

Visualizing and Understanding Neural Machine Translation

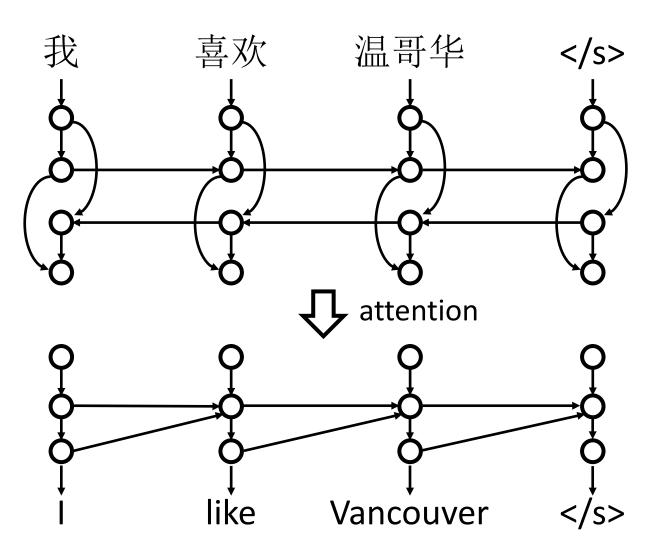
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Neural Machine Translation

• Idea: using neural networks to translate languages (Bahdanau et al., 2015)

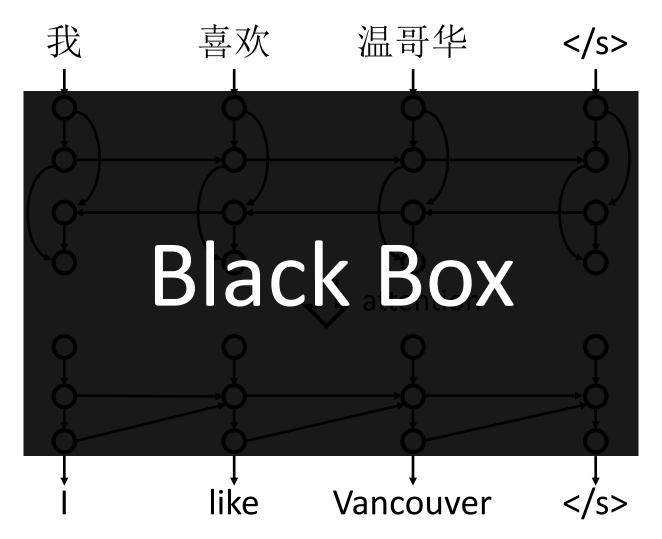
source words
source word embeddings
source forward hidden states
source backward hidden states
source hidden states



Challenge

• It is hard to visualize and understand the internal workings

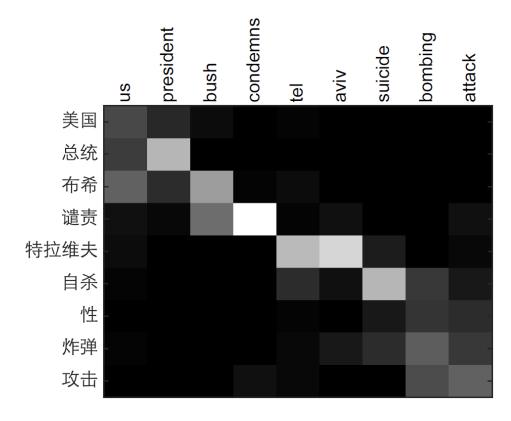
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Related Work

attention mechanism

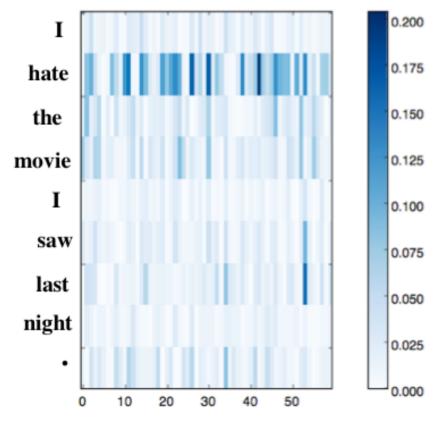
(Bahdanau et al., 2015)



restricted to the connection between input and output

first-derivative saliency

(Li et al., 2016)



require neural activations to be differentiable

Related Work

layer-wise relevance propagation (LRP)

(Bach et al., 2015)

Classification cat = no cat = no cat = Classifier output f(x)

∑ Pixel Relevances

Pixel-wise Explanation

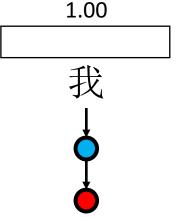
∑ Feature Relevances

calculating the relevance between two arbitrary neurons without requiring differentiability

 $f(\mathbf{x})$

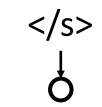
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source words 我喜欢温哥华 </s>
source word embeddings o o o

