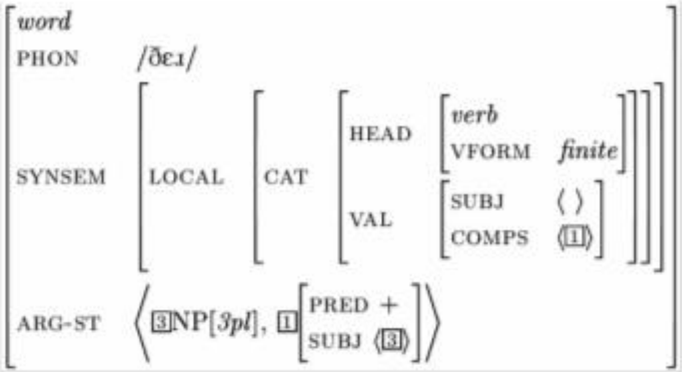
Text Seminar

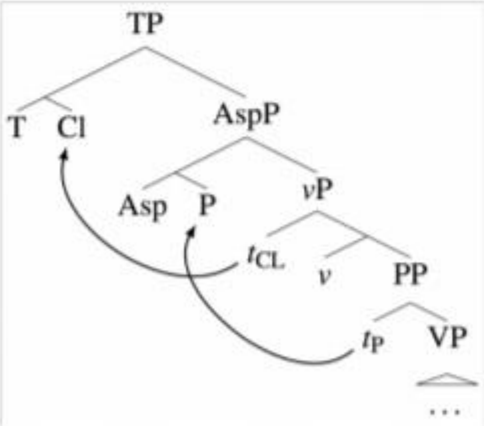
ToBig's 13기 정민준

Constituency Parsing

TreeRNNs

Lecture 18 | Consituency Parsing & Tree RNNs





어떻게 하면 큰 구절의 의미를 알아낼 수 있을까?

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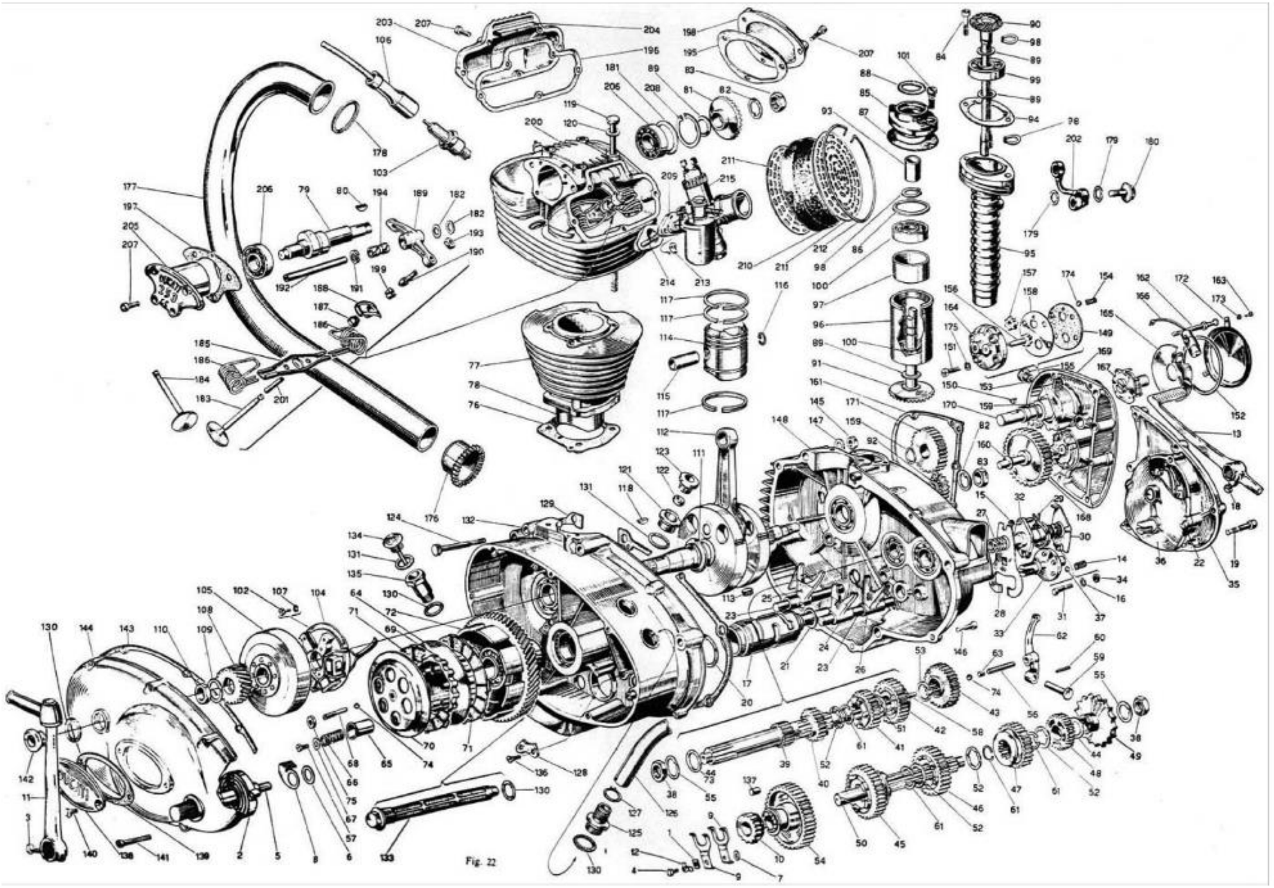
Compositionality



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The $\boxed{\text{snowboarder}}$ is leaping over a mogul

=

$\boxed{\text{A person on a snowboard}}$ jumps into the air

사람들은 큰 텍스트 단위의 의미를 작은 요소의 조합을 통해 의미를 표현한다!

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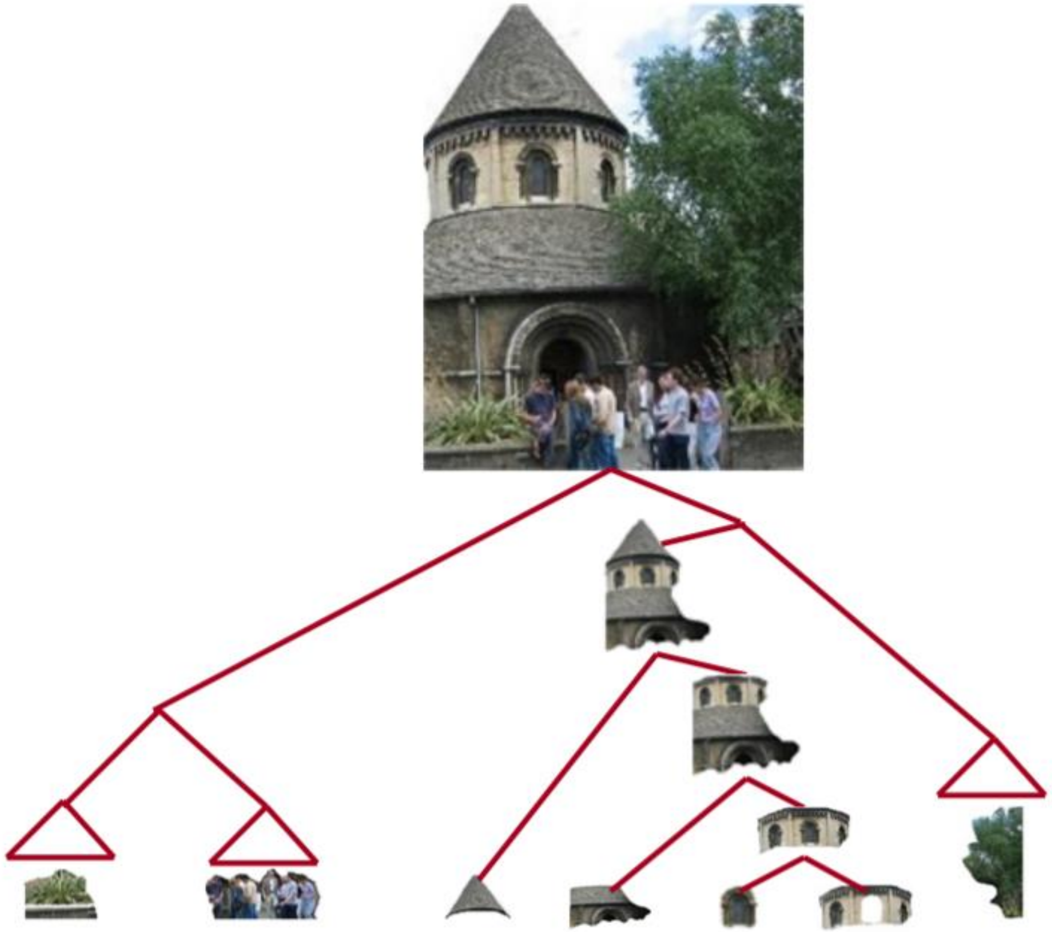
작은 부분들이 합쳐짐!



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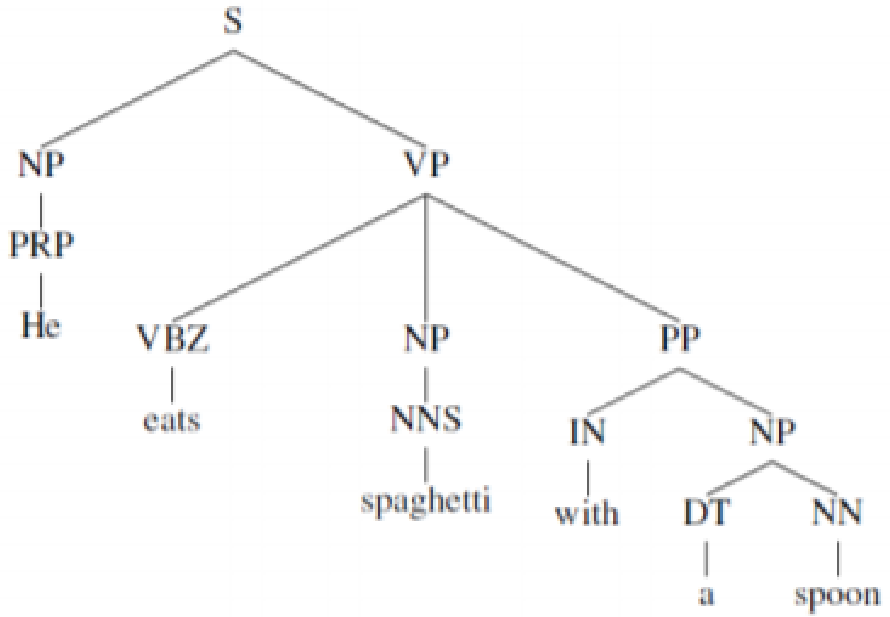

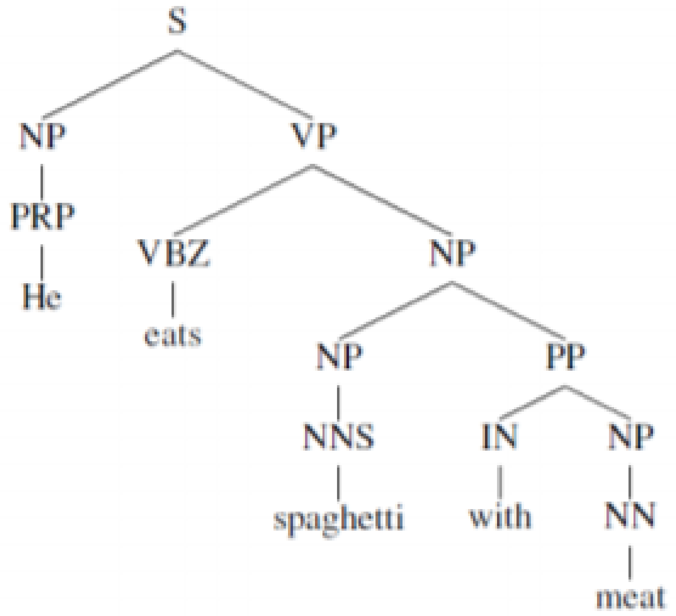

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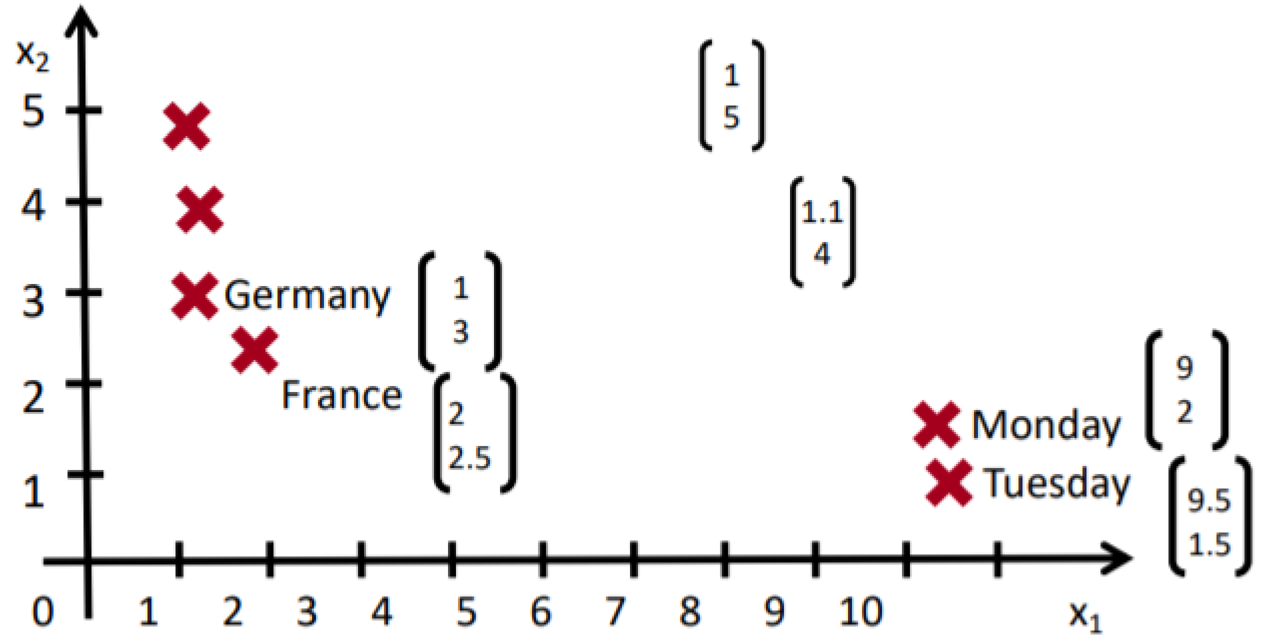

