Structured Attention Networks

Yoon Kim* Carl Denton* Luong Hoang Alexander M. Rush

HarvardNLP

1. Deep Neural Networks for Text Processing and Generation

2. Attention Networks

3. Structured Attention Networks
   - Computational Challenges
   - Structured Attention In Practice

4. Conclusion and Future Work

Pure Encoder-Decoder Network

Input (sentence, image, etc.)

Fixed-Size Encoder (MLP, RNN, CNN)

Encoder(input) $\in \mathbb{R}^D$

Decoder

Decoder(Encoder(input))

Pure Encoder-Decoder Network

Input (sentence, image, etc.)

$\Downarrow$

Fixed-Size Encoder (MLP, RNN, CNN)

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Decoder(Encoder(input))

Pure Encoder-Decoder Network

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Fixed-Size Encoder (MLP, RNN, CNN)

$\text{Encoder}(\text{input}) \in \mathbb{R}^D$

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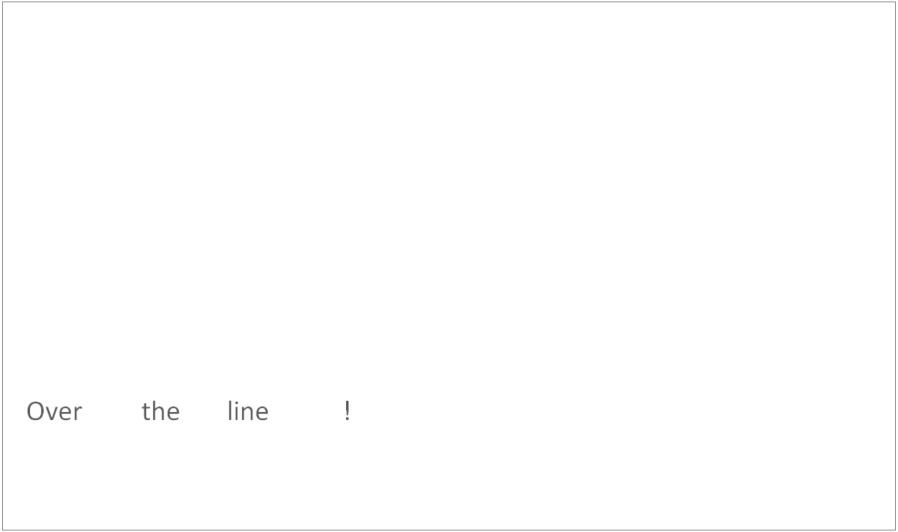
Decoder

$\text{Decoder}(\text{Encoder}(\text{input}))$

Example: Neural Machine Translation (Sutskever et al., 2014)



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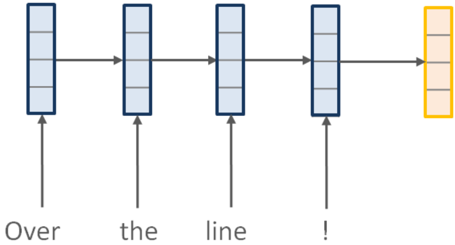

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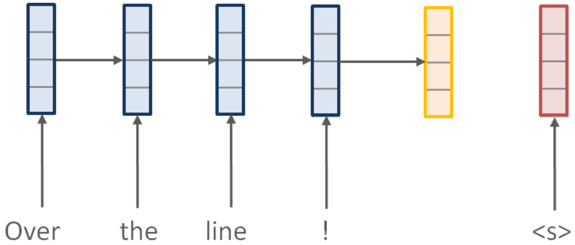

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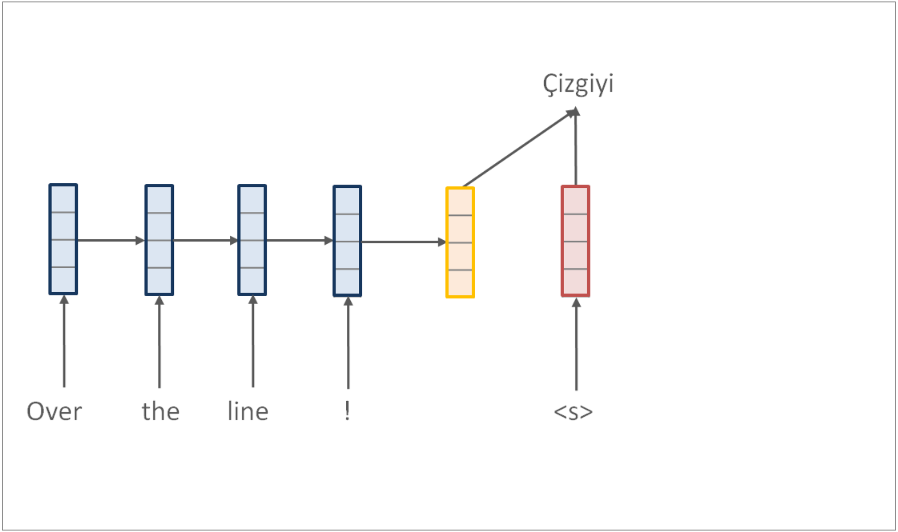

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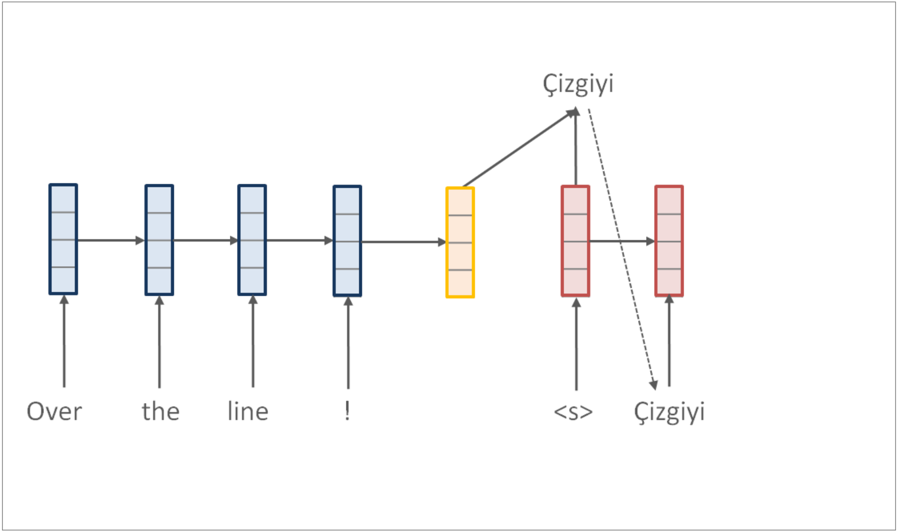

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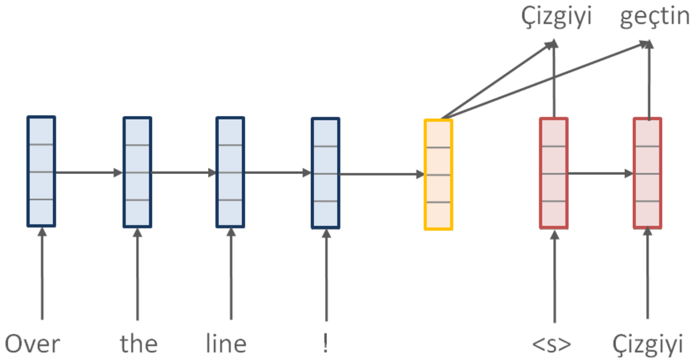

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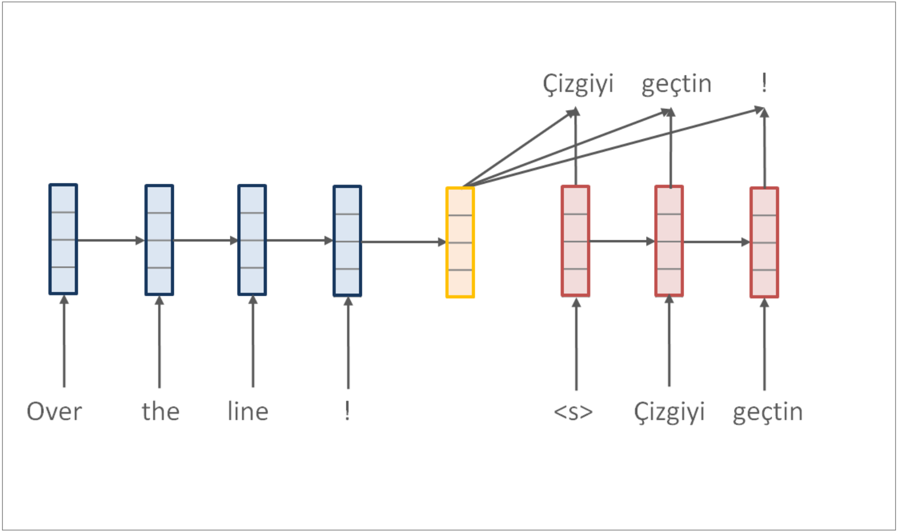

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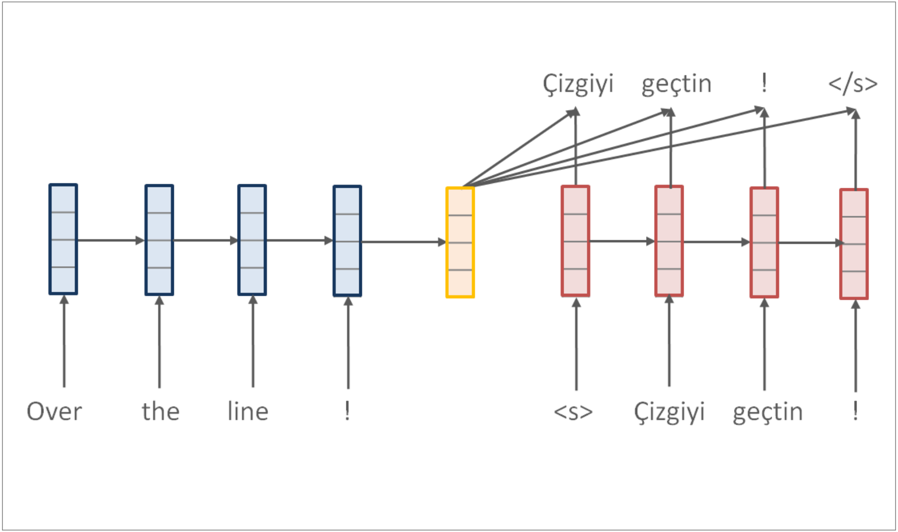

Communication Bottleneck

All input information communicated through fixed-size hidden vector.

$$\text{Encoder}(\text{input})$$

- Training: All gradients have to flow through single bottleneck.
- Test: All input encoded in single vector.

Neural Attention

Input (sentence, image, etc.)

Memory-Bank Encoder (MLP, RNN, CNN)

Encoder(input) $= x_1, x_2, \ldots, x_T$

Attention Distribution

"where"

Annotation Function

"what"

Context Vector ("soft selection")

Decoder

Neural Attention

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⇩

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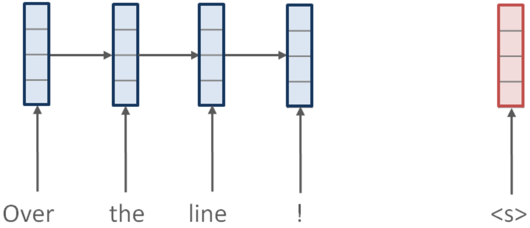
Attention-based Neural Machine Translation (Bahdanau et al., 2015)



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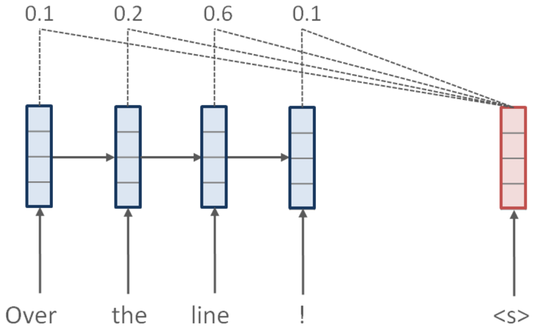

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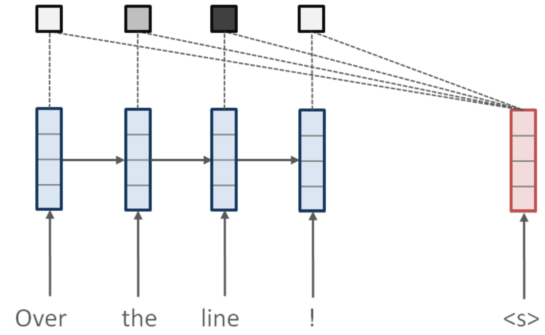

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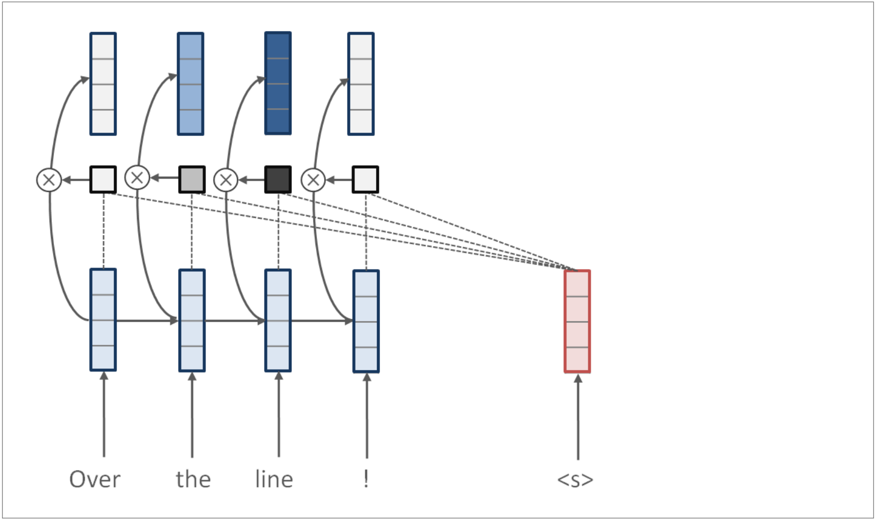