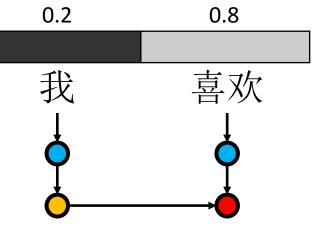




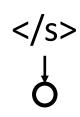


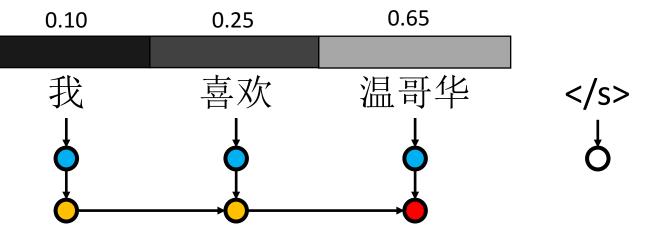


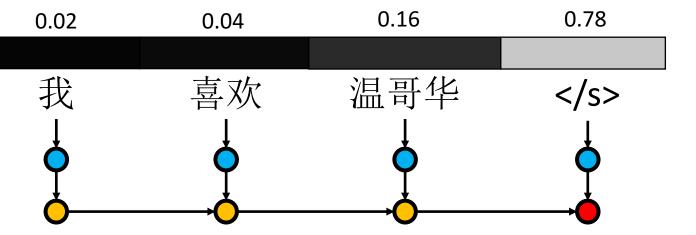
- targeted vector of neurons
- relevant vector of neurons
- intermediate vector of neurons
- O irrelevant vector of neurons
- 1.0 relevance



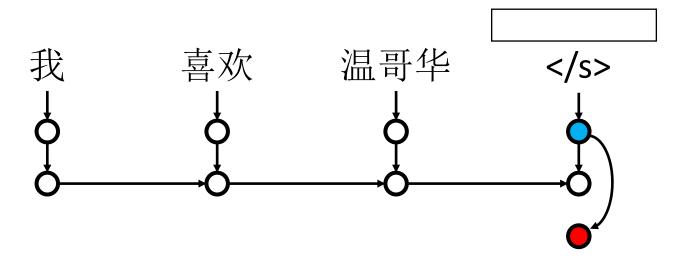




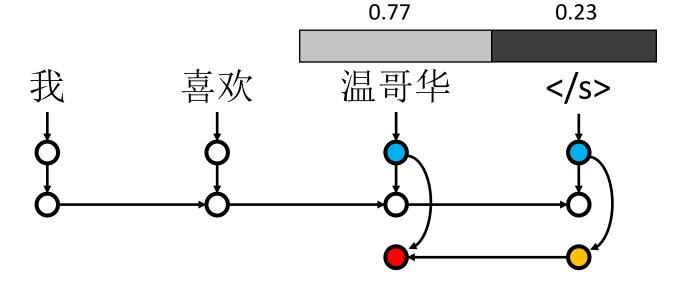


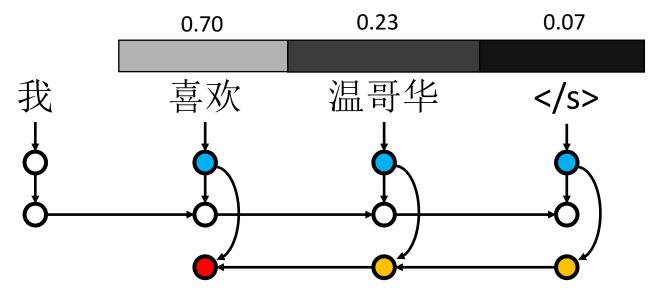


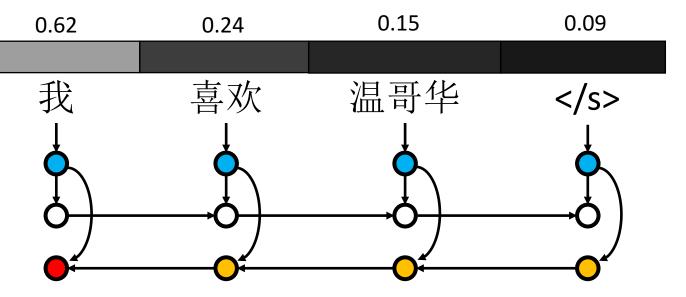
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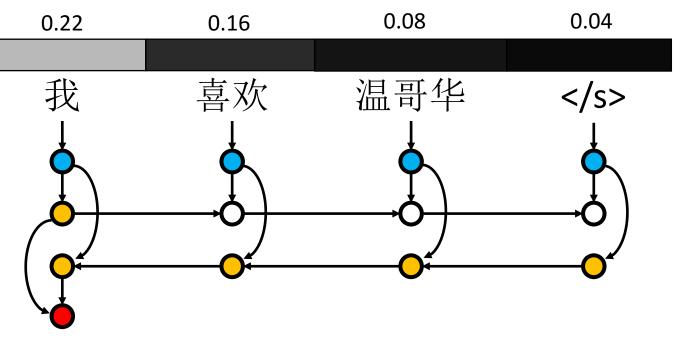