더 큰 구절은 어떻게 매핑시킬까?
ex) the country of my birth, the place where I was born

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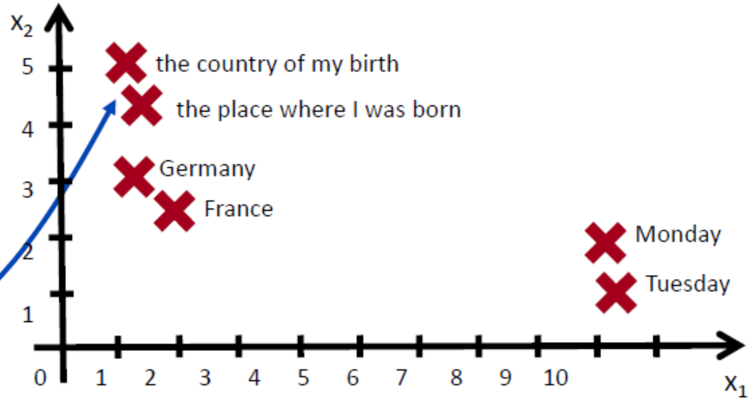
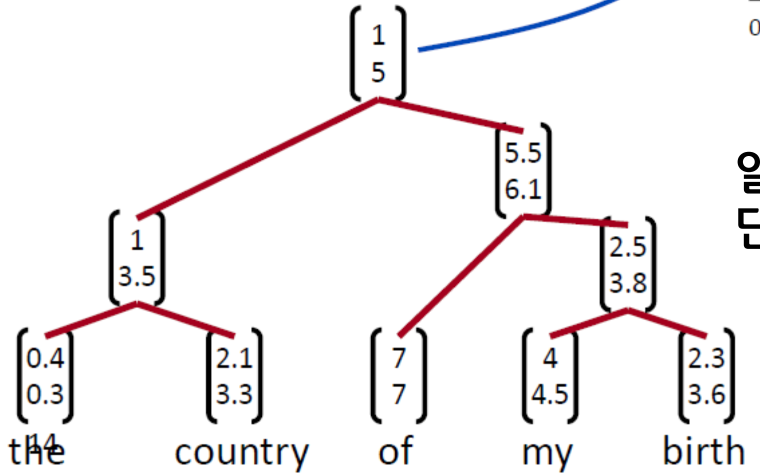
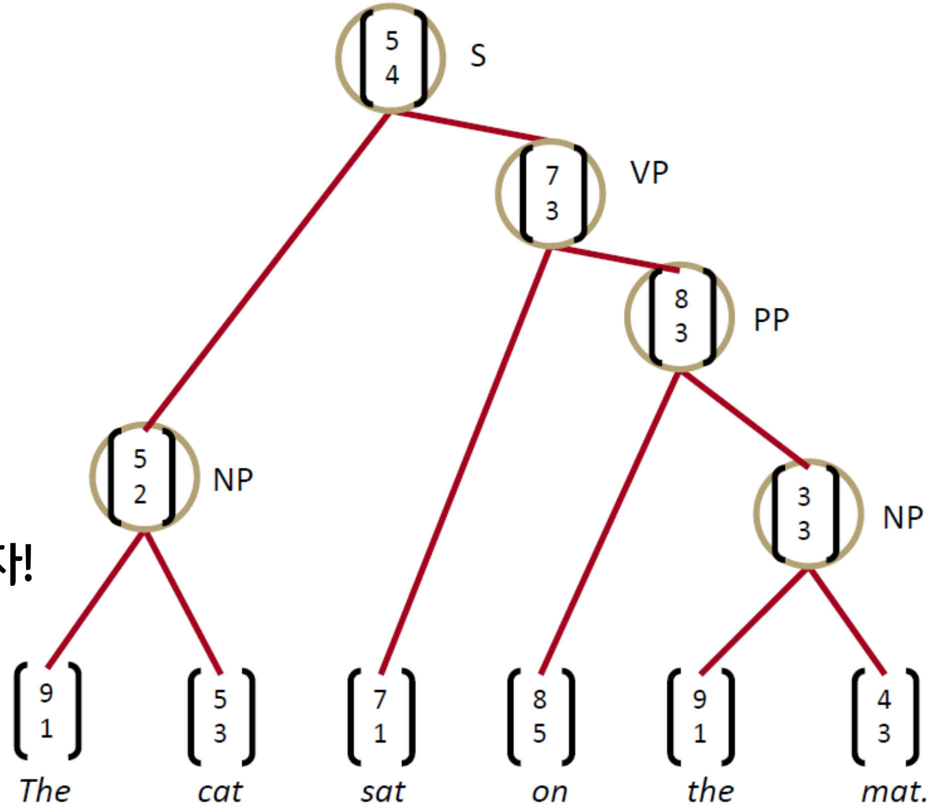
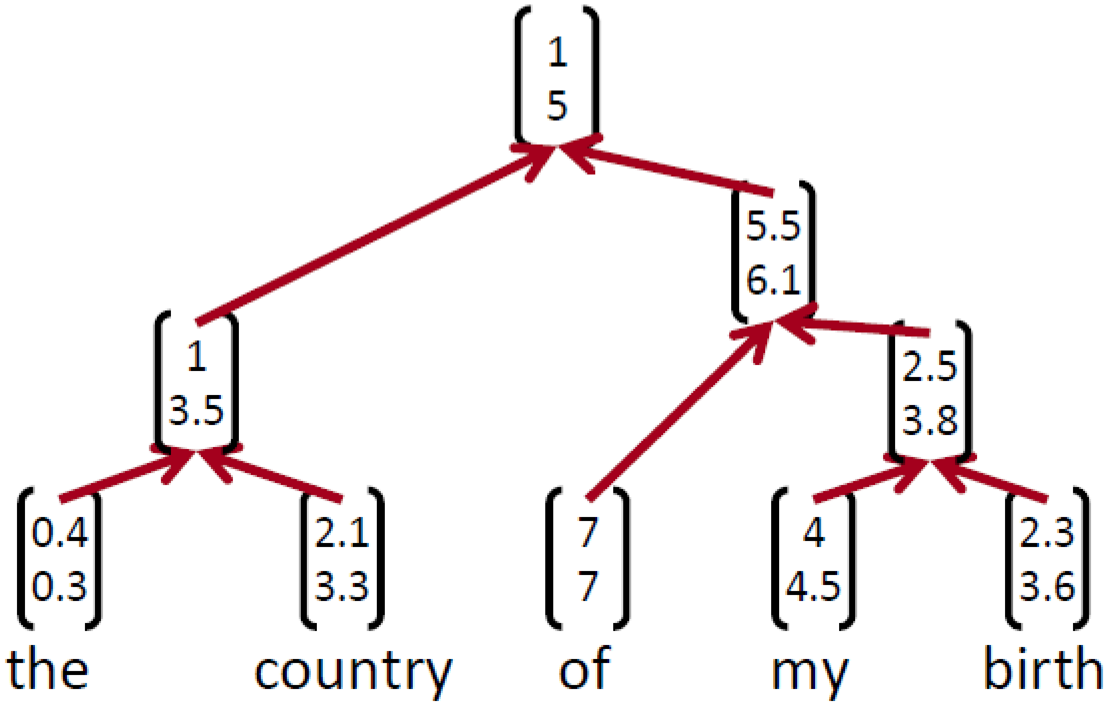


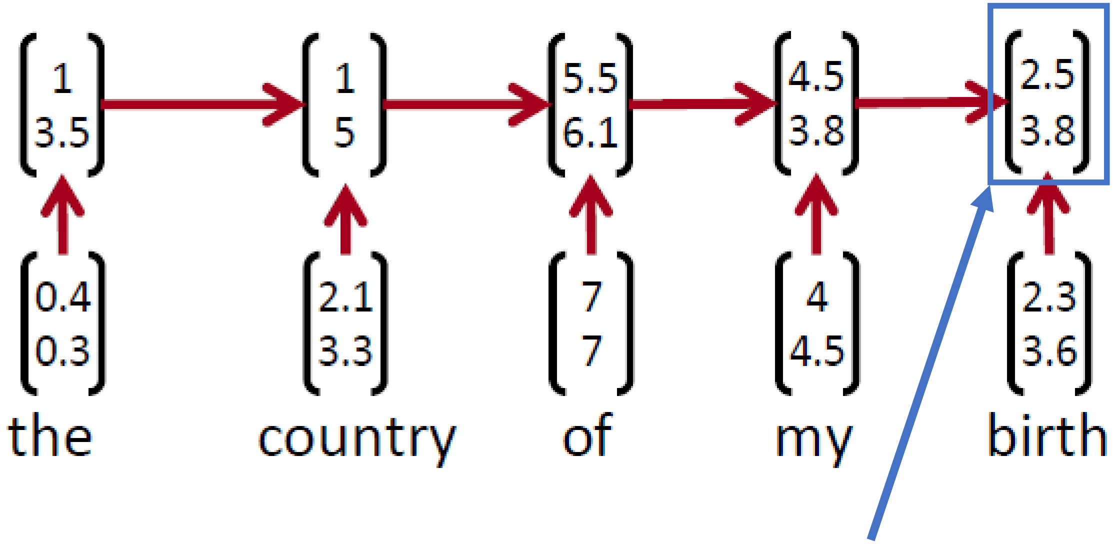


일정한 규칙을 정하여
단어간 조합을 하고 의미 벡터를 만들자!



Recursive vs RNN





인접 단어를 합친 단어의 의미는 충분히 반영하지 못한다!
주로 마지막 단어 벡터를 주목하는 경향이 있음.

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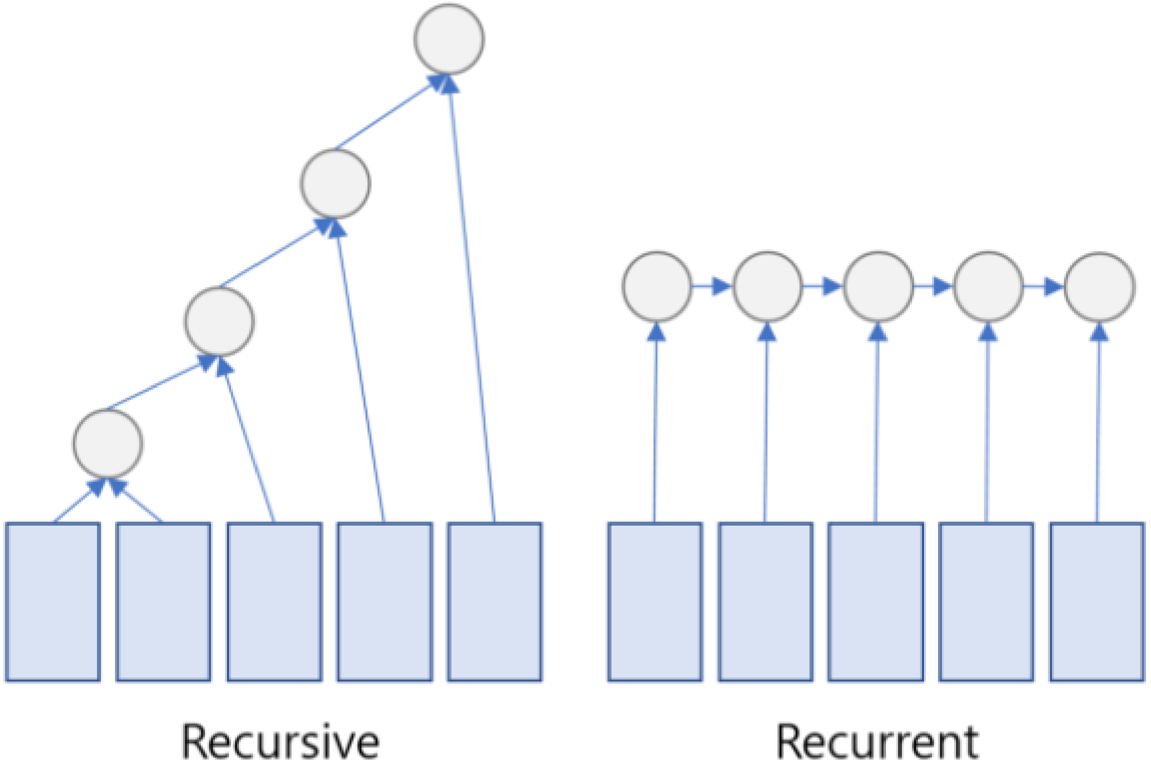