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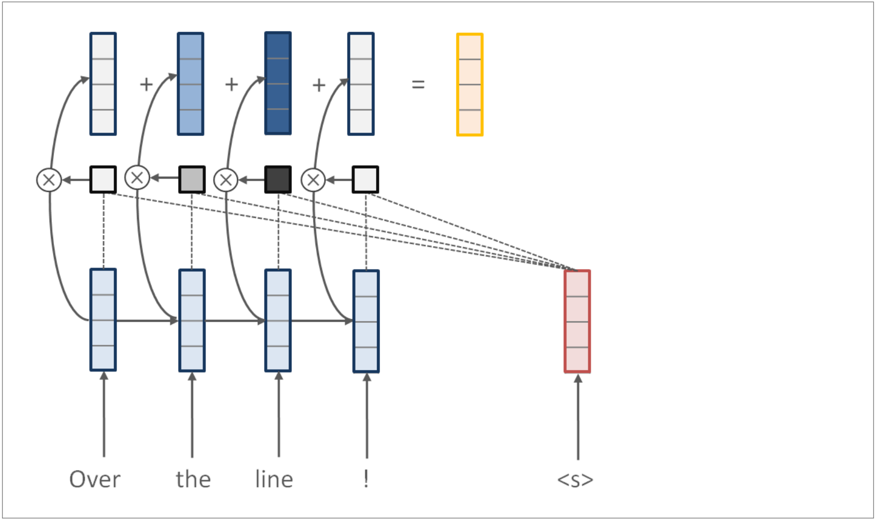

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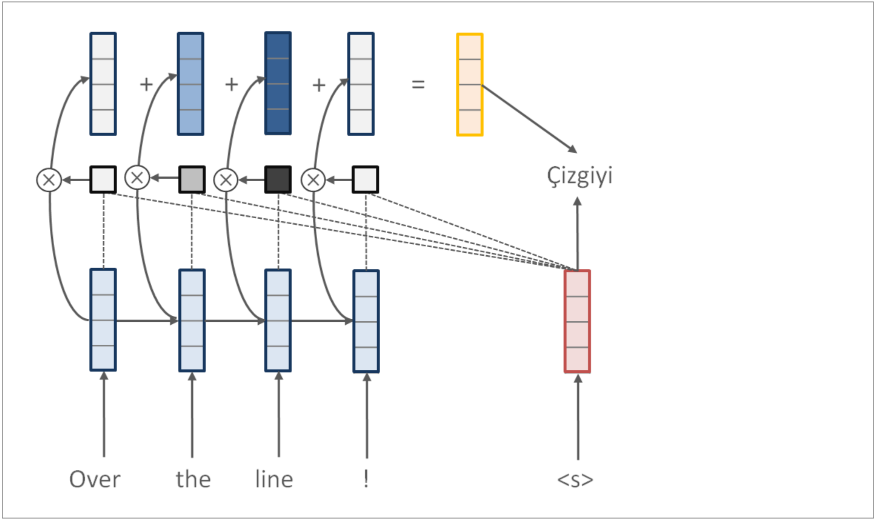

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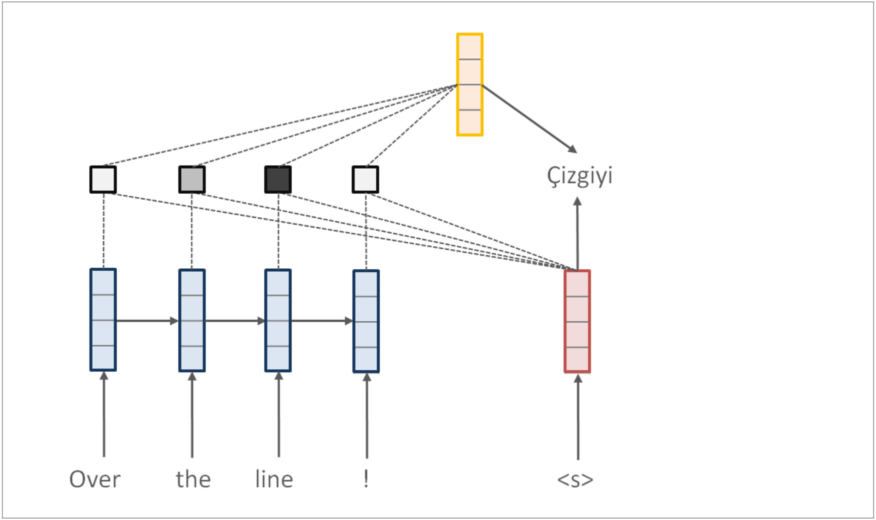

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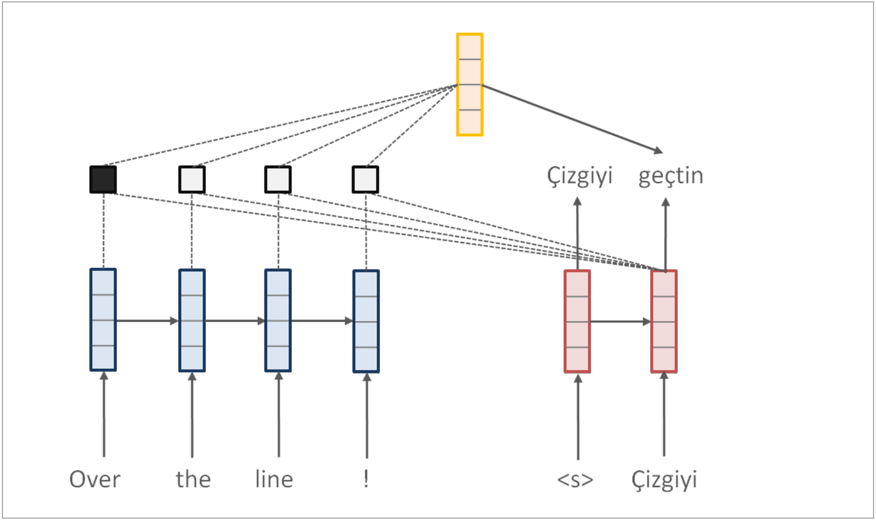

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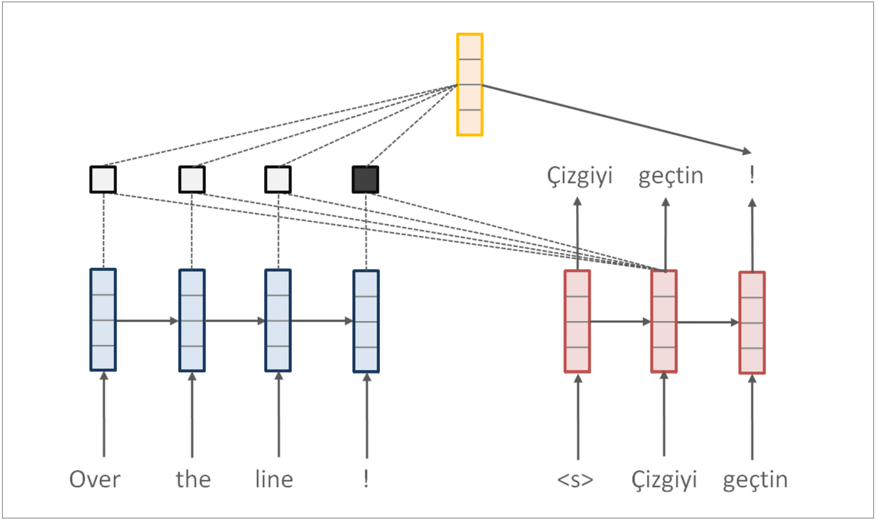

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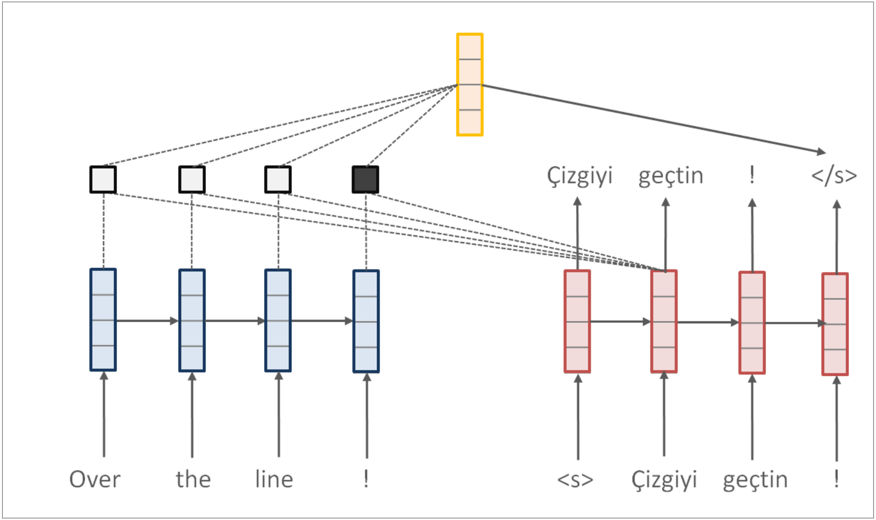


Question Answering (Sukhbaatar et al., 2015)

Greg is a frog

Brian is a rhino

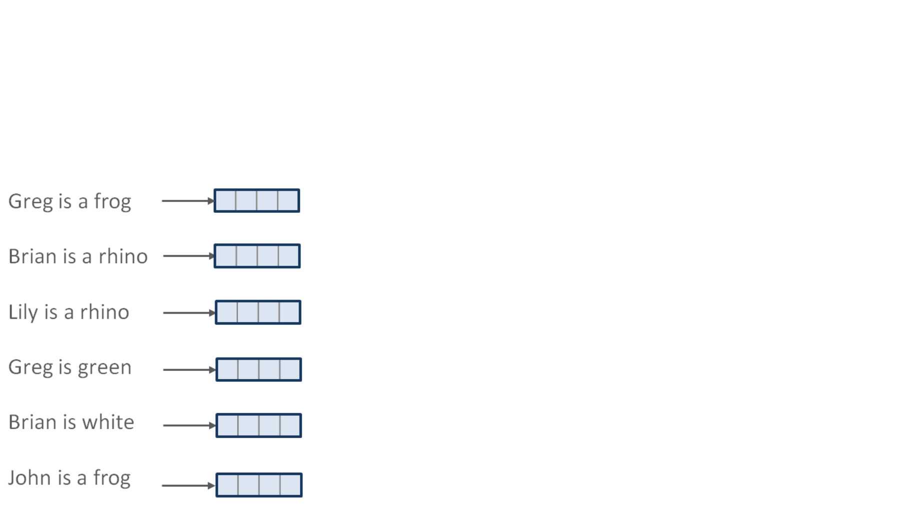
Lily is a rhino

Greg is green

Brian is white

John is a frog

Question Answering (Sukhbaatar et al., 2015)



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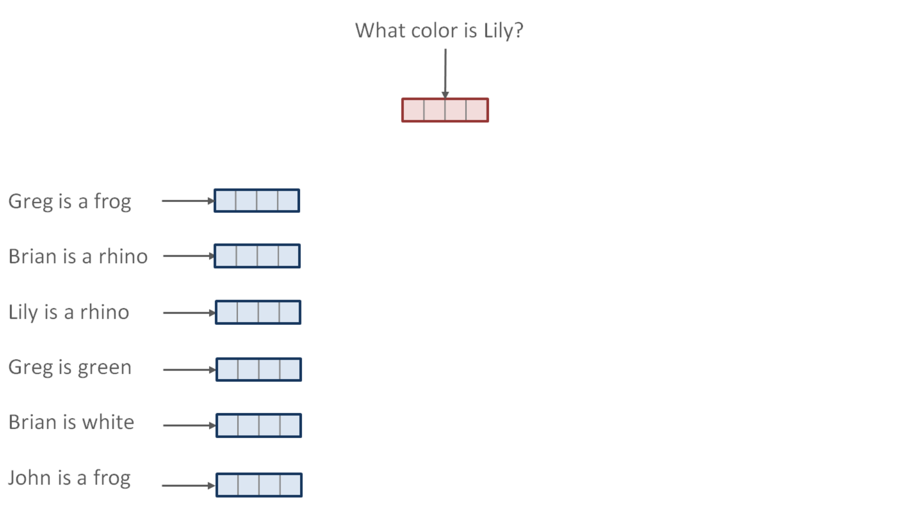

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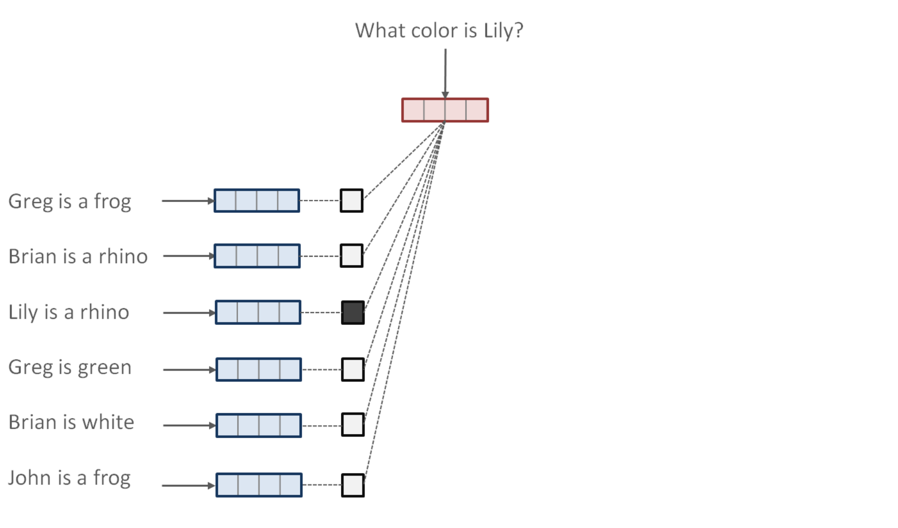

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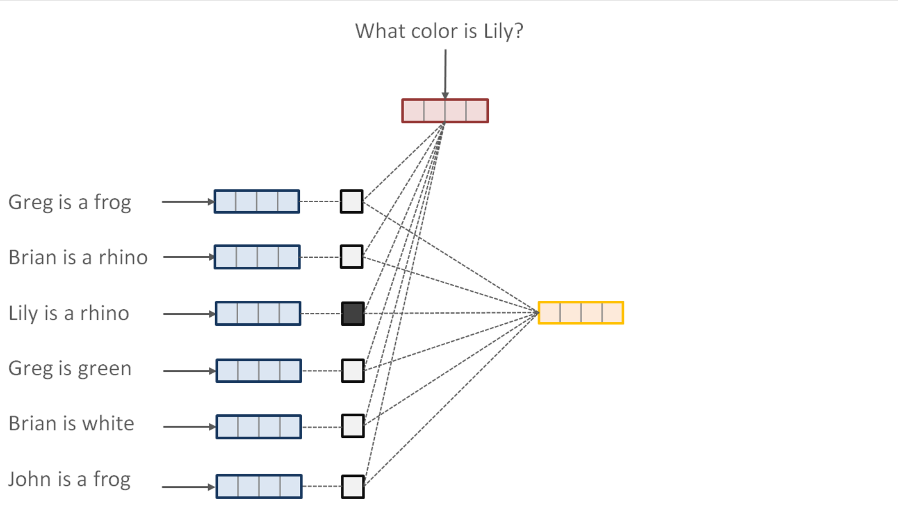

