Text Sequence Processing

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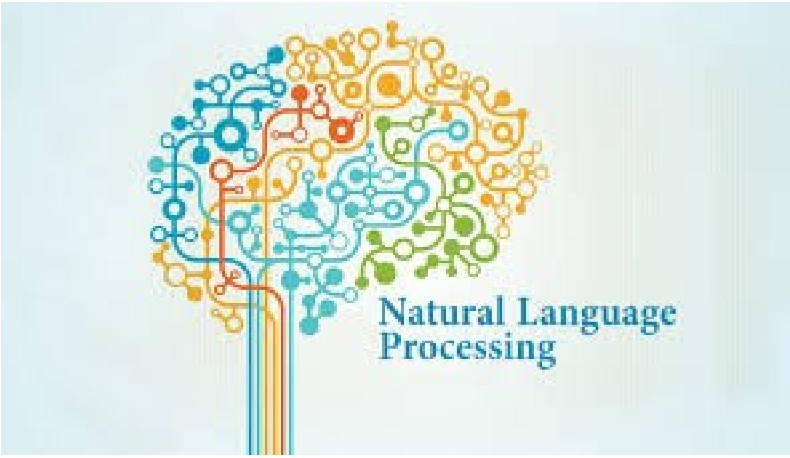


Topics

- Word Representations
- Sequence-to-sequence transformation
  - Recurrent networks
  - Convolutions networks
  - Self-attention (Transformers)
- Reinforcement Learning

Word Representations

Why Word Representations?

- Words are symbols
- Neural networks operate on numerical values

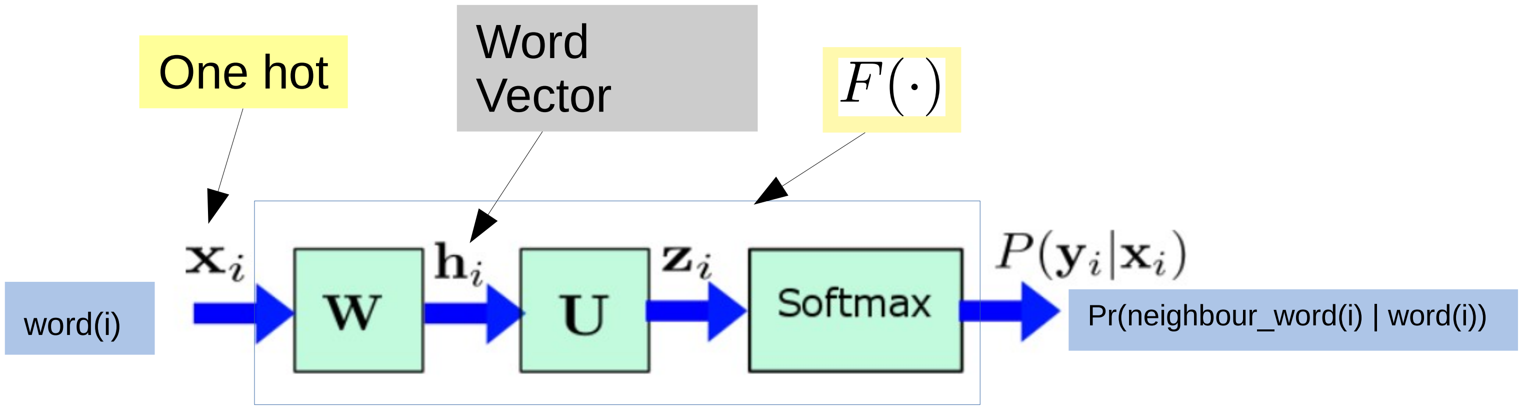
Trivial Approach

- One Hot encoding
  - Use the word index in vector form
- Example
  - Consider a vocabulary of 5 words

1	Man	[1,0,0,0,0]
2	Woman	[0,1,0,0,0]
3	Boy	[0,0,1,0,0]
4	Girl	[0,0,0,1,0]
5	House	[0,0,0,0,1]

- Disadvantages
  - Dimension of the representation vector would be very high for natural vocabularies
  - All vectors are equally spread (vector similarity does not represent semantic similarity)

Better Approach



$\mathbf{x}_i \in \mathbb{R}^{V\times 1}$, $\mathbf{h}_i \in \mathbb{R}^{d\times 1}$, $\mathbf{W} \in \mathbb{R}^{V\times d}$, $\mathbf{U} \in \mathbb{R}^{V\times d}$

- Projection:

$$\mathbf{h}_i = \mathbf{W}^T \mathbf{x}_i$$

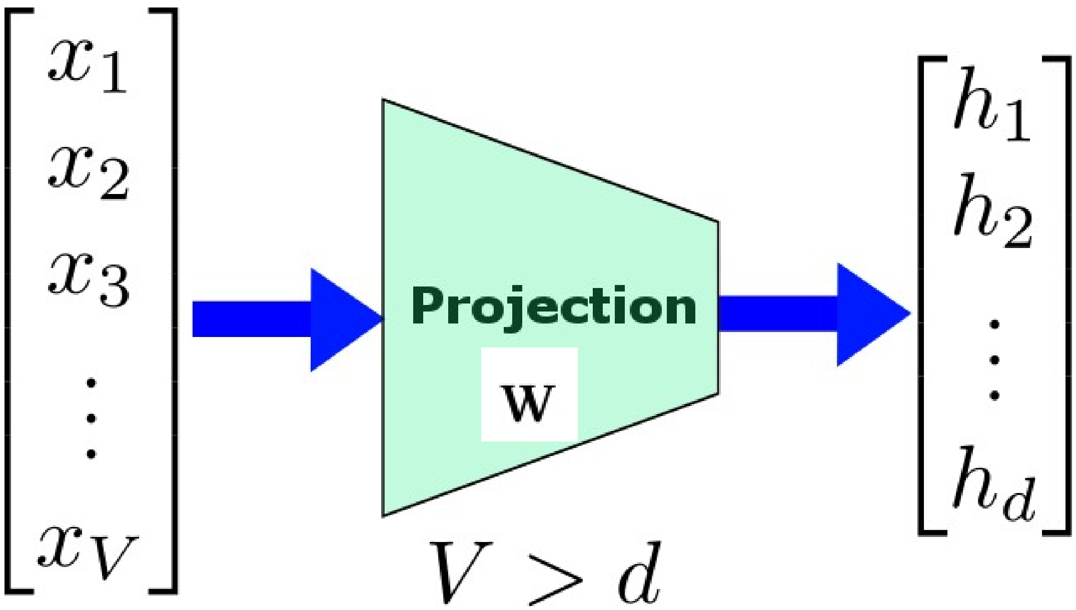
- Second layer:

$$\mathbf{z}_i = \mathbf{U}\mathbf{h}_i$$

- Softmax:

$$P(y_i = j|\mathbf{x}_i) = \frac{\exp(z_i(j))}{\sum_k \exp(z_i(k))}$$

Issue1: High Dimension

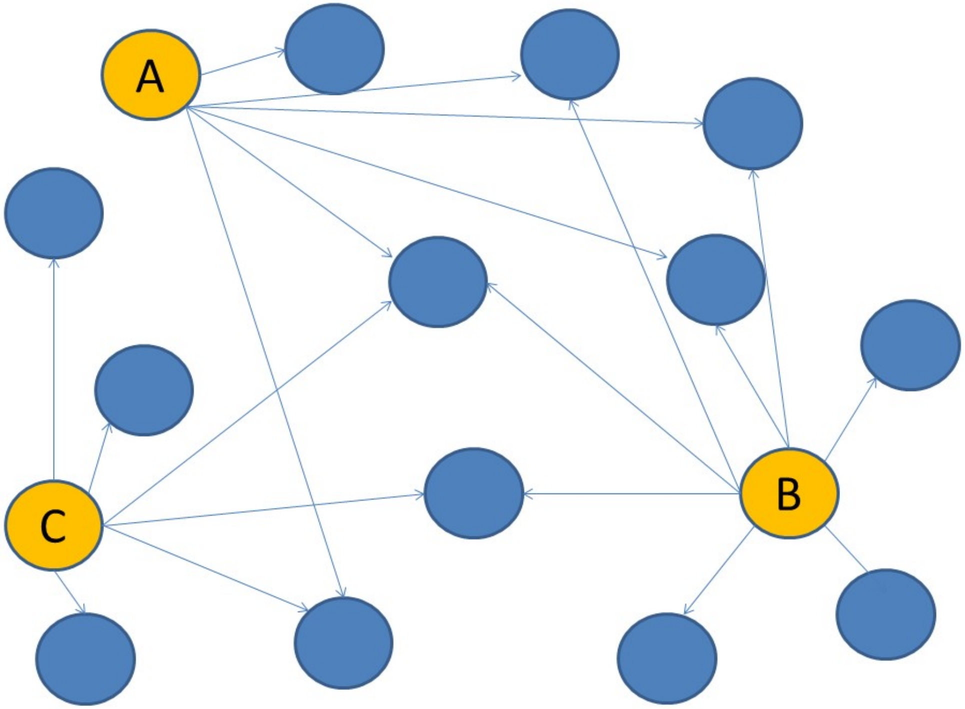


- Project one-hot encoded vectors to a lower dimensional space (Reduce the dimension of the representation)
- Also known as ***embedding***
- Linear projection = Multiplication by a $\mathbf{h}_{1\times d} = \mathbf{x}_{1\times V}\mathbf{W}_{V\times d}$

Issue 2: Similar Words

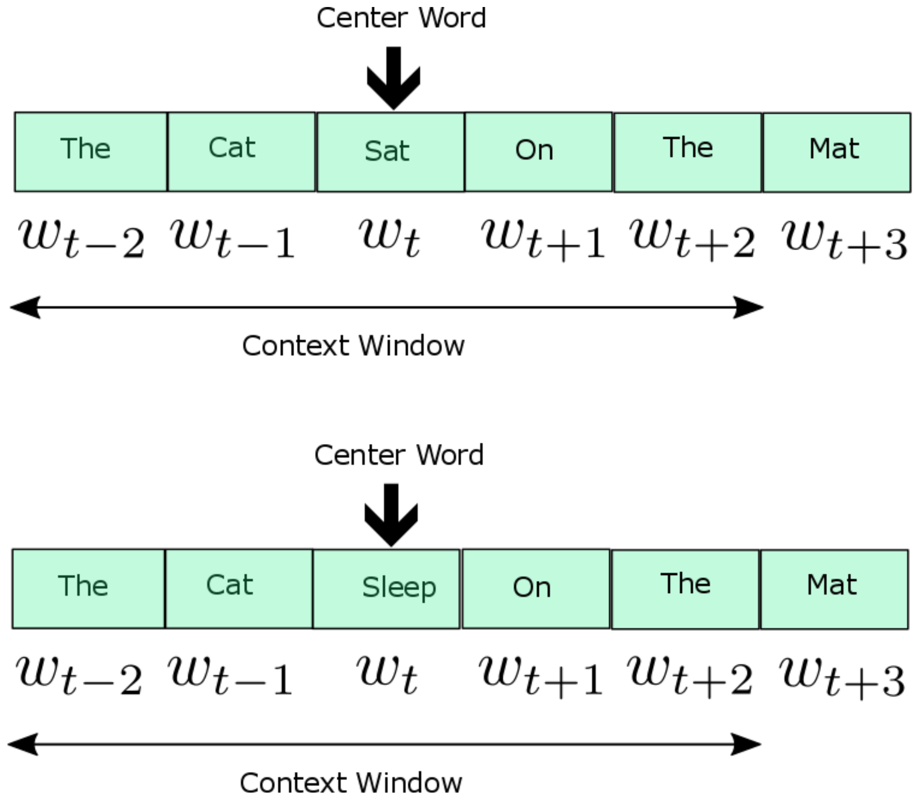
- Force vector distance between similar words to be low
- How to quantify word similarity?

Quantifying Word Similarity



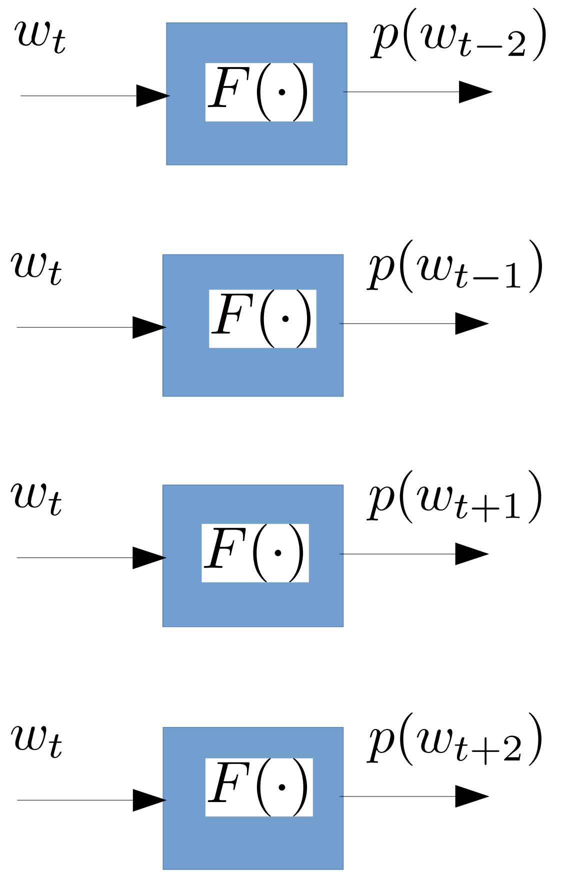
- A is ”more similar” to B than C ?
- A is ”more similar” to C than B ?