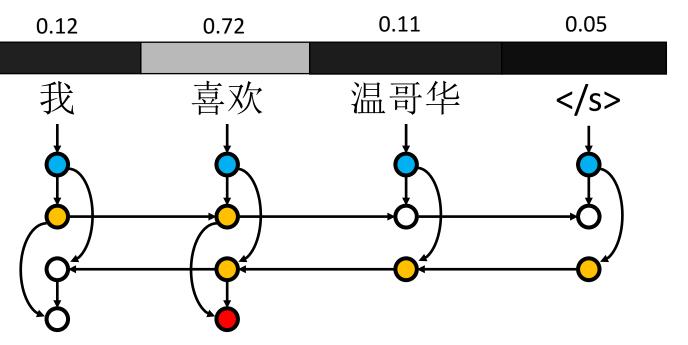
1.00

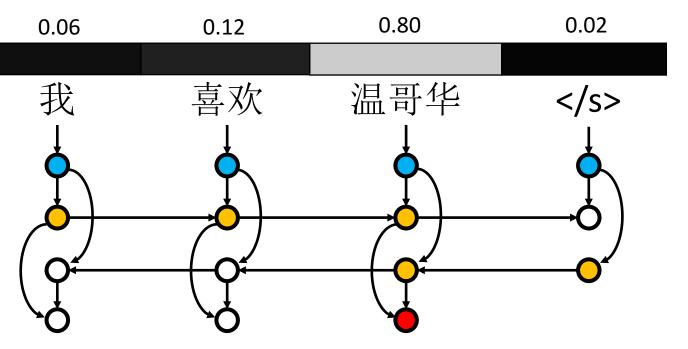


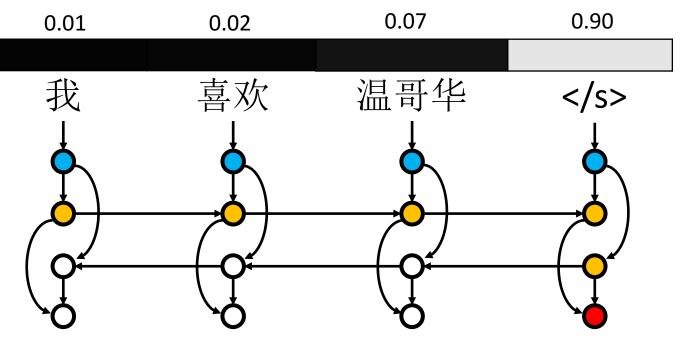






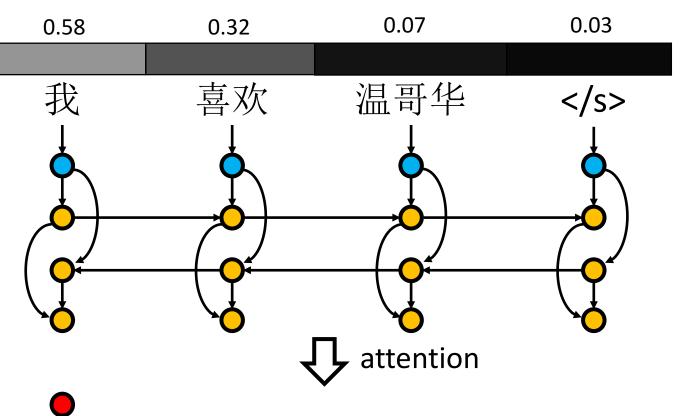






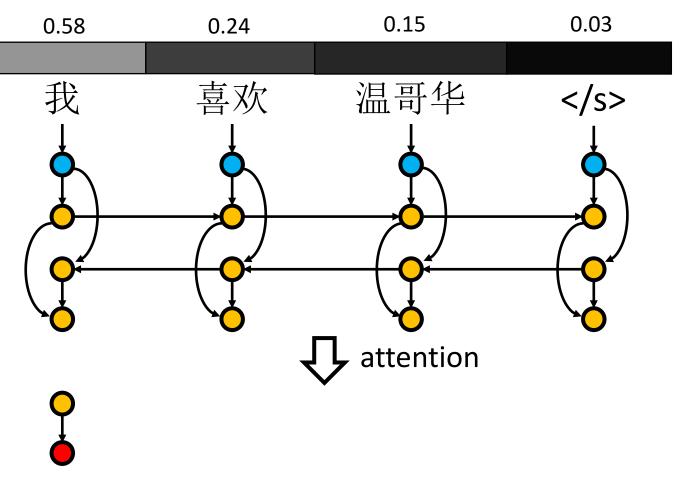
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source contexts