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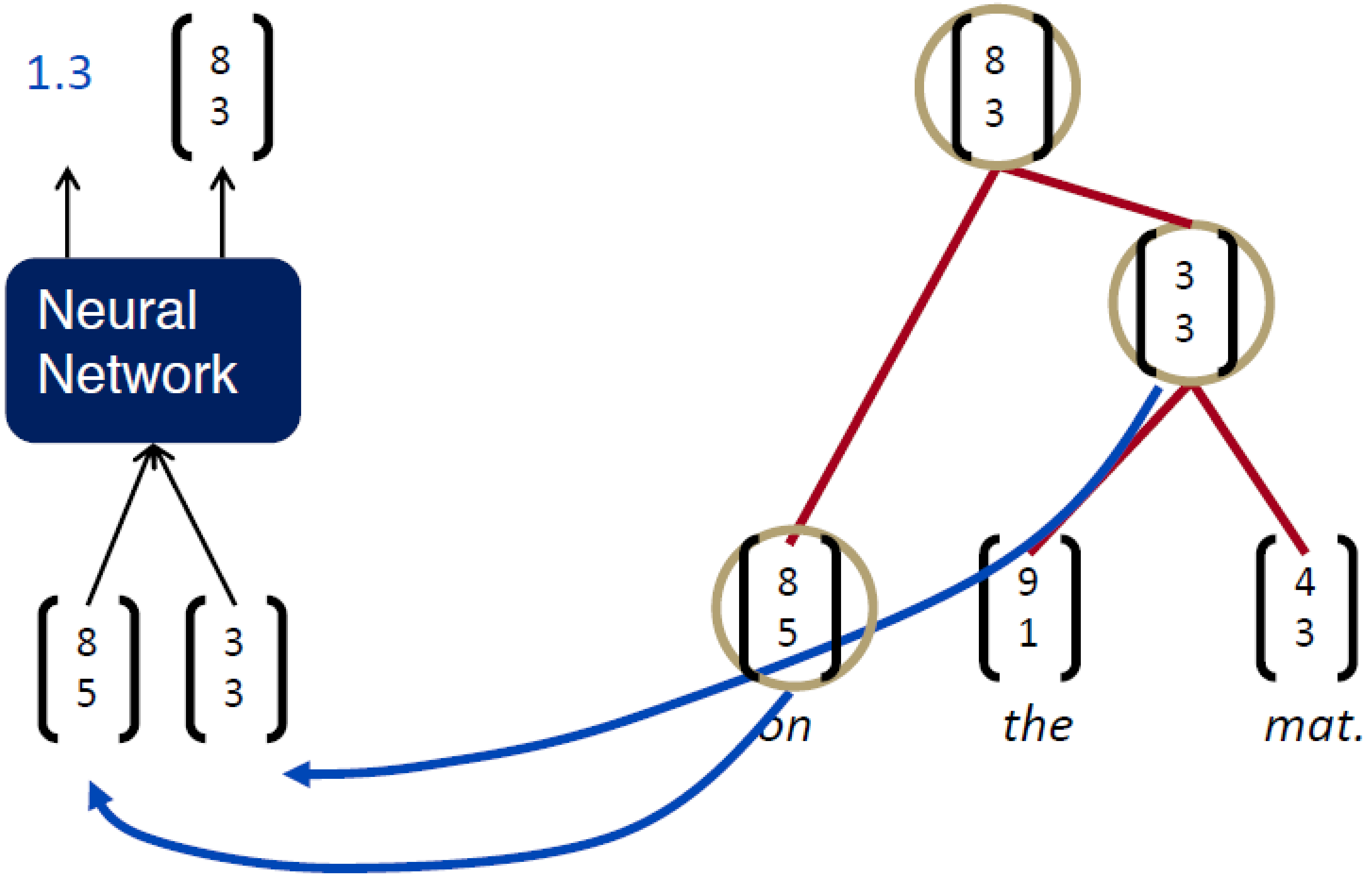

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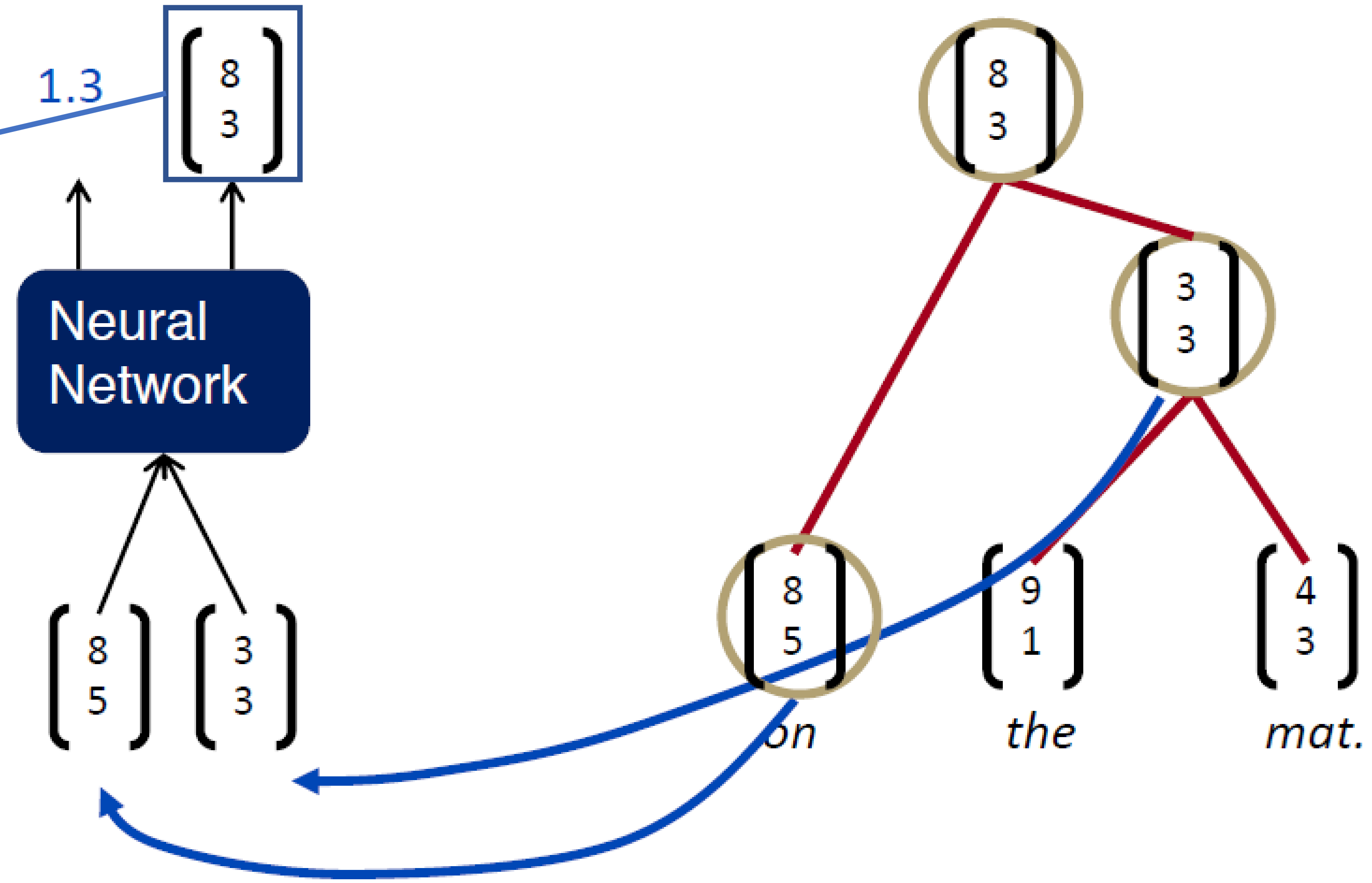
Parent

$$p = \tanh\left(W\begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right)$$

Concat!

여기서 W 변수는
모든 노드에서 동일!



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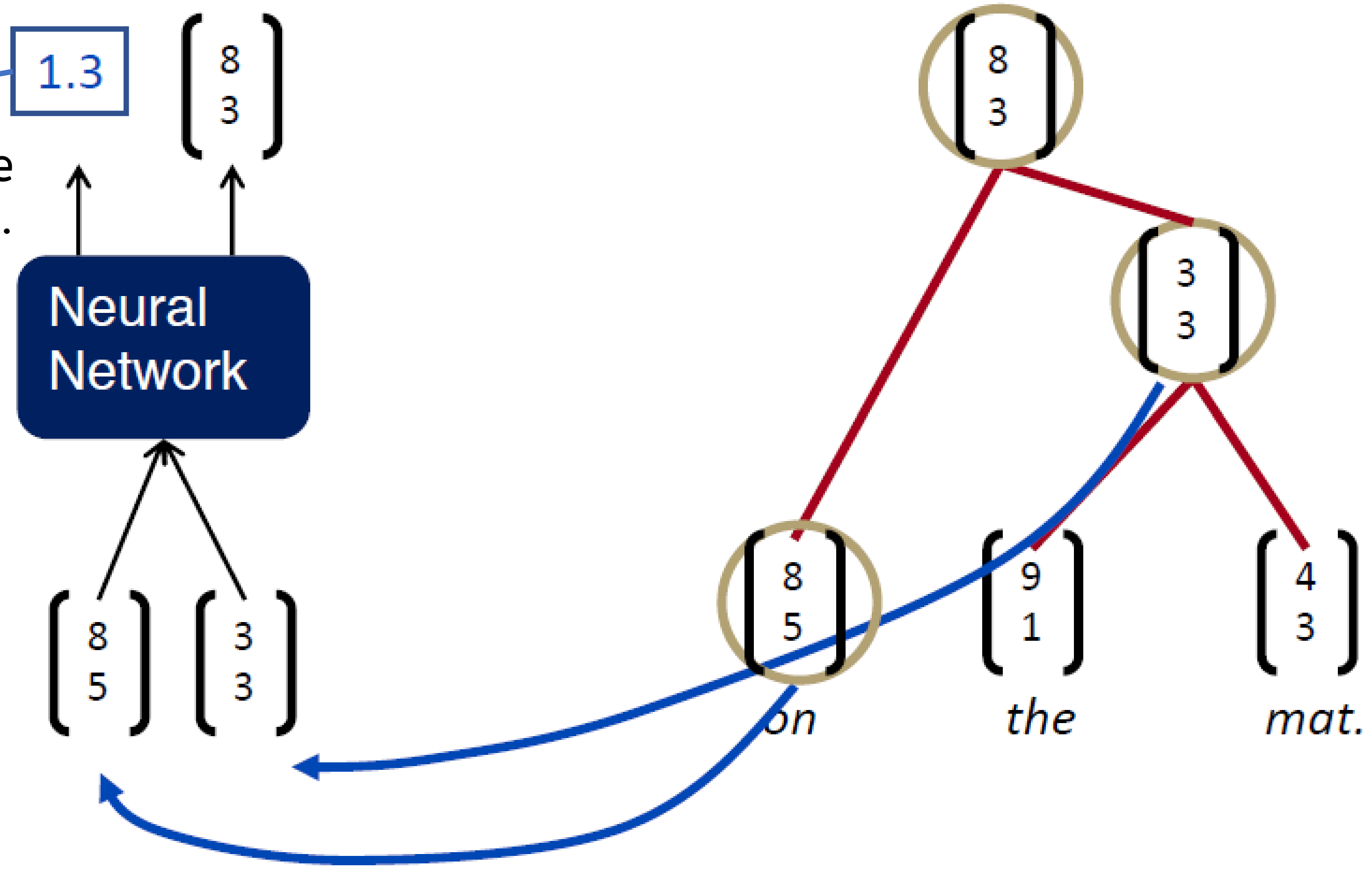
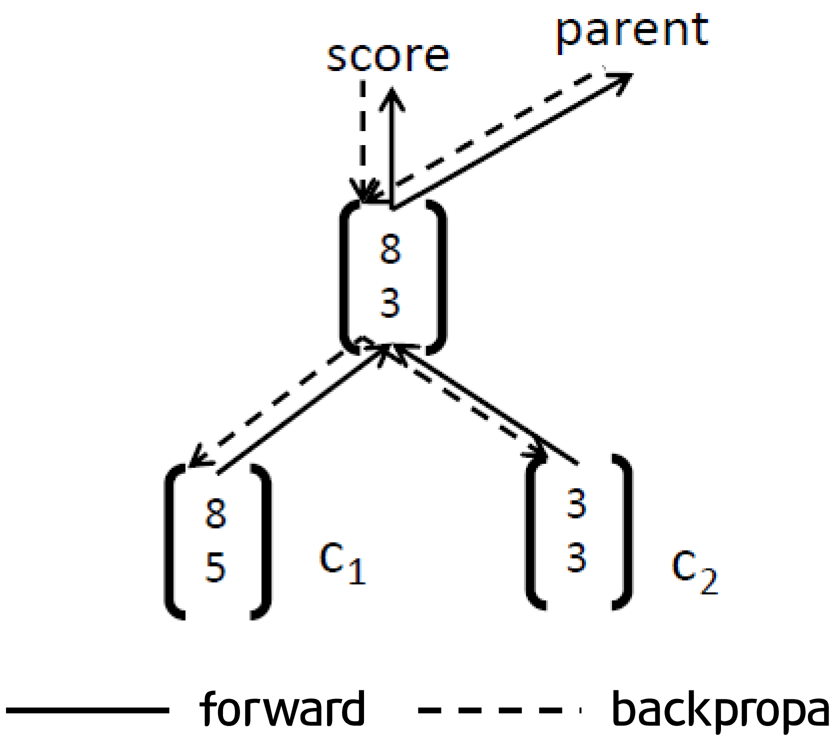
Score of how plausible the new node would be.

$$\text{score} = U^{\mathsf{T}} p$$

$$p = \tanh\left(W \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right)$$



