On metric embedding for boosting semantic similarity computations

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Word to Word Semantic Similarity

Distributional semantics

Word Embedding: learn a real-valued vector representation of words so that any vector distance – usually the cosine similarity – encodes the word-to-word semantic similarity

Knowledge base semantic similarity

Uses a taxonomy, usually Wordnet to compute semantic similarity between words. Methods based on graph metrics or information content

- **Graph metrics** HSO [Hirst and St-Onge, 1998], LCH [Leacock and Chodorow, 1998], WUP [Wu and Palmer, 1994]
- **Information Content** LESK [Banerjee and Pedersen, 2002], JCN [Jiang and Conrath, 1997]
- **Hybrid** RES [Resnik, 1995], LIN [Lin, 1998]

Performance

Quality

JCN and LCH present the best correlation with human ranking

Runtime

Both methods are slow, tens/hundreds of milliseconds for cold start, milliseconds afterward.

Going Faster

Finding Binary Codes

Is it possible to find binary codes so that their hamming distance preserve the semantic similarity ?

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Hint

For LCH, the similarity is a monotonic function of the shortest path distance in the Wordnet hypernym structure. => Metric Embedding

Metric Embedding

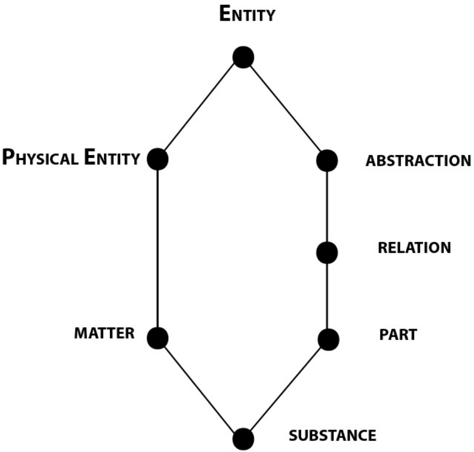
Definition

A metric embedding function f from a metric space (A, d_1) into (B, d_2) the is defined as follows

$$\forall(w_i, w_j), d_1(w_i, w_j) = \lambda \cdot d_2(f(w_i), f(w_j))$$

$w_i, w_j \in A$
λ is a scalar

Wordnet Hypernyms: a lattice



Sample lattice from Wordnet

Embedding, first try

Lattice into Hypercube

Deza and Laurent (1997) showed that a lattice with shortest path distance can be isometrically embedded into an hypercube of 2^n dimensions.

Issues

Dimensions too high: $\approx 2^{84.000}$ for Wordnet Synsets. Not a constructive proof.

Embedding, second try

Lattice is too complicated. What about a tree ?

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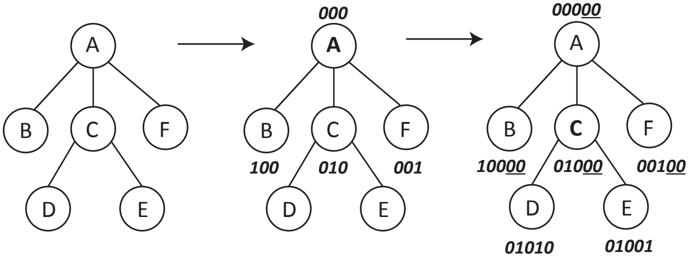
What the theory says

Isometric embedding: $n-1$ dimensions.

Isometric embedding of a tree



Construction of isometric embedding on a sample tree. For this six nodes tree, the embedding requires five bits.

Let's relax

Non isometric embedding

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Huge search space

$$C = \frac{(2^n)!}{(n-r)!}$$

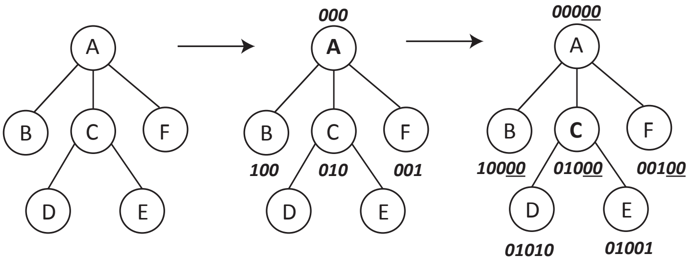
For 84K nodes (n) into a 64 (r) dimensional hypercube: $C > 10^{100,000}$

Let's be specific

Wordnet data

- *Branching factor* AVG: 4.9 - STD: 14. 96% of nodes < 20.
- *Depth* AVG: 8.5 - STD: 2. MAX: 18.

Let's recall



A
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C
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10000
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00100
D
E
01010
01001

Heuristic

We choose to preserve the parent-child distance instead of siblings distance.