Quantifying Word Similarity



- Context of a word = Words occurring before and after within a predefined window
- Words that have similar contexts, should be represented by word vectors close to each other

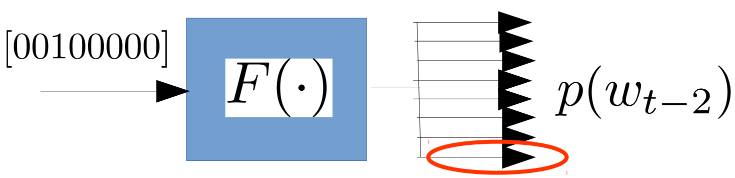
Training Objective

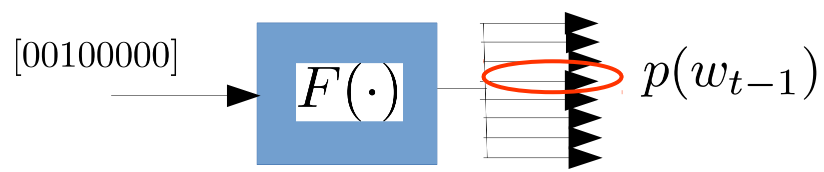


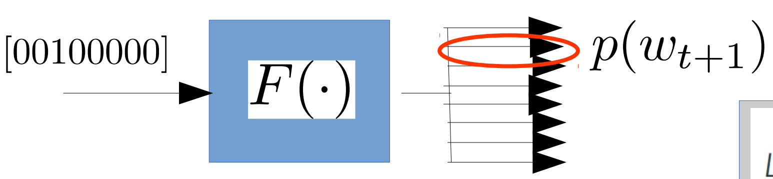
- Train $F(\cdot)$ to maxi $L = \prod_{t=1}^{T} \prod_{-C \leq j \leq C, j \neq 0} P(w_{t+j} | w_t)$

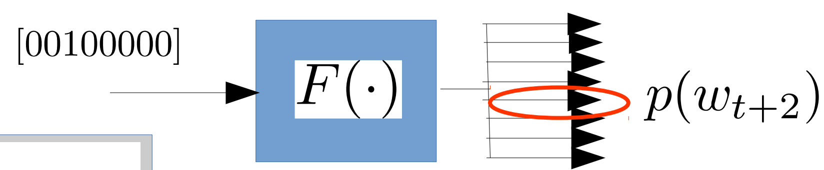
Practical Details

Word Index y	One Hot representation $\boldsymbol{x}$	Word
1	00000001	
2	00000010	w_{t+1}
3	00000100	
4	00001000	w_{t-1}
5	00010000	w_{t+2}
6	00100000	w_t
7	01000000	
8	10000000	w_{t-2}



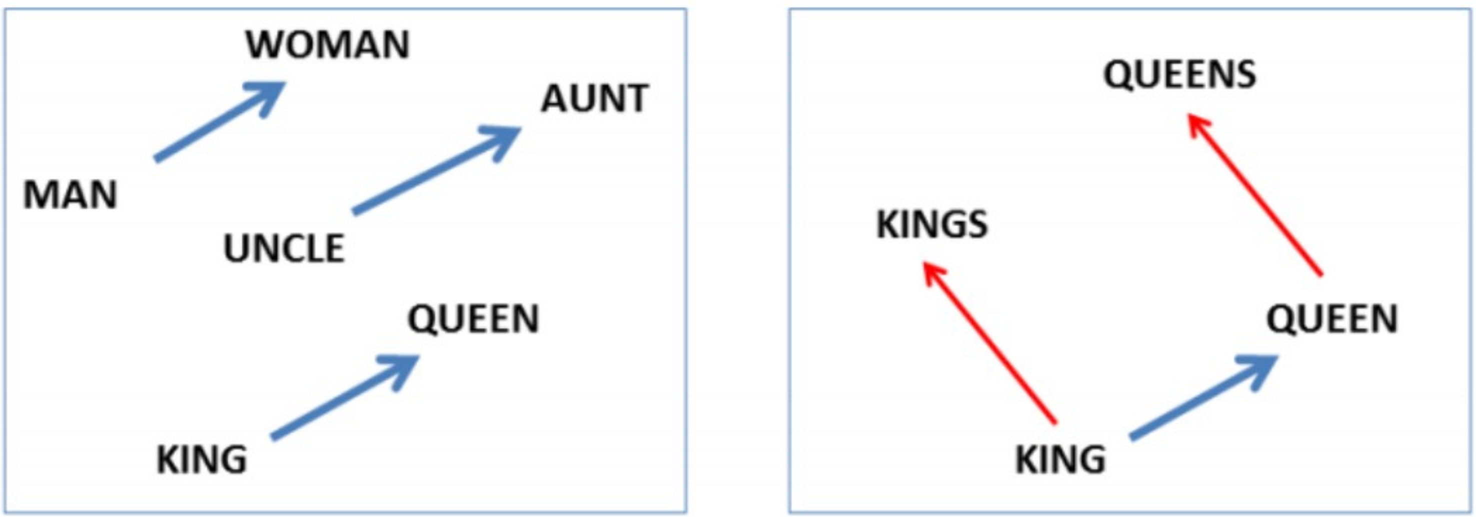






$$L = \prod_{t=1}^{T} \prod_{-C \leq j \leq C, j \neq 0} P(w_{t+j} | w_t)$$

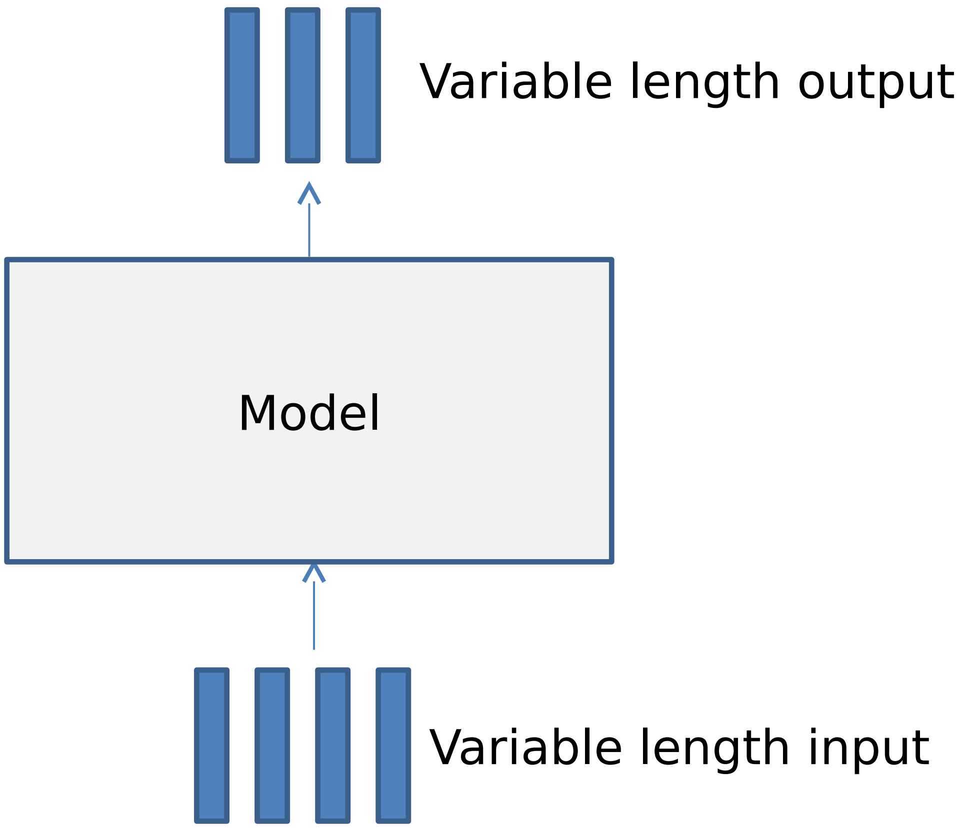
Word Vector Visualization



(Mikolov et al., NAACL HLT, 2013)

Sequence-to-sequence Transforms

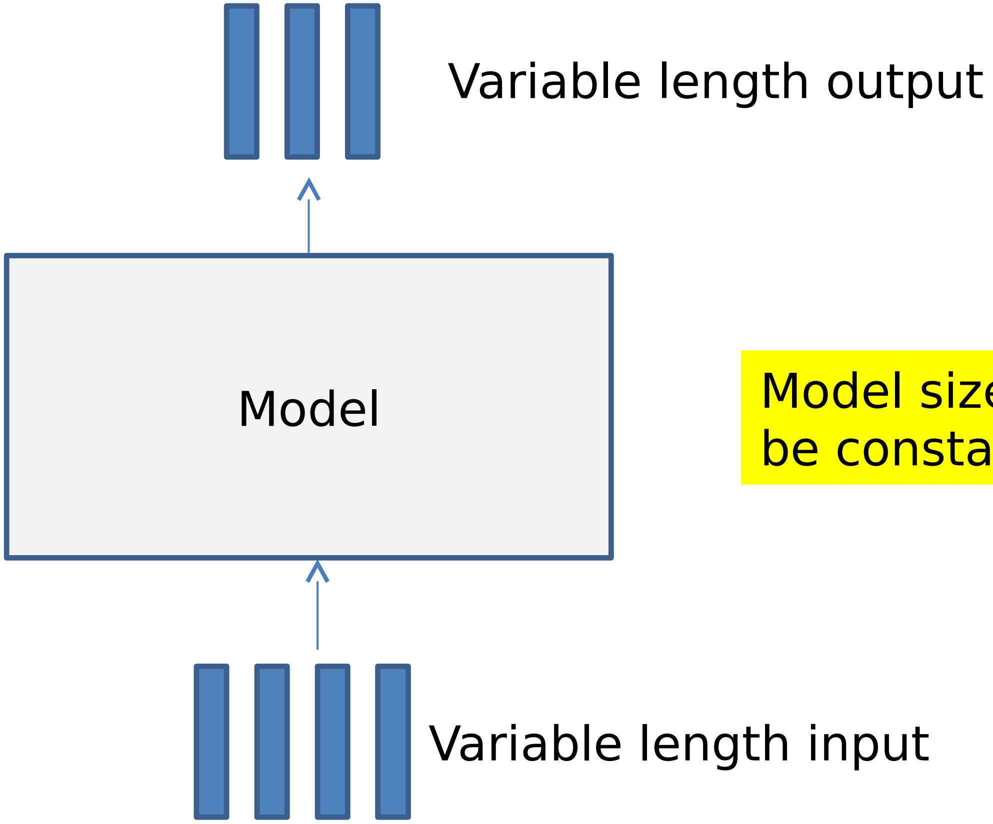
Seq2seq Transformation



Example Applications

- Summarization (extractive/abstractive)
- Machine translation
- Dialog systems /chatbots
- Text generation
- Question answering

Seq2seq Transformation



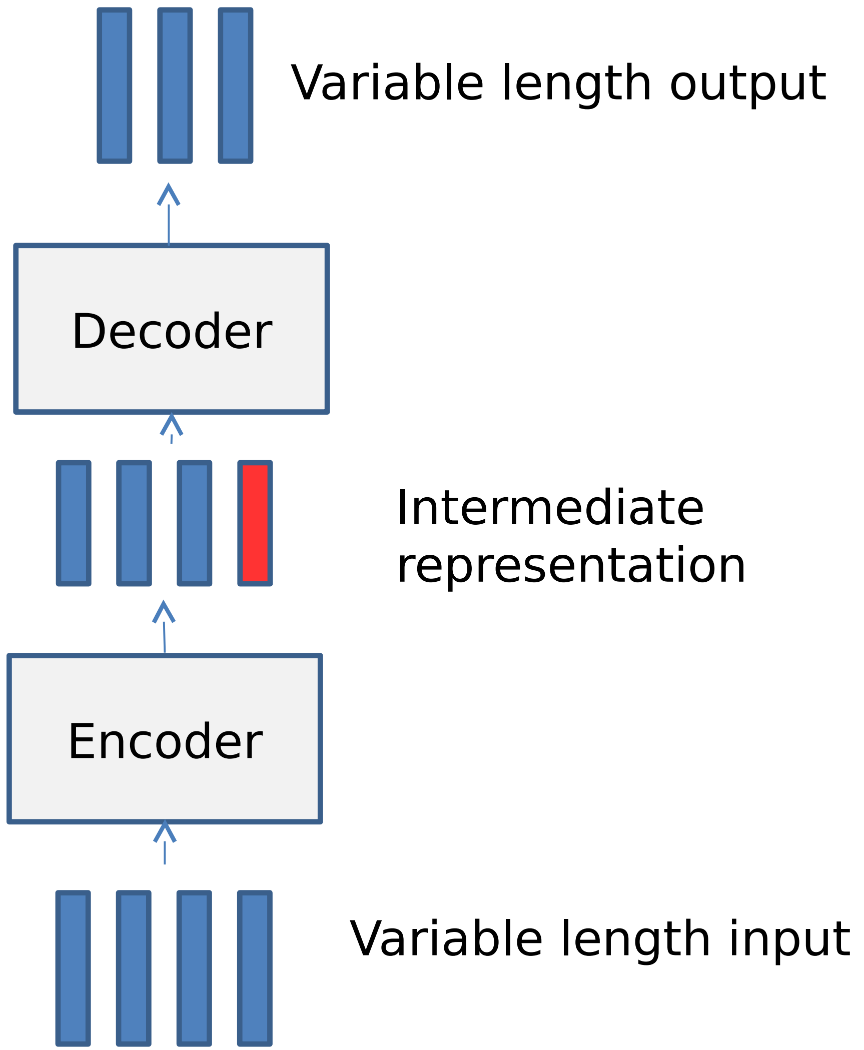
Model size should be constant.

Solution: Apply a constant sized neural net module repeatedly on the data

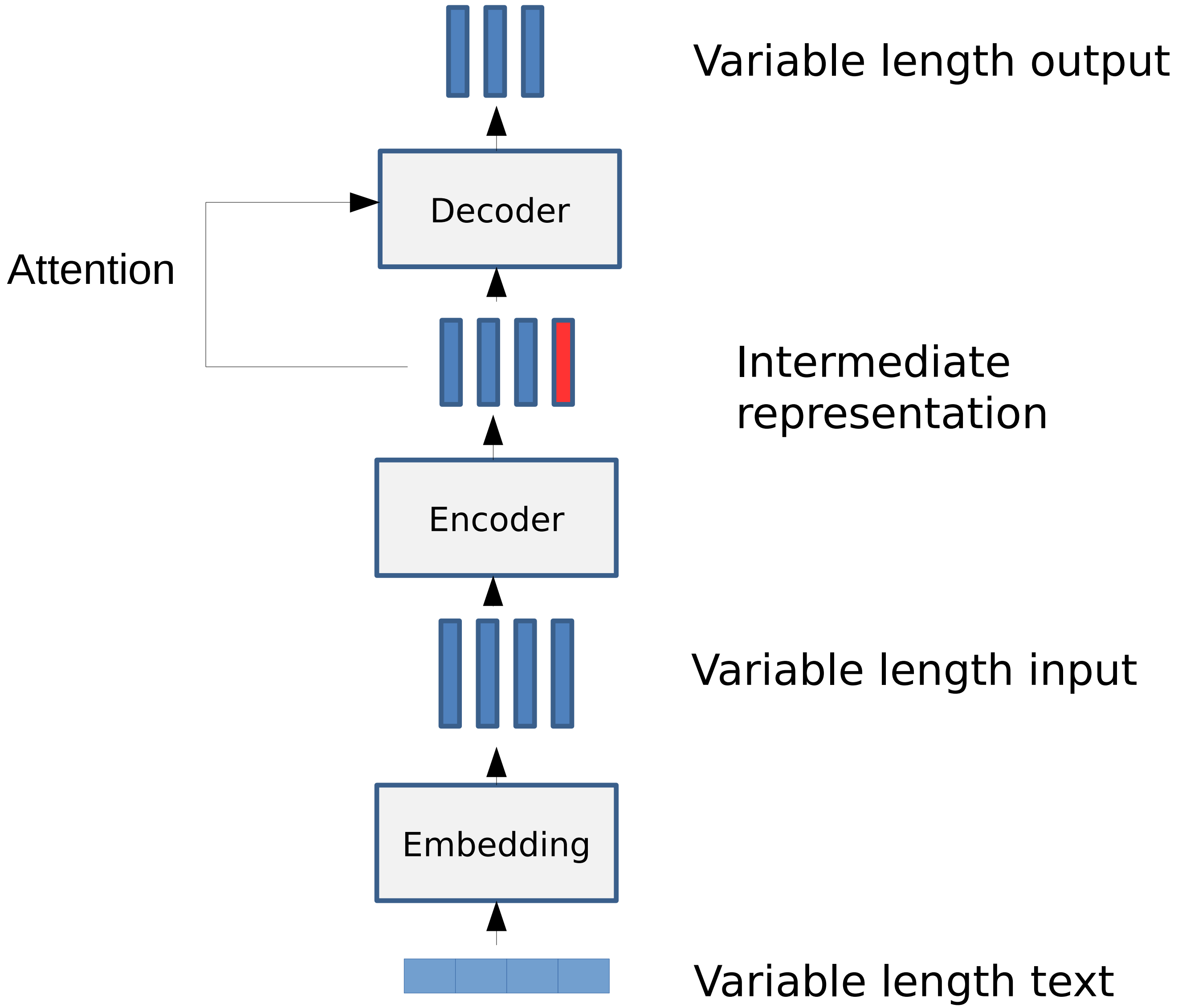
Possible Approaches

- Recurrent networks
  - Apply the NN module in a serial fashion
- Convolutions networks
  - Apply the NN modules in a hierarchical fashion
- Self-attention (Transformers)
  - Direct interaction in the inputs