Simple TreeRNN



$$p_i = \tanh\left(W \cdot \begin{bmatrix} p_{left} \\ p_{right} \end{bmatrix} + b\right)$$

$$W \cdot \begin{bmatrix} p_{left} \\ p_{right} \end{bmatrix} = \begin{bmatrix} w_1 & w_2 \end{bmatrix} \cdot \begin{bmatrix} p_{left} \\ p_{right} \end{bmatrix} = w_1 \times p_{left} + w_2 \times p_{right}$$

$$s_i = W_s p_i + b_s$$

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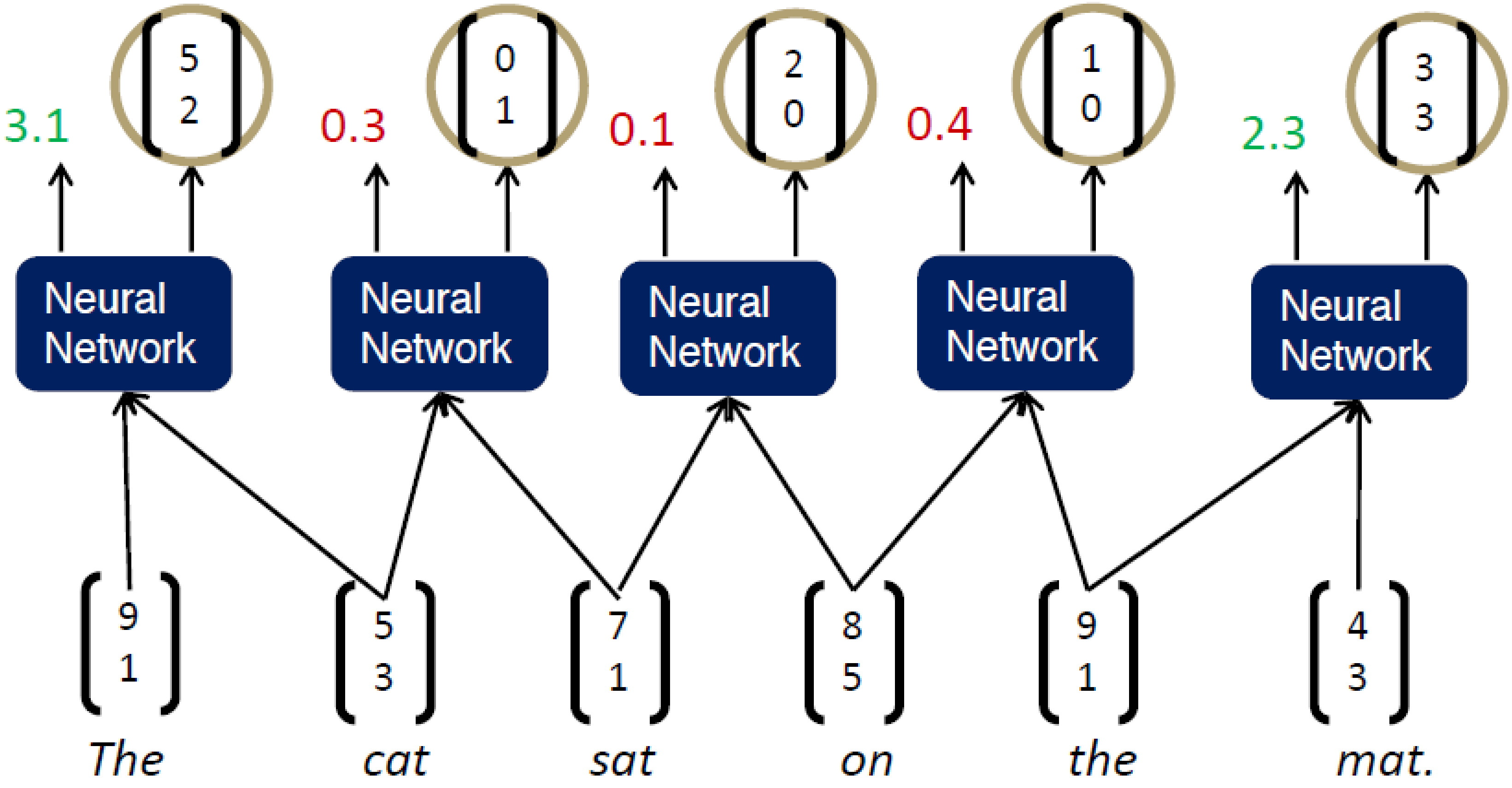

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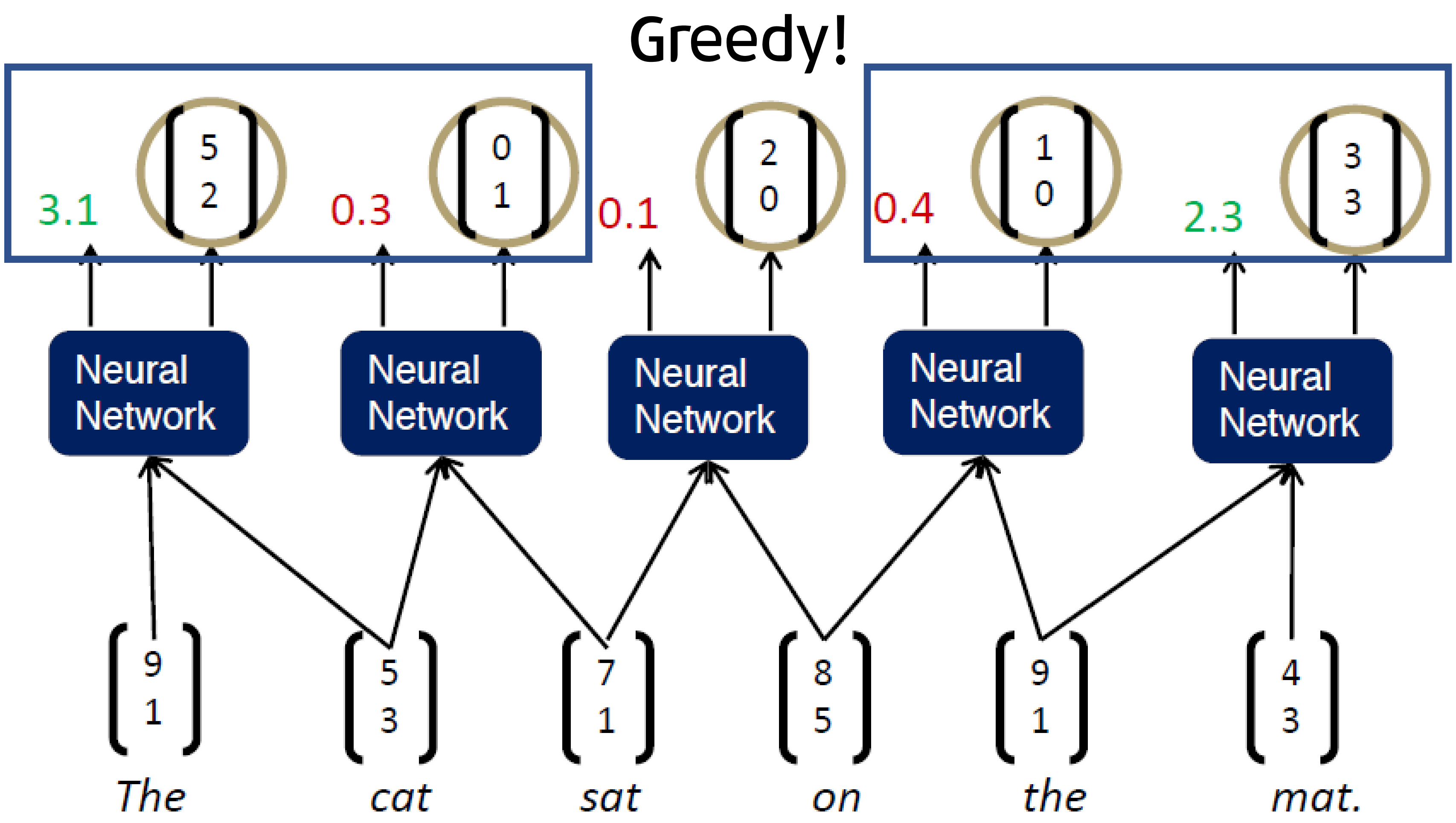

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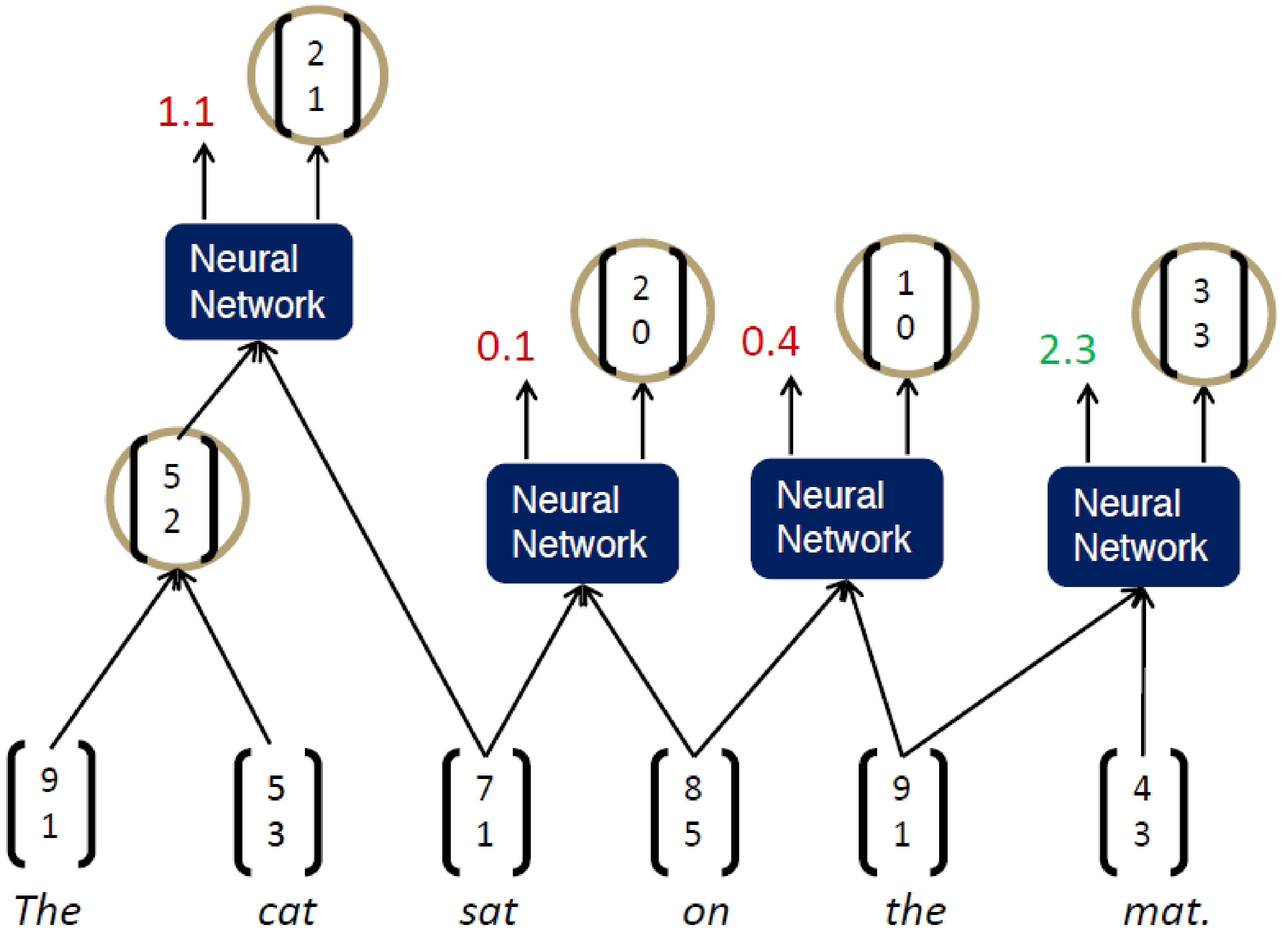

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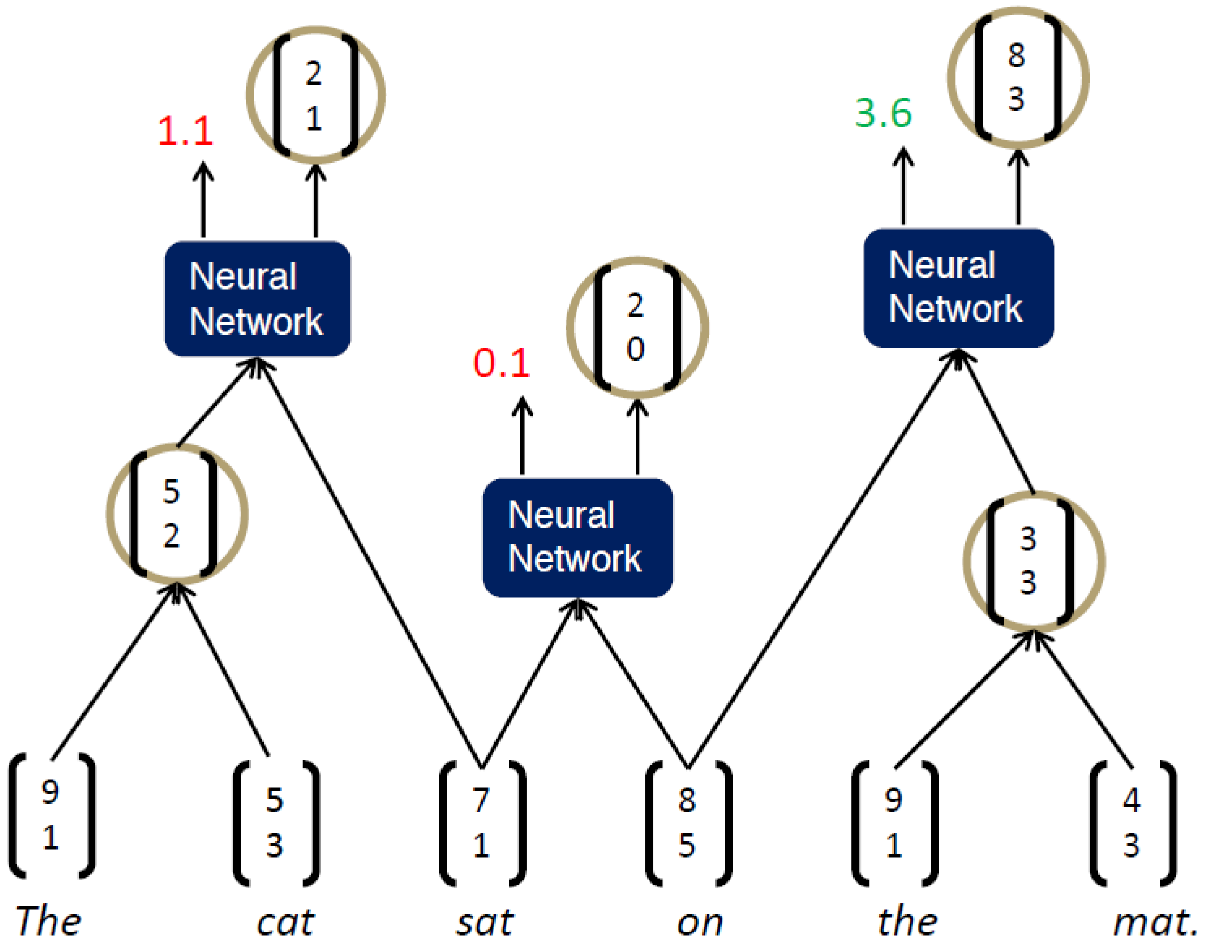
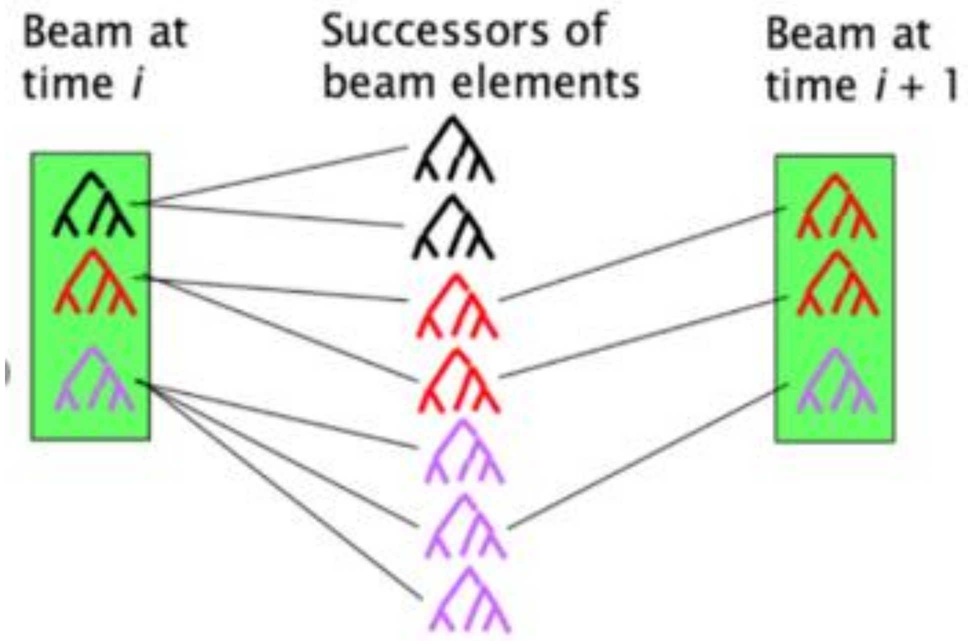


뜬금 알고리즘 시간!