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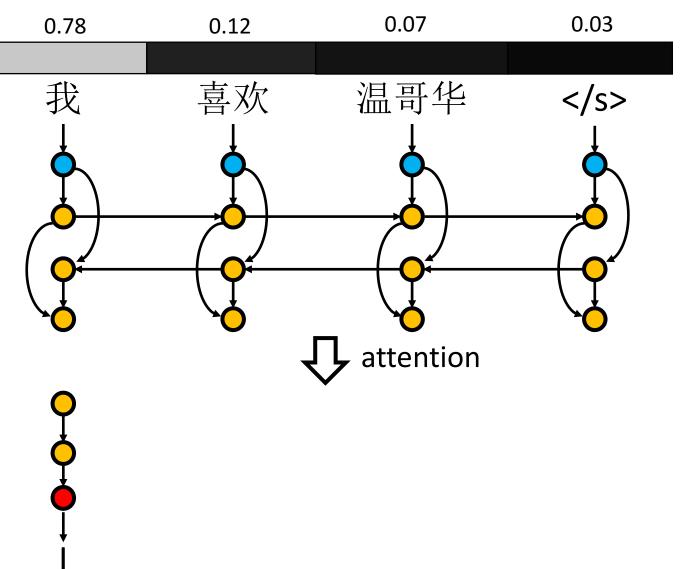
source contexts target hidden states



source words
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source forward hidden states
source backward hidden states

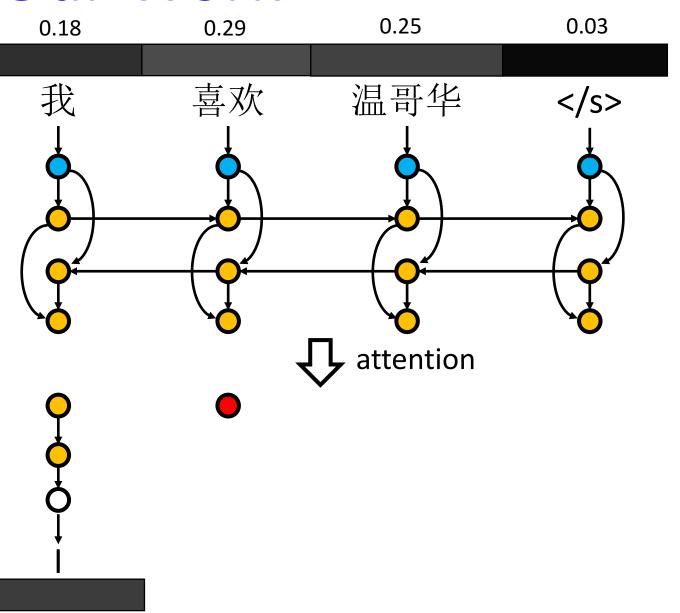
target hidden states
target word embeddings
target words