Processing Pipeline



Processing Pipeline



Architecture Variants

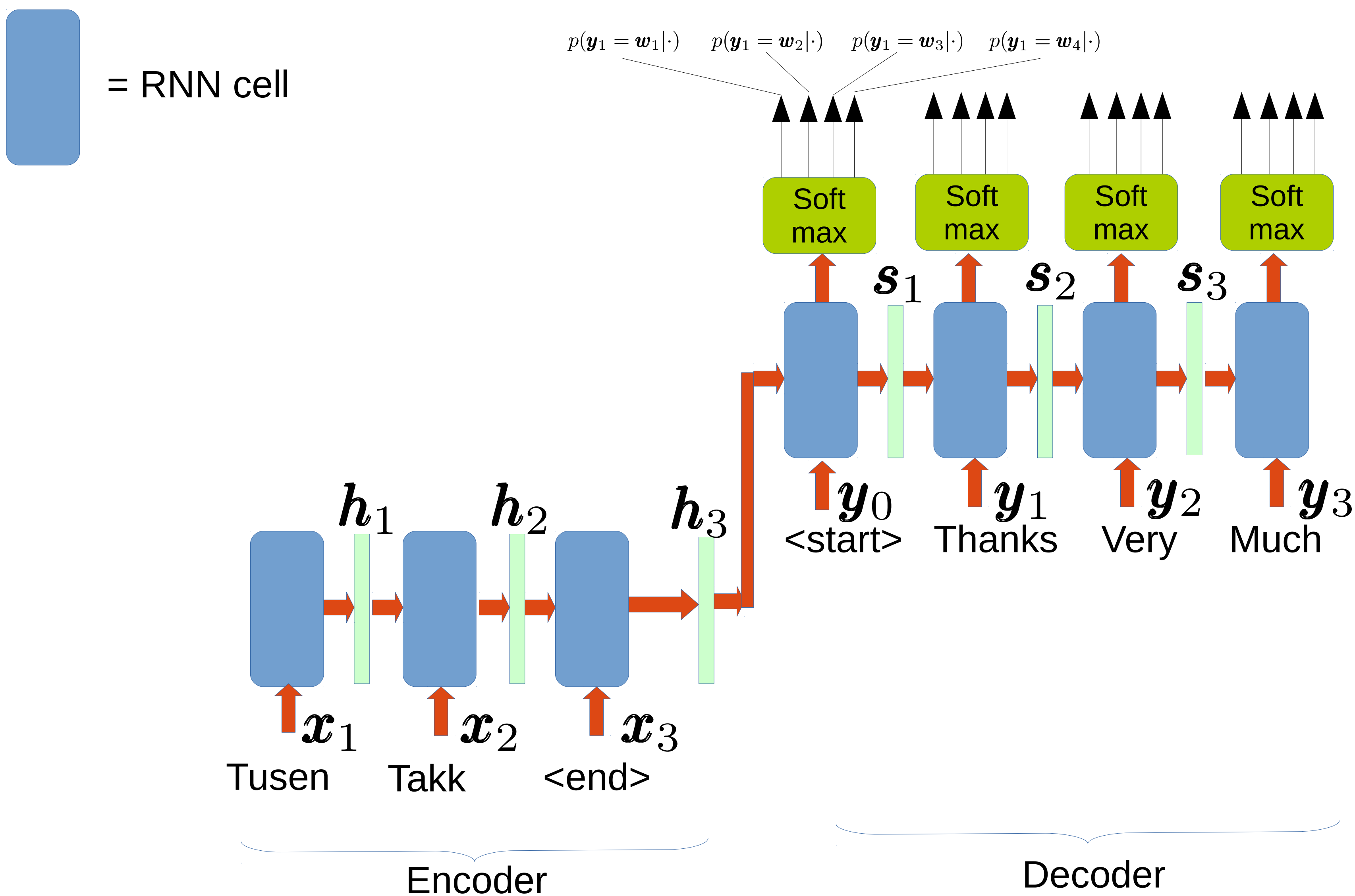
Encoder	**Decoder**	**Attention**
Recurrent net	Recurrent net	No
Recurrent net	Recurrent net	Yes
Convolutional net	Convolutional net	No
Convolutional net	Recurrent net	Yes
Convolutional net	Convolutional net	Yes
Fully connected net with self-attention	Fully connected net with self-attention	Yes

Possible Approaches

- Recurrent networks
  - Apply the NN module in a serial fashion
- Convolutions networks
  - Apply the NN modules in a hierarchical fashion
- Self-attention
  - Direct interaction in the inputs

RNN-decoder with RNN-encoder

$$\text{Decoder vocabulary} = \{\text{Much } (\boldsymbol{w}_1),\ \text{Thanks } (\boldsymbol{w}_2),\ \text{Very } (\boldsymbol{w}_3), <\text{end}> (\boldsymbol{w}_4)\}$$

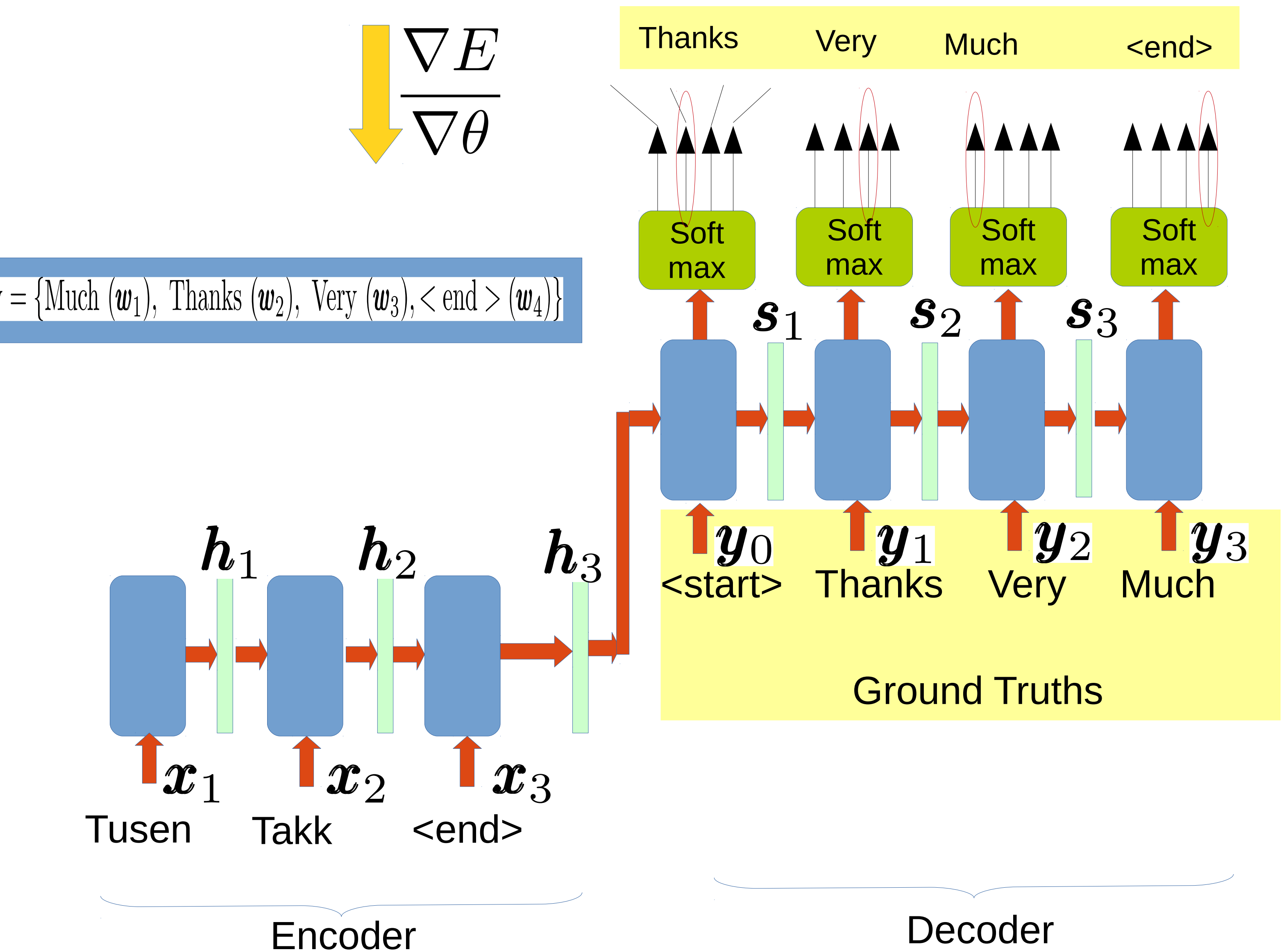


RNN-dec with RNN-enc, Training

$$E = \log L = \log \left[p(\boldsymbol{y}_1 = w_2 | \boldsymbol{X}) \cdot p(\boldsymbol{y}_2 = w_3 | w_2, \boldsymbol{X}) \cdot p(\boldsymbol{y}_3 = w_1 | w_2, w_3, \boldsymbol{X}) \cdot p(\boldsymbol{y}_4 = w_4 | w_2, w_3, w_1, \boldsymbol{X}) \right]$$

$$\frac{\nabla E}{\nabla \theta}$$

Decoder vocabulary = $\{$Much $(\boldsymbol{w}_1)$, Thanks $(\boldsymbol{w}_2)$, Very $(\boldsymbol{w}_3)$, $<$ end $>$ $(\boldsymbol{w}_4)\}$

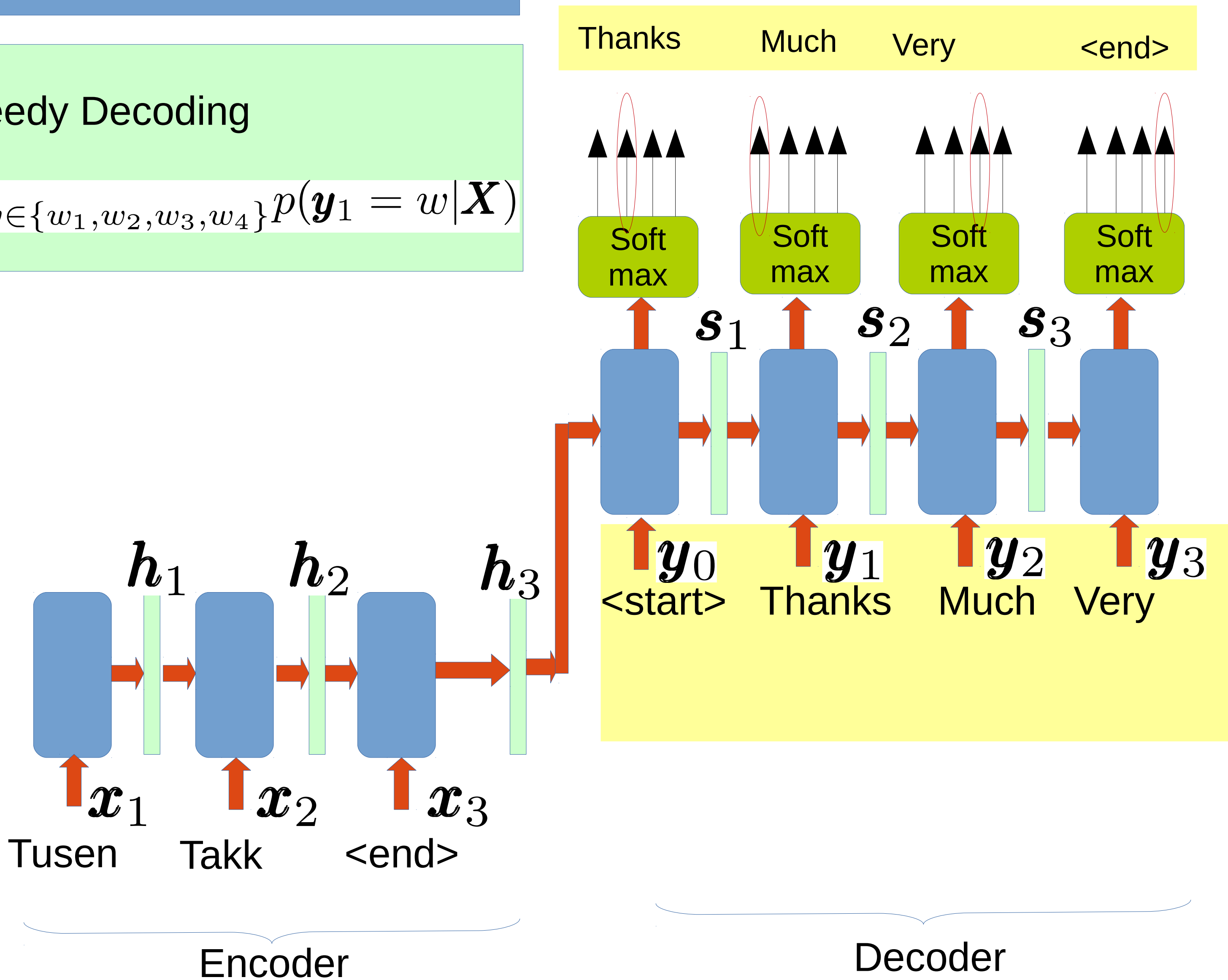


RNN-dec with RNN-enc, Decoding

Decoder vocabulary = {Much ($\boldsymbol{w}_1$), Thanks ($\boldsymbol{w}_2$), Very ($\boldsymbol{w}_3$), < end > ($\boldsymbol{w}_4$)}

Greedy Decoding

$$\boldsymbol{y}_1 = \text{argmax}_{w \in \{w_1, w_2, w_3, w_4\}} p(\boldsymbol{y}_1 = w | \boldsymbol{X})$$