Dynamic programming Vs greedy algorithm

Beam Search Algorithm



BFS + greedy!

Simple TreeRNN의 한계점

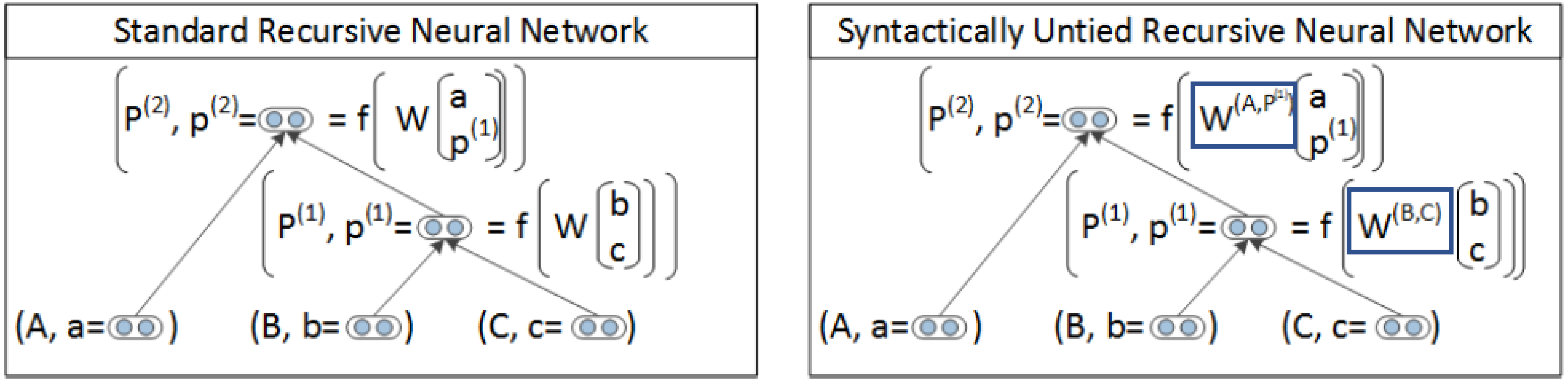
1. 앞서 W가 모든 노드에서 동일하다고 설명. 이러한 Simple TreeRNN은 일부 현상에선 적합할 수 있지만 더 복잡하고, 고차 구성 및 긴 문장에서는 적절치 못하다.

2. 인풋 단어간 실제 상호작용이 없다.

3. 조합 함수가 모든 경우에 대해서 동일하게 작용한다.

Syntactically-United RNN

PCFG 사용. 기능이 다른 표현에 각기 다른 가중치를 적용, case by case. Simple TreeRNN 개선.



Probabilistic Context Free Grammar(PCFG)

각 규칙은 생성 확률을 가지고 있으며 해당 Non-terminal로 부터 생성하는 규칙들의 확률의 합은 1.

S -> NP VP	0.8	
S -> Adj NP VP	0.1	1.0
S -> VP	0.1	

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Grammar	Prob	
S → NP VP	0.8	+ 1.0
S → Aux NP VP	0.1	
S → VP	0.1	
NP → Pronoun	0.2	+ 1.0
NP → Proper-Noun	0.2	
NP → Det Nominal	0.6	
Nominal → Noun	0.3	+ 1.0
Nominal → Nominal Noun	0.2	
Nominal → Nominal PP	0.5	
VP → Verb	0.2	+ 1.0
VP → Verb NP	0.5	
VP → VP PP	0.3	
PP → Prep NP	1.0	

Lexicon

Det → the | a | that | this
0.6 0.2 0.1 0.1

Noun → book | flight | meal | money
0.1 0.5 0.2 0.2

Verb → book | include | prefer
0.5 0.2 0.3

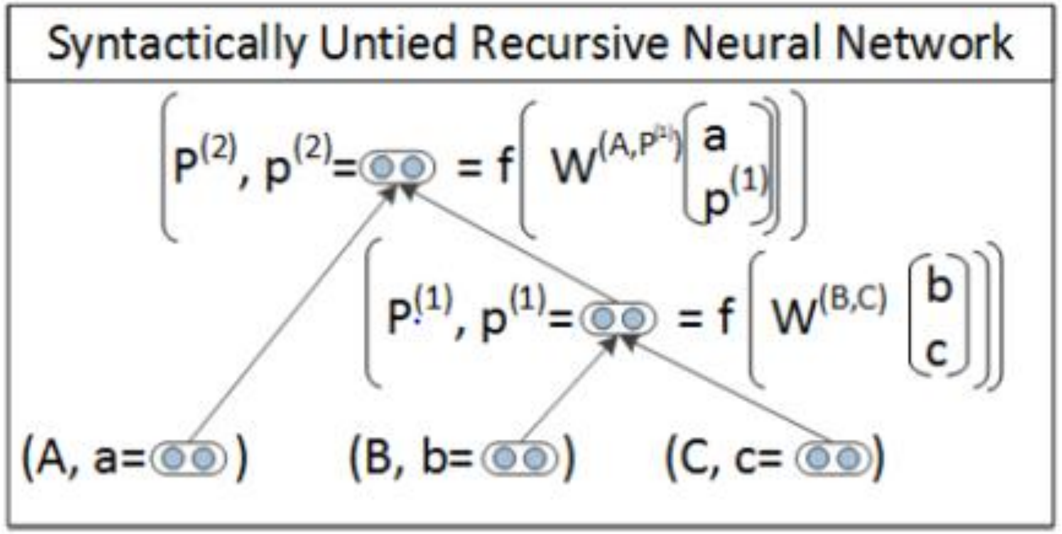
Pronoun → I | he | she | me
0.5 0.1 0.1 0.3

Proper-Noun → Houston | NWA
0.8 0.2

Aux → does
1.0

Prep → from | to | on | near | through
0.25 0.25 0.1 0.2 0.2

Syntactically-United RNN



PCFG + TreeRNNs

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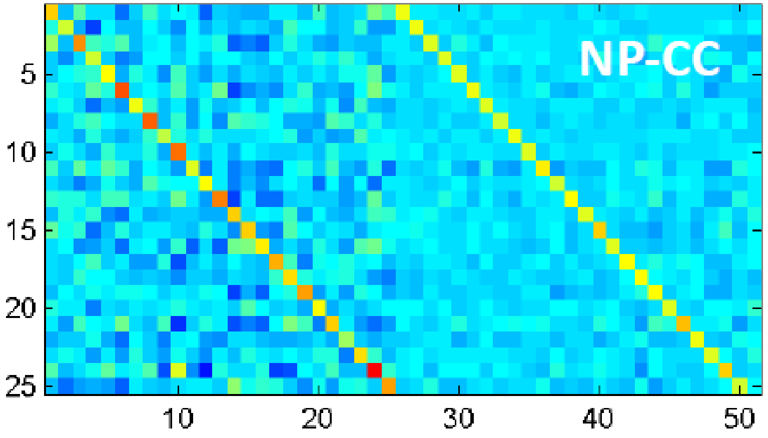
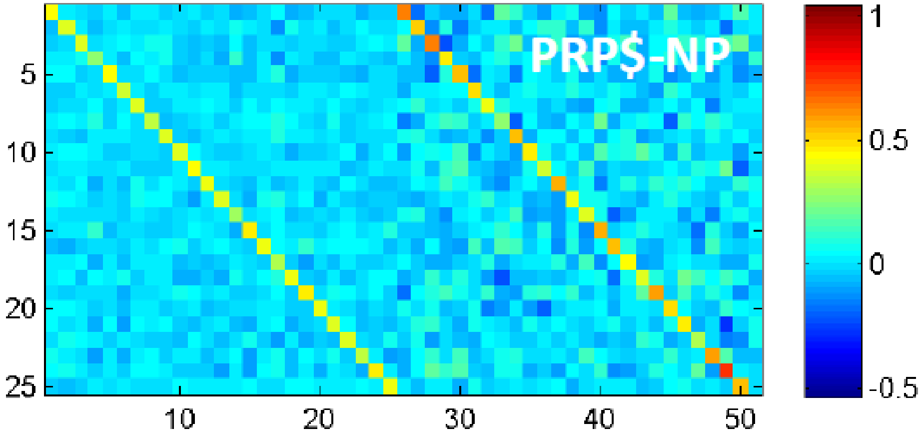
Initialization: $W^{(\cdot\cdot)} = 0.5[I_{n\times n} I_{n\times n} 0_{n\times 1}] + \epsilon$





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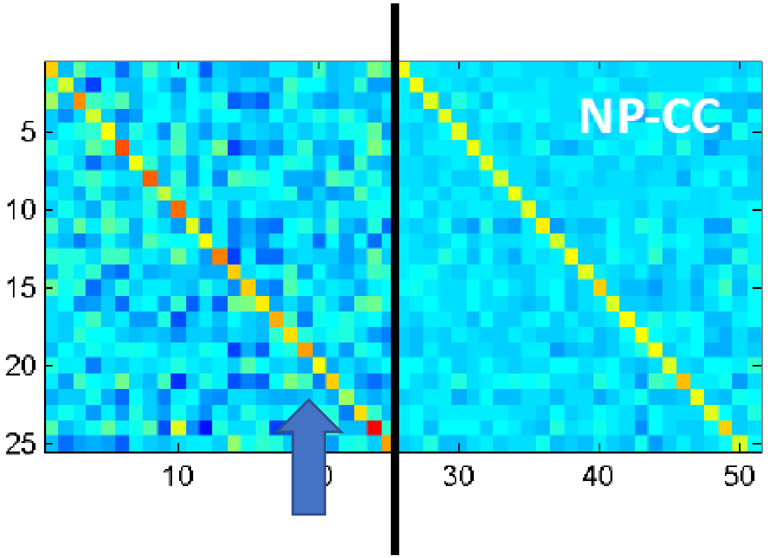
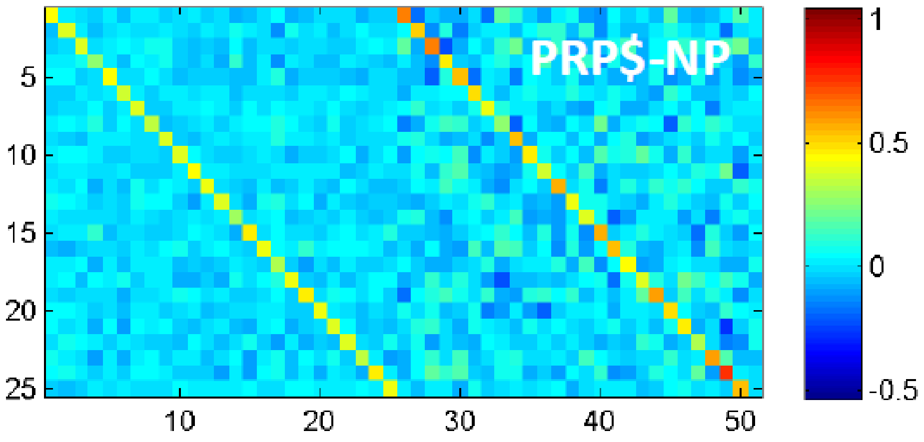
Initialization: $W^{(\cdot\cdot)} = 0.5[I_{n\times n} I_{n\times n} 0_{n\times 1}] + \epsilon$

