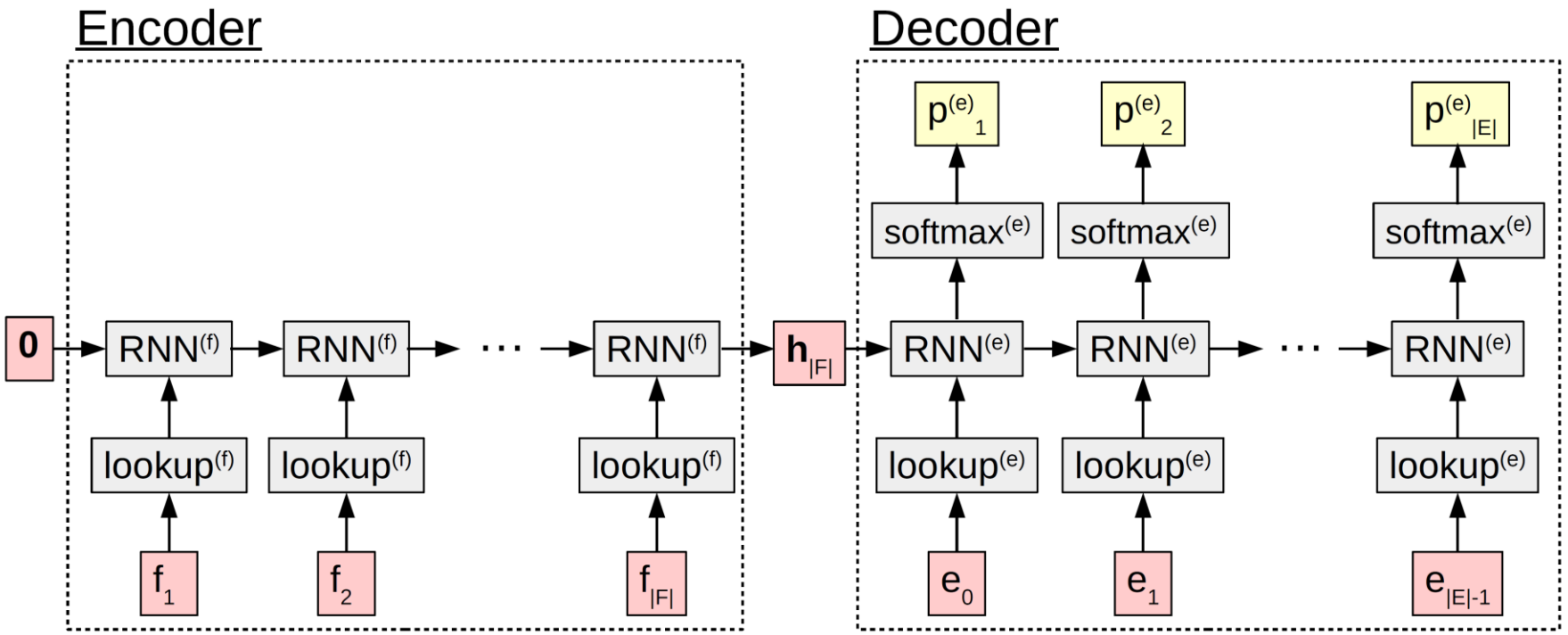


$$\boldsymbol{m}_t = M_{\cdot,e_{t-1}}$$

$$\boldsymbol{h}_t = \mathrm{RNN}(\boldsymbol{m}_t, \boldsymbol{h}_{t-1})$$

$$\boldsymbol{p}_t = \mathrm{softmax}(W_{hs}\boldsymbol{h}_t + b_s).$$

Encoder-decoder model



Encoder-decoder model

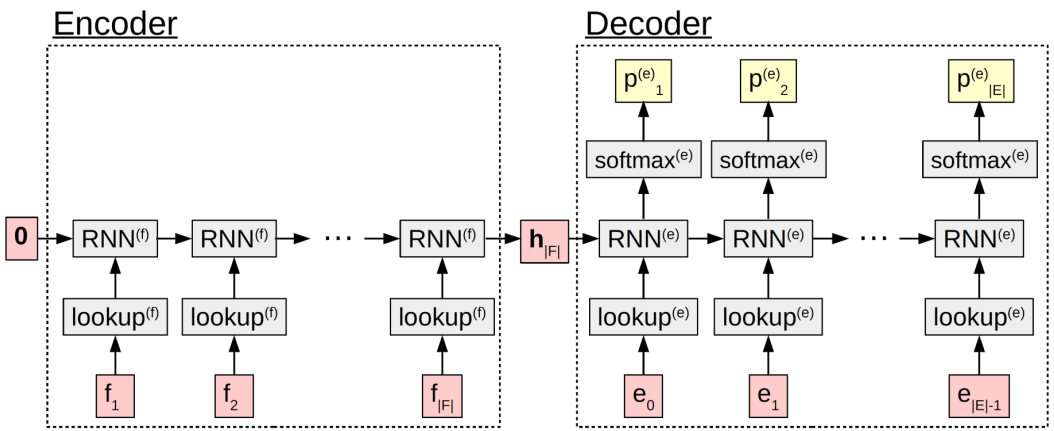
$$\boldsymbol{m}_t^{(f)} = M_{\cdot,f_t}^{(f)}$$

$$\boldsymbol{h}_t^{(f)} = \begin{cases} \mathrm{RNN}^{(f)}(\boldsymbol{m}_t^{(f)}, \boldsymbol{h}_{t-1}^{(f)}) & t \geq 1, \\ \mathbf{0} & \text{otherwise.} \end{cases}$$

$$\boldsymbol{m}_t^{(e)} = M_{\cdot,e_{t-1}}^{(e)}$$

$$\boldsymbol{h}_t^{(e)} = \begin{cases} \mathrm{RNN}^{(e)}(\boldsymbol{m}_t^{(e)}, \boldsymbol{h}_{t-1}^{(e)}) & t \geq 1, \\ \boldsymbol{h}_{|F|}^{(f)} & \text{otherwise.} \end{cases}$$

$$\boldsymbol{p}_t^{(e)} = \mathrm{softmax}(W_{hs}\boldsymbol{h}_t^{(e)} + b_s)$$



Generating Output

- We have a model P(E|F), how can we generate translations?
- 2 methods
  - **Sampling**: generate a random sentence according to probability distribution
  - **Argmax**: generate sentence with highest probability

Training

- Same as for RNN language modeling

- Loss function
  - Negative log-likelihood of training data