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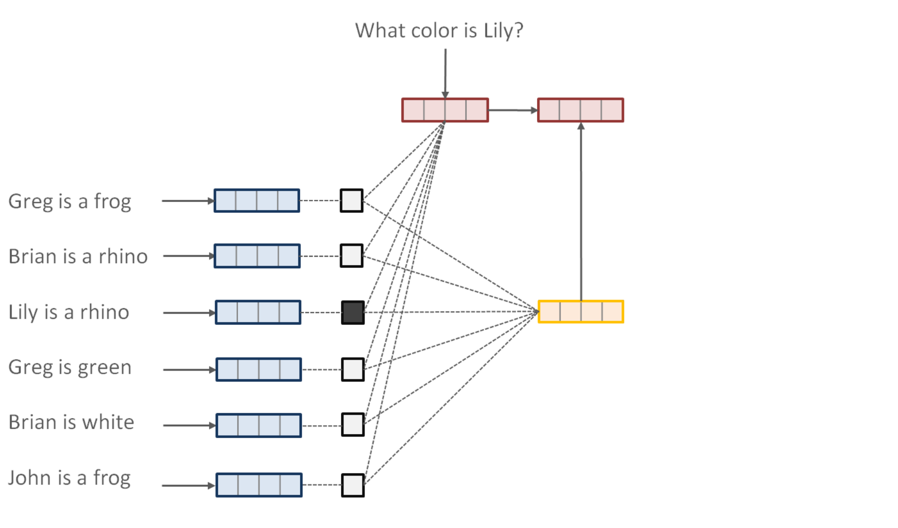

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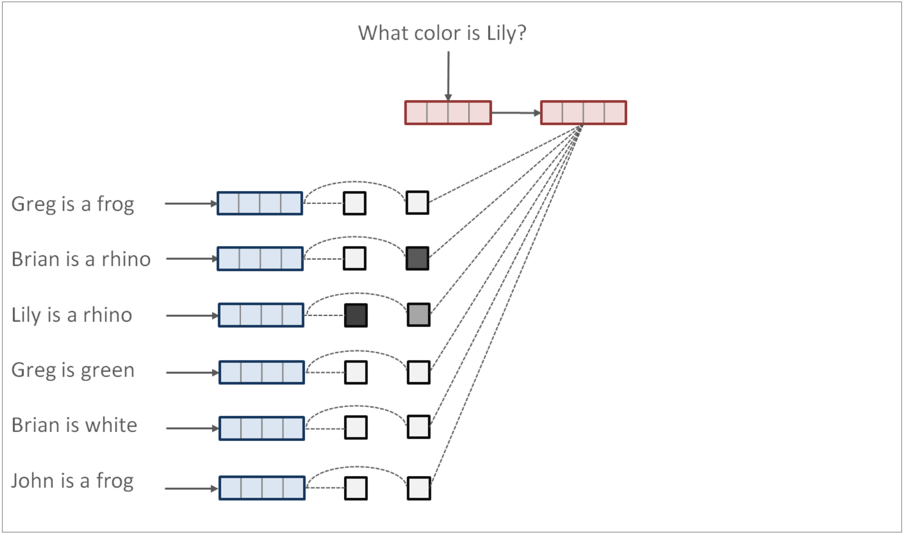

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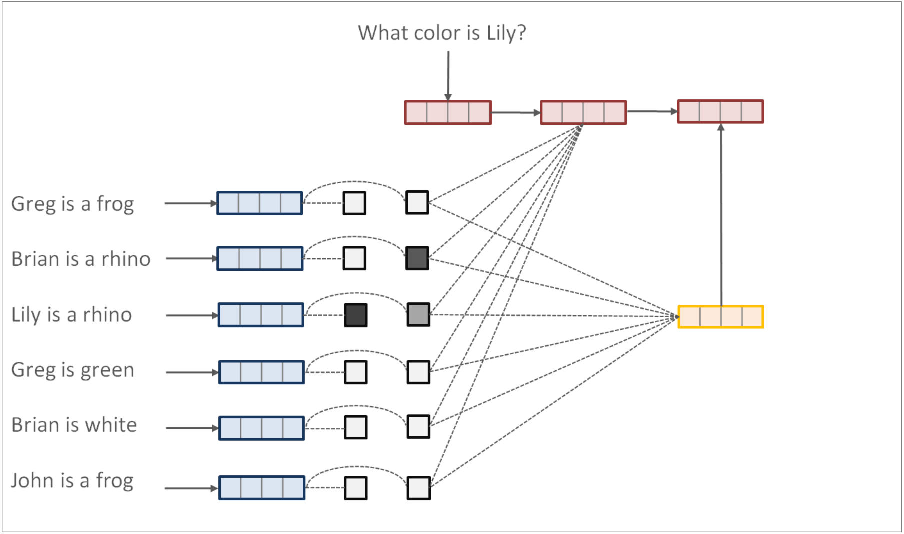

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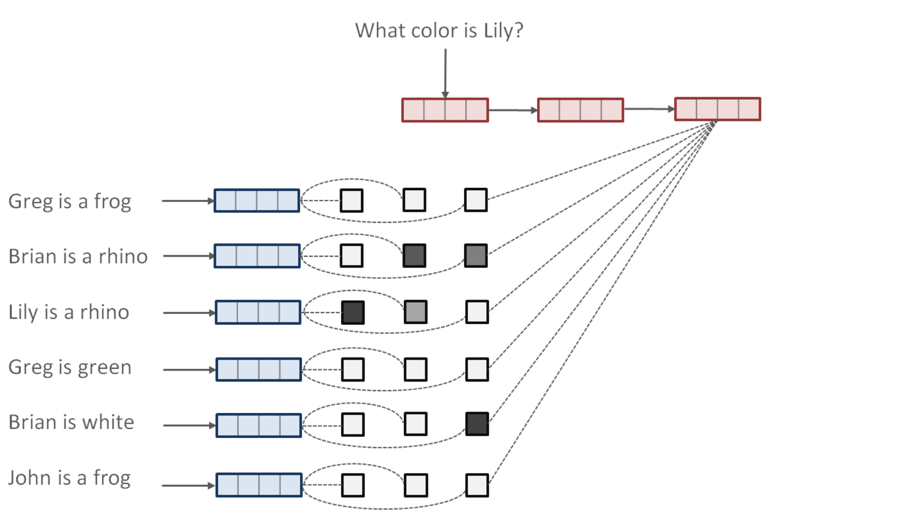

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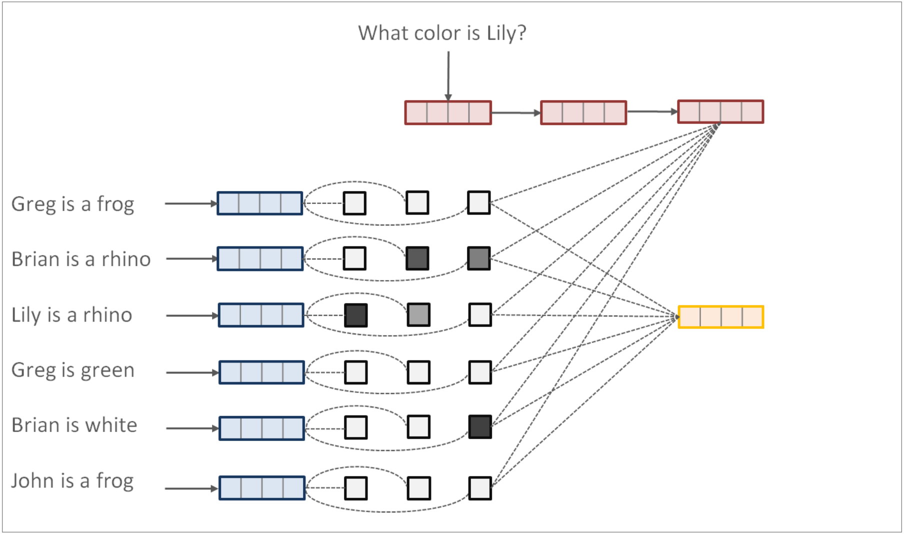

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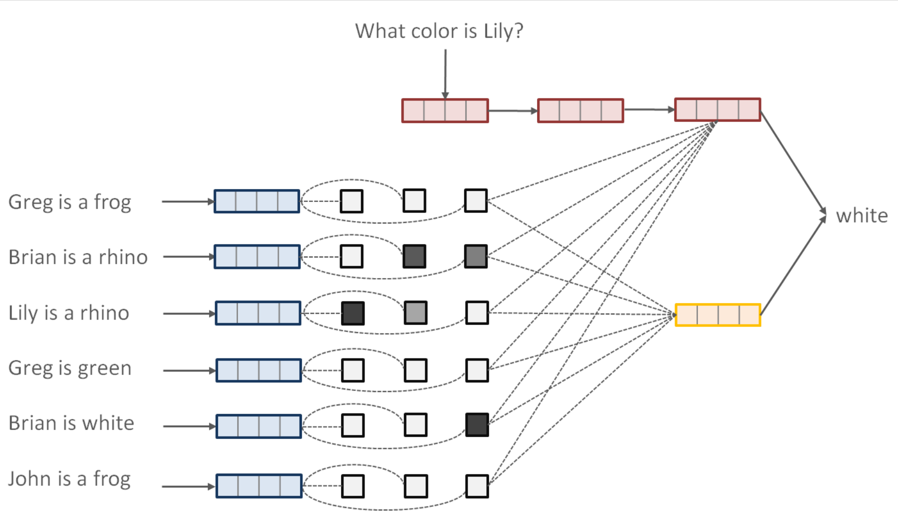


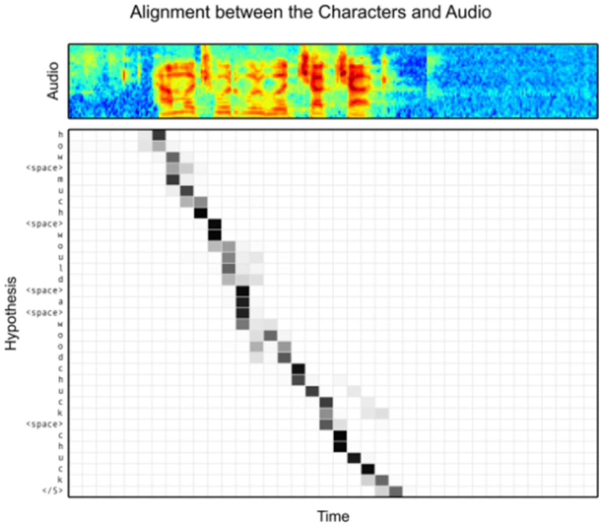
Other Applications of Attention Networks

- Machine Translation (Bahdanau et al., 2015; Luong et al., 2015)
- Question Answering (Hermann et al., 2015; Sukhbaatar et al., 2015)
- Natural Language Inference (Rocktäschel et al., 2016; Parikh et al., 2016)
- Algorithm Learning (Graves et al., 2014, 2016; Vinyals et al., 2015a)
- Parsing (Vinyals et al., 2015b)
- Speech Recognition (Chorowski et al., 2015; Chan et al., 2015)
- Summarization (Rush et al., 2015)
- Caption Generation (Xu et al., 2015)
- and more...

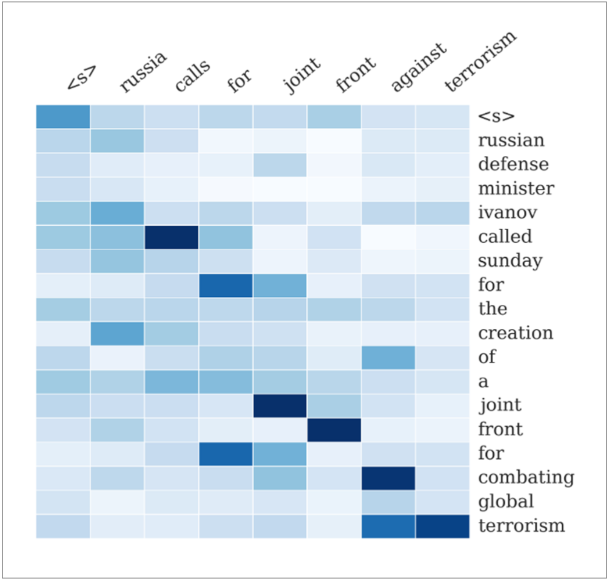
Other Applications: Image Captioning (Xu et al., 2015)

(b) A woman is throwing a frisbee in a park.