source hidden states

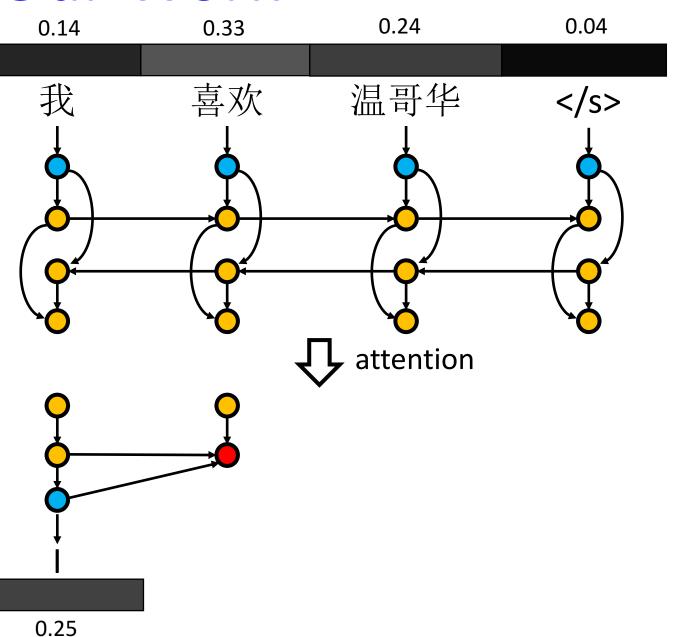


0.23

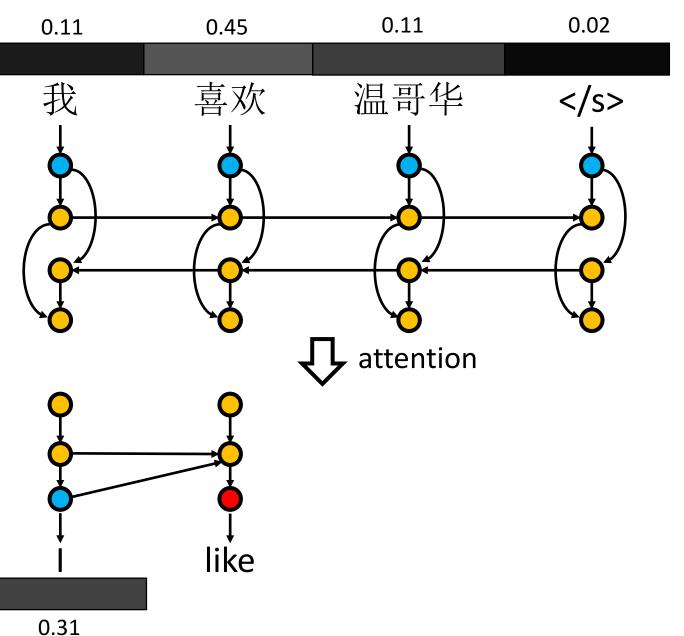
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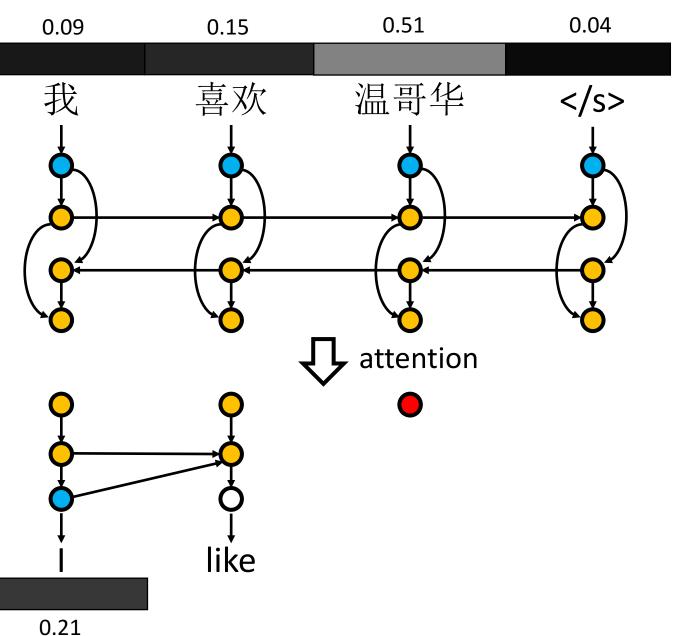


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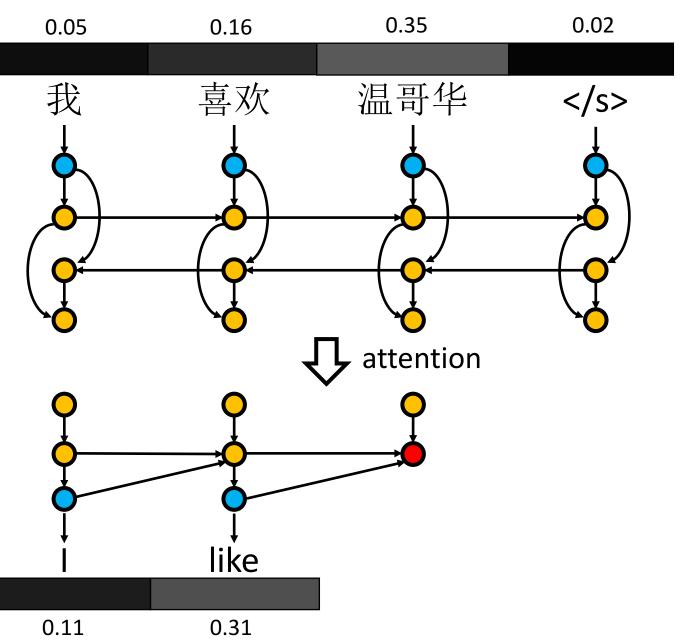


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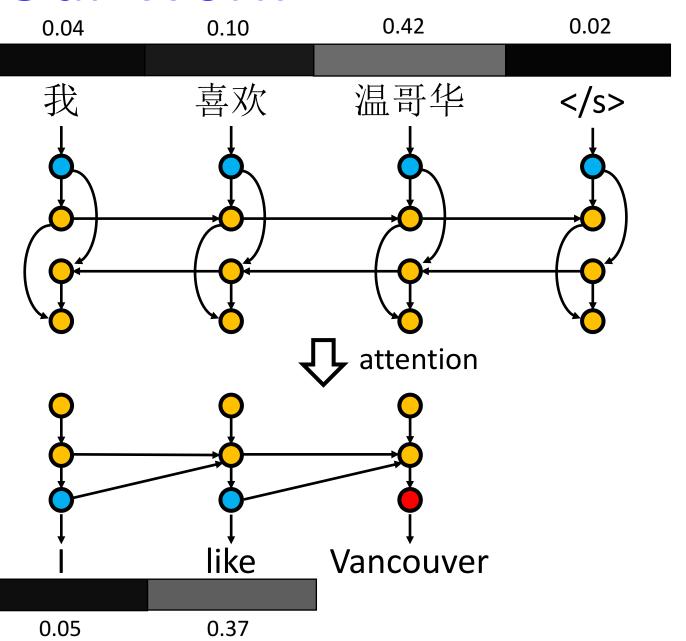
target hidden states
target word embeddings
target words