  - Total loss for one example (sentence) = sum of loss at each time step (word)

- BackPropagation Through Time (BPTT)
  - Gradient of loss at time step t is propagated through the network all the way back to 1st time step

Note that training loss differs from evaluation metric (BLEU)

N-gram overlap between machine translation output and reference translation

Compute precision for n-grams of size 1 to 4

Add brevity penalty (for too short translations)

$$\text{BLEU} = \min\left(1, \frac{\textit{output-length}}{\textit{reference-length}}\right) \left(\prod_{i=1}^{4} \textit{precision}_i\right)^{\frac{1}{4}}$$

Typically computed over the entire corpus, not single sentences

Other encoder structures: Bidirectional encoder

$$\overrightarrow{\boldsymbol{h}}_t^{(f)} = \begin{cases} \overrightarrow{\mathrm{RNN}}^{(f)}(\boldsymbol{m}_t^{(f)}, \overrightarrow{\boldsymbol{h}}_{t+-}^{(f)}) & t \geq 1, \\ \mathbf{0} & \text{otherwise.} \end{cases}$$

$$\overleftarrow{\boldsymbol{h}}_t^{(f)} = \begin{cases} \overleftarrow{\mathrm{RNN}}^{(f)}(\boldsymbol{m}_t^{(f)}, \overleftarrow{\boldsymbol{h}}_{t+1}^{(f)}) & t \leq |F|, \\ \mathbf{0} & \text{otherwise.} \end{cases}$$