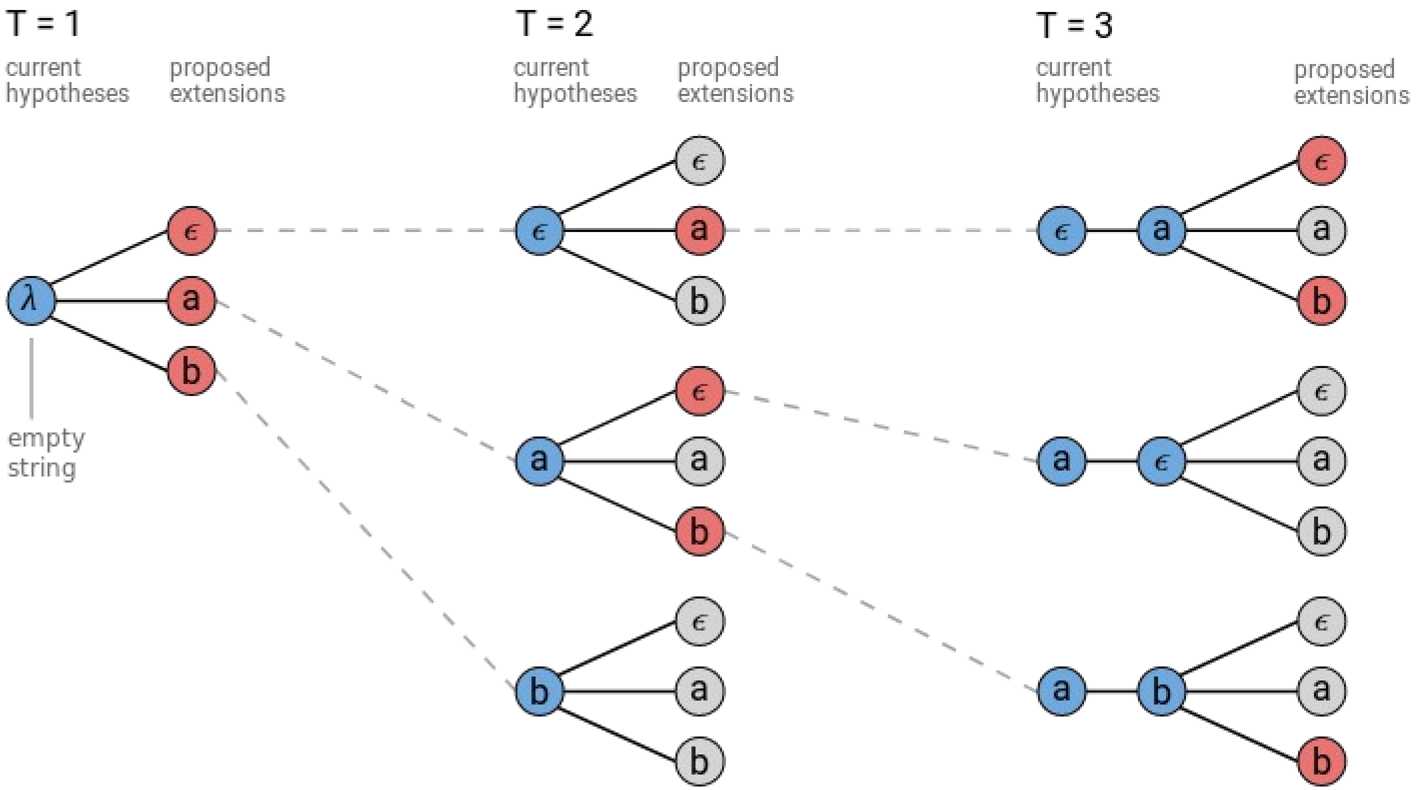
Decoding Approaches

- Optimal decoding

  Find $\boldsymbol{w} = \{w_1, w_2, w_3, w_4\}$ such that $p(w_1, w_2, w_3, w_4|\boldsymbol{X})$ is maximum

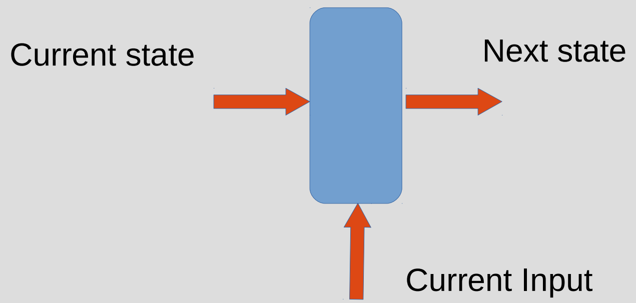
- Greedy decoding
  - Easy
  - Not optimal
- Beam search
  - Closer to optimal decoder
  - Choose top N candidates instead of the best one at each step.

Beam Search Decoding

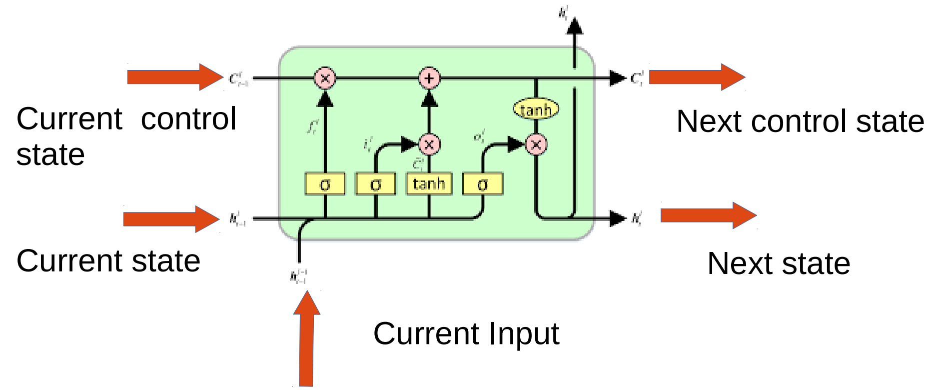


Beam Width = 3

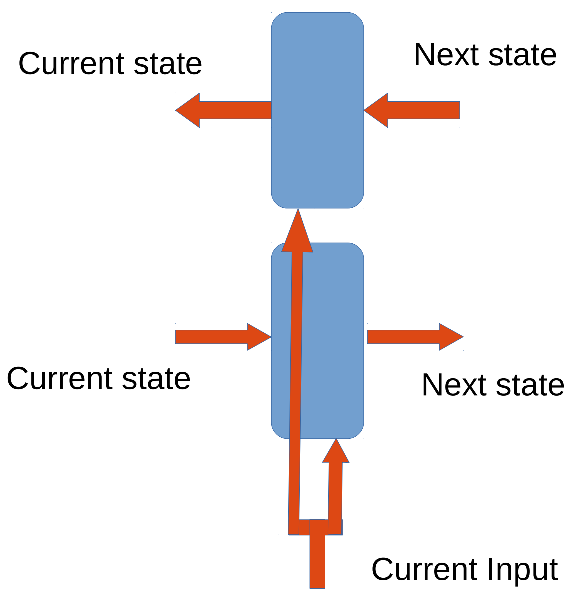
Straight-forward Extensions



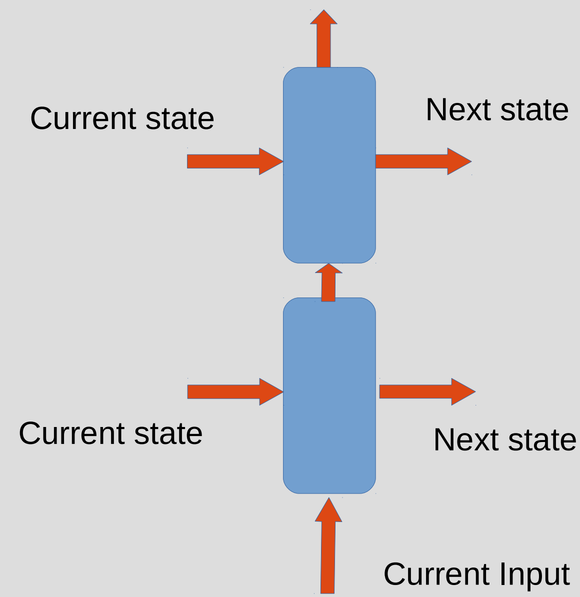
RNN Cell



LSTM Cell



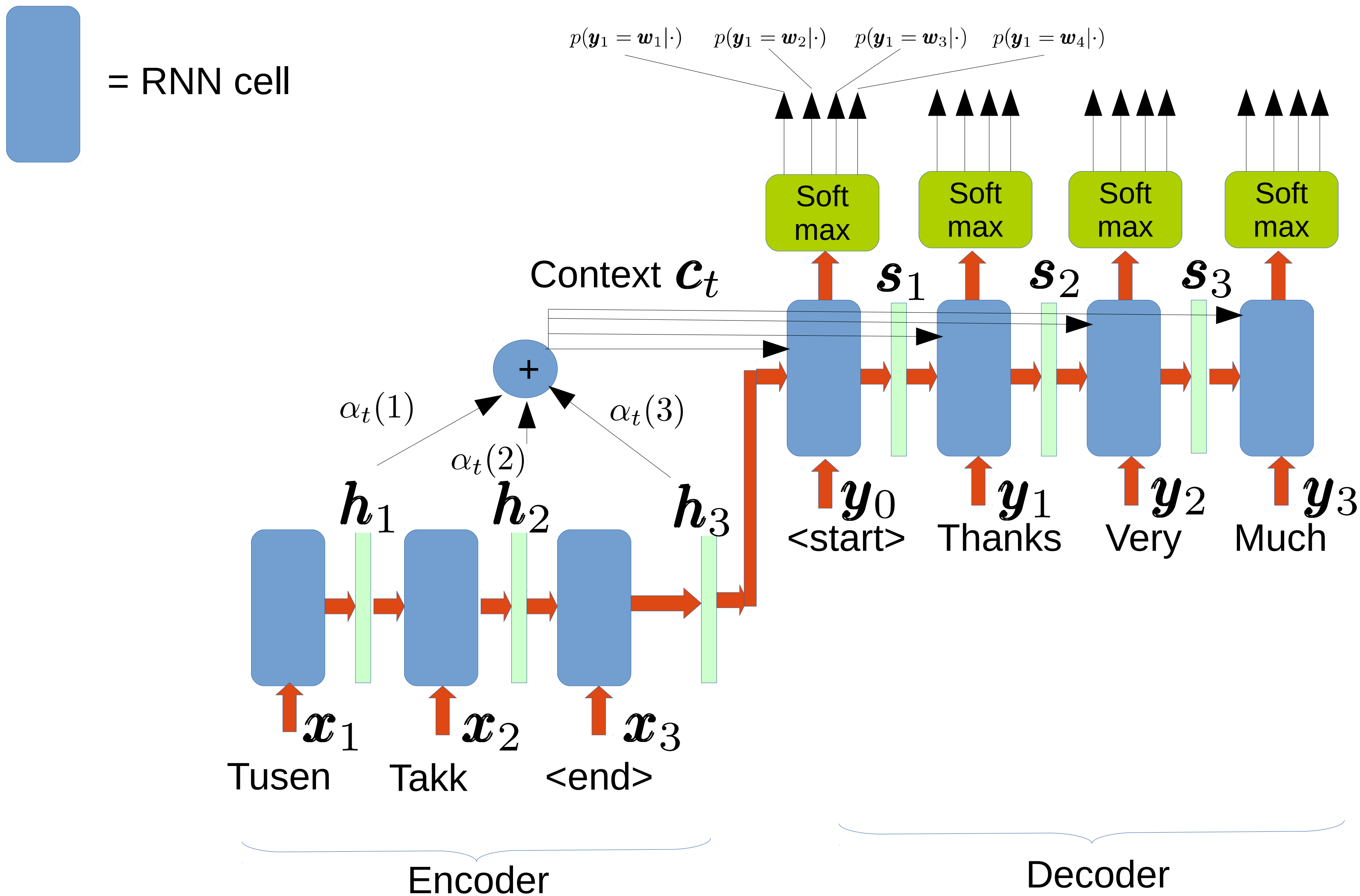
Bidirectional Cell



Stacked Cell

RNN-decoder with RNN-encoder with Attention

Decoder vocabulary $= \{\text{Much } (\boldsymbol{w}_1),\ \text{Thanks } (\boldsymbol{w}_2),\ \text{Very } (\boldsymbol{w}_3), <\text{end}> (\boldsymbol{w}_4)\}$



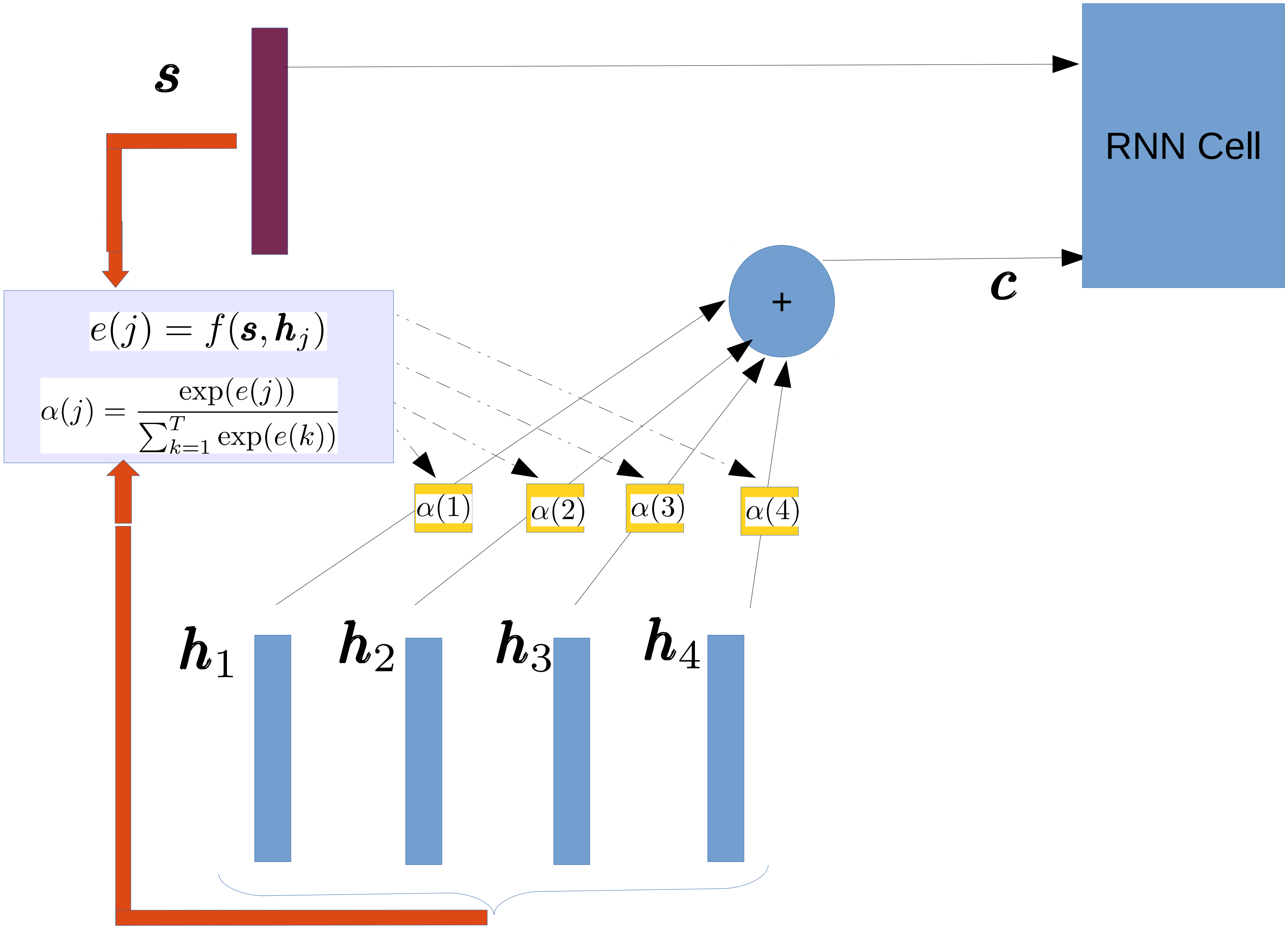
Attention

- Context is given by $\boldsymbol{c}_t = \sum_{j=1}^{T_x} \alpha_t(j) \boldsymbol{h}_j$