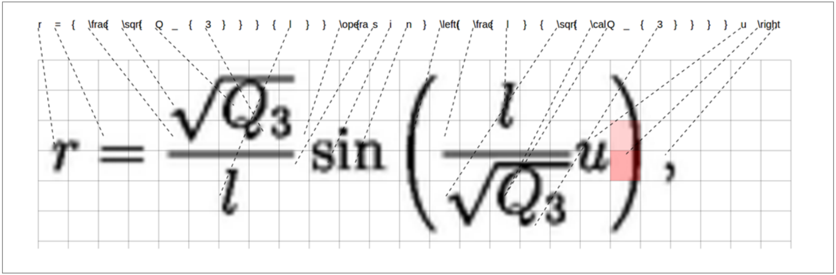
Other Applications: Speech Recognition (Chan et al., 2015)



Applications From HarvardNLP: Summarization (Rush et al., 2015)



Applications From HarvardNLP: Image-to-Latex (Deng et al., 2016)



Attention Networks: Notation

$x_1, \dots, x_T$	Memory bank
q	Query
z	Memory selection ("where")
$p(z = i \mid x, q; \theta)$	Attention distribution
$f(x, z)$	Annotation function ("what")
$c = \mathbb{E}_z[f(x, z)]$	Context vector ("soft selection")

End-to-End Requirements:

1. Need to compute attention distribution $p(z = i \mid x, q; \theta)$
2. Need to backpropagate to learn parameters θ

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Attention Networks: Machine Translation

$x_1, \ldots, x_T$	Memory bank	Source RNN hidden states
q	Query	Decoder hidden state
z	Memory selection	Source position $\{1, \ldots, T\}$
$p(z = i \mid x, q; \theta)$	Attention distribution	$\mathrm{softmax}(x_i^\top q)$
$f(x, z)$	Annotation function	Memory at time z, i.e. x_z
$c = \mathbb{E}_z[f(x, z)]$	Context vector	$\sum_{i=1}^{T} p(z = i \mid x, q) x_i$

End-to-End Requirements:

1. Need to compute attention $p(z = i \mid x, q; \theta)$
   $\Longrightarrow$ softmax function
2. Need to backpropagate to learn parameters θ
   $\Longrightarrow$ Backprop through softmax function

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   $\implies$ Backprop through softmax function

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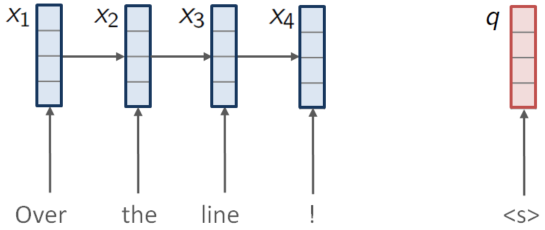
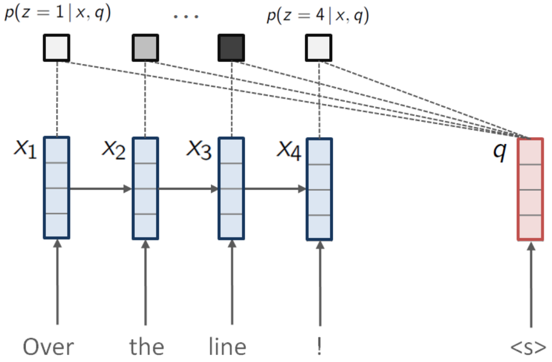


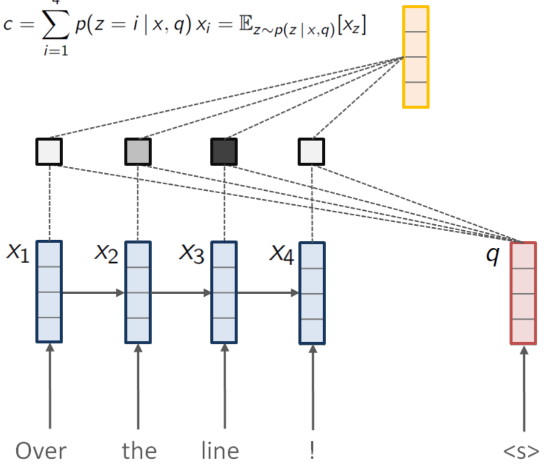
Attention Networks: Machine Translation

$$p(z = i \mid x, q) = \text{softmax}(x_i^\top q) = \frac{\exp(x_i^\top q)}{\sum_{k=1}^{4} \exp(x_k^\top q)}$$



Attention Networks: Machine Translation

$$c = \sum_{i=1}^{4} p(z = i \mid x, q)\, x_i = \mathbb{E}_{z \sim p(z \mid x, q)}[x_z]$$



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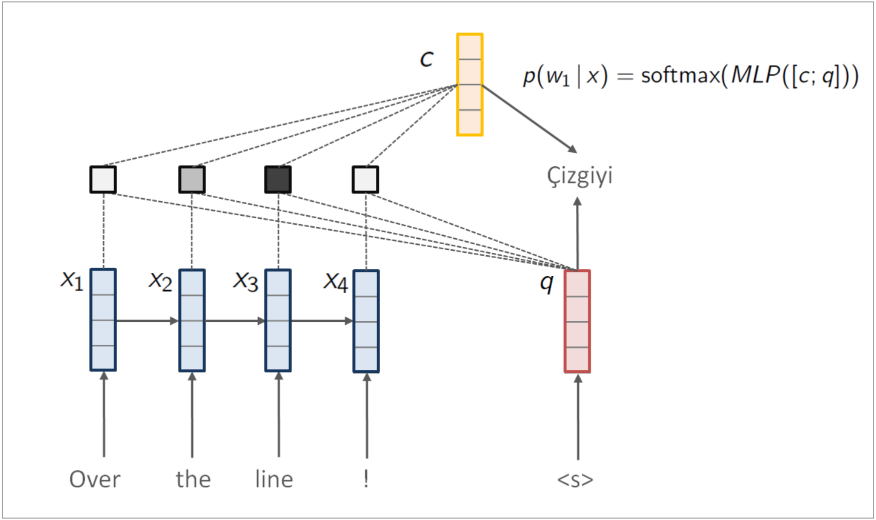

Structured Attention Networks

- Replace simple attention with distribution over a combinatorial set of structures
- Attention distribution represented with graphical model over multiple latent variables
- Compute attention using embedded inference

New Model

$p(z \,|\, x, q; \theta)$ Attention distribution over structures z

Structured Attention Networks: Notation

$x_1, \ldots, x_T$	Memory bank
q	Query
$z = z_1, \ldots, z_T$	Memory selection over structures
$p(z \mid x, q; \theta)$	Attention distribution over structures
$f(x, z)$	Annotation function (Neural representation)
$c = \mathbb{E}_{z \sim p(z \mid x, q)}[f(x, z)]$	Context vector

Consider family of functions $f(x, z)$ that makes $\mathbb{E}_{z \sim p(z \mid x, q)}[f(x, z)]$ computationally tractable

Structured Attention Networks: Notation

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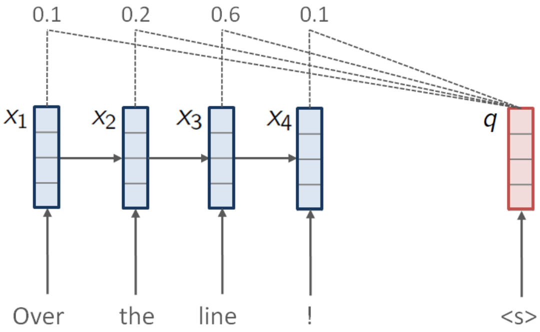
Structured Attention Networks for Neural Machine Translation

$\sum_{i=1}^{4} p(z = i \mid x, q) = 1$



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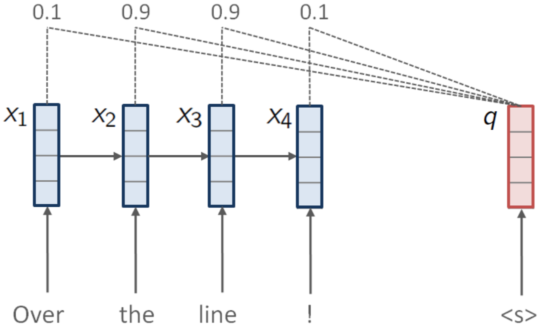

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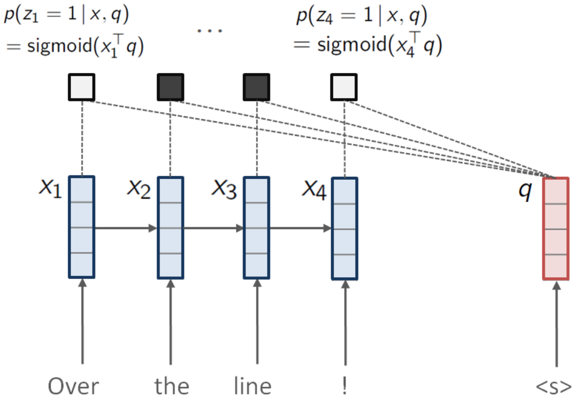
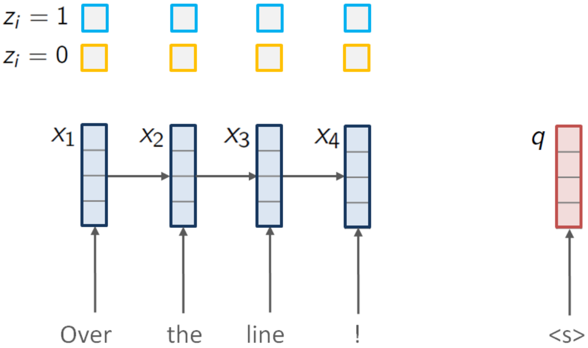


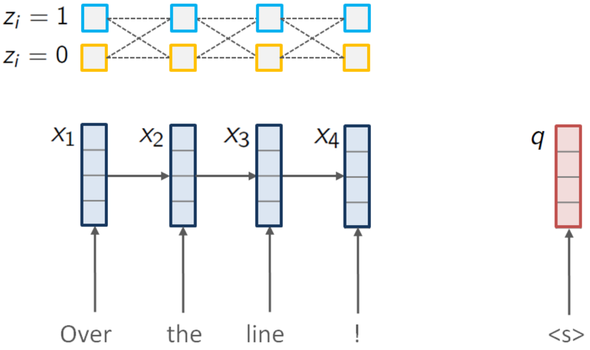
Structured Attention Networks for Neural Machine Translation

$p(z_1, z_2, z_3, z_4 \mid x, q) = \prod_{i=1}^{4} p(z_i \mid x, q)$



Structured Attention Networks for Neural Machine Translation

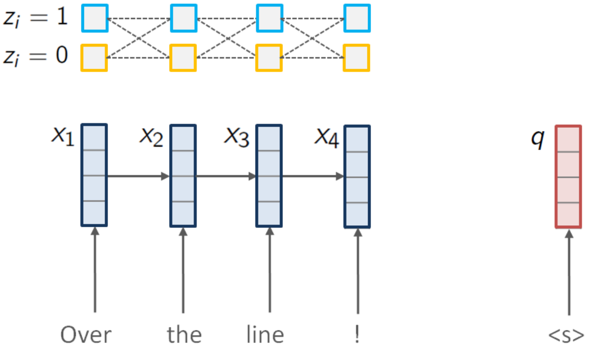
$$p(z_1, z_2, z_3, z_4 \mid x, q) = \text{softmax}\{\theta(z_1, z_2, z_3, z_4)\}$$
$$= \frac{1}{Z} \exp(\theta(z_1, z_2, z_3, z_4))$$

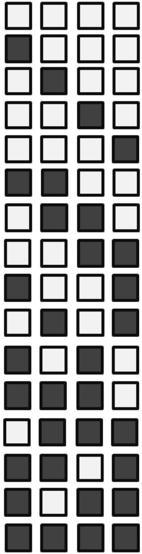


Structured Attention Networks for Neural Machine Translation

$$p(z_1, z_2, z_3, z_4 \mid x, q) = \text{softmax}\{\theta(z_1, z_2, z_3, z_4)\}$$
$$= \frac{1}{Z} \exp(\theta(z_1, z_2, z_3, z_4))$$

$$Z = \sum_{[z'_1, z'_2, z'_3, z'_4] \in \{0,1\}^4} \exp(\theta(z'_1, z'_2, z'_3, z'_4))$$





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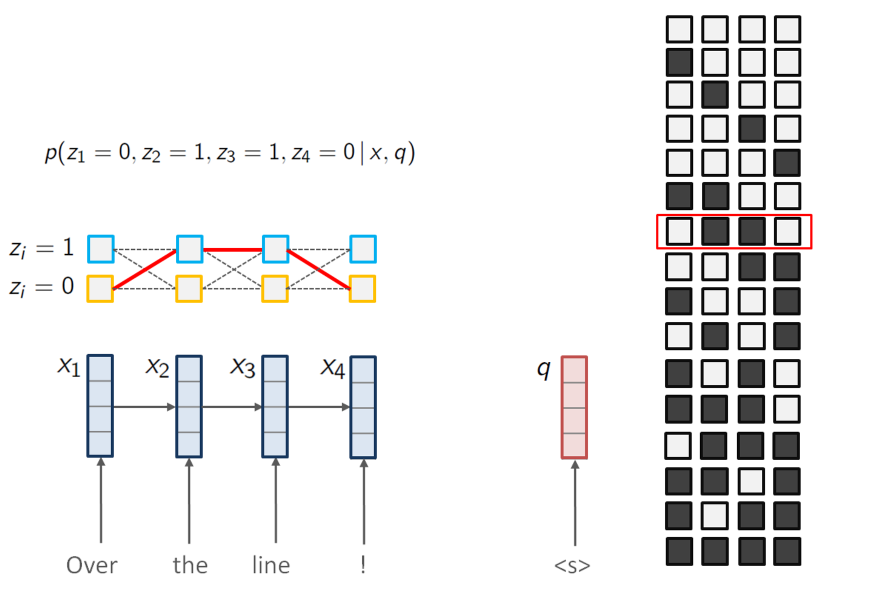
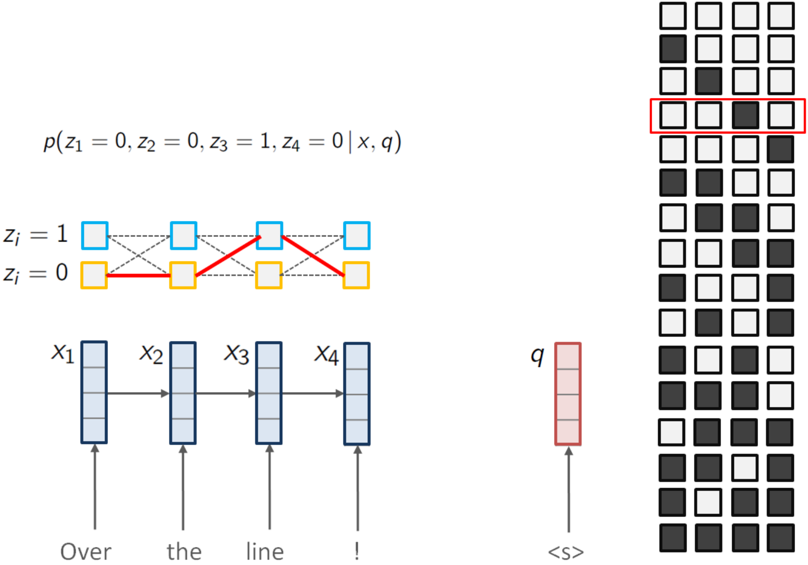


