

Learning Continuous Phrase Representations and Syntactic Parsing with Recursive Neural Networks

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Introduction Motivation

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- Proper syntactic representations are of importance to tasks such as relation extraction and semantic role labeling
- *Recursive Neural Networks* (RNNs) can provide us with vector space representations that can be exploited during parsing
- It is even possible to jointly learn representation and parse using the same deep network

Introduction

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Vector Space Representation with Deep Learning

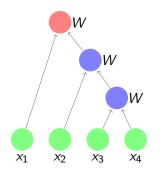
 Deep networks are commonly used to learn vector space representation of words → Word Embeddings

• RNNs generalize these embeddings for entire sentences

Methodology Recursive Neural Networks

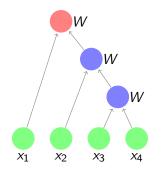
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They are deep networks where we use the same set of weights recursively over a deep hierarchical structure



Methodology Recursive Neural Networks

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score =
$$U^T p$$

 $p = tanh(W[x; y] + b)$

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Methodology

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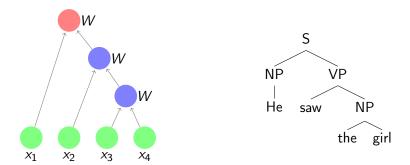
Recursive Neural Networks

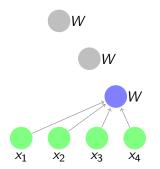
You might ask: Why do we believe RNNs are good for this?

Methodology Recursive Neural Networks

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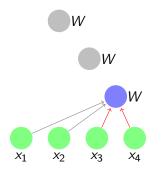


$$\forall i, j$$

$$score_{i,j} = U^{T} p_{i,j}$$

$$p_{i,j} = tanh(W[x_i; x_j] + b)$$

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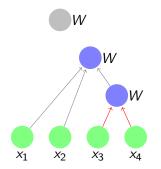


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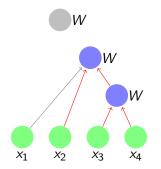
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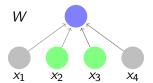
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Methodology Model 2: Greedy Context-aware RNN

Context introduced in the first layer by allowing the representations of context words to modify the parsing decision



$$score_{2,3} = U^T p_{2,3}$$

 $p_{2,3} = tanh(W[x_1; x_2; x_3; x_4] + b)$

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Methodology

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Model 3: Greedy, Context-aware RNN and Category Classifier

Extension to greedy CRNN model: adding to each node a layer to predict class labels.

$$P(y = c | \mathbf{x}) = softmax(\mathbf{w}_c^{\mathsf{T}} \mathbf{x}) = \frac{e^{\mathbf{w}_c^{\mathsf{T}} \mathbf{x}}}{\sum_{c=1}^{C} e^{\mathbf{w}_c^{\mathsf{T}} \mathbf{x}}}$$

Methodology

Model 4: Max-Margin Framework with Beam-Search

Instead of greedily collapse the best pairs:

• Formulate a global objective function that penalises choices far from the correct choice

$$\sum_i s(x_i, y_i) - \max_y (s(x_i, y) + \Delta(y, y_i)))$$

• Beam Search instead of Greedy Search to find the best parse

Methodology Training the RNN

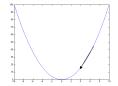
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We need to determine the set of weights W:

• Backpropagation

$$(f(g(x)))' = f'(g(x))g'(x)$$

Gradient descent



Methodology Training the RNN

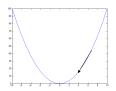
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Actually..

- Backpropagation Through Structure (BTS)
- Subgradient method

Experiments Word embeddings

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Word	Initial Collobert&Weston embedding	After RNN training
the	a, its, an, this, his, their, UNK	an, The, no, some, A, these, another
and	,, or, but, as, -, ., that, for, in	or, but, And, But, &, least
in	at, on, from, for, over, after, and, as	In, from, into, since, for, For, like, with,
that	which, but, " and, -, as, for, or, about, if	what, who, if, this, some, which, If
said	added, says, -, while, but, reported, on	says, fell, added, did, rose, sold, reported
he	she, it, they, which, also, now, who, we	they, I, we, you, It, she, it, He, We, They
share	high, higher, business, market, current, stock,	increase, bank, income, industry, issue, state,
	lower, increase, price, financial	sale, growth, unit, president
when	after, while, before, if, but, where, as	where, how, which, during, including

Experiments Sentence embeddings

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Center Phrase and Nearest Neighbors

(A) Sales grew almost 2 % to 222.2 million from 222.2 million.

- 1. Sales surged 22 % to 222.22 billion yen from 222.22 billion.
- 2. Revenue fell 2 % to 2.22 billion from 2.22 billion.
- 3. Sales rose more than 2 % to 22.2 million from 22.2 million.
- 4. Volume was 222.2 million shares, more than triple recent levels.

Experiments Parsing

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Method	F1
Model 1 (Greedy RNN)	76.55
Model 2 (Greedy, context-aware RNN)	83.36
Model 3 (Greedy, context-aware RNN + category classifier)	87.05
Model 4 (Beam, context-aware RNN + category classifier)	
Left Corner PCFG, [MC97]	90.64
Current Implementation of the Stanford Parser, [KM03]	93.98

Conclusion

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- Better word embeddings
- Sentence embeddings entailing syntactic and semantic information
- Almost state-of-the-art parsing