Motivation:
- Help bootstrap learning
- By shortening length of dependencies

$$\boldsymbol{h}_0^{(e)} = \tanh(W_{\overrightarrow{f}\,e}\overrightarrow{\boldsymbol{h}}_{|F|} + W_{\overleftarrow{f}\,e}\overleftarrow{\boldsymbol{h}}_1 + \boldsymbol{b}_e)$$

Motivation:
- Take 2 hidden vectors from source encoder
- Combine them into a vector of size required by decoder

A few more tricks: addressing length bias

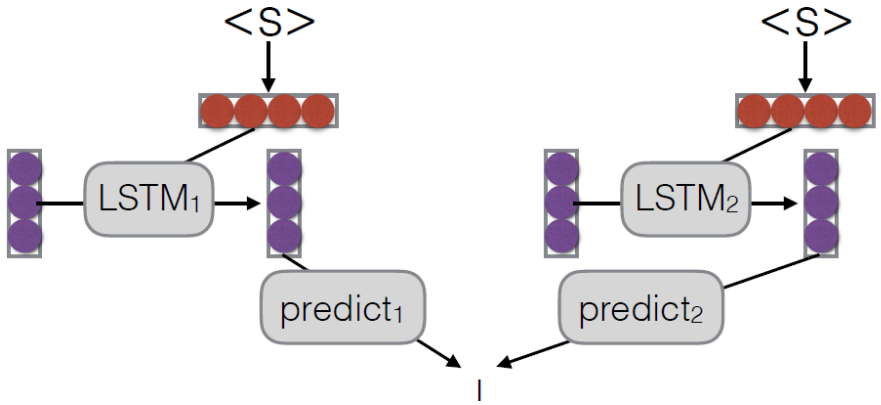
- Default models tend to generate short sentences
- Solutions:
  - Prior probability on sentence length

$$\hat{E} = \underset{E}{\operatorname{argmax}} \ \log P(|E| \mid |F|) + \log P(E \mid F).$$

  - Normalize by sentence length

$$\hat{E} = \underset{E}{\operatorname{argmax}} \ \log P(E \mid F)/|E|.$$

A few more tricks: ensembling



- Combine predictions from multiple models
- Methods
  - Linear or log-linear interpolation
  - Parameter averaging

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- **Sequence to sequence models for other NLP tasks**

- **Attention mechanism**

Beyond MT: Encoder-Decoder can be used as Conditioned Language Models to generate text Y according to some specification X

Input *X*	Output *Y* (**Text**)	Task
Structured Data	NL Description	NL Generation
English	Japanese	Translation
Document	Short Description	Summarization
Utterance	Response	Response Generation
Image	Text	Image Captioning
Speech	Transcript	Speech Recognition

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Problem with previous encoder-decoder model

- Long-distance dependencies remain a problem
- A single vector represents the entire source sentence
  - No matter its length
- Solution: attention mechanism
  - An example of incorporating inductive bias in model architecture

Attention model intuition

- Encode each word in source sentence into a vector
- When decoding, perform a linear combination of these vectors, weighted by “attention weights”
- Use this combination when predicting next word

[Bahdanau et al. 2015]

Attention model
Source word representations

- We can use representations from bidirectional RNN encoder

$$\overrightarrow{\boldsymbol{h}}_j^{(f)} = \mathrm{RNN}(\mathrm{embed}(f_j), \overrightarrow{\boldsymbol{h}}_{j-1}^{(f)})$$
$$\overleftarrow{\boldsymbol{h}}_j^{(f)} = \mathrm{RNN}(\mathrm{embed}(f_j), \overleftarrow{\boldsymbol{h}}_{j+1}^{(f)}).$$

$$\boldsymbol{h}_j^{(f)} = [\overleftarrow{\boldsymbol{h}}_j^{(f)}; \overrightarrow{\boldsymbol{h}}_j^{(f)}].$$