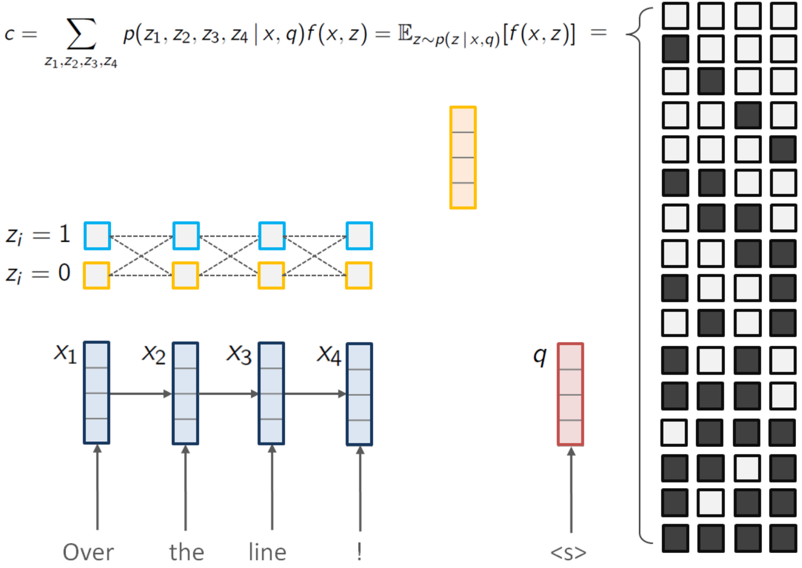
Structured Attention Networks for Neural Machine Translation

$$p(z_1 = 0, z_2 = 0, z_3 = 1, z_4 = 0 \,|\, x, q)$$



Structured Attention Networks for Neural Machine Translation

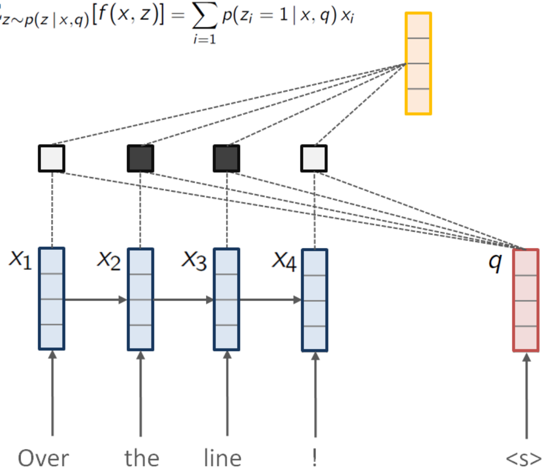
$$c = \sum_{z_1, z_2, z_3, z_4} p(z_1, z_2, z_3, z_4 \,|\, x, q) f(x, z) = \mathbb{E}_{z \sim p(z \,|\, x, q)}[f(x, z)] =$$



Structured Attention Networks for Neural Machine Translation

$$f(x, z) = \sum_{i=1}^{4} \mathbb{1}\{z_i = 1\} x_i$$

$$\mathbb{E}_{z \sim p(z \mid x, q)}[f(x, z)] = \sum_{i=1}^{4} p(z_i = 1 \mid x, q)\, x_i$$



Motivation: Structured Output Prediction

Modeling the structured **output** (i.e. graphical model on top of a neural net) has improved performance (LeCun et al., 1998; Lafferty et al., 2001; Collobert et al., 2011)

- Given a sequence $x = x_1, \ldots, x_T$
- Factored potentials $\theta_{i,i+1}(z_i, z_{i+1}; x)$

$$p(z_1 \ldots, z_T \mid x; \theta) = \text{softmax}\left(\sum_{i=1}^{T-1} \theta_{i,i+1}(z_i, z_{i+1}; x)\right)$$

$$= \frac{1}{Z} \exp\left(\sum_{i=1}^{T-1} \theta_{i,i+1}(z_i, z_{i+1}; x)\right)$$

$$Z = \sum_{z' \in \mathcal{C}} \exp\left(\sum_{i=1}^{T-1} \theta_{i,i+1}(z'_i, z'_{i+1}; x)\right)$$

Example: Part-of-Speech Tagging

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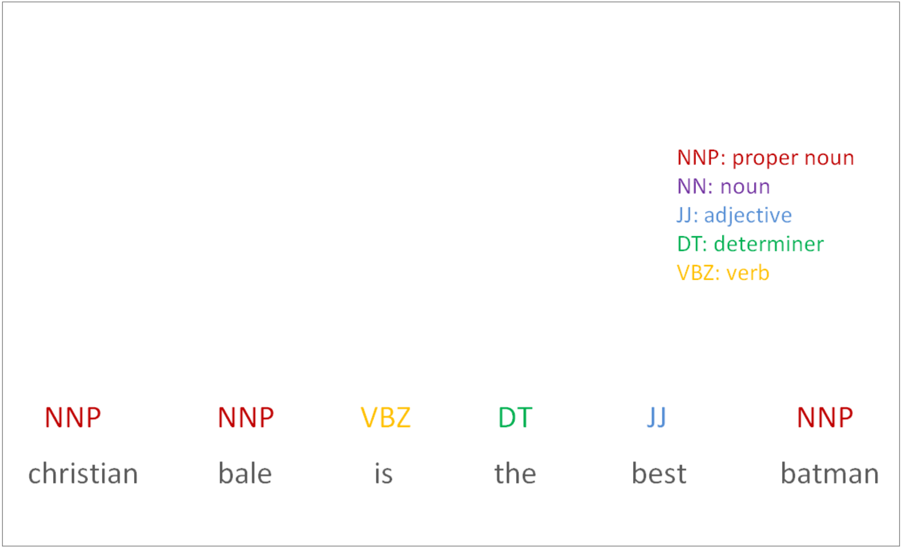
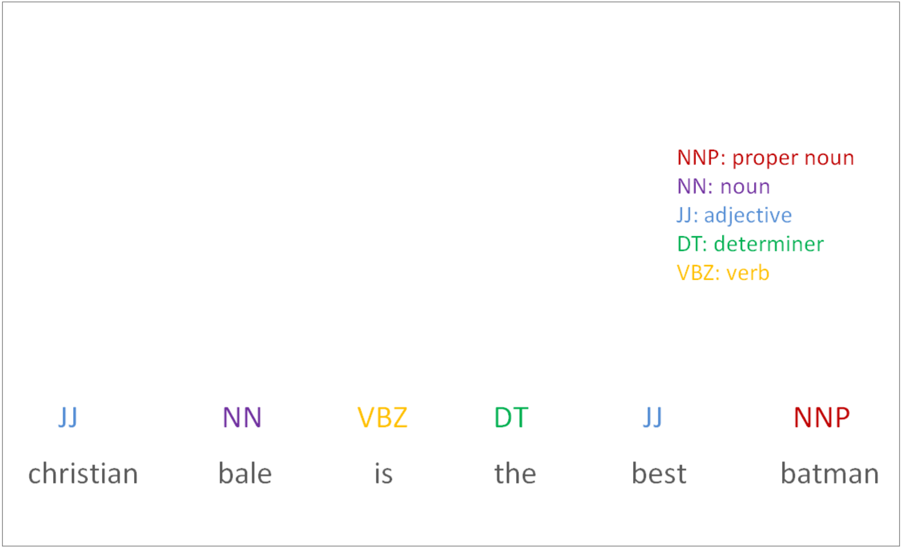


Example: Part-of-Speech Tagging

NNP: proper noun
NN: noun
JJ: adjective
DT: determiner
VBZ: verb

NNP	NNP	VBZ	DT	JJ	NNP
christian	bale	is	the	best	batman

Example: Part-of-Speech Tagging



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JJ	NN	VBZ	DT	JJ	NNP
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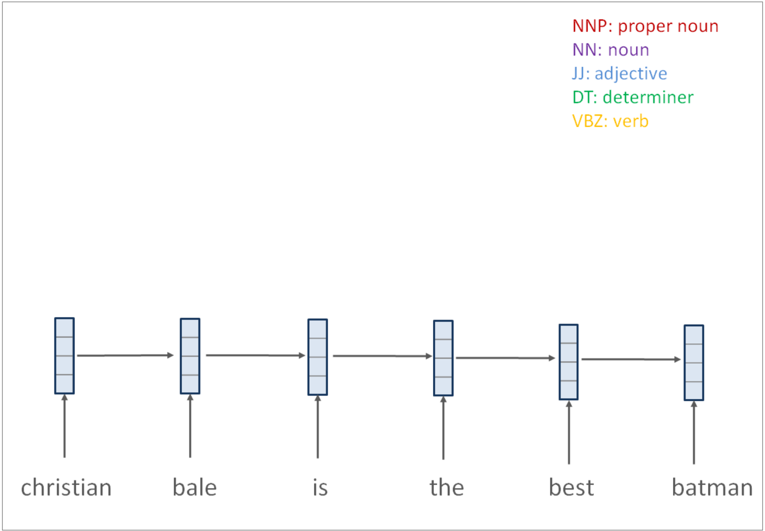
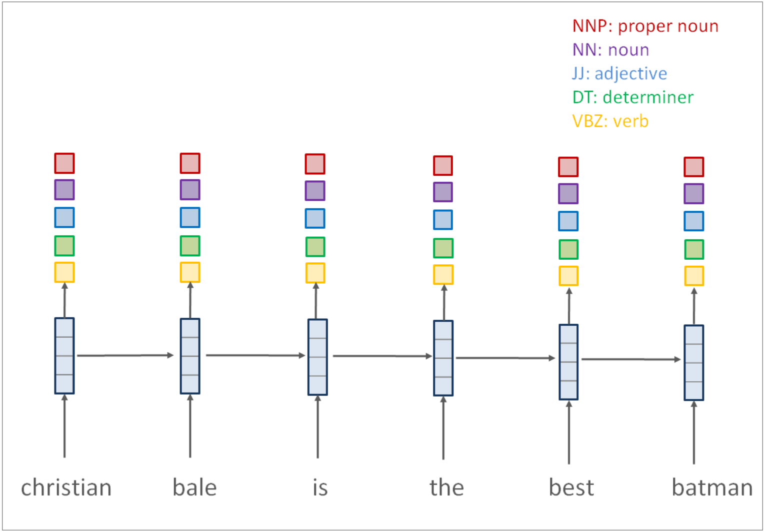
Neural CRF for Sequence Tagging (Collobert et al., 2011)



Neural CRF for Sequence Tagging (Collobert et al., 2011)

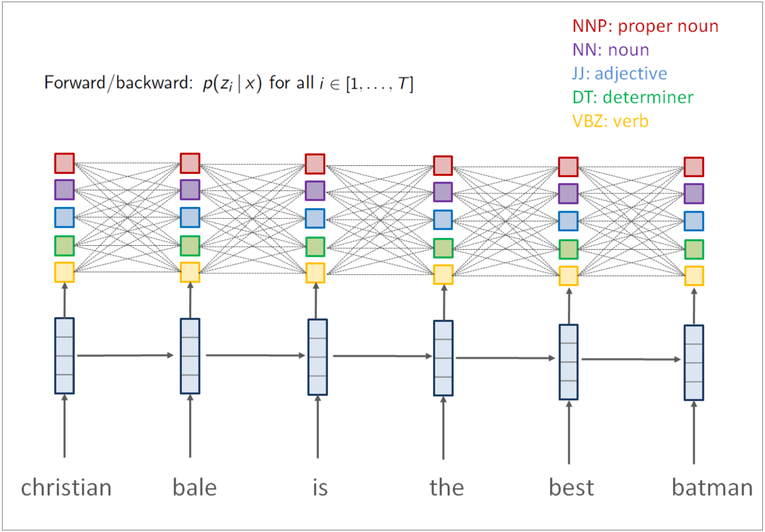
Unary potentials $\theta_i(c) = w_c^\top x_i$ come from neural network



Inference in Linear-Chain CRF

Pairwise potentials are simple parameters b, so altogether

$$\theta_{i,i+1}(c,d) = \theta_i(c) + \theta_{i+1}(d) + b_{c,d}$$



Structured Attention Networks: Notation

$x_1, \ldots, x_T$	Memory bank
q	Query
$z = z_1, \ldots, z_T$	Memory selection over structures
$p(z \mid x, q; \theta)$	Attention distribution over structures
$f(x, z)$	Annotation function (Neural representation)
$c = \mathbb{E}_{z \sim p(z \mid x, q)}[f(x, z)]$	Context vector

Need to calculate

$$c = \sum_{i=1}^{T} p(z_i = 1 \mid x, q) x_i$$

Challenge: End-to-End Training

Requirements:

1. Compute attention distribution (marginals) $p(z_i \mid x, q; \theta)$

   $\Longrightarrow$ Forward-backward algorithm

2. Gradients wrt attention distribution parameters θ

   $\Longrightarrow$ Backpropagation through forward-backward algorithm

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   $\implies$ Forward-backward algorithm

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   $\implies$ Backpropagation through forward-backward algorithm

Review: Forward-Backward Algorithm

θ: input potentials (e.g. from NN)

α, β: dynamic programming tables

procedure $\textsc{ForwardBackward}(\theta)$

Forward

for $i = 1, \ldots, n; z_i$ **do**

$\alpha[i, z_i] \leftarrow \sum_{z_{i-1}} \alpha[i-1, z_{i-1}] \times \exp(\theta_{i-1,i}(z_{i-1}, z_i))$

Backward

for $i = n, \ldots, 1; z_i$ **do**

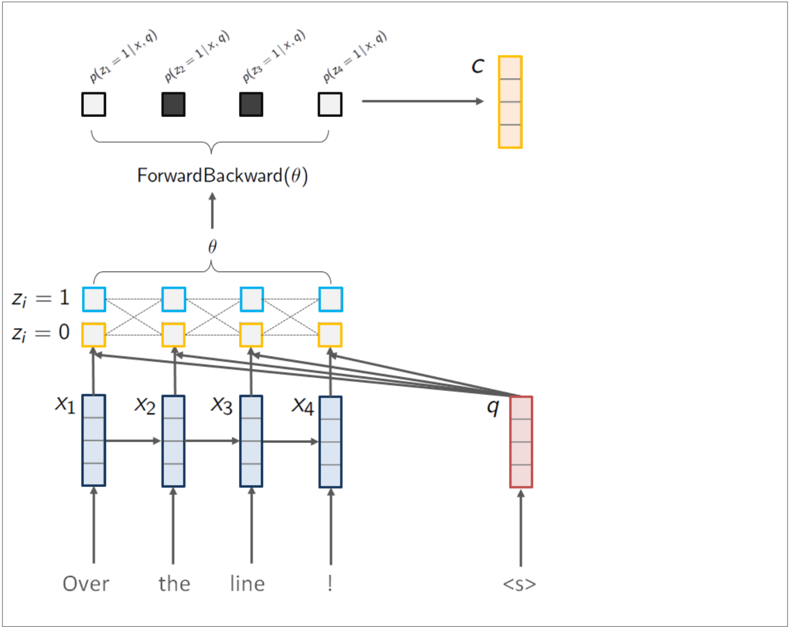
$\beta[i, z_i] \leftarrow \sum_{z_{i+1}1} \beta[i+1, z_{i+1}] \times \exp(\theta_{i,i+1}(z_i, z_{i+1}))$