- Attention weights $\alpha_t(j)$ are dynamic
- Generally defined by $\alpha_t(j) = \frac{\exp(e_t(j))}{\sum_{k=1}^{T_x} \exp(e_t(k))}$ $e_t(j) = f(\boldsymbol{s}_{t-1}, \boldsymbol{h}_j)$

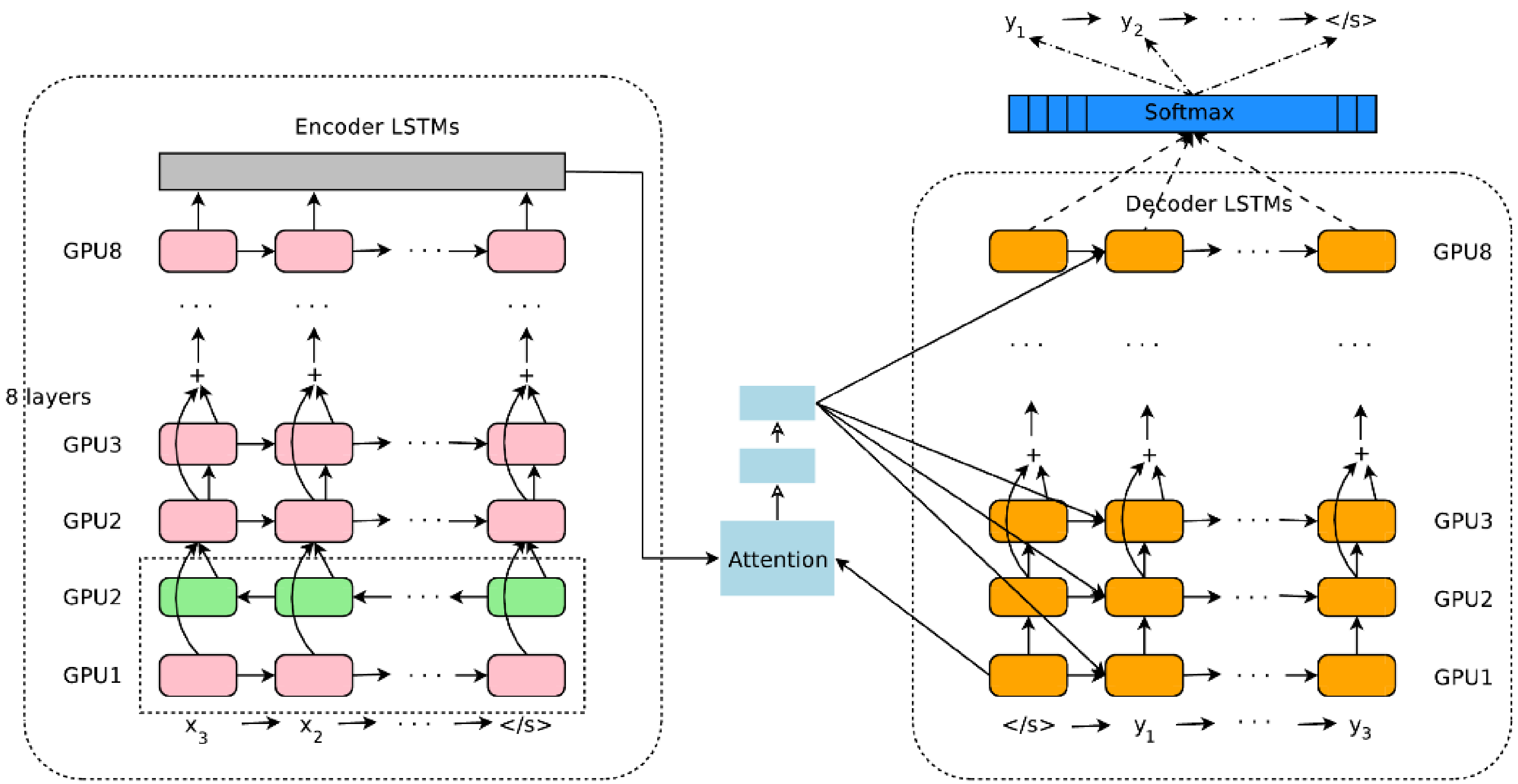
  where function f can be defined in several ways.
  - Dot product $e_t(j) = \boldsymbol{s}_{t-1}^T \cdot \boldsymbol{h}_j$
  - Weighted dot product $e_t(j) = \boldsymbol{s}_{t-1}^T \cdot \boldsymbol{W} \cdot \boldsymbol{h}_j$
  - Use another MLP (eg: 2 layer) $e_t(j) = \boldsymbol{v}^T \cdot \tanh(\boldsymbol{W} \cdot [\boldsymbol{h}_j; \boldsymbol{s}_{t-1}])$

Attention



s
RNN Cell
+
c
$e(j) = f(\boldsymbol{s}, \boldsymbol{h}_j)$
$\alpha(j) = \frac{\exp(e(j))}{\sum_{k=1}^{T} \exp(e(k))}$
$\alpha(1)$
$\alpha(2)$
$\alpha(3)$
$\alpha(4)$
$\boldsymbol{h}_1$
$\boldsymbol{h}_2$
$\boldsymbol{h}_3$
$\boldsymbol{h}_4$

Example: Google Neural Machine Translation



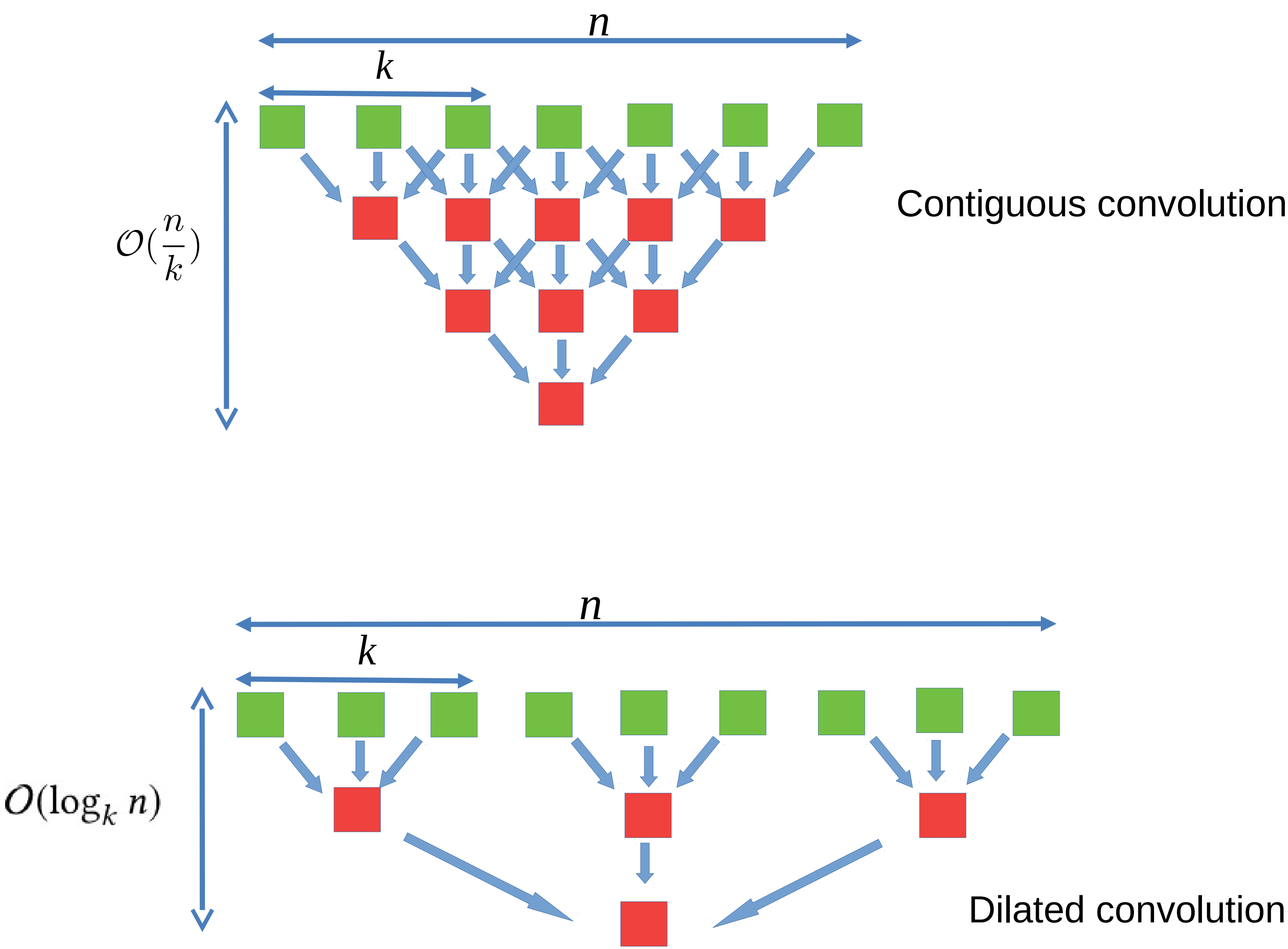
Possible Approaches

- Recurrent networks
  - Apply the NN module in a serial fashion
- Convolutions networks
  - Apply the NN modules in a hierarchical fashion
- Self-attention
  - Direct interaction in the inputs

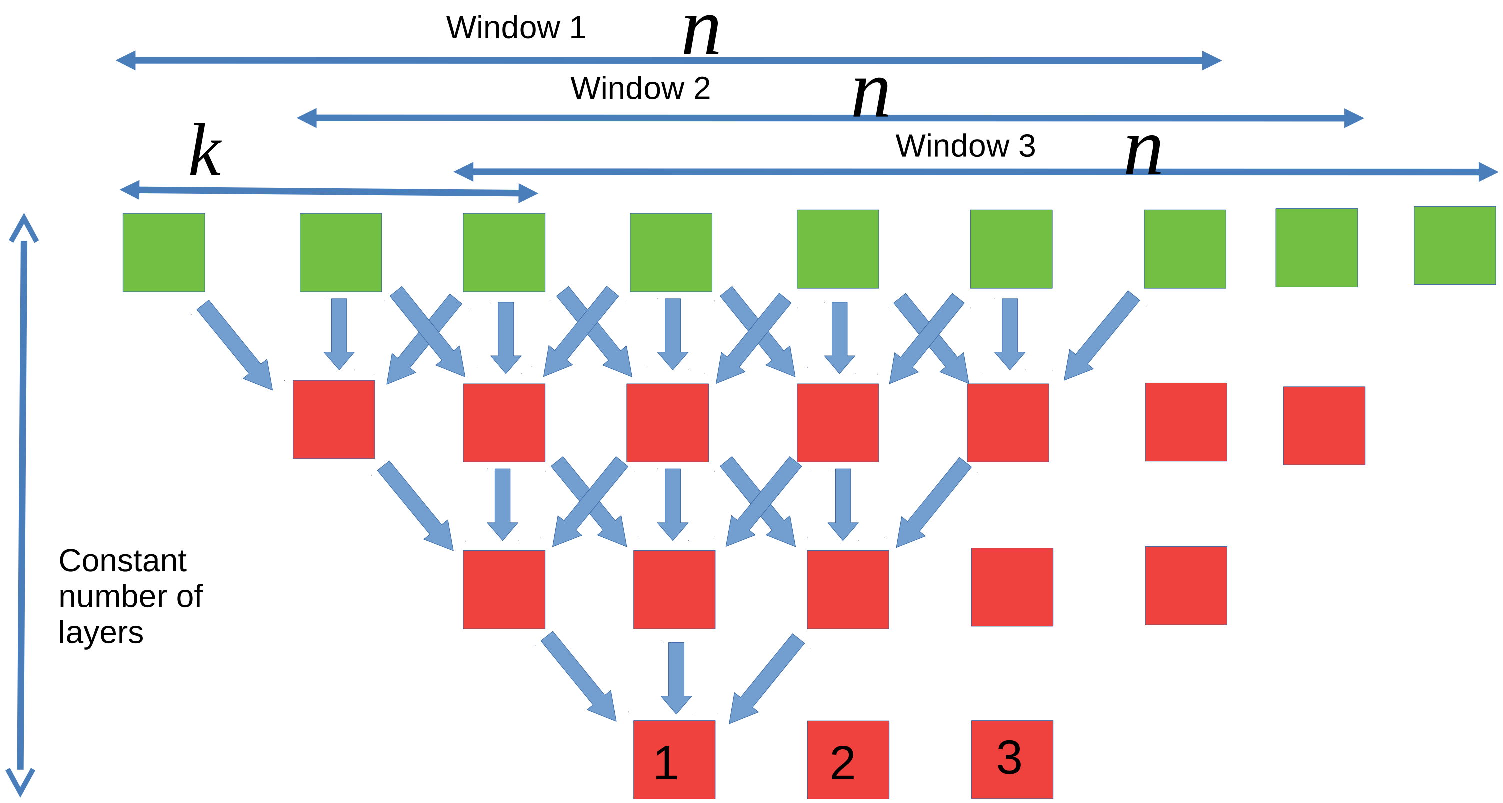
Why Convolution

- Recurrent networks are serial
  - Unable to be parallelized
  - “Distance” between feature vector and different inputs are not constant
- Convolutions networks
  - Can be parallelized (faster)
  - “Distance” between feature vector and different inputs are constant