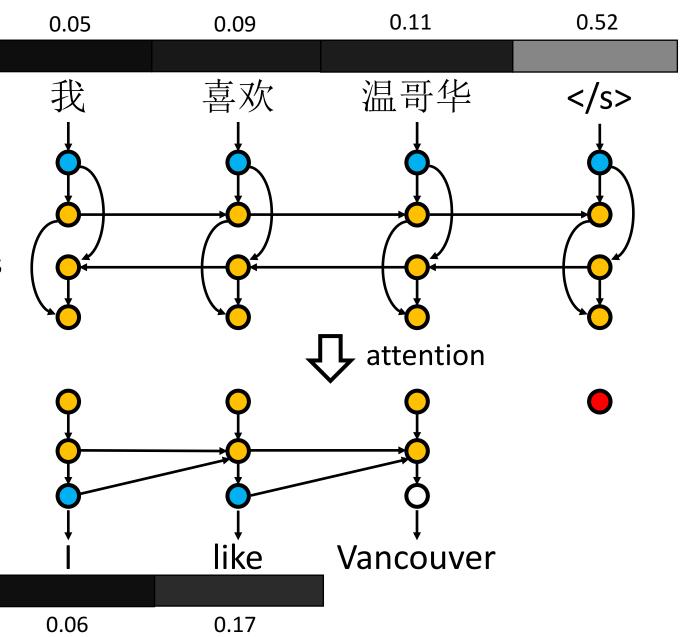
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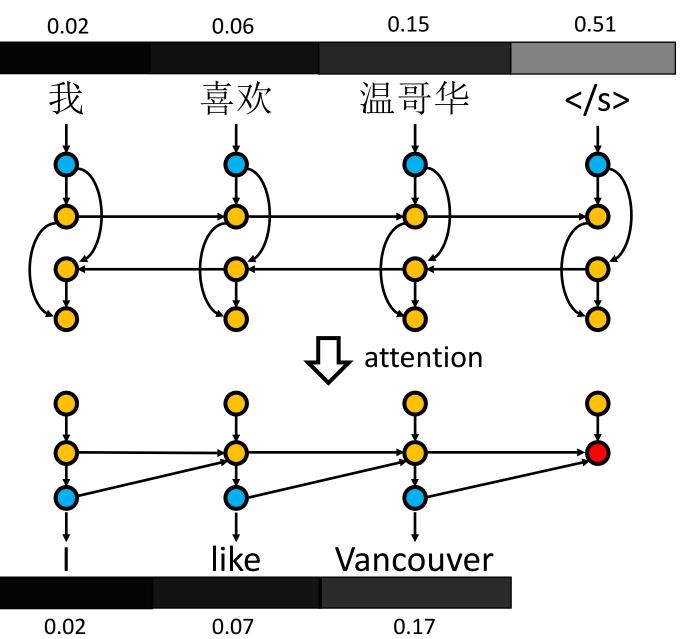
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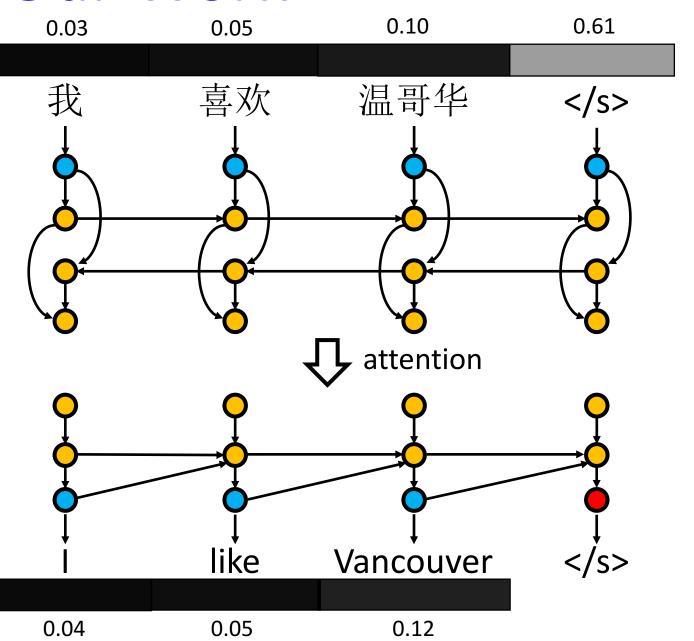
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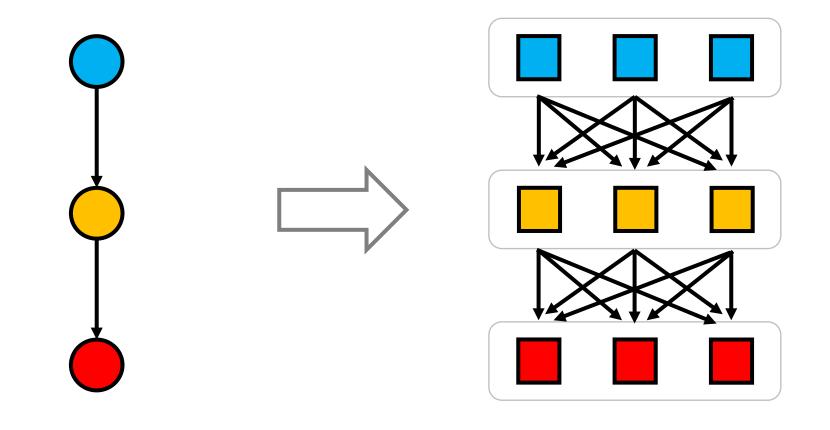
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Vector- and Neuron-Level Relevance