Marginals

for $i = 1, \ldots, n; c \in \mathcal{C}$ **do**

$p(z_i = c \mid x) \leftarrow \alpha[i, c] \times \beta[i, c]/Z$

Structured Attention Networks for Neural Machine Translation



Forward-Backward Algorithm in Practice (Log-Space Semiring Trick)

$x \oplus y = \log(\exp(x) + \exp(y))$

$x \otimes y = x + y$

procedure $\textsc{ForwardBackward}(\theta)$

Forward

for $i = 1, \ldots, n; z_i$ **do**

$\alpha[i, z_i] \leftarrow \bigoplus_{z_{i-1}} \alpha[i-1, y] \otimes \theta_{i-1,i}(z_{i-1}, z_i)$

Backward

for $i = n, \ldots, 1; z_i$ **do**

$\beta[i, z_i] \leftarrow \bigoplus_{z_{i+1}} \beta[i+1, z_{i+1}] \otimes \theta_{i,i+1}(z_i, z_{i+1})$

Marginals

for $i = 1, \ldots, n; c \in \mathcal{C}$ **do**

$p(z_i = c \mid x) \leftarrow \exp(\alpha[i, c] \otimes \beta[i, c] \otimes -\log Z)$

Backpropagating through Forward-Backward

$\nabla_p^{\mathcal{L}}$: Gradient of arbitrary loss $\mathcal{L}$ with respect to marginals p

procedure $\textsc{BackpropForwardBackward}(\theta, p, \nabla_p^{\mathcal{L}})$

Backprop Backward

for $i = n, \ldots 1; z_i$ **do**

$$\hat{\beta}[i, z_i] \leftarrow \nabla_\alpha^{\mathcal{L}}[i, z_i] \oplus \bigoplus_{z_{i+1}} \theta_{i,i+1}(z_i, z_{i+1}) \otimes \hat{\beta}[i+1, z_{i+1}]$$

Backprop Forward

for $i = 1, \ldots, n; z_i$ **do**

$$\hat{\alpha}[i, z_i] \leftarrow \nabla_\beta^{\mathcal{L}}[i, z_i] \oplus \bigoplus_{z_{i-1}} \theta_{i-1,i}(z_{i-1}, z_i) \otimes \hat{\alpha}[i-1, z_{i-1}]$$

Potential Gradients

for $i = 1, \ldots, n; z_i, z_{i+1}$ **do**

$$\nabla_{\theta_{i-1,i}(z_i, z_{i+1})}^{\mathcal{L}} \leftarrow \exp(\hat{\alpha}[i, z_i] \otimes \beta[i+1, z_{i+1}] \oplus \alpha[i, z_i] \otimes \hat{\beta}[i+1, z_{i+1}] \oplus \ \alpha[i, z_i] \otimes \beta[i+1, z_{i+1}] \otimes -\log Z)$$

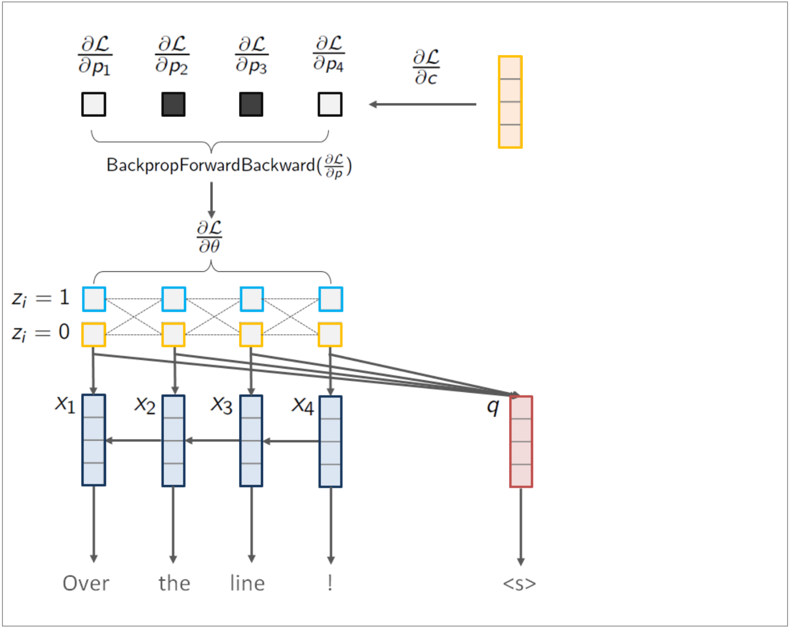
Interesting Issue: Negative Gradients Through Attention

- $\nabla_p^{\mathcal{L}}$: Gradient could be negative, but working in log-space!
- Signed Log-space semifield trick (Li and Eisner, 2009)
- Use tuples (l_a, s_a) where $l_a = \log|a|$ and $s_a = \mathrm{sign}(a)$

		$\oplus$	
s_a	s_b	l_{a+b}	s_{a+b}
$+$	$+$	$l_a + \log(1+d)$	$+$
$+$	$-$	$l_a + \log(1-d)$	$+$
$-$	$+$	$l_a + \log(1-d)$	$-$
$-$	$-$	$l_a + \log(1+d)$	$-$

(Similar rules for $\otimes$)

Structured Attention Networks for Neural Machine Translation



Implementation

`http://github.com/harvardnlp/struct-attn`

- General-purpose structured attention unit
- "Plug-and-play" neural network layers
- Dynamic programming is GPU-optimized for speed

NLP Experiments

Replace existing attention layers for

- Machine Translation

  Segmental Attention: 2-state linear-chain CRF
- Question Answering

  Sequential Attention: N-state linear-chain CRF
- Natural Language Inference

  Syntactic Attention: graph-based dependency parser

Segmental Attention for Neural Machine Translation

- Use segmentation CRF for attention, i.e. binary vectors of length n
- $p(z_1, \dots, z_T \mid x, q)$ parameterized with a linear-chain CRF.

Unary potentials (Encoder RNN):

$$\theta_i(k) = \begin{cases} x_i W q, & k = 1 \\ 0, & k = 0 \end{cases}$$

Pairwise potentials (Simple Parameters):

4 additional binary parameters (i.e., $b_{0,0}, b_{0,1}, b_{1,0}, b_{1,1}$)

Segmental Attention for Neural Machine Translation

Data:

- Japanese $\rightarrow$ English (from WAT 2015)
- Traditionally, word segmentation as a preprocessing step
- Use structured attention learn an implicit segmentation model

Experiments:

- Japanese characters $\rightarrow$ English words
- Japanese words $\rightarrow$ English words

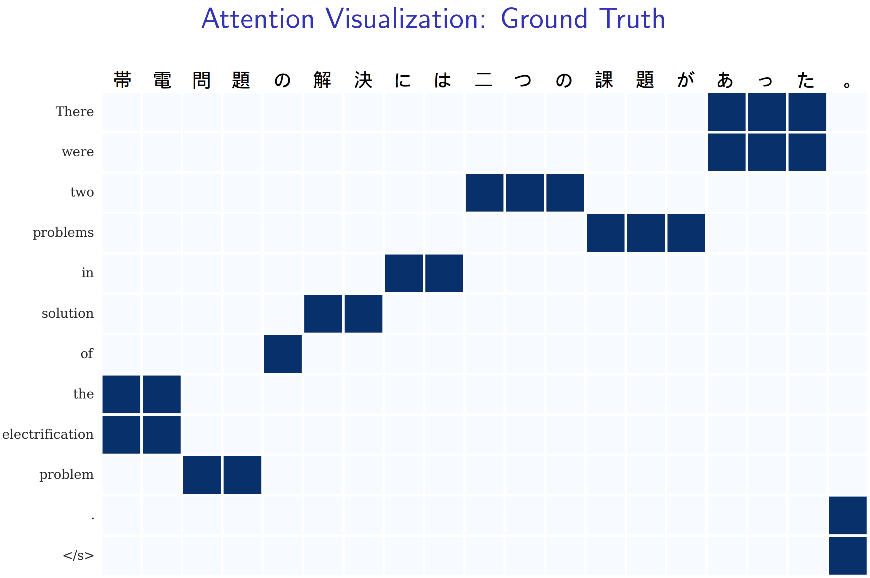
Segmental Attention for Neural Machine Translation

	Simple	Sigmoid	Structured
Char → Word	12.6	13.1	14.6
Word → Word	14.1	13.8	14.3

BLEU scores on test set (higher is better)

Models:

- Simple softmax attention: $\mathrm{softmax}(\theta_i)$
- Sigmoid attention: $\mathrm{sigmoid}(\theta_i)$
- Structured attention: $\mathrm{ForwardBackward}(\theta)$


Attention Visualization: Ground Truth
帯 電 問 題 の 解 決 に は 二 つ の 課 題 が あ っ た 。
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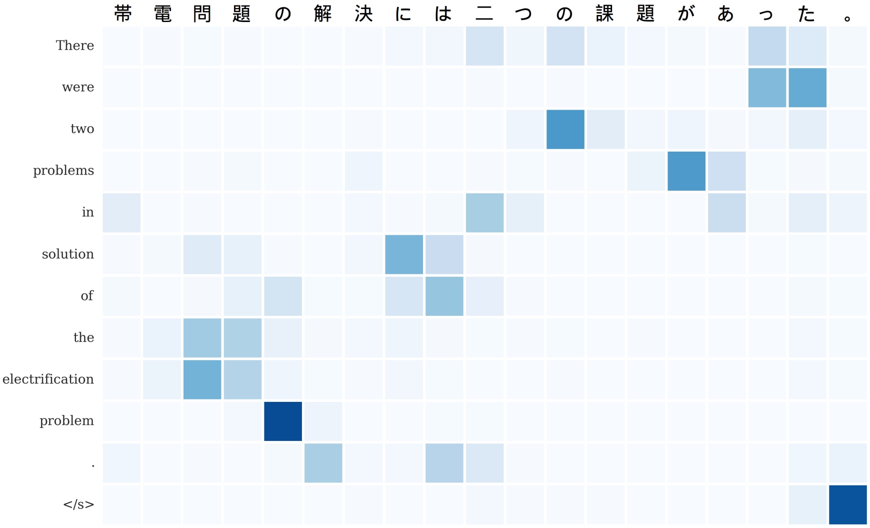
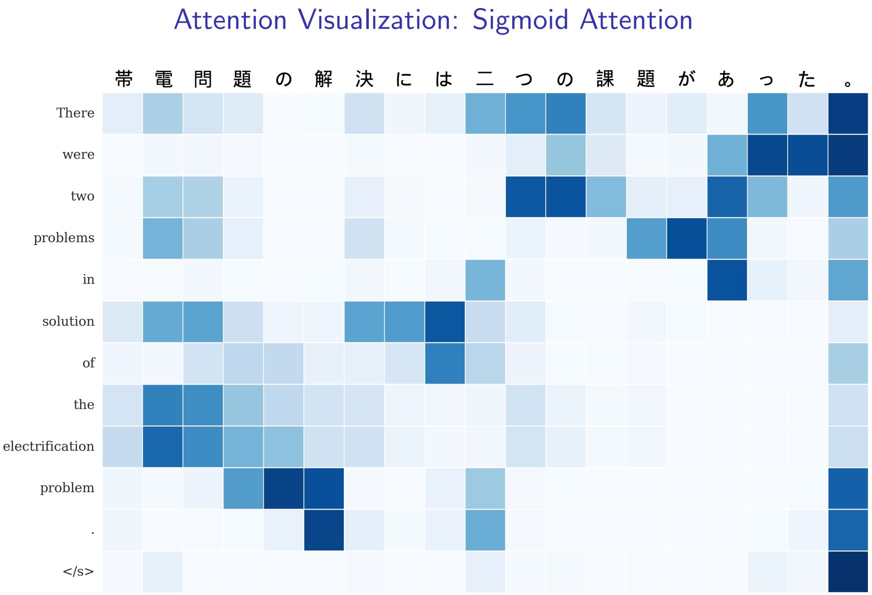
Attention Visualization: Simple Attention




Attention Visualization: Sigmoid Attention
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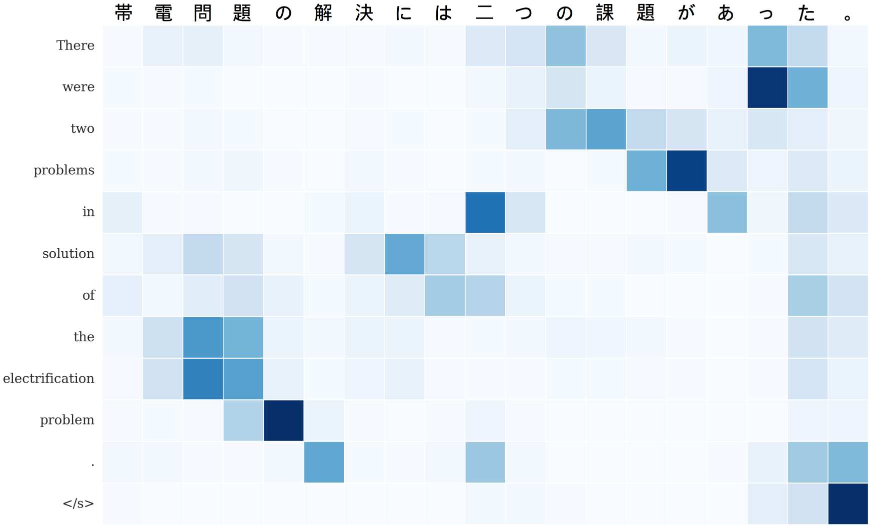
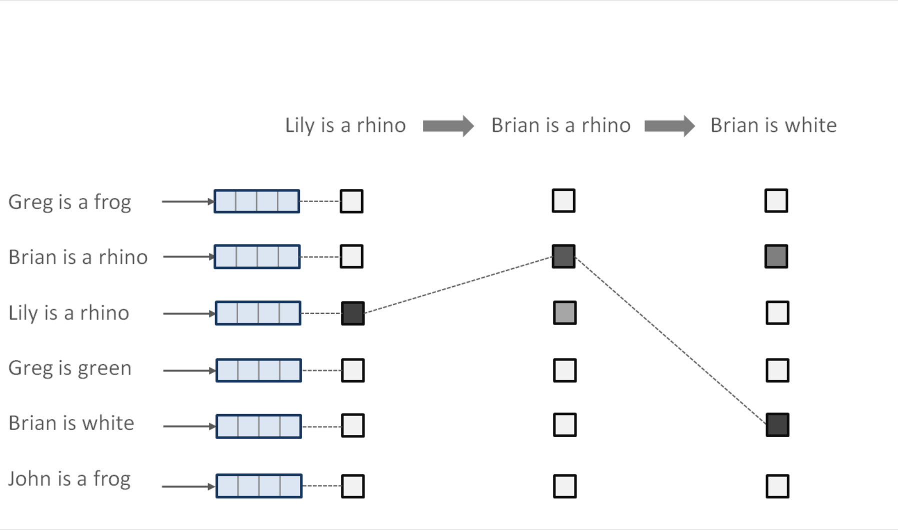
Attention Visualization: Structured Attention