- And concatenate them in a matrix

$$H^{(f)} = \mathrm{concat\_col}(\boldsymbol{h}_1^{(f)}, \ldots, \boldsymbol{h}_{|F|}^{(f)}).$$

Attention model
Create a source context vector

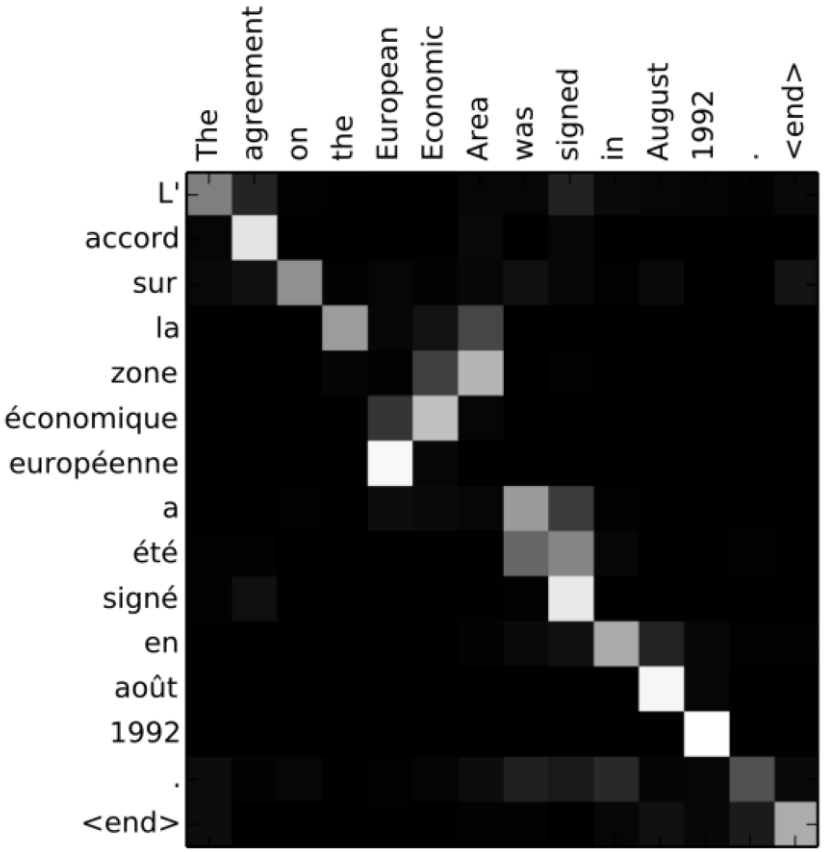
$$\boldsymbol{c}_t = H^{(f)}\boldsymbol{\alpha}_t.$$

Context vector

Attention vector

- Attention vector:
  - Entries between 0 and 1
  - Interpreted as weight given to each source word when generating output at time step t

Attention model
Illustrating attention weights



Attention model
How to calculate attention scores

$$\boldsymbol{h}_t^{(e)} = \text{enc}([\text{embed}(e_{t-1}); \boldsymbol{c}_{t-1}], \boldsymbol{h}_{t-1}^{(e)}).$$

$$a_{t,j} = \text{attn\_score}(\boldsymbol{h}_j^{(f)}, \boldsymbol{h}_t^{(e)}).$$

$$\boldsymbol{\alpha}_t = \text{softmax}(\boldsymbol{a}_t).$$

$$\boldsymbol{p}_t^{(e)} = \text{softmax}(W_{hs}[\boldsymbol{h}_t^{(e)}; \boldsymbol{c}_t] + b_s).$$