avg Concat bias error





CC 품사보다 NP 품사의 의미가 더 반영되었음! Ex) the cat | and

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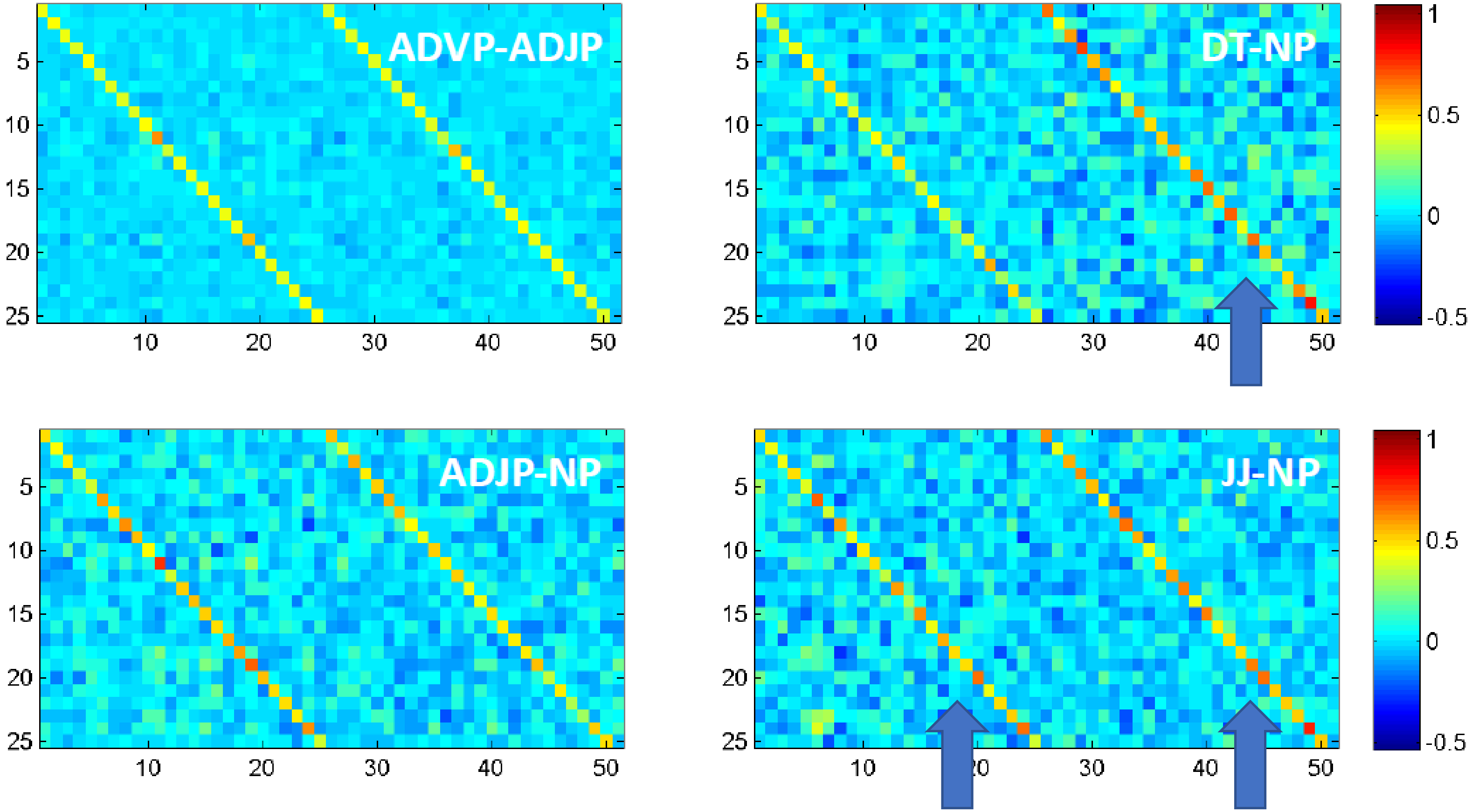
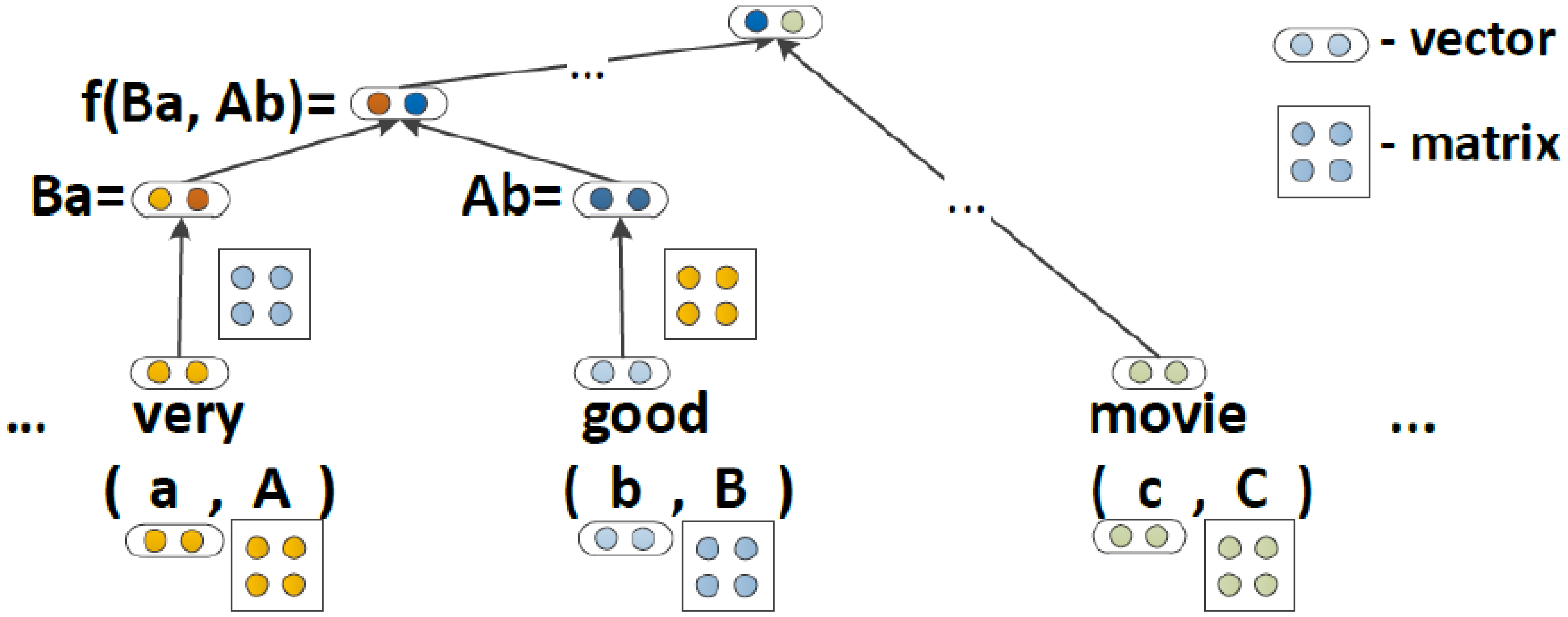
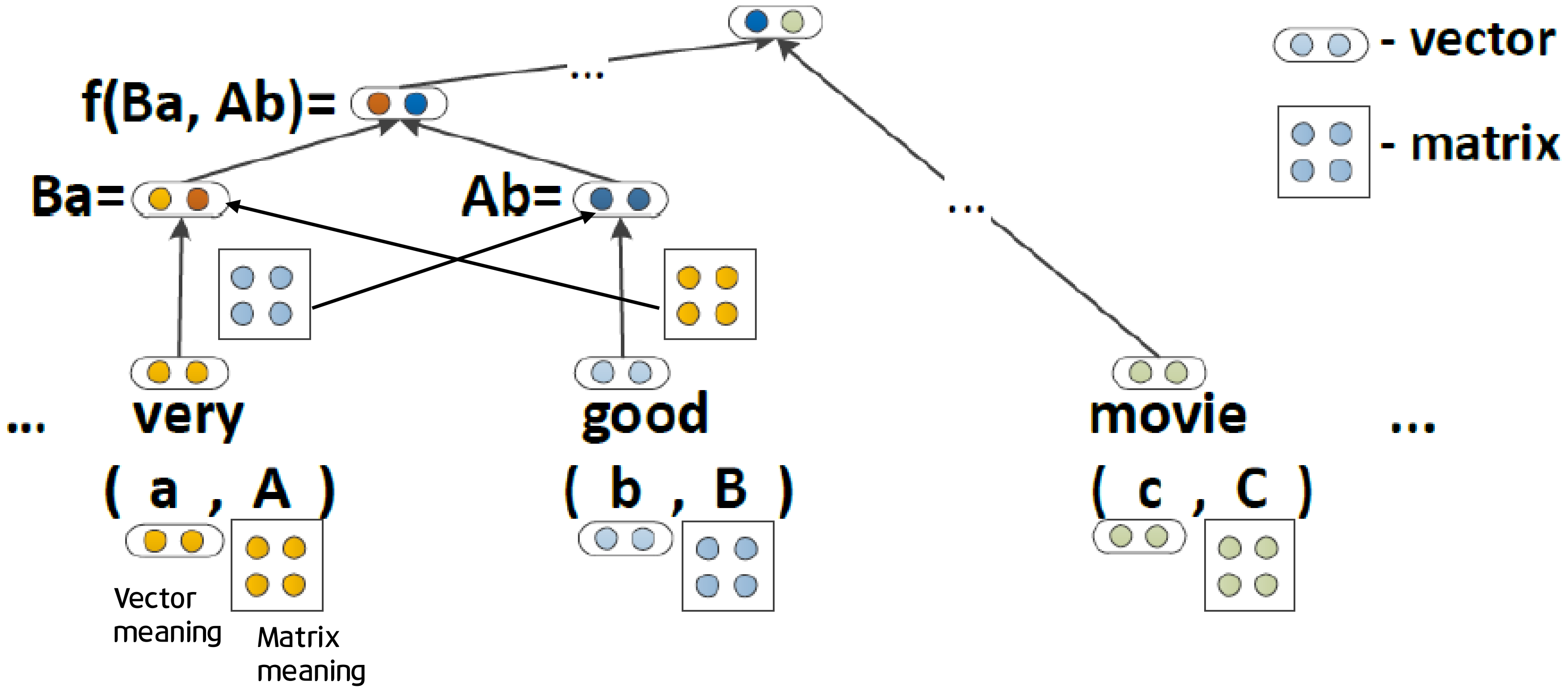


Matrix-Vector RNN

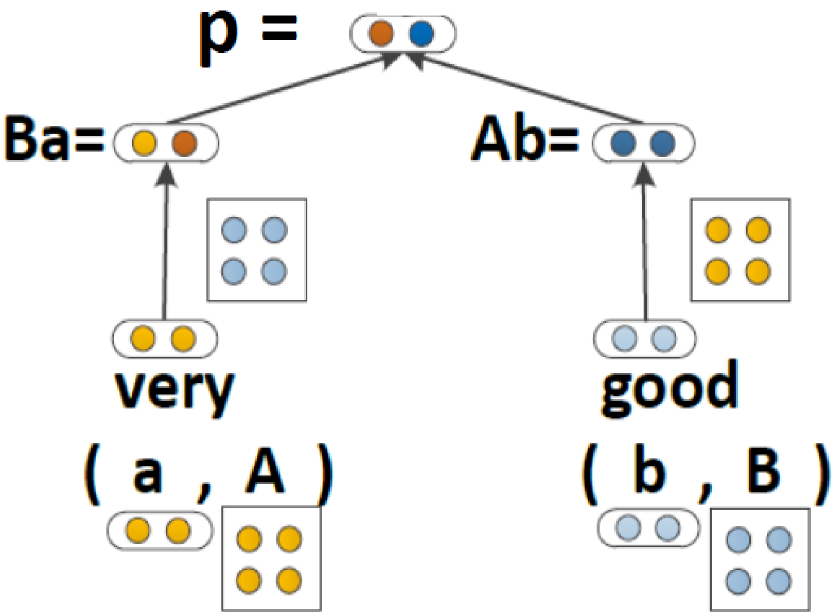


Matrix-Vector RNN



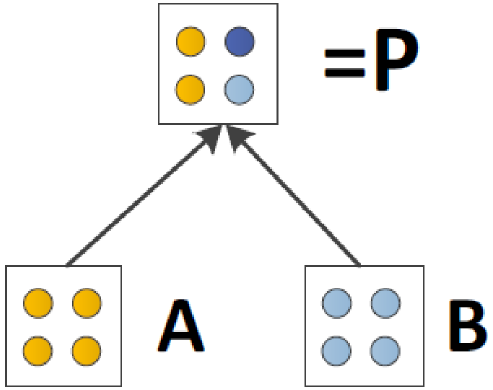
Matrix-Vector RNN

$$p = f\left(W \begin{bmatrix} Ba \\ Ab \end{bmatrix}\right)$$



$$P = g(A, B) = W_M \begin{bmatrix} A \\ B \end{bmatrix}$$

$$W_M \in \mathbb{R}^{n \times 2n}$$



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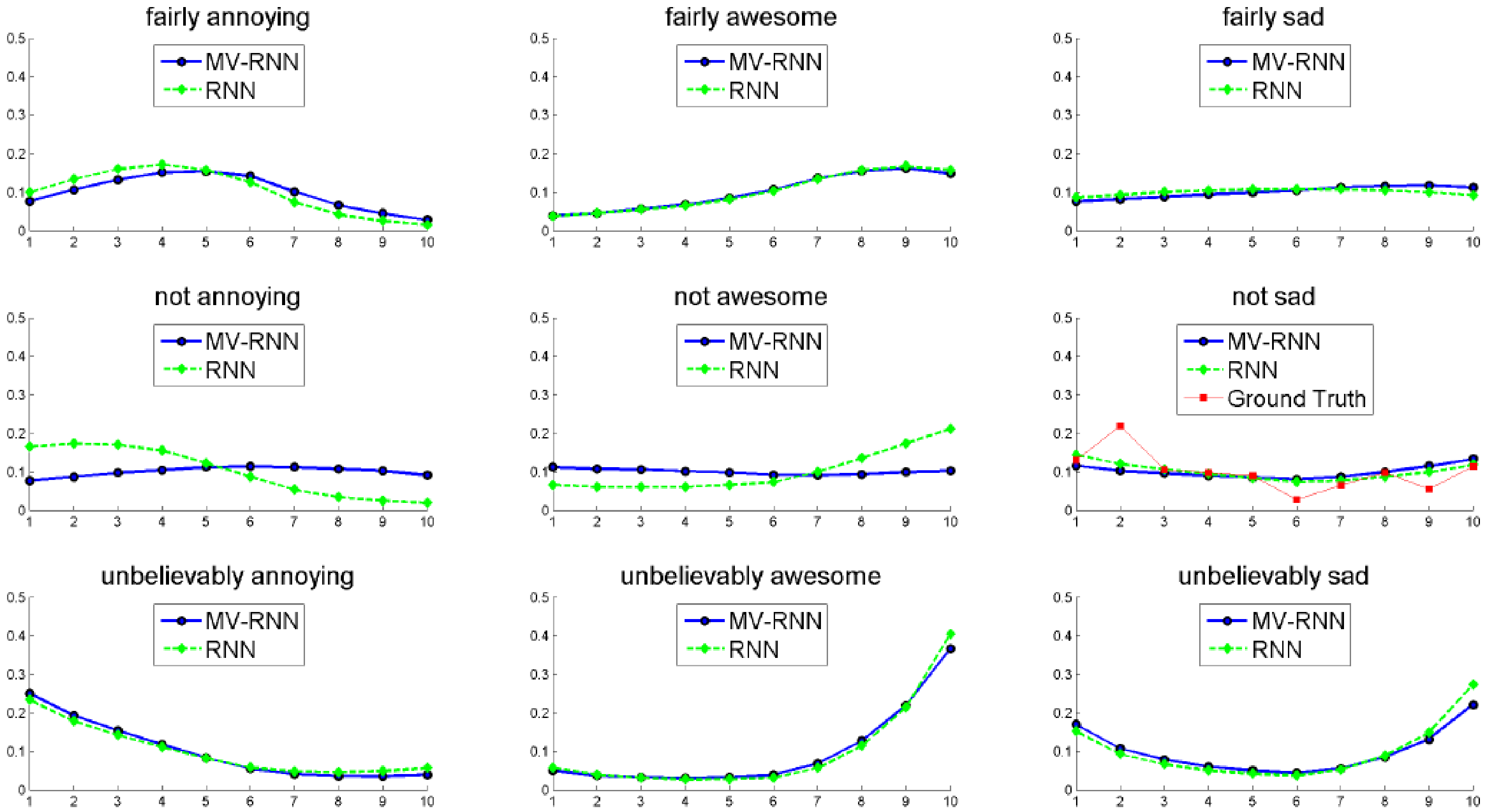

Sentiment detection

사실 감정분석을 하는건 어려운일은 아님.