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Unique signature

For each node with k children, we allocate $\lceil log_2(k+1) \rceil$ bits. Use best extension first (i.e respecting both distances).

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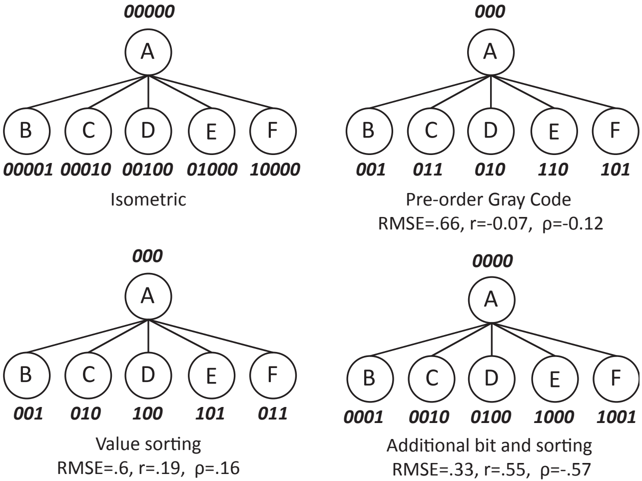
Word alignment

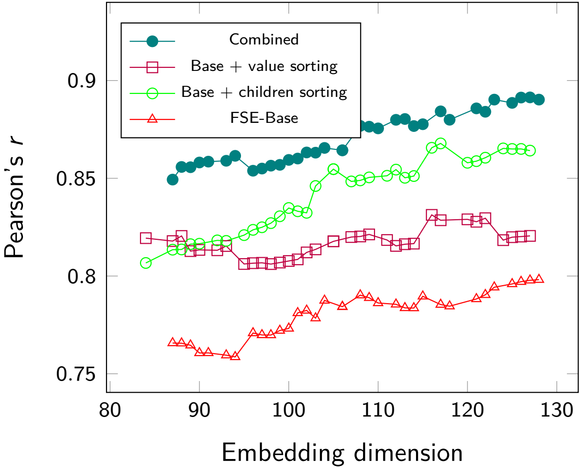
If the obtained embedding is not word aligned, we can use the remaining bits to enhance the embedding.

Example



Approaches to reduce the tree embedding dimensions.

Numerical Experiment I



FSE: influence of optimizations and dimensions on the correlation over the tree distance on Wordnet.

Numerical Experiment II

Embedding	Bits	Pearson's r	Spearman's ρ
Chen et al.	17	.235	.186
FSE-Base	84	.699	.707
FSE-Best	**128**	**.819**	**.829**
Isometric	84K	.919	.931

Correlations between LCH, isometric embedding, and FSE for all distances on all Wordnet-Core noun pairs (p-values $\leq 10^{-14}$).

Numerical Experiment III

Algo	Measure	Amount of pairs (n)				
		10^3	10^4	10^5	10^6	10^7
WS4J	$10^3 \cdot$ ms	0.156	1.196	11.32	123.89	1,129.3
FSE-Best	ms	0.04	0.59	14.15	150.58	1,482
speedup		$\times$3900	$\times$2027	$\times$800	$\times$822	$\times$762

Running time or pairwise similarity computations.

Application

Similar Sentence retrieval

Find semantic similar sentences using the hash values. Hash of a sentence is obtained using Simhash. [Bamba et al., 2012, Subercaze et al., 2013]

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Example

Token	Weight	Hash
a	3	1 0 1 1 0 1
b	2	0 1 1 0 0 1
c	1	1 0 0 1 1 1

Application

Similar Sentence retrieval

Find semantic similar sentences using the hash values. Hash of a sentence is obtained using Simhash. [Bamba et al., 2012, Subercaze et al., 2013]

Example - Set bit value to +/- weight

Token	Weight	Hash
a	3	3 -3 3 3 -3 3
b	2	-2 2 2 -2 -2 2
c	1	1 -1 -1 1 1 1

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Example - Sum the values

Token	Weight	Hash
a	3	3 -3 3 3 -3 3
b	2	-2 2 2 -2 -2 2
c	1	1 -1 -1 1 1 1
total		2 -2 4 2 -4 6

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Similar Sentence retrieval

Find semantic similar sentences using the hash values. Hash of a sentence is obtained using Simhash. [Bamba et al., 2012, Subercaze et al., 2013]

Example - Final hash

Token	Weight	Hash
a	3	3 -3 3 3 -3 3
b	2	-2 2 2 -2 -2 2
c	1	1 -1 -1 1 1 1
total		2 -2 4 2 -4 6
hash		1 0 1 1 0 1

Demonstration

Semantic similarity: short sentences.

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