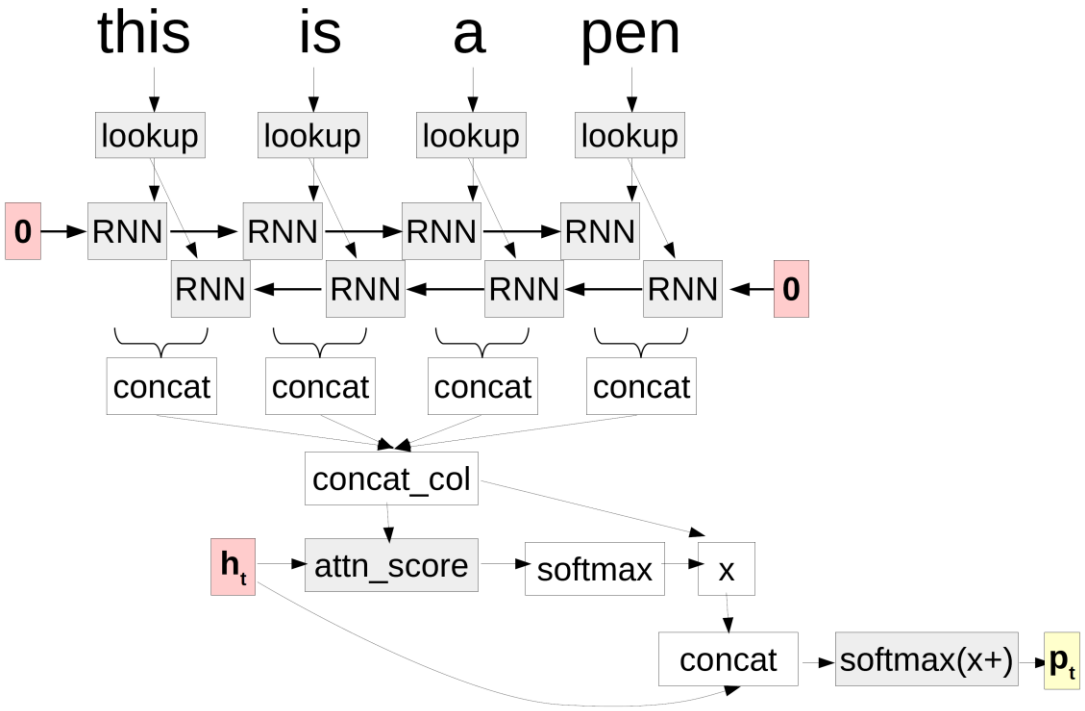


Figure 28: A computation graph for attention.

Attention model
Various ways of calculating attention score

- Dot product

$$\text{attn\_score}(\boldsymbol{h}_j^{(f)}, \boldsymbol{h}_t^{(e)}) := \boldsymbol{h}_j^{(f)\intercal} \boldsymbol{h}_t^{(e)}$$

- Bilinear function

$$\text{attn\_score}(\boldsymbol{h}_j^{(f)}, \boldsymbol{h}_t^{(e)}) := \boldsymbol{h}_j^{(f)\intercal} W_a \boldsymbol{h}_t^{(e)}.$$

- Multi-layer perceptron (original formulation in Bahdanau et al.)

$$\text{attn\_score}(\boldsymbol{h}_t^{(e)}, \boldsymbol{h}_j^{(f)}) := \boldsymbol{w}_{a2}^{\intercal} \tanh(W_{a1}[\boldsymbol{h}_t^{(e)}; \boldsymbol{h}_j^{(f)}])$$

Advantages of attention

- Helps illustrate/interpret translation decisions
- Can help insert translations for OOV
  - By copying or look up in external dictionary
- Can incorporate linguistically motivated priors in model

Attention extensions
An active area of research

- Attend to multiple sentences (Zoph et al. 2015)
- Attend to a sentence and an image (Huang et al. 2016)
- Incoprorate bias from alignment models

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