Bag of Words를 통해 임베딩하여 문장을 분류하여도 90% 정도의 성능을 보인다고함.

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With this cast, and this subject matter, the movie

should have been funnier and more entertaining

슈드 해브 피피..

후회 + 긍정 -> 부정, meaning composition을 위해선 또 다른 무언가 필요!

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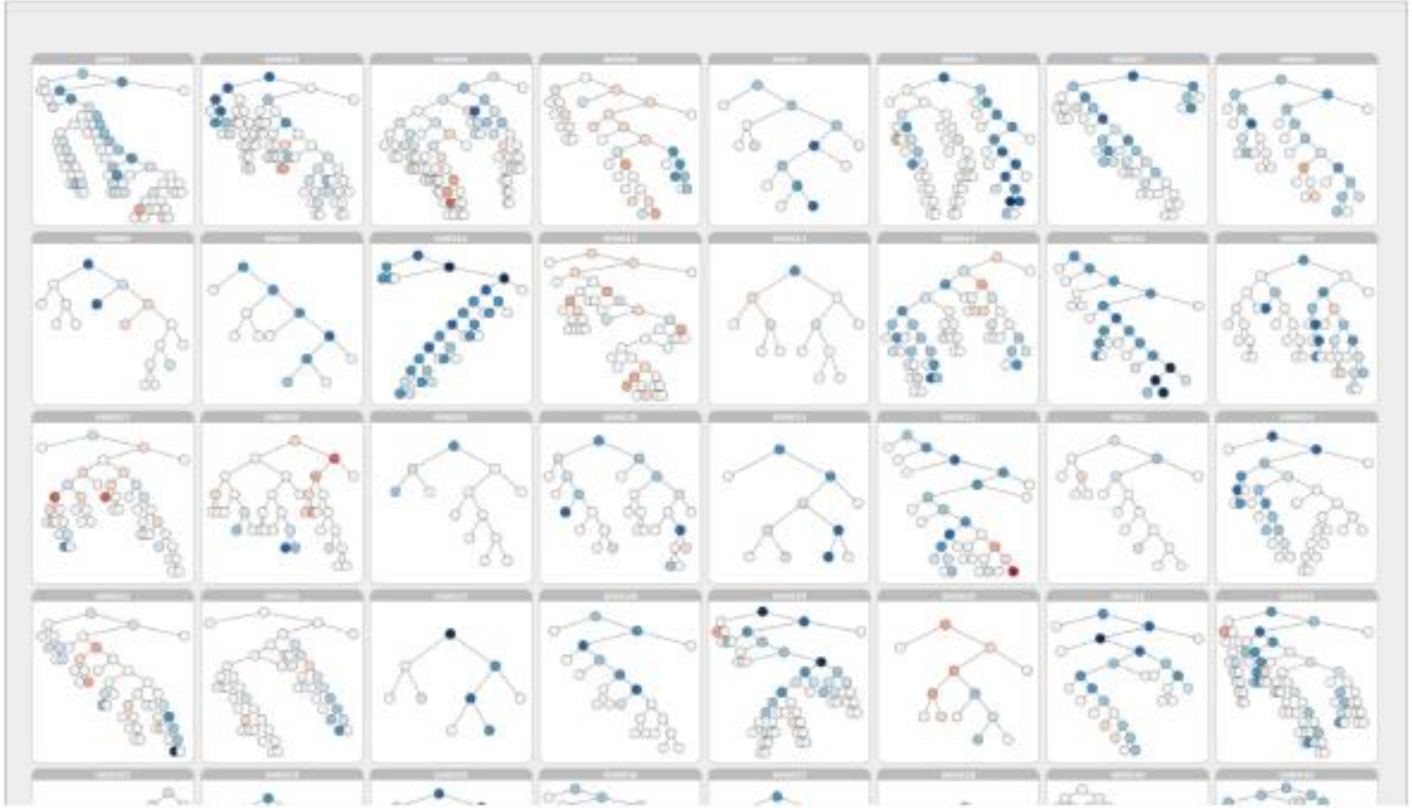
Stanford Sentiment Treebank



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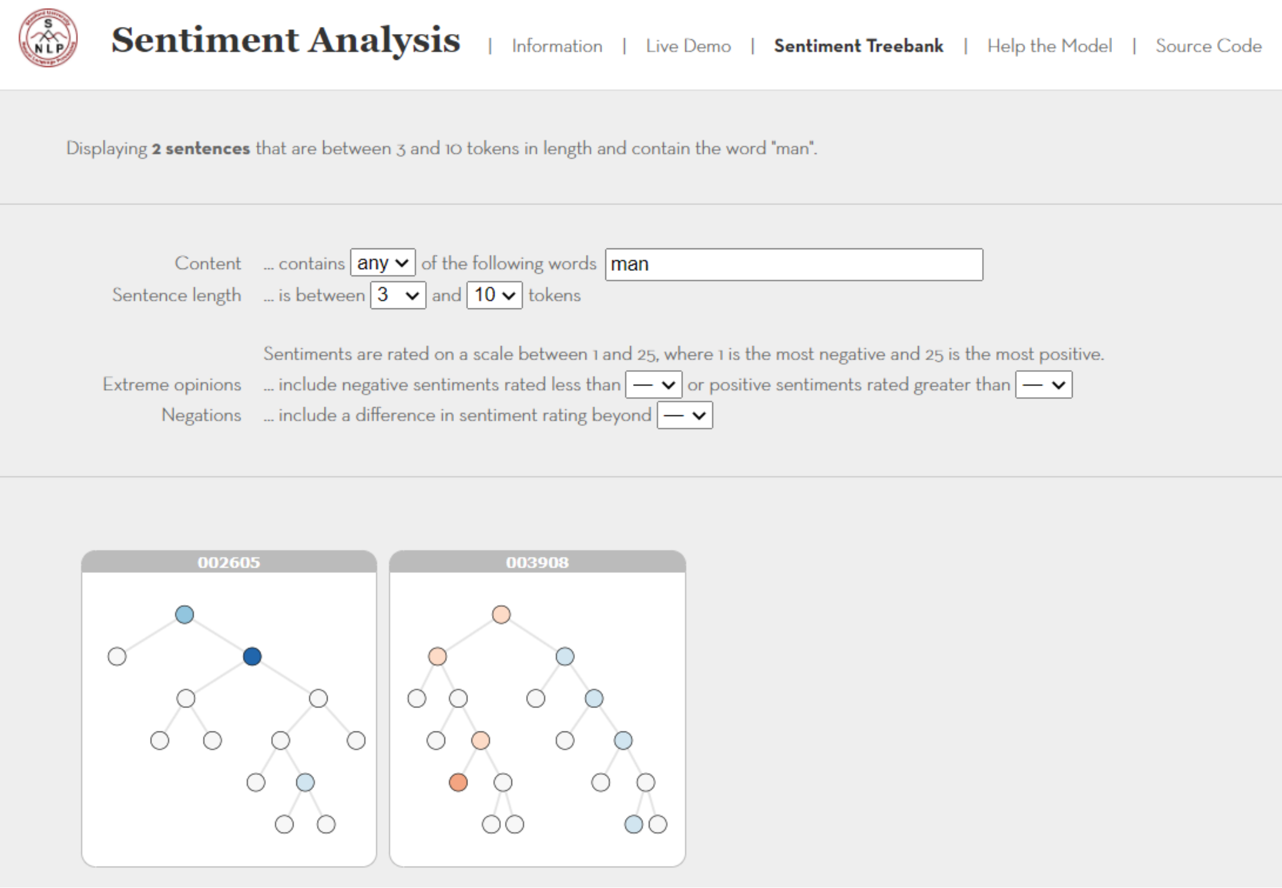
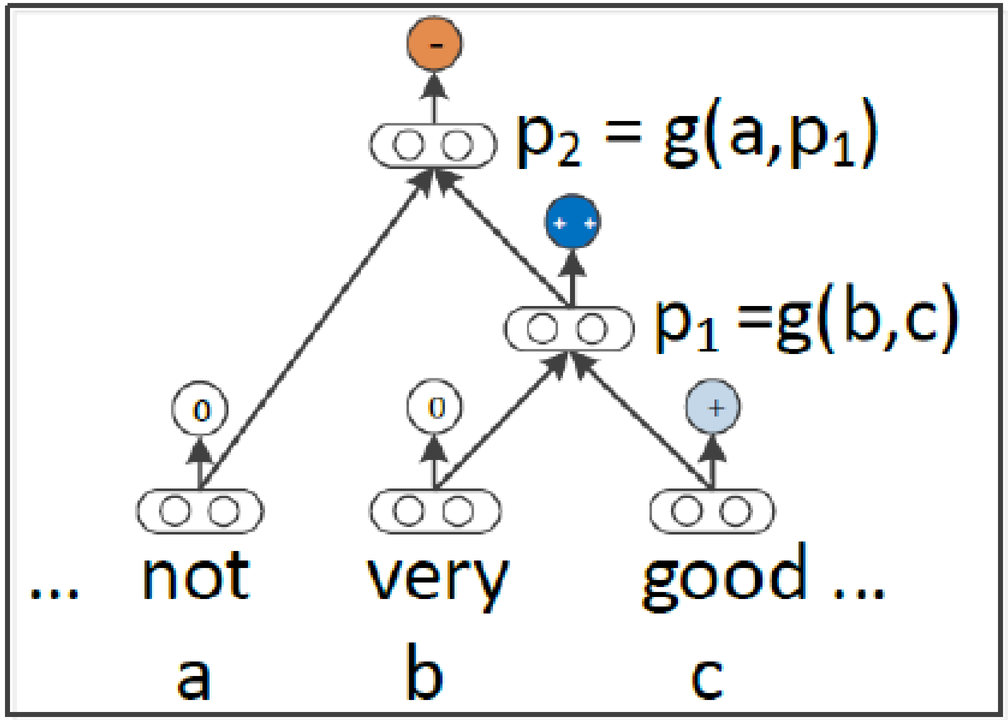
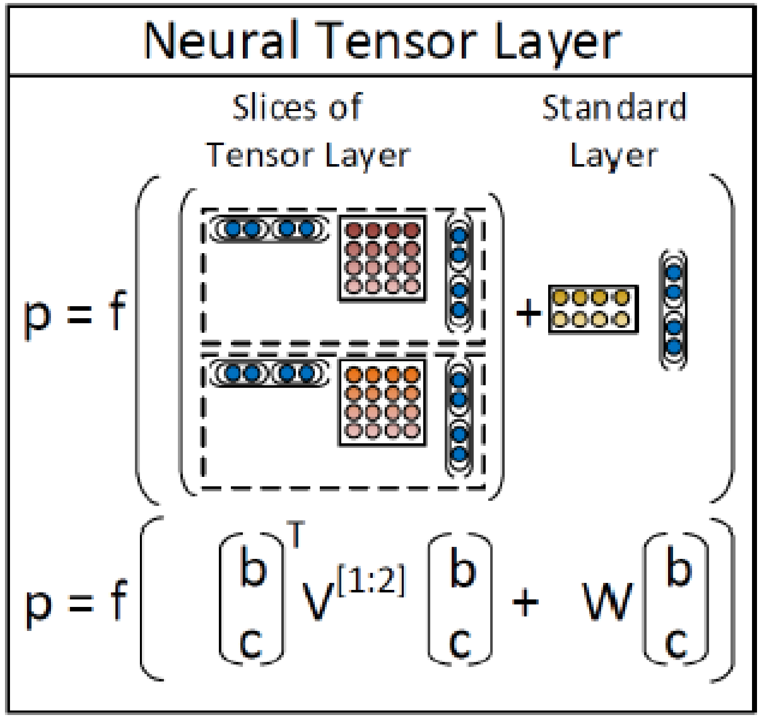


https://nlp.stanford.edu/sentiment/treebank.html

Recursive Neural Tensor Network





MV-RNN보다 더 적은 파라미터를 가짐.

MV-RNN은 모든 결합에 대해 각 노드마다 행렬을 생성하기 때문에 cost가 높음.