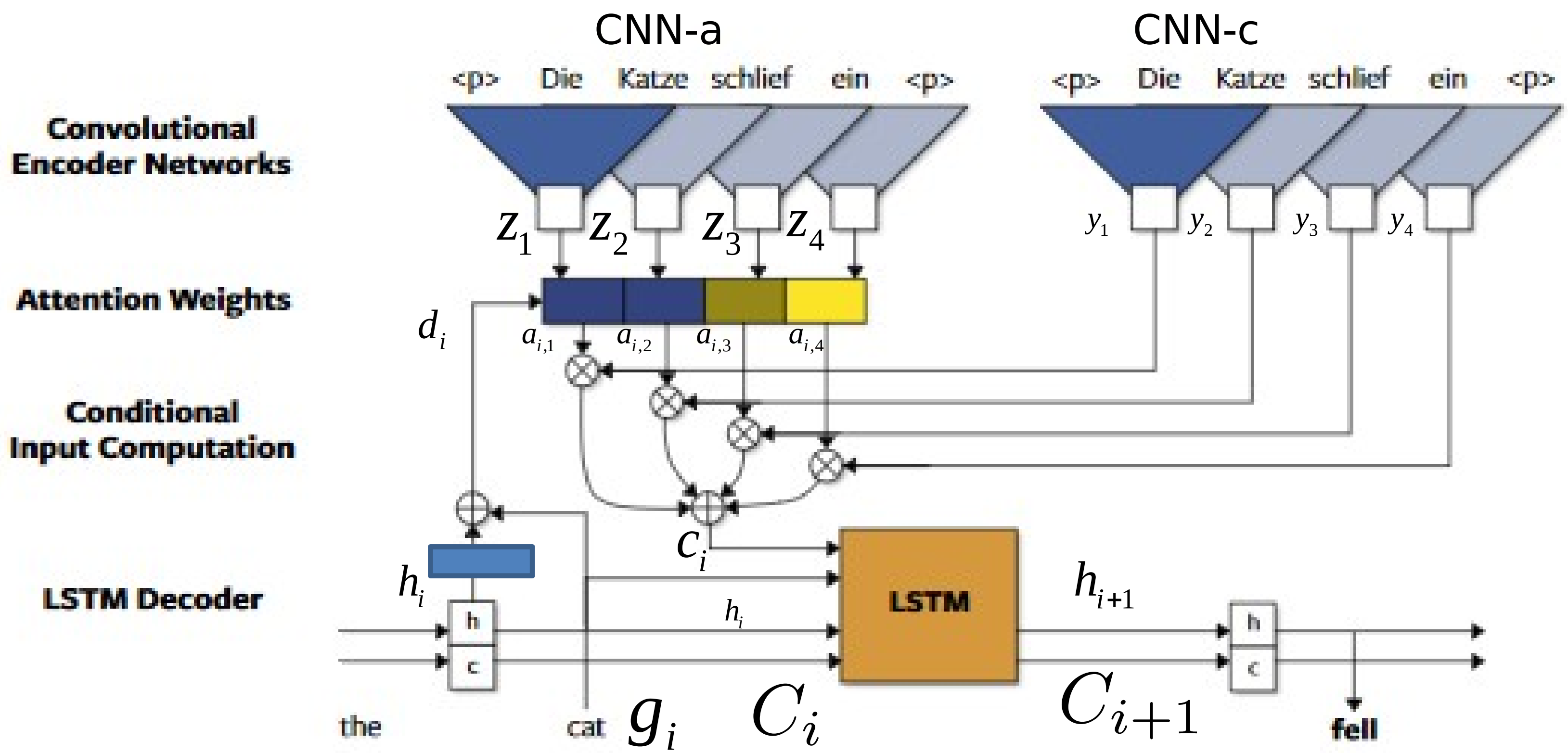
Distance to feature vector in conv nets



Context capture with Convolution Networks



Conv net, Recurrent net with Attention



$$d_i = W_d h_i + g_i$$

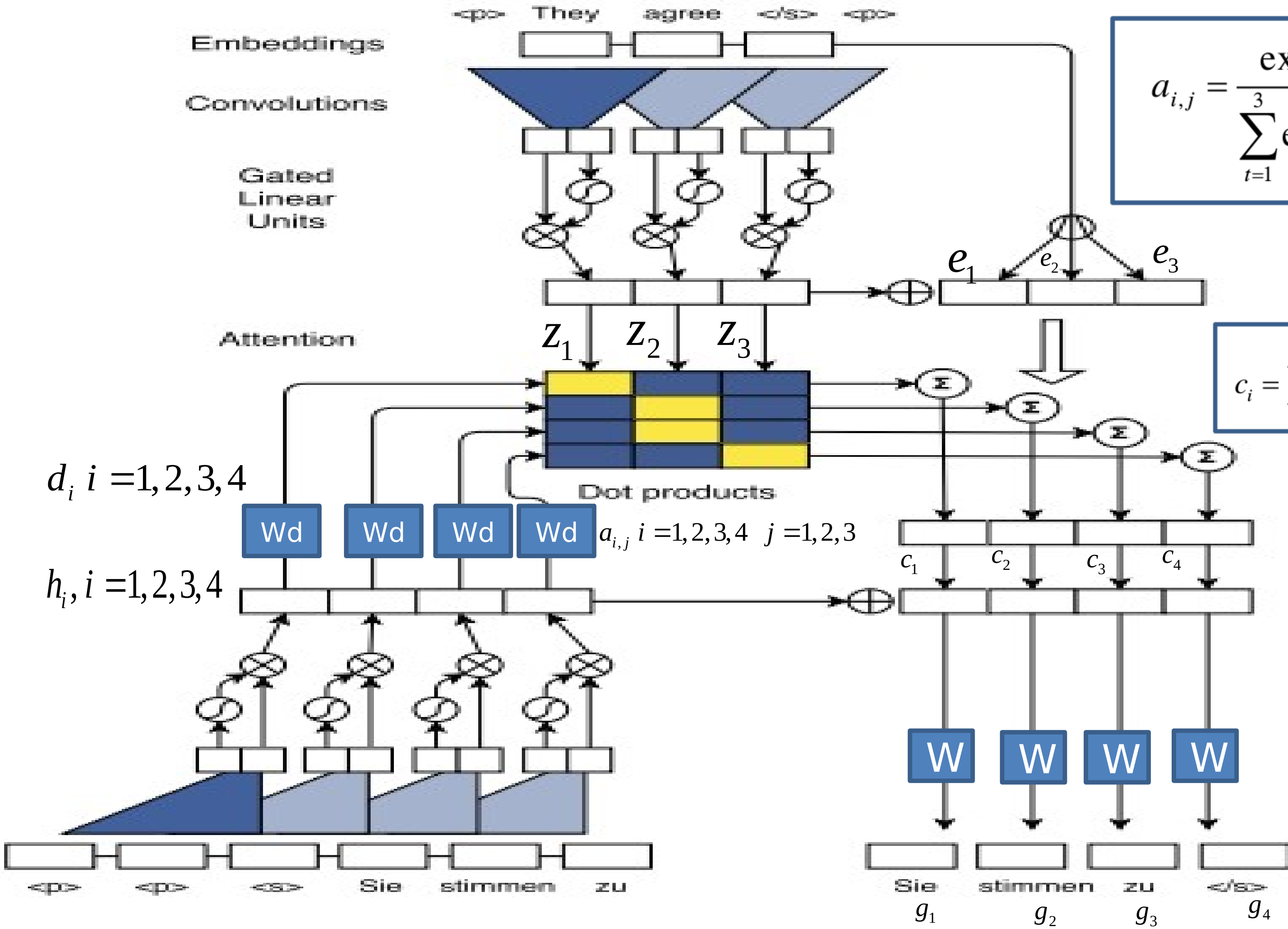
$$a_{i,j} = \frac{\exp(d_i \cdot z_j)}{\sum_{t=1}^{4} \exp(d_i \cdot z_t)}$$

$$c_i = \sum_{j=1}^{4} a_{i,j} y_j$$

$$h_{i+1}, C_{i+1} = \mathrm{LSTM}(c_i, h_i, g_i, C_i)$$

Gehring et.al. *A Convolutional Encoder Model for Neural Machine Translation (2016)*

Two conv nets with attention



$$a_{i,j} = \frac{\exp(d_i \cdot z_j)}{\sum_{t=1}^{3} \exp(d_i \cdot z_j)}$$

$$c_i = \sum_{j=1}^{3} a_{i,j}(z_j + e_j)$$

$$P(g_i \mid g_{i-1}, g_{i-2}, \ldots) = \text{softmax}(W(c_{i-1} + h_{i-1}))$$

Gehring et.al, *Convolutional Sequence to Sequence Learning*, 2017

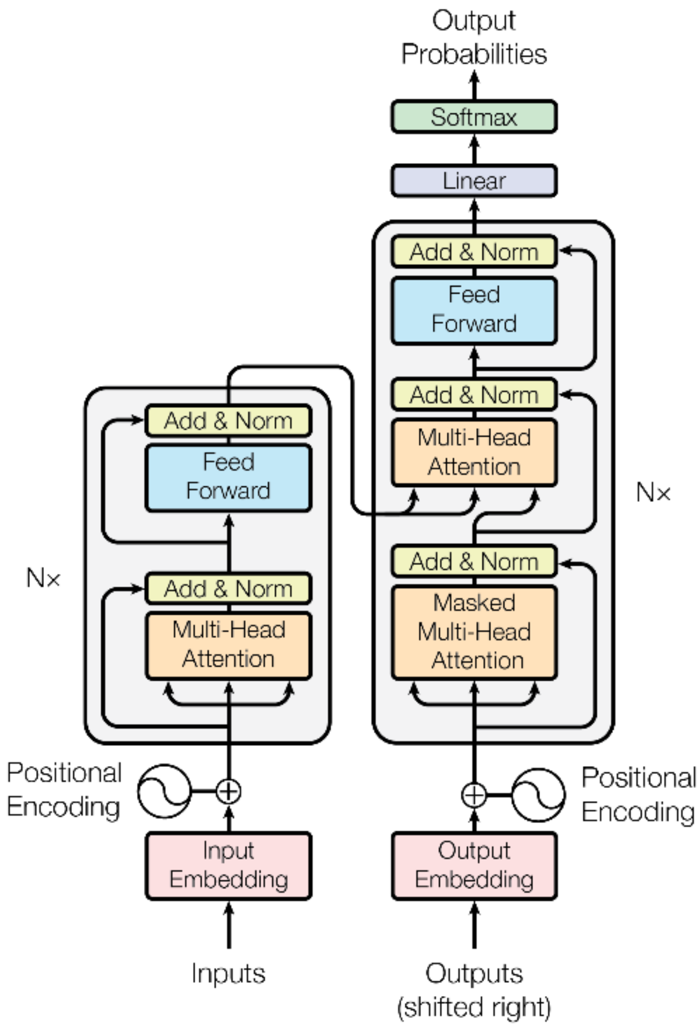
Possible Approaches

- Recurrent networks
  - Apply the NN module in a serial fashion
- Convolutions networks
  - Apply the NN modules in a hierarchical fashion
- Self-attention
  - Direct interaction in the inputs

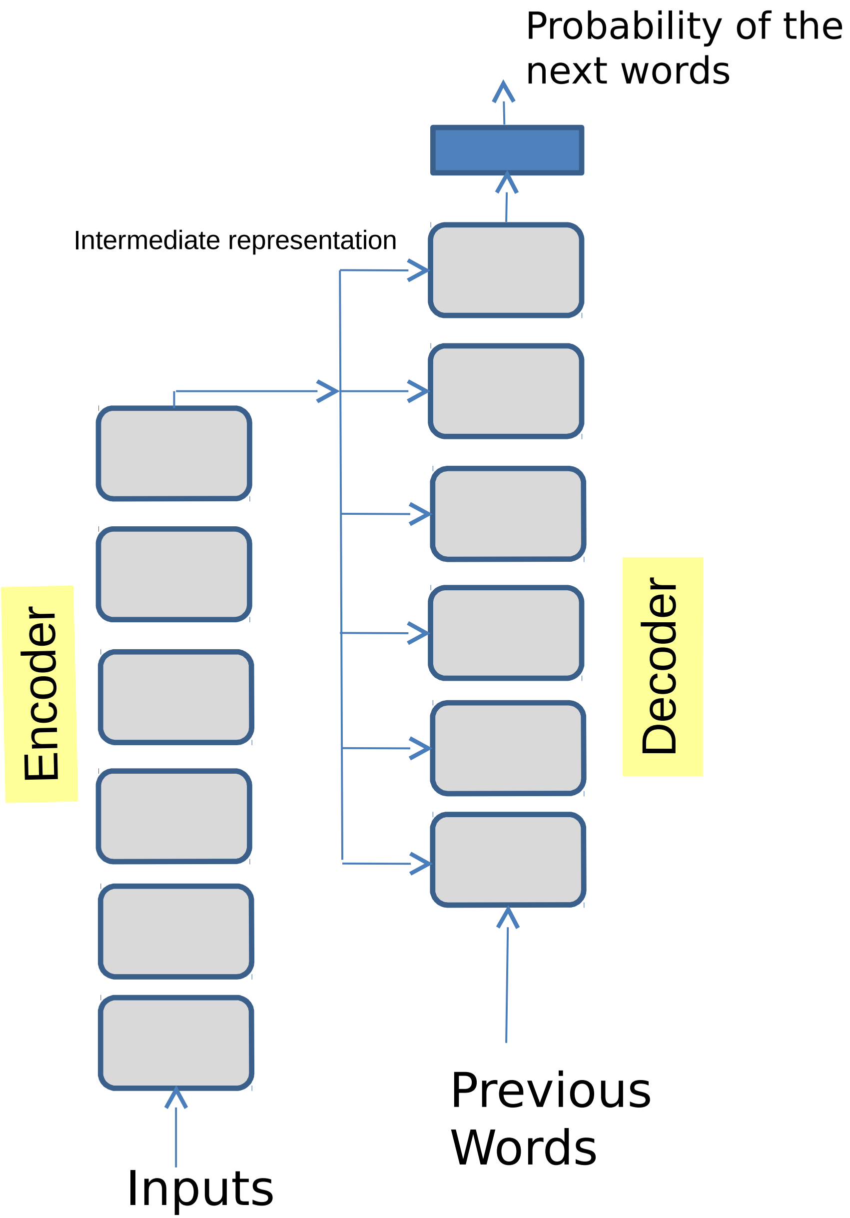
Why Self-attention

- Recurrent networks are serial
  - Unable to be parallelized
  - “Distance” between feature vector and different inputs are not constant
- Self-attention networks
  - Can be parallelized (faster)
  - “Distance” between feature vector and different inputs does not depend on the input length

