Linguistic Regularities in Continuous Space Word Representations

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NAACL 2013

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Abstract

- Neural network language model and distributed representation for words (Vector representation)
- Capture syntactic and remantic regularities in language

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• Outperform state-of-the-art

Word Representation

• One-hot Representation:

Example:

"nervous" : [0 1 0 0 0 0 0 0 0 0 0 0 0...] "tense " : [0 0 0 0 0 1 0 0 0 0 0 0...]

• Distributed Representation:

Example:

"nervous" : [0.792,-0.177,-0.107,0.109,...]

How to learn it?

- Neural Network Language Model
- Yoshua Bengio, 2003, A neural probabilistic language model

Language Model

• The essence of language model

- input: $w_1, w_2, ..., w_{t-1}$
- output: $P(w_t|w_1, w_2, ..., w_{t-1})$
- Traditional language model: N-gram
 - Let $p(w_t|w_{t-1}, w_{t-2}, ..., w_{t-n+1}) = P(w_t|w_1, w_2, ..., w_{t-1})$
 - Weakness: curse of dimensionality
 - Weakness: not considering the "similarity" between words

Example:

"The cat is walking in the bedroom" in the trainning corpus contributes little to

"The dog was running in a room"

Neural Network Language Model

- Associate with each word in the vocabulary a distributed word feature vector(a real-valued vector in ℝ^m)
 C("nervous") = [0.792, -0.177, -0.107, 0.109, ...]
- Express the joint probability function of word sequences in terms of the feature vectors
 p(w_t|w_{t-1},...,w_{t-n+1}) = f(C(w_t),...,C(w_{t-n+1}))

• Learn simultaneously the *word feature vectors* and the parameters of that *probability function*

Neural Network Language Model



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Neural Network Language Model

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- Layer1:(Input Layer)
 - Input vector x: m(n-1)
 - Matrix C: $|V| \times m$
- Layer2:(Hidden Layer)
 - Hidden vector $\vec{h} = d + Hx$
 - Matrix H: $h \times m(n-1)$
 - Vector d: h
- Layer3:(Output Layer)
 Output vector y: |V|
 y = b + Wx + Utanh(d + Hx)
- Softmax output layer: - $P(w_t|w_{t-1}, ..., w_{t-n+1}) = \frac{exp(y_{w_t})}{\sum_i exp(y_i)}$

Neural Network Language Model Extention

• CW

Collobert & Weston, 2011, JMLR Natural Language Processing(Almost) from Scratch

HLBL

Mnih & Hinton, 2007, ICML Three new graphical models for statistical language model

• RNN

Mikolov(RNN), 2012, PhD thesis Statistical Language Models based on Neural Networks

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Measuring Linguistic Regularity

• Syntactic test

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- "a is to b as c is to ?"
- base/comparative/superlative forms of adjectives
- singular/plural forms of common nouns

Category	Relation	Patterns Tested	# Questions	Example
Adjectives	Base/Comparative	JJ/JJR, JJR/JJ	1000	good:better rough:
Adjectives	Base/Superlative	JJ/JJS, JJS/JJ	1000	good:best rough:
Adjectives	Comparative/ Superlative	JJS/JJR, JJR/JJS	1000	better:best rougher:
Nouns	Singular/Plural	NN/NNS, NNS/NN	1000	year:years law:
Nouns	Non-possessive/ Possessive	NN/NN_POS, NN_POS/NN	1000	city:city's bank:
Verbs	Base/Past	VB/VBD, VBD/VB	1000	see:saw return:
Verbs	Base/3rd Person Singular Present	VB/VBZ, VBZ/VB	1000	see:sees return:
Verbs	Past/3rd Person Singular Present	VBD/VBZ, VBZ/VBD	1000	saw:sees returned:

Measuring Linguistic Regularity

Semantic test

- SemEval-2012 Task 2, Measuring Relation Similarity
- Given a group of word pairs, order the target pairs according to the degree to which this relation holds.

Subcategory	Relation name	Relation schema	Paradigms	Responses
8(e)	AGENT:GOAL	"Y is the goal of X "	pilgrim:shrine assassin:death climber:peak	patient:health runner:finish astronaut:space
5(e)	OBJECT: TYPICAL ACTION	"an X will typically Y"	glass:break soldier:fight juggernaut:crush	ice:melt lion:roar knife:stab
4(h)	DEFECTIVE	"an X is is a defect in Y "	fallacy:logic astigmatism:sight limp:walk	pimple:skin ignorance:learning tumor:body

Vector Offset Method

• To answer question a : b c : d where d is unknown compute $y = x_b - x_a + x_c$ $\omega^* = argmax_{\omega} \frac{x_{\omega}y}{\|x_{\omega}\| \|y\|}$



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Experimental Results

• Syntactic regularities identifying test

Method	Adjectives	Nouns	Verbs	All
LSA-80	9.2	11.1	17.4	12.8
LSA-320	11.3	18.1	20.7	16.5
LSA-640	9.6	10.1	13.8	11.3
RNN-80	9.3	5.2	30.4	16.2
RNN-320	18.2	19.0	45.0	28.5
RNN-640	21.0	25.2	54.8	34.7
RNN-1600	23.9	29.2	62.2	39.6

Experimental Results

• Syntactic regularities identifying test

Compared with other Neural Network Language Model

Method	Adjectives	Nouns	Verbs	All
RNN-80	10.1	8.1	30.4	19.0
CW-50	1.1	2.4	8.1	4.5
CW-100	1.3	4.1	8.6	5.0
HLBL-50	4.4	5.4	23.1	13.0
HLBL-100	7.6	13.2	30.2	18.7

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Experimental Results

• Semantic similarity test

Method	Spearman's ρ	MaxDiff Acc.
LSA-640	0.149	0.364
RNN-80	0.211	0.389
RNN-320	0.259	0.408
RNN-640	0.270	0.416
RNN-1600	0.275	0.418
CW-50	0.159	0.363
CW-100	0.154	0.363
HLBL-50	0.149	0.363
HLBL-100	0.146	0.362
UTD-NB	0.230	0.395

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