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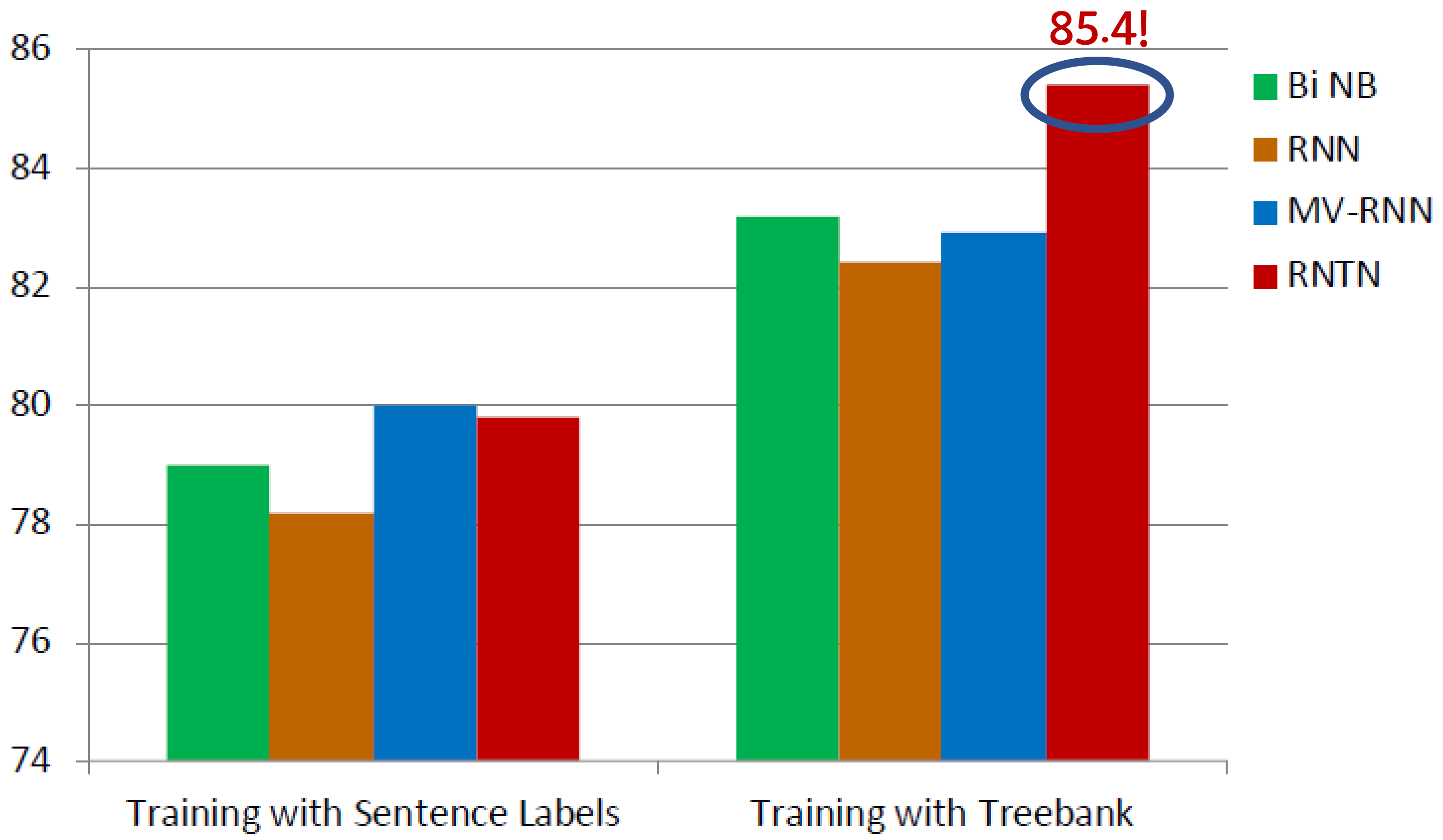
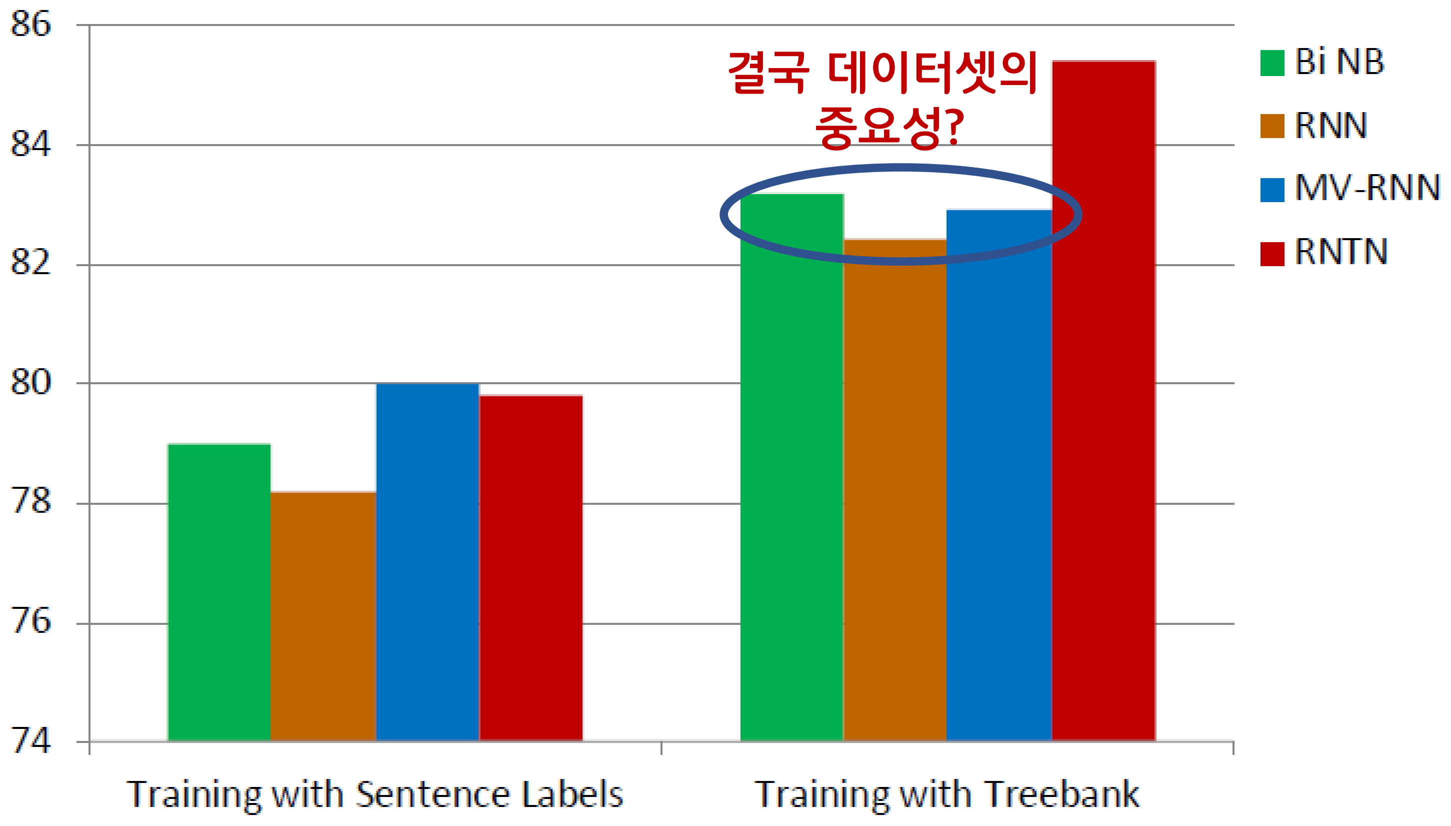
구분	simple Recursive Neural Network	MV-RNN	RNTN
Word Vector	$d \times 1$	$d \times 1$	$d \times 1$
Softmax W_S	$C \times d$	$C \times d$	$C \times d$
Compostion Weights	$W : d \times 2d$	$W : d \times 2d,$ $W_M : d \times 2d,$ $A, B, C \ldots : d \times d \times \lvert v \rvert$	$W : d \times 2d,$ $V^{[1:d]} : 2d \times 2d \times d$

Positive/Negative Results on Treebank



Positive/Negative Results on Treebank



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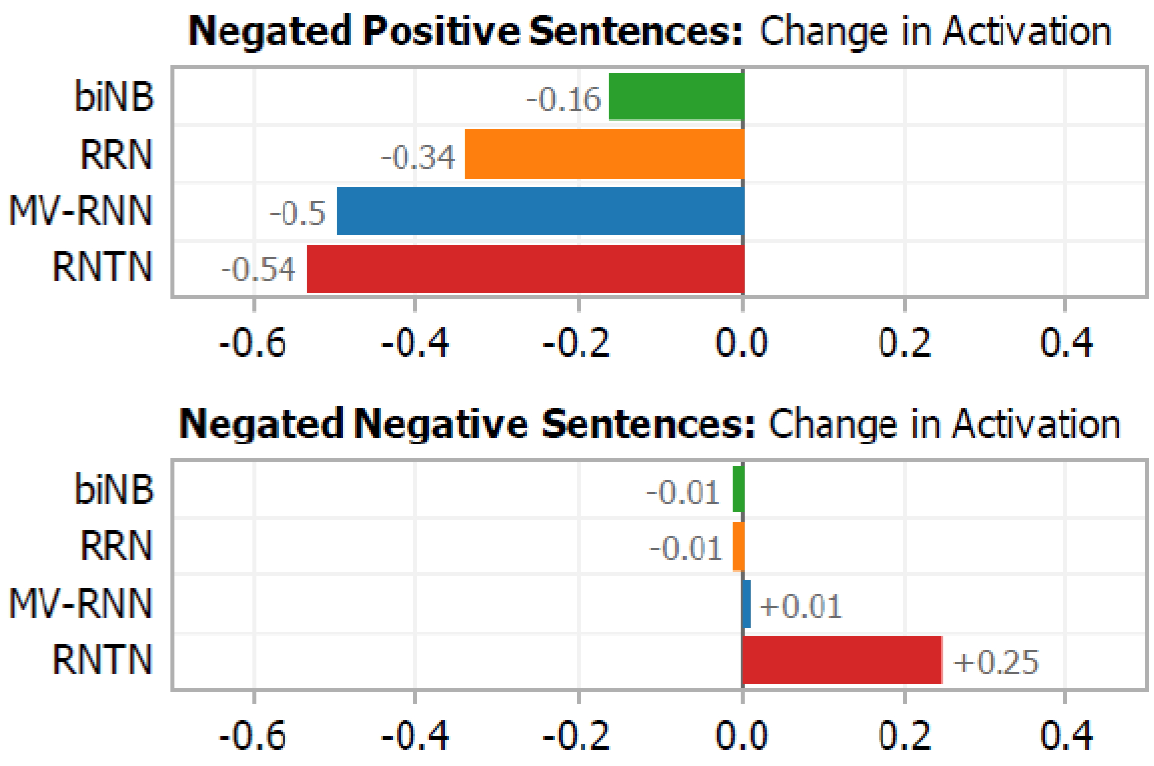

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한계점

1. Gpu 연산이 힘듦. 병렬적으로 이루어 져야하는데 모든 task 마다 연산 구조가 동일하지 않음. Tree 모양이 다름.

2. 데이터셋 구축이 어려움. 라벨링 ㅠ

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Tree-to-tree Neural Networks for Program Translation

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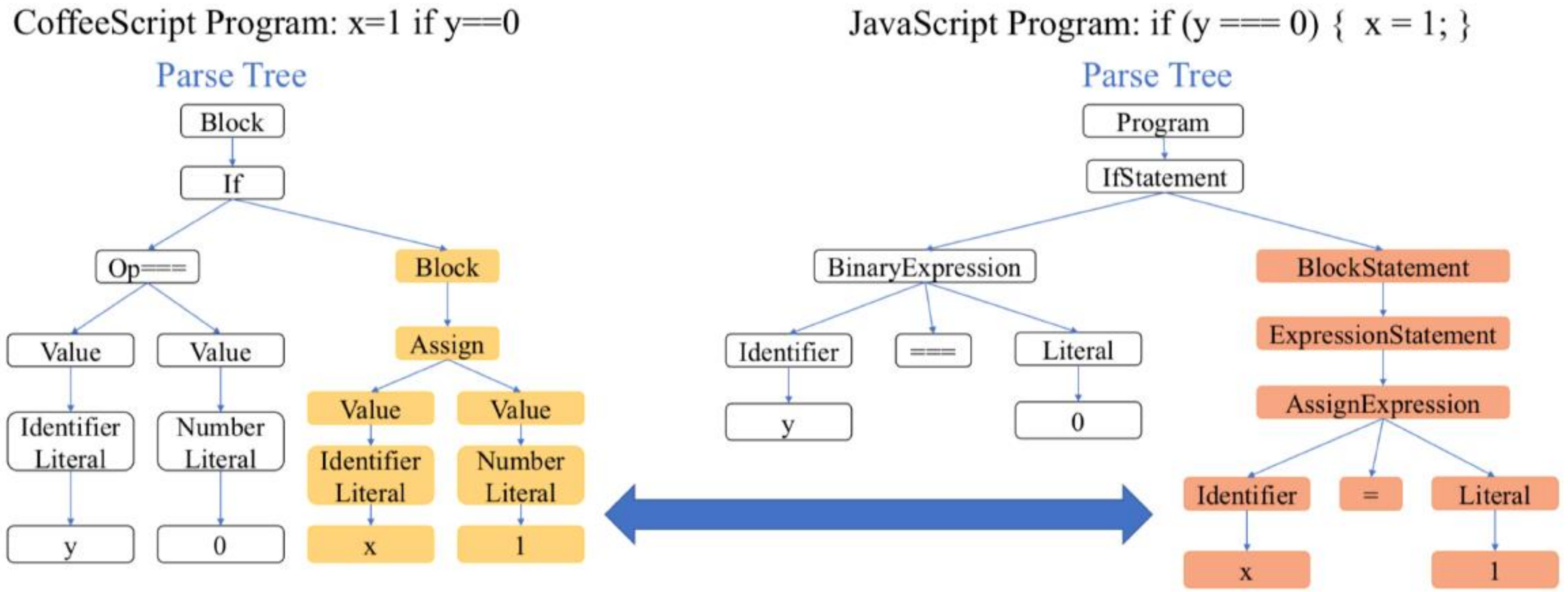
Abstract

Program translation is an important tool to migrate legacy code in one language into an ecosystem built in a different language. In this work, we are the first to employ deep neural networks toward tackling this problem. We observe that program translation is a modular procedure, in which a sub-tree of the source tree is translated into the corresponding target sub-tree at each step. To capture this intuition, we design a tree-to-tree neural network to translate a source tree into a target one. Meanwhile, we develop an attention mechanism for the tree-to-tree model, so that when the decoder expands one non-terminal in the target tree, the attention mechanism locates the corresponding sub-tree in the source tree to guide the expansion of the decoder. We evaluate the program translation capability of our tree-to-tree model against several state-of-the-art approaches. Compared against other neural translation models, we observe that our approach is consistently better than the baselines with a margin of up to 15 points. Further, our approach can improve the previous state-of-the-art program translation approaches by a margin of 20 points on the translation of real-world projects.

https://papers.nips.cc/paper/2018/file/d759175de8ea5b1d9a2660e45554894f-Paper.pdf

Tree-to-tree Nerual Networks for Program Translation



References

1. CS224n lecture 18: Consituency Parsing, Tree RNNs

2. https://ratsgo.github.io/deep%20learning/2017/04/03/recursive/

3. https://ratsgo.github.io/deep%20learning/2017/06/24/RNTN/

4. https://www.youtube.com/watch?v=TcNvkPoaXas&ab_channel=KoreaUnivDSBA