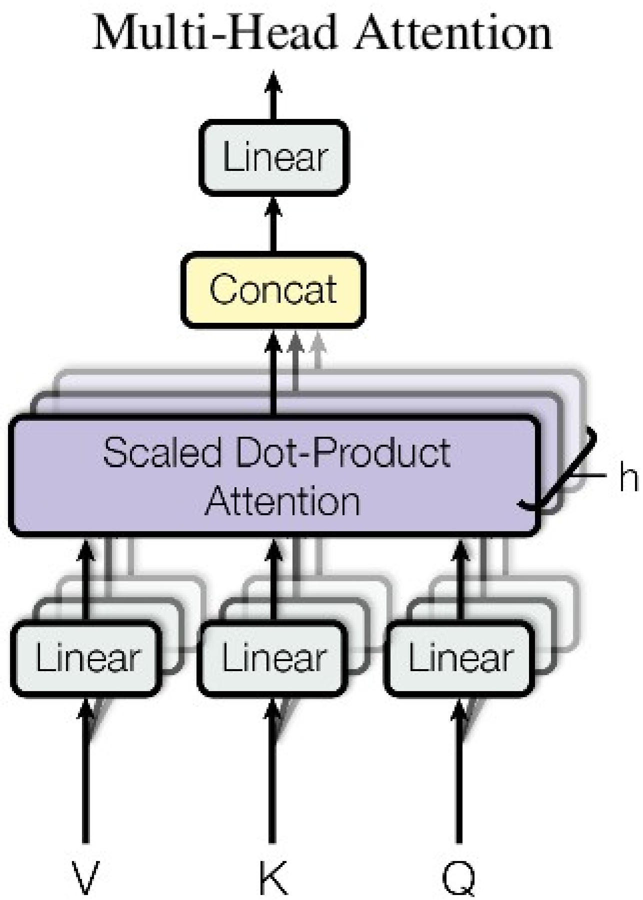
Transformer network with self-attention



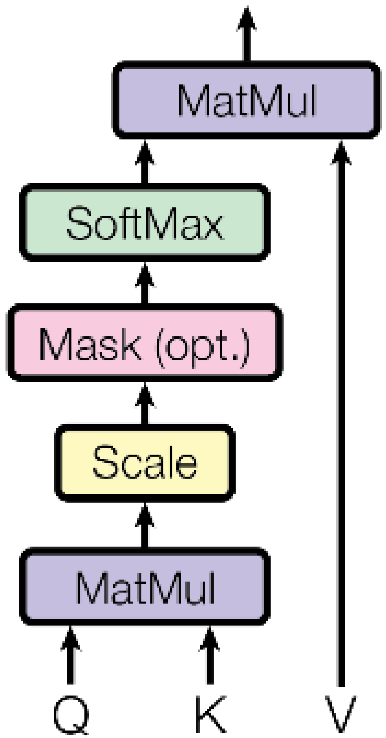
Vasvani et.al, *Attention is all you need*, 2017



Multi-Head Attention



Scaled dot product attention



Query Keys Values

Input word vectors $\boldsymbol{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_n]^T$

Query $\boldsymbol{Q} = [\boldsymbol{q}_1, \boldsymbol{q}_2, \cdots, \boldsymbol{q}_n]^T$

Keys $\boldsymbol{K} = [\boldsymbol{k}_1, \boldsymbol{k}_2, \cdots, \boldsymbol{k}_n]^T$

Values $\boldsymbol{V} = [\boldsymbol{v}_1, \boldsymbol{v}_2, \cdots, \boldsymbol{v}_n]^T$

$$\boldsymbol{Q} = \boldsymbol{X}\boldsymbol{W}^Q$$

$$\boldsymbol{K} = \boldsymbol{X}\boldsymbol{W}^K$$

$$\boldsymbol{V} = \boldsymbol{X}\boldsymbol{W}^V$$

$\boldsymbol{W}^Q, \boldsymbol{W}^K, \boldsymbol{W}^V$ Trainable weight vectors

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Encoder Self-attention

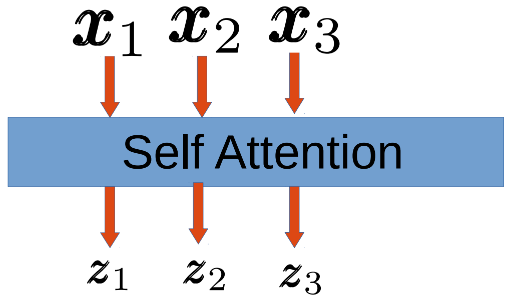
$\boldsymbol{q}_1$	$\boldsymbol{q}_2$	$\boldsymbol{q}_3$
$\boldsymbol{k}_1$	$\boldsymbol{k}_2$	$\boldsymbol{k}_3$
$\boldsymbol{v}_1$	$\boldsymbol{v}_2$	$\boldsymbol{v}_3$
$\boldsymbol{x}_1$	$\boldsymbol{x}_2$	$\boldsymbol{x}_3$

$$\alpha_{1,1} = \frac{\exp(\boldsymbol{q}_1 \boldsymbol{k}_1^T)}{\sum_j \exp(\boldsymbol{q}_1 \boldsymbol{k}_j^T)} \qquad \alpha_{1,2} = \frac{\exp(\boldsymbol{q}_1 \boldsymbol{k}_2^T)}{\sum_j \exp(\boldsymbol{q}_1 \boldsymbol{k}_j^T)} \qquad \alpha_{1,3} = \frac{\exp(\boldsymbol{q}_1 \boldsymbol{k}_3^T)}{\sum_j \exp(\boldsymbol{q}_1 \boldsymbol{k}_j^T)}$$

$$\boldsymbol{z}_1 = \alpha_{1,1}\boldsymbol{v}_1 + \alpha_{1,2}\boldsymbol{v}_2 + \alpha_{1,3}\boldsymbol{v}_3$$

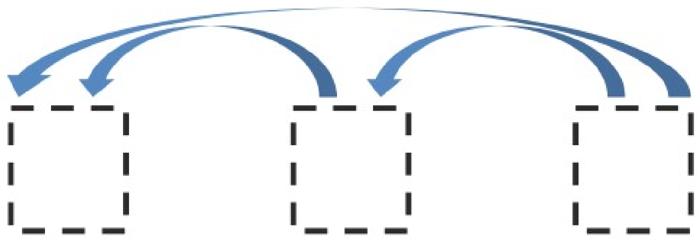
$$\boldsymbol{z}_2 = \alpha_{2,1}\boldsymbol{v}_1 + \alpha_{2,2}\boldsymbol{v}_2 + \alpha_{2,3}\boldsymbol{v}_3$$

$$\boldsymbol{z}_3 = \alpha_{3,1}\boldsymbol{v}_1 + \alpha_{3,2}\boldsymbol{v}_2 + \alpha_{3,3}\boldsymbol{v}_3$$



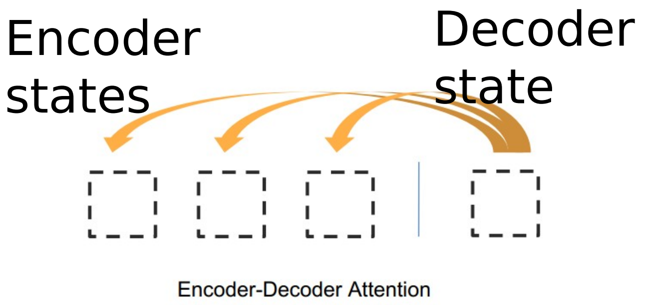
Decoder Self-attention

- Almost same as encoder self attention
- But only leftward positions are considered.



MaskedDecoder Self-Attention

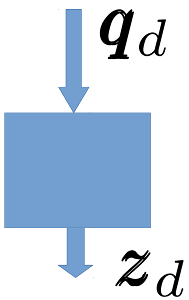
Encoder-decoder attention



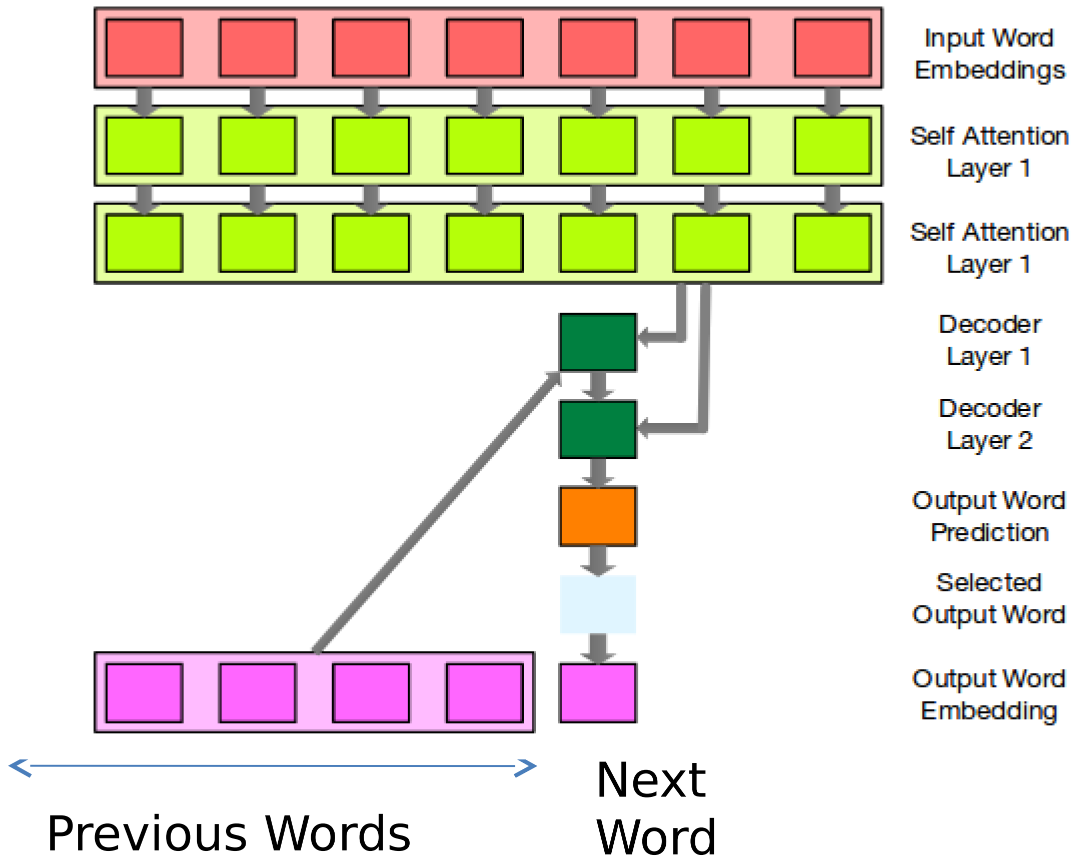
$$\boldsymbol{q}_1 \quad \boldsymbol{q}_2 \quad \boldsymbol{q}_3 \qquad \boldsymbol{q}_d$$
$$\boldsymbol{k}_1 \quad \boldsymbol{k}_2 \quad \boldsymbol{k}_3 \qquad \boldsymbol{k}_d$$
$$\boldsymbol{v}_1 \quad \boldsymbol{v}_2 \quad \boldsymbol{v}_3 \qquad \boldsymbol{v}_d$$

$$\alpha_{1,1} = \frac{\exp(\boldsymbol{q}_d \boldsymbol{k}_1^T)}{\sum_j \exp(\boldsymbol{q}_d \boldsymbol{k}_j^T)} \qquad \alpha_{1,2} = \frac{\exp(\boldsymbol{q}_d \boldsymbol{k}_2^T)}{\sum_j \exp(\boldsymbol{q}_d \boldsymbol{k}_j^T)} \qquad \alpha_{1,3} = \frac{\exp(\boldsymbol{q}_d \boldsymbol{k}_3^T)}{\sum_j \exp(\boldsymbol{q}_d \boldsymbol{k}_j^T)}$$

$$\boldsymbol{z}_d = \alpha_{1,1}\boldsymbol{v}_1 + \alpha_{1,2}\boldsymbol{v}_2 + \alpha_{1,3}\boldsymbol{v}_3$$



Overall Operation



Neural machine translation, philipp Koehn

Comparison of Seq2Seq Methods

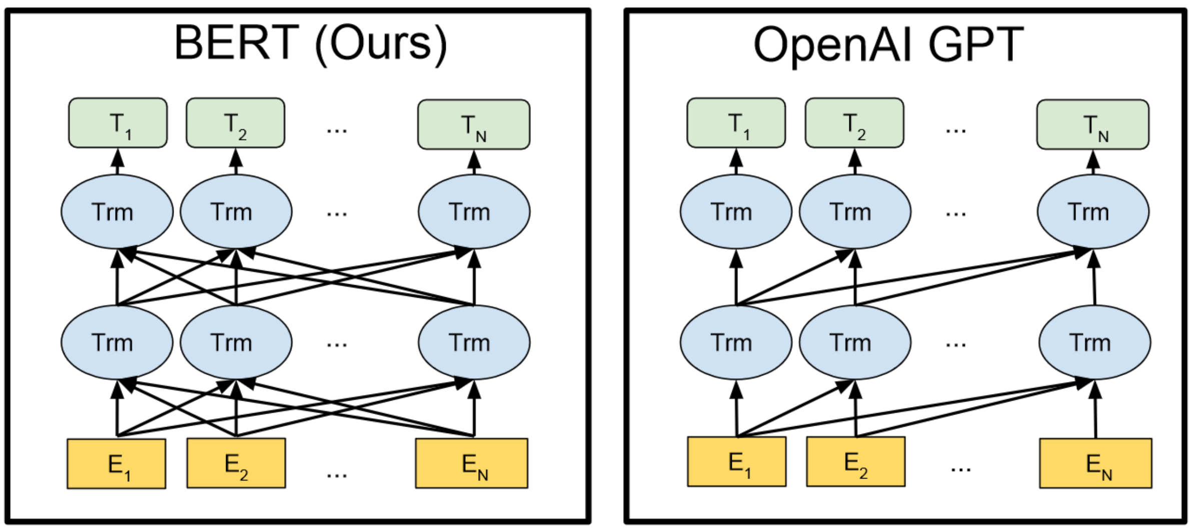
Table 1: Maximum path lengths, per-layer complexity and minimum number of sequential operations for different layer types. n is the sequence length, d is the representation dimension, k is the kernel size of convolutions and r the size of the neighborhood in restricted self-attention.

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

Famous Transformer Systems

- BERT (Bidirectional Encoder Representations from Transformers)
  - Based on Transformer Encoder block
  - Self-supervised learning approach and pretrained with
    - Masked Language model
    - Next sentence prediction
  - Several down-stream tasks (classification, QA etc.)

- GPT-2 (Generalized Pre-Training)
  - Based on Transformer Decoder block (Masked Self attention)
  - Self-supervised learning and pre-trained with
    - Next word prediction (given the previous prediction)
  - Several down-stream tasks (classification, similarity etc.)