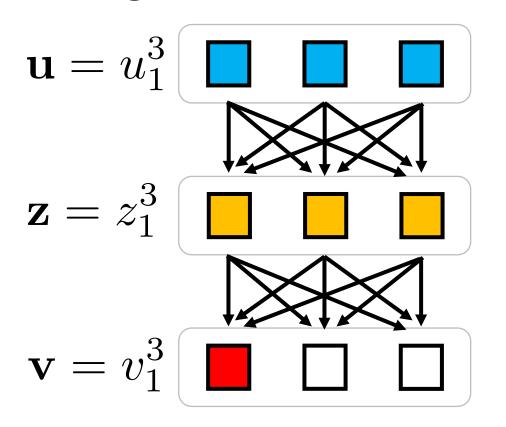


vector-level relevance

neural-level relevance

Neuron-Level Relevance

 Idea: decompose the activation of the targeted neuron among relevant neurons



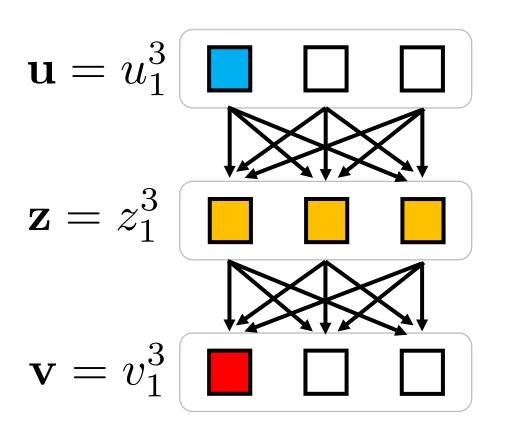
$$v_m = \sum_{\mathbf{u} \in \mathcal{C}(v_m)} \sum_{n=1}^{N} r_{u_n \leftarrow v_m}$$

For example

$$v_1 = \sum_{n=1}^{3} r_{u_n \leftarrow v_1}$$

Calculating Neuron-Level Relevance

Recursive calculation in a backward propagation



$$r_{u \leftarrow v} = \sum_{z \in \text{OUT}(u)} w_{u \to z} r_{z \leftarrow v}$$

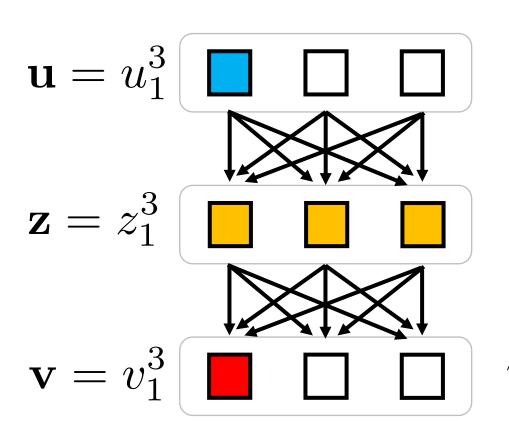
For example

$$r_{u_1 \leftarrow v_1} = \sum_{k=1}^{3} w_{u_1 \rightarrow z_k} r_{z_k \leftarrow v_1}$$

$$r_{z_k \leftarrow w_1} = w_{z_k \rightarrow v_1} v_1$$

Calculating Weight Ratios

Recursive calculation in a forward propagation

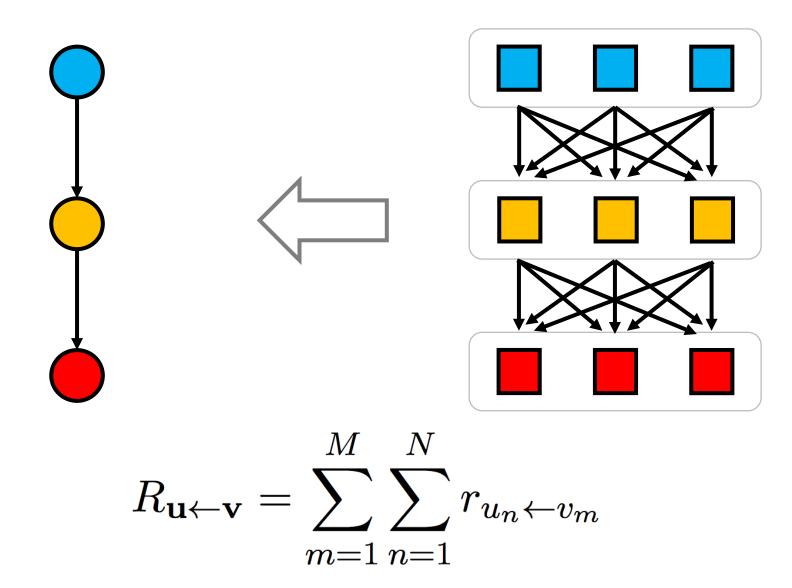


$$w_{u \to v} = \frac{\mathbf{W}_{u,v} u}{\sum_{u' \in \text{IN}(v)} \mathbf{W}_{u',v} u'}$$