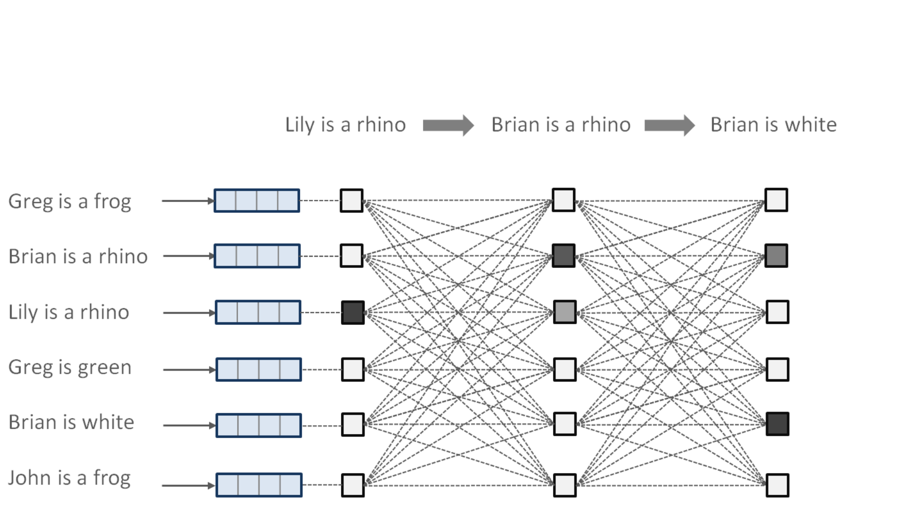
Sequential Attention over Facts for Question Answering

Simple attention: Greedy soft-selection of K supporting facts



Sequential Attention over Facts for Question Answering

Structured attention: Consider all possible sequences

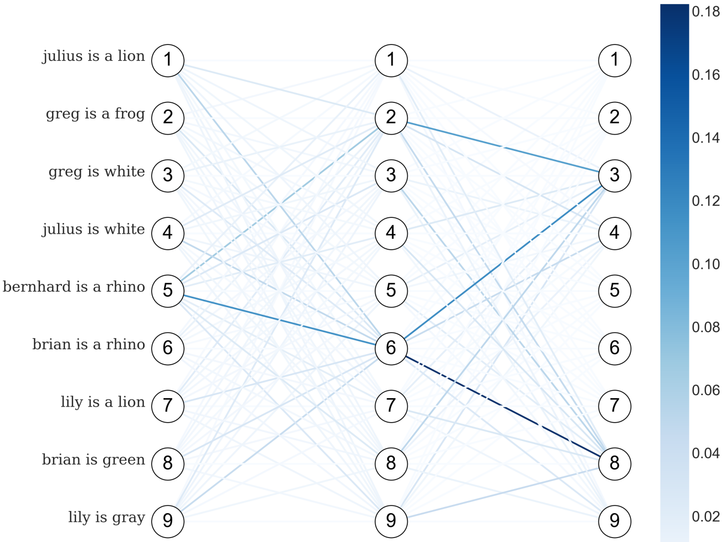


Sequential Attention over Facts for Question Answering

baBi tasks (Weston et al., 2015): 1k questions per task

Task	K	Simple Ans %	Simple Fact %	Structured Ans %	Structured Fact %
Task 02	2	87.3	46.8	84.7	81.8
Task 03	3	52.6	1.4	40.5	0.1
Task 11	2	97.8	38.2	97.7	80.8
Task 13	2	95.6	14.8	97.0	36.4
Task 14	2	99.9	77.6	99.7	98.2
Task 15	2	100.0	59.3	100.0	89.5
Task 16	3	97.1	91.0	97.9	85.6
Task 17	2	61.1	23.9	60.6	49.6
Task 18	2	86.4	3.3	92.2	3.9
Task 19	2	21.3	10.2	24.4	11.5
Average	–	81.4	39.6	81.0	53.7

Sequential Attention over Facts for Question Answering



Question: what color is bernhard? green

Correct Facts: 5, 6, 8

Natural Language Inference

Given a premise (P) and a hypothesis (H), predict the relationship: Entailment (E), Contradiction (C), Neutral (N)

P	The boy is running through a grassy area.	
H	The boy is in his room.	C
	A boy is running outside.	E
	The boy is in a park.	N

Many existing models run parsing as a preprocessing step and attend over parse trees.

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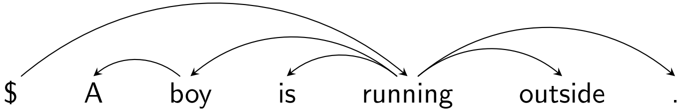

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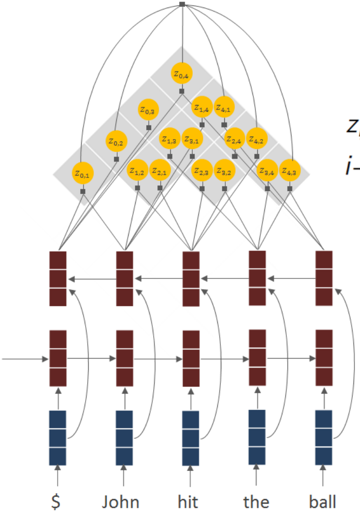
Neural CRF Parsing (Durrett and Klein, 2015; Kipperwasser and Goldberg, 2016)



$z_{ij} = 1 \implies$

i-th word is parent of j-th word

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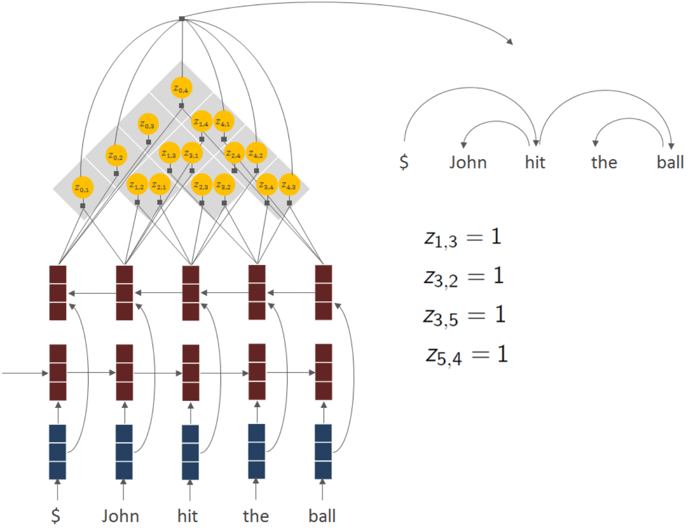

$$z_{1,3} = 1$$
$$z_{3,2} = 1$$
$$z_{3,5} = 1$$
$$z_{5,4} = 1$$

Syntactic Attention Network

1. Attention distribution (probability of a parse tree)

   $\Longrightarrow$ Inside/outside algorithm

2. Gradients wrt attention distribution parameters: $\frac{\partial \mathcal{L}}{\partial \theta}$

   $\Longrightarrow$ Backpropagation through inside/outside algorithm

Forward/backward pass on inside-outside version of Eisner's algorithm (Eisner, 1996) takes $O(T^3)$ time.

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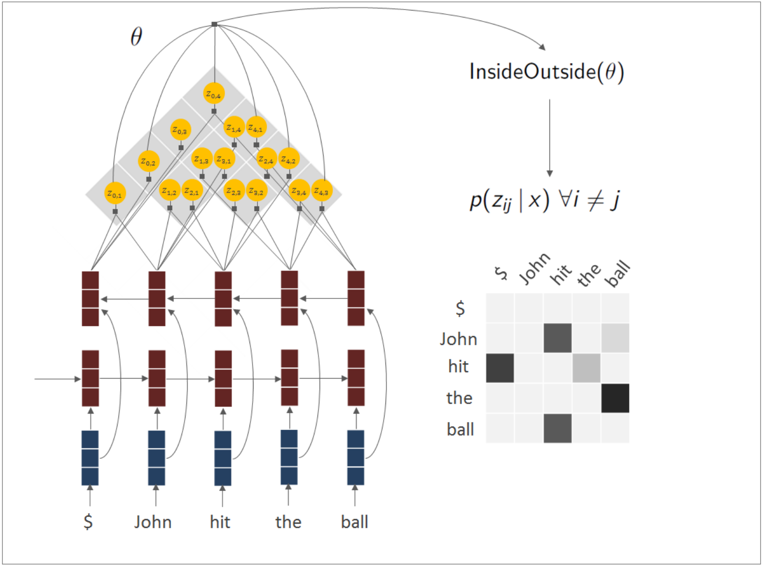
Forward/Back-propagation through Inside-Outside Algorithm