Reinforcement Learning

Reinforcement Learning

- Machine Translation/Summarization
- Dialog Systems
-
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Reinforcement Learning

- Machine Translation/Summarization
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-
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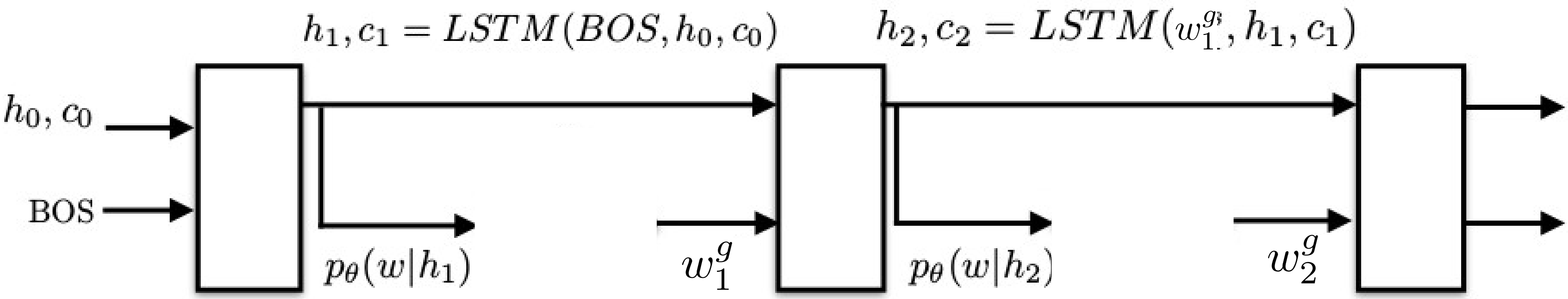
Why Reinforcement Learning

- Exposure bias
  - In training ground truths are used. In testing, generated word in the previous step is used to generate the next word.
  - Use generated words in training needs sampling : Non differentiable
- Maximum Likelihood criterion is not directly relevant to evaluation metrics
  - BLEU (Machine translation)
  - ROUGE (Summarization)
  - Use BLEU/ROUGE in training: Non differentiable

Sequence Generation as Reinforcement Learning

- **Agent:** The Recurrent Net
- **State:** Hidden layers, Attention weights etc.
- **Action:** Next Word
- **Policy:** Generate the next word (*action*) given the current hidden layers and attention weights (*state*)
- **Reward:** Score computed using the evaluation metric (eg: BLEU)

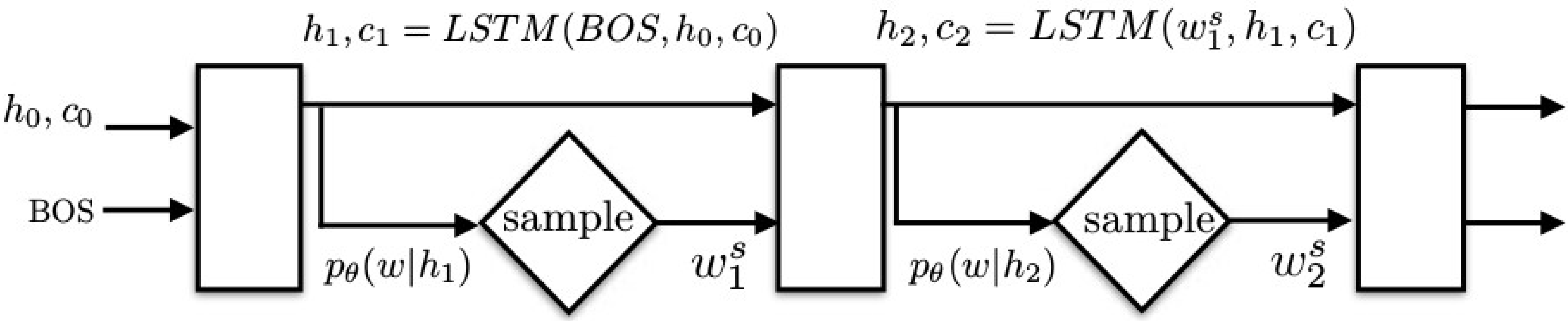
Maximum Likelihood Training (Revisit)



$$\text{Log Likelihood} = \sum_{t=1}^{T} \log p_\theta(w_t^g | h_t)$$

Minimize the negative log likelihood

Reinforcement Learning Formulation



$$\text{Reward} = r(w^s) = r(w_1^s, w_2^s, \cdots, w_T^s)$$

Minimize the expected negative reward, $L(\theta) = -\mathbb{E}_{w^s \sim p_\theta}\left[r(w^s)\right]$
using REINFORCE algorithm

Reinforcement Learning Details

- Expected reward $$L(\theta) = -\sum_w p_\theta(w) r(w)$$
- We need the gradient $$\nabla_\theta L(\theta) = -\sum_w r(w) \nabla_\theta p_\theta(w)$$
- Need to write this as an expectation, so that we can evaluate it using samples. Use the log derivative trick: $$\nabla_\theta L(\theta) = -\sum_w r(w) p_\theta(w) \nabla_\theta \log p_\theta(w)$$
- This is an expectation $$\nabla_\theta L(\theta) = -\mathbb{E}_{w^s \sim p_\theta}\left[r(w^s) \nabla_\theta \log p_\theta(w^s)\right]$$
- Approximate this with sample mean

$$\nabla_\theta L(\theta) \approx -\frac{1}{N} \sum_{s=1}^{N} r(w^s) \nabla_\theta \log p_\theta(w^s)$$

- In practice we use only one sample

$$\nabla_\theta L(\theta) \approx -r(w^s) \nabla_\theta \log p_\theta(w^s)$$

Reinforcement Learning Details

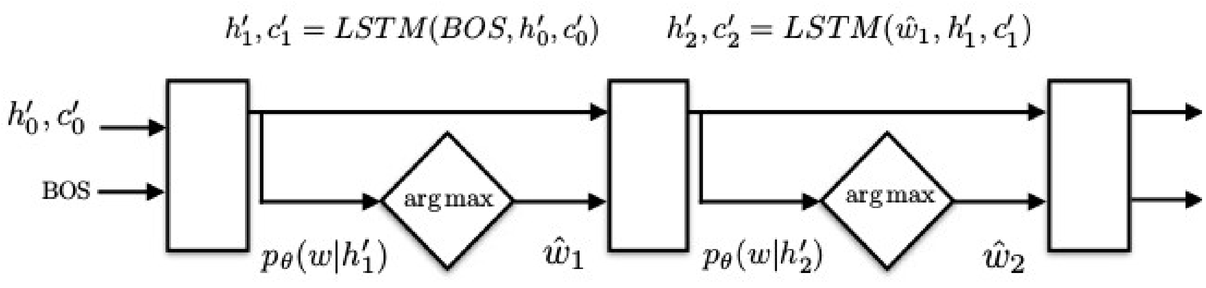
- Gradient $\nabla_\theta L(\theta) \approx -r(w^s)\nabla_\theta \log p_\theta(w^s)$

- This estimation has high variance. Use a baseline to combat this problem.

$$\nabla_\theta L(\theta) \approx -(r(w^s) - b)\nabla_\theta \log p_\theta(w^s)$$

- Baseline can be anything independent of w^s

- It can for example be estimated as the reward for word sequence generated using argmax at each cell. $b = r(\hat{w}_1, \hat{w}_2, \hat{w}_3, \cdots, \hat{w}_T)$



Reinforcement Learning

- Machine Translation/Summarization
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-
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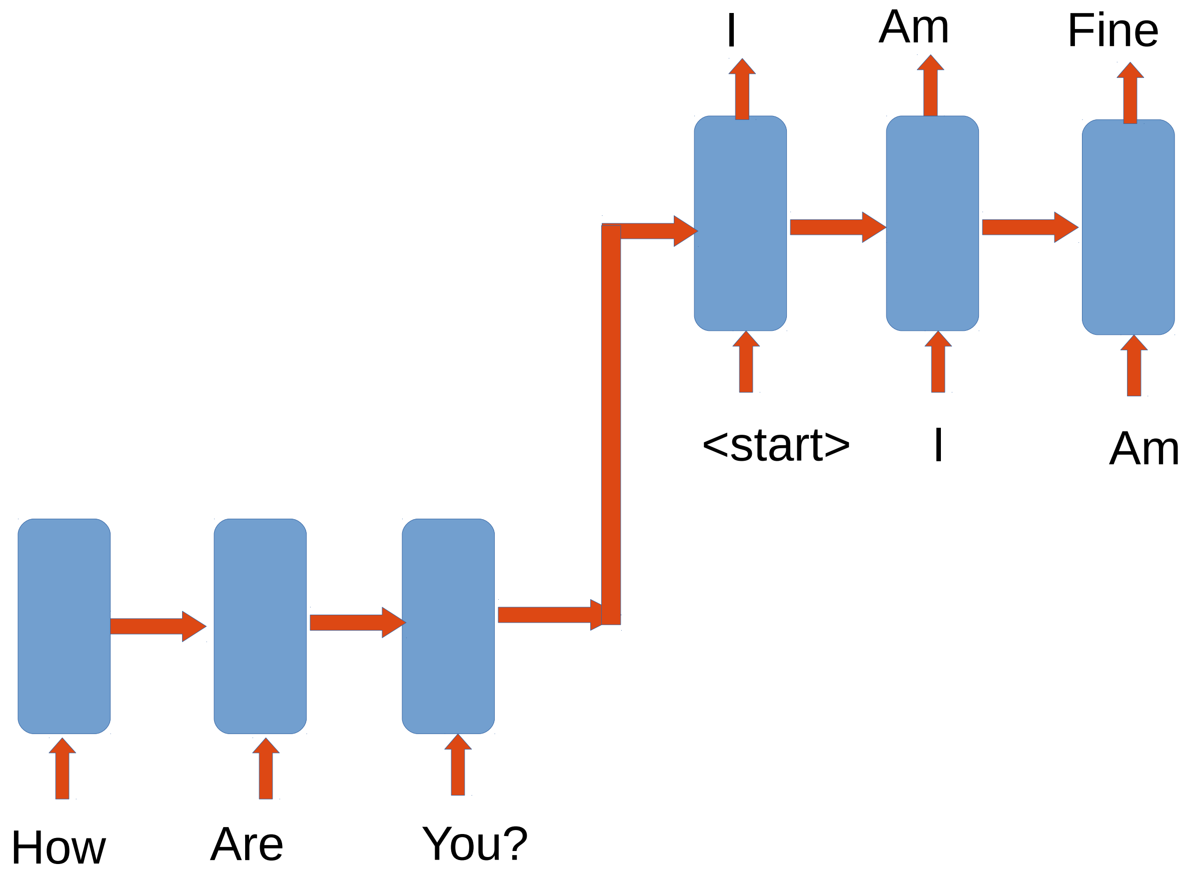
Maximum Likelihood Dialog Systems



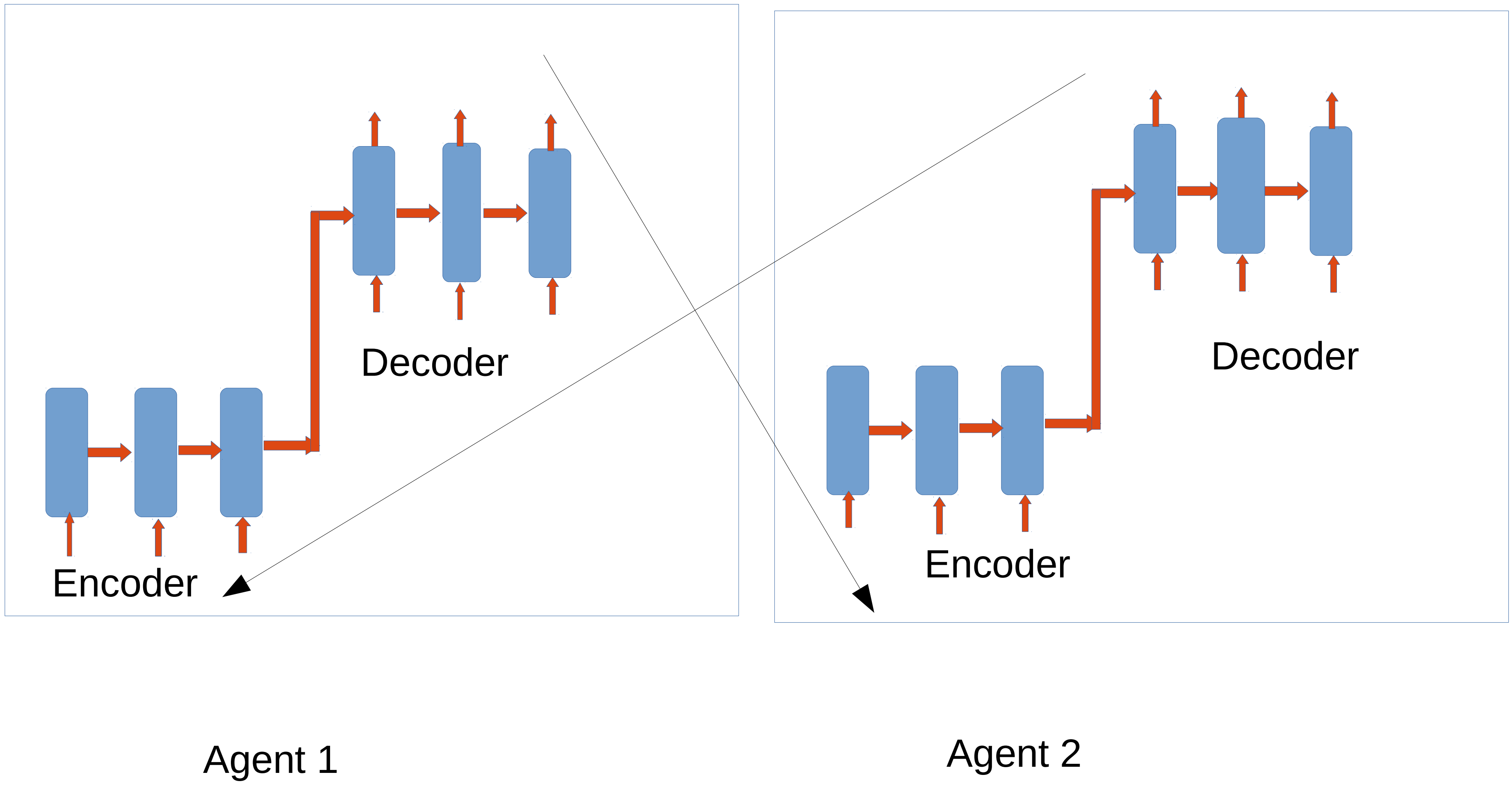
Why Reinforcement Learning

- Maximum Likelihood criterion is not directly relevant to successful dialogs
  - Dull responses (“I don’t know”)
  - Repetitive responses
- Need to integrate developer defined rewards relevant to longer term goals of the dialog

Dialog Generation as Reinforcement Learning

- **Agent:** The Recurrent Net
- **State:** Previous dialog turns
- **Action:** Next dialog utterance
- **Policy:** Generate the next dialog utterance (*action*) given the previous dialog turns (*state*)
- **Reward:** Score computed based on relevant factors such as ease of answering, information flow, semantic coherence etc.

Training Setup



Training Procedure

- From the viewpoint of a given agent, the procedure is similar to that of sequence generation
  - REINFORCE algorithm
- Appropriate rewards must be calculated based on current and previous dialog turns.
- Can be initialized with maximum likelihood trained models.

Adversarial Learning

- Use a discriminator as in GANs to calculate the reward
- Same training procedure based on REINFORCE for generator