For example

$$w_{u_1 \to z_1} = \frac{\mathbf{W}_{1,1}^{(1)} u_1}{\mathbf{W}_{1,1}^{(1)} u_1 + \mathbf{W}_{2,1}^{(1)} u_2 + \mathbf{W}_{3,1}^{(1)} u_3}$$

Calculating Vector-Level Relevance



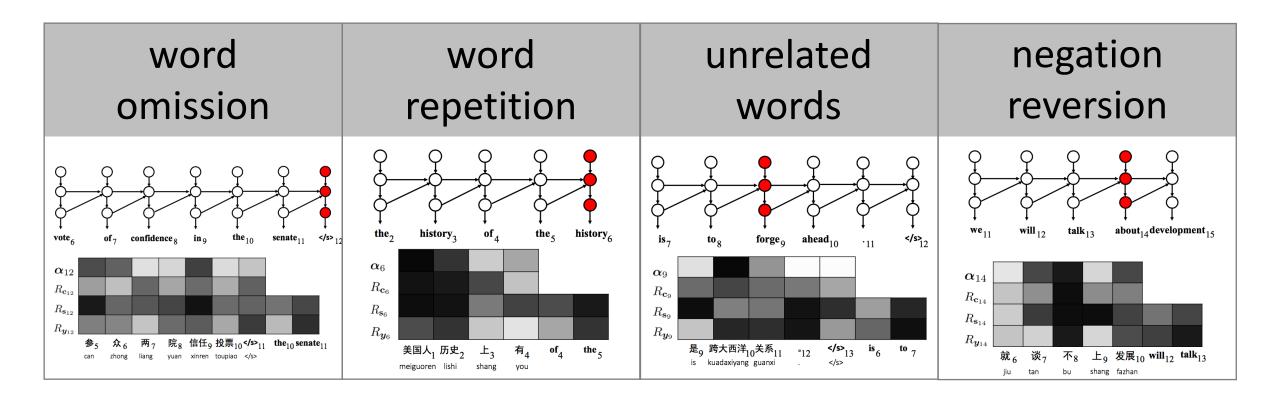
Algorithm

- Specify targeted vector of neurons
- Calculate weight ratios in a forward propagation
- Calculate relevance in a backward propagation

layer-wise propagation for neural machine translation

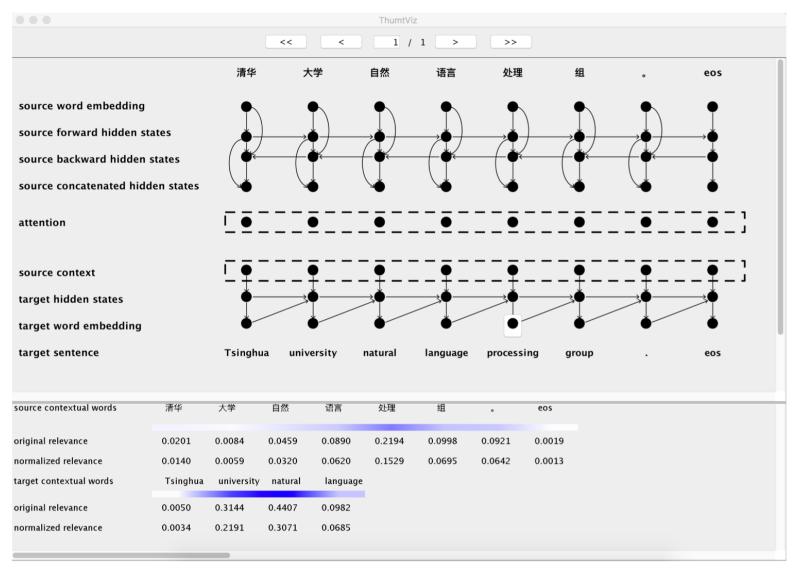
Application

Help to debug attention-based NMT systems



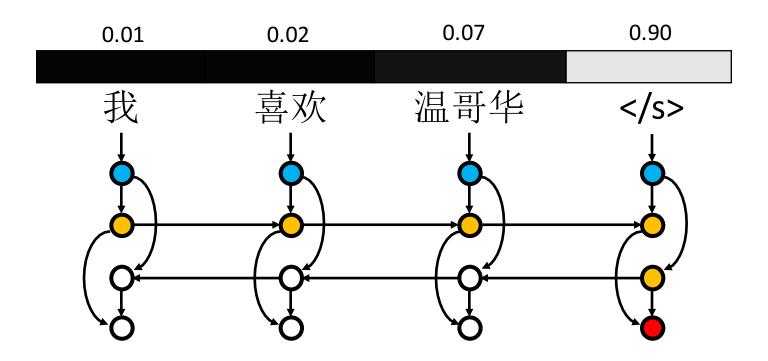
analyzing major translation error types by visualizing relevance step by step

Open-Source Toolkit



http://thumt.thunlp.org

Conclusion



- It is challenging to interpret how neural networks work
- We leverage layer-wise relevance propagation to visualize NMT
- Our approach can be applied to networks in other NLP tasks

Thanks

http://thumt.thunlp.org