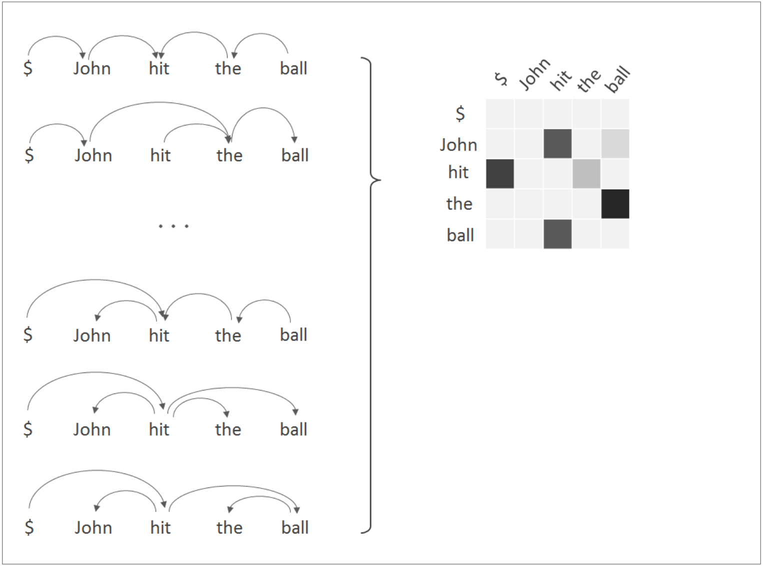
```
procedure InsideOutside(θ)
  α, β ← −∞                                          ▷ Initialize log of inside (α), outside (β) tables
  for i = 1, ..., n do
    α[i, i, L, 1] ← 0
    α[i, i, R, 1] ← 0
  β[1, n, R, 1] ← 0
  for k = 1, ..., n do                               ▷ Inside step
    for s = 1, ..., n − k do
      t ← s + k
      α[s, t, R, 0] ← ⊕_{u∈[s,t−1]} α[s, u, R, 1] ⊗ α[u + 1, t, L, 1] ⊗ θ_st
      α[s, t, L, 0] ← ⊕_{u∈[s,t−1]} α[s, u, R, 1] ⊗ α[u + 1, t, L, 1] ⊗ θ_ts
      α[s, t, R, 1] ← ⊕_{u∈[s+1,t]} α[s, u, R, 0] ⊗ α[u, t, R, 1]
      α[s, t, L, 1] ← ⊕_{u∈[s,t−1]} α[s, u, L, 1] ⊗ α[u, t, L, 0]
  for k = n, ..., 1 do                               ▷ Outside step
    for s = 1, ..., n − k do
      t ← s + k
      for u = s + 1, ..., t do
        β[s, u, R, 0] ←_⊕ β[s, t, R, 1] ⊗ α[u, t, R, 1]
        β[u, t, R, 1] ←_⊕ β[s, t, R, 1] ⊗ α[s, u, R, 0]
      if s > 1 then
        for u = s, ..., t − 1 do
          β[s, u, L, 1] ←_⊕ β[s, t, L, 1] ⊗ α[u, t, L, 0]
          β[u, t, L, 0] ←_⊕ β[s, t, L, 1] ⊗ α[s, u, L, 1]
      for u = s, ..., t − 1 do
        β[s, u, R, 1] ←_⊕ β[s, t, R, 0] ⊗ α[u + 1, t, L, 1] ⊗ θ_st
        β[u + 1, t, L, 1] ←_⊕ β[s, t, R, 0] ⊗ α[s, u, R, 1] ⊗ θ_st
      if s > 1 then
        for u = s, ..., t − 1 do
          β[s, u, R, 1] ←_⊕ β[s, t, L, 0] ⊗ α[u + 1, t, L, 1] ⊗ θ_ts
          β[u + 1, t, L, 1] ←_⊕ β[s, t, L, 0] ⊗ α[s, u, R, 1] ⊗ θ_ts
  A ← α[1, n, R, 1]                                  ▷ Log partition
  for s = 1, ..., n − 1 do                           ▷ Compute marginals. Note that p[s, t] = p(z_st = 1 | x)
    for t = s + 1, ..., n do
      p[s, t] ← exp(α[s, t, R, 0] ⊗ β[s, t, R, 0] ⊗ −A)
      if s > 1 then
        p[t, s] ← exp(α[s, t, L, 0] ⊗ β[s, t, L, 0] ⊗ −A)
  return p
```

```
procedure BackpropInsideOutside(θ, p, ∇^ℓ_p)
  for s, t = 1, ..., n; s ≠ t do                     ▷ Backpropagation uses the identity ∇^ℓ_θ = (p ⊙ ∇^ℓ_p)∇^{log p}_θ
    δ[s, t] ← log p[s, t] ⊗ log ∇^ℓ_p[s, t]          ▷ δ = log(p ⊙ ∇^ℓ_p)
  ∇^ℓ_α, ∇^ℓ_β, log ∇^ℓ_θ ← −∞                       ▷ Initialize inside (∇^ℓ_α), outside (∇^ℓ_β) gradients, and log of ∇^ℓ_θ
  for s = 1, ..., n − 1 do                           ▷ Backpropagate δ to ∇^ℓ_α and ∇^ℓ_β
    for t = s + 1, ..., n do
      ∇^ℓ_α[s, t, R, 0], ∇^ℓ_β[s, t, R, 0] ← δ[s, t]
      ∇^ℓ_α[1, n, R, 1] ←_⊕ −δ[s, t]
      if s > 1 then
        ∇^ℓ_α[s, t, L, 0], ∇^ℓ_β[s, t, L, 0] ← δ[t, s]
        ∇^ℓ_α[1, n, R, 1] ←_⊕ −δ[s, t]
  for k = 1, ..., n do                               ▷ Backpropagate through outside step
    for s = 1, ..., n − k do
      t ← s + k
      ν ← ∇^ℓ_β[s, t, R, 0] ⊗ β[s, t, R, 0]           ▷ ν, γ are temporary values
      for u = t, ..., n do
        ∇^ℓ_β[s, u, R, 1], ∇^ℓ_α[t, u, R, 1] ←_⊕ ν ⊗ β[s, u, R, 1] ⊗ α[t, u, R, 1]
      if s > 1 then
        ν ← ∇^ℓ_β[s, t, L, 0] ⊗ β[s, t, L, 0]
        for u = 1, ..., s do
          ∇^ℓ_β[u, t, L, 1], ∇^ℓ_α[u, s, L, 1] ←_⊕ ν ⊗ β[u, t, L, 1] ⊗ α[u, s, L, 1]
        ν ← ∇^ℓ_β[s, t, L, 1] ⊗ β[s, t, L, 1]
        for u = t, ..., n do
          ∇^ℓ_β[s, u, L, 1], ∇^ℓ_α[t, u, L, 0] ←_⊕ ν ⊗ β[s, u, L, 1] ⊗ α[t, u, L, 1]
        for u = 1, ..., s − 1 do
          γ ← β[u, t, R, 0] ⊗ α[u, s − 1, R, 1] ⊗ θ_ut
          ∇^ℓ_β[u, t, R, 0], ∇^ℓ_α[u, s − 1, R, 1], log ∇^ℓ_θ[u, t] ←_⊕ ν ⊗ γ
          γ ← β[u, t, L, 0] ⊗ α[u, s − 1, R, 1] ⊗ θ_tu
          ∇^ℓ_β[u, t, L, 0], ∇^ℓ_α[u, s − 1, R, 1], log ∇^ℓ_θ[t, u] ←_⊕ ν ⊗ γ
      ν ← ∇^ℓ_β[s, t, R, 1] ⊗ β[s, t, R, 1]
      for u = 1, ..., s do
        ∇^ℓ_β[u, t, R, 1], ∇^ℓ_α[u, s, R, 0] ←_⊕ ν ⊗ β[u, t, R, 1] ⊗ α[u, s, R, 0]
      for u = t + 1, ..., n do
        γ ← β[s, u, R, 0] ⊗ α[t + 1, u, L, 1] ⊗ θ_su
        ∇^ℓ_β[s, u, R, 0], ∇^ℓ_α[t + 1, u, L, 1], log ∇^ℓ_θ[s, u] ←_⊕ ν ⊗ γ
        γ ← β[s, u, L, 0] ⊗ α[t + 1, u, L, 1] ⊗ θ_us
        ∇^ℓ_β[s, u, L, 0], ∇^ℓ_α[t + 1, u, L, 1], log ∇^ℓ_θ[u, s] ←_⊕ ν ⊗ γ
  for k = n, ..., 1 do                               ▷ Backpropagate through inside step
    for s = 1, ..., n − k do
      t ← s + k
      ν ← ∇^ℓ_α[s, t, R, 1] ⊗ α[s, t, R, 1]
      for u = s + 1, ..., t do
        ∇^ℓ_α[u, t, R, 0], ∇^ℓ_α[u, t, R, 1] ←_⊕ ν ⊗ α[s, u, R, 0] ⊗ α[u, t, R, 1]
      if s > 1 then
        ν ← ∇^ℓ_α[s, t, L, 1] ⊗ α[s, t, L, 1]
        for u = s, ..., t − 1 do
          ∇^ℓ_α[s, u, L, 1], ∇^ℓ_α[u, t, L, 0] ←_⊕ ν ⊗ α[s, u, L, 1] ⊗ α[u, t, L, 0]
        ν ← ∇^ℓ_α[s, t, L, 0] ⊗ α[s, t, L, 0]
        for u = s, ..., t − 1 do
          γ ← α[s, u, R, 1] ⊗ α[u + 1, t, L, 1] ⊗ θ_ts
          ∇^ℓ_α[s, u, R, 1], ∇^ℓ_α[u + 1, t, L, 1], log ∇^ℓ_θ[t, s] ←_⊕ ν ⊗ γ
      ν ← ∇^ℓ_α[s, t, R, 0] ⊗ α[s, t, R, 0]
      for u = s, ..., t − 1 do
        γ ← α[s, u, R, 1] ⊗ α[u + 1, t, L, 1] ⊗ θ_st
        ∇^ℓ_α[s, u, R, 1], ∇^ℓ_α[u + 1, t, L, 1], log ∇^ℓ_θ[s, t] ←_⊕ ν ⊗ γ
  return signexp log ∇^ℓ_θ                           ▷ Exponentiate log gradient, multiply by sign, and return ∇^ℓ_θ
```

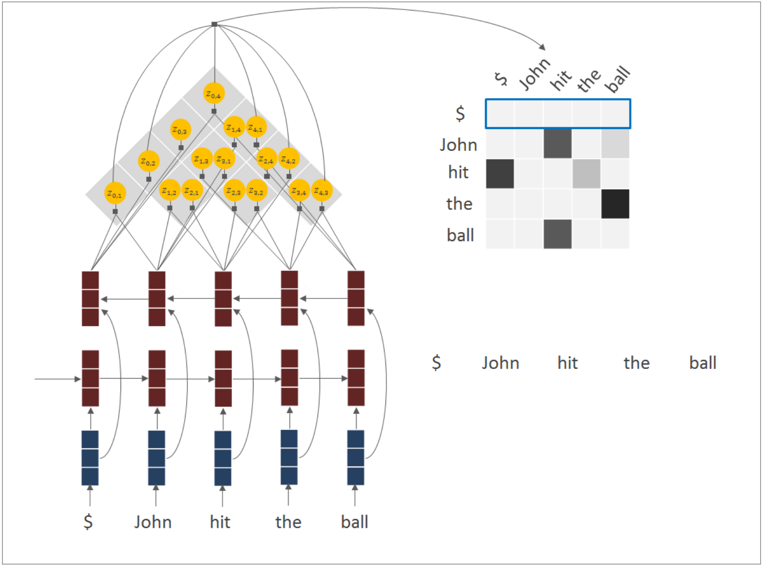
Syntactic Attention



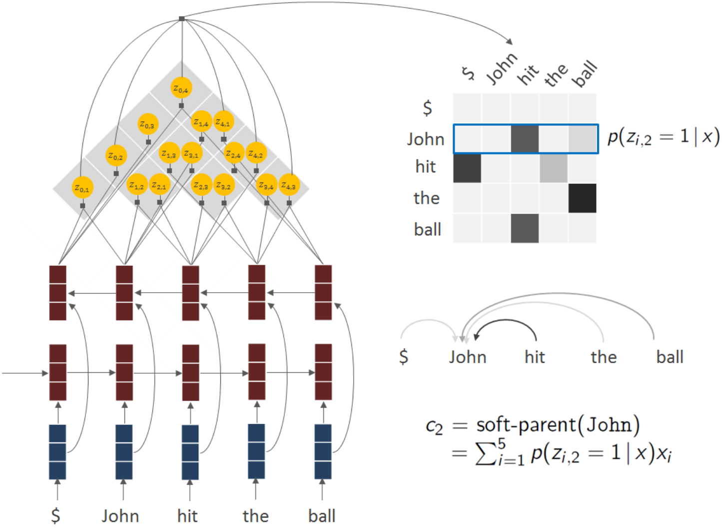
Syntactic Attention



Syntactic Attention

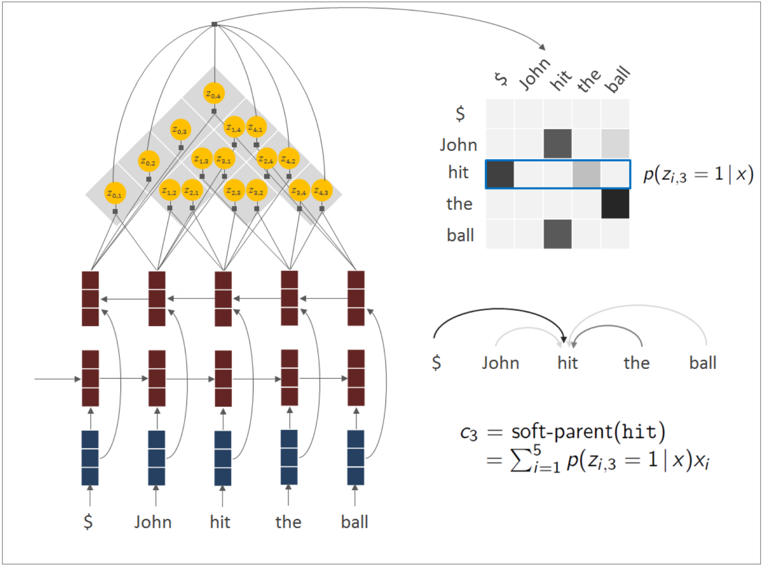


Syntactic Attention

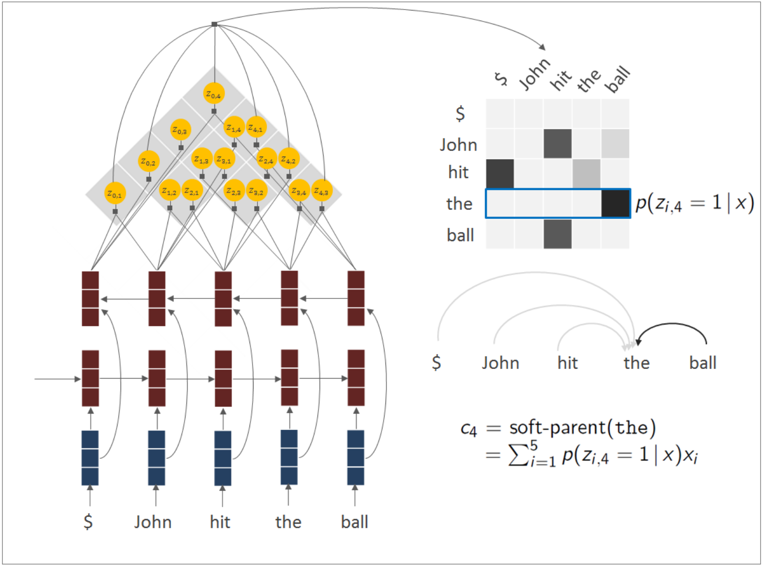


$$
\begin{aligned}
c_2 &= \text{soft-parent}(\text{John}) \\
&= \sum_{i=1}^{5} p(z_{i,2} = 1 \mid x) x_i
\end{aligned}
$$

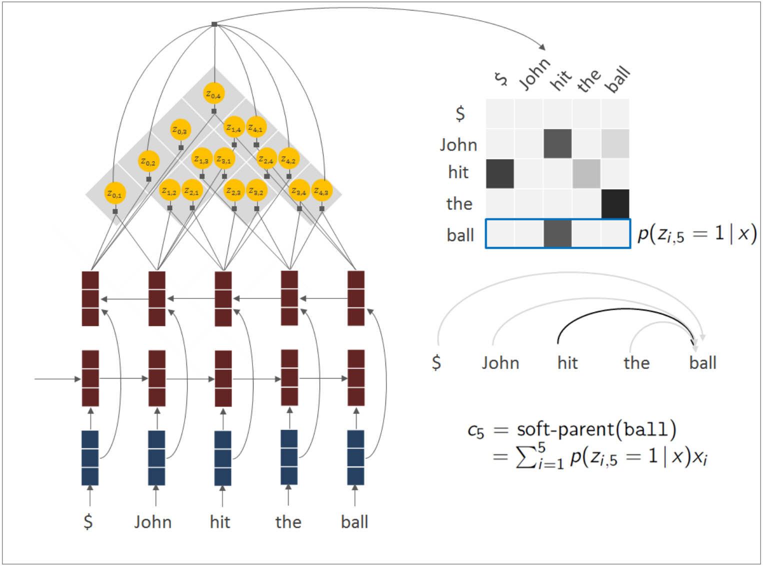
Syntactic Attention



Syntactic Attention



Syntactic Attention



Syntactic Attention for Natural Language Inference

Dataset: Stanford Natural Language Inference (Bowman et al., 2015)

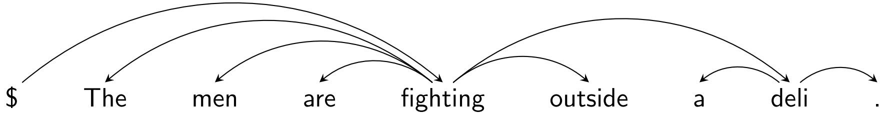
Model	Accuracy %
No Attention	85.8
Hard parent	86.1
Simple Attention	86.2
Structured Attention	86.8

- No attention: word embeddings only
- "Hard" parent from a pipelined dependency parser
- Simple attention (simple softmax instead of syntanctic attention)
- Structured attention (soft parents from syntactic attention)

Syntactic Attention for Natural Language Inference

Run Viterbi algorithm on the parsing layer to get the MAP parse:

$$\hat{z} = \arg\max_{z} p(z \mid x, q)$$



Structured Attention Networks

- Generalize attention to incorporate latent structure
- Exact inference through dynamic programming
- Training remains end-to-end

Future work

- Approximate differentiable inference in neural networks
- Incorporate other probabilistic models into deep learning
- Compare further to methods using EM or hard structures

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