Distributed Semantic Models for Word Vectors

Ramaseshan Ramachandran

Hyperspace Analogue To Language[1] (HAL)

HIGHLIGHTS OF THE HAL PAPER

Motivation

Human semantic memories are presumably constructed through experience with the world; as concepts are encountered, information about their meanings is accumulated.

Two problems of constructing semantic spaces manually

- Find a set of axes that define a concept
- Determine where each word should fall on each axis

This is a tedious process and an error-prone

HAL METHODOLOGY

1. A **weighted window** representing a span of words(n-grams) is moved across the corpus in one-word increments.

   Example

   Small corpus: A weighted window representing a span of words(n-grams) is moved across the corpus in one-word increments.

   n-grams

   ('By', 'moving', 'this') ('moving', 'this', 'window') ('this', 'window', 'over') ('window', 'over', 'the') ('over', 'the', 'source') ('the', 'source', 'corpus') $(\cdots)$
2. Capture the co-occurrence values of the words within it at every window movement to form a co-occurrence matrix.
3. Each cell of the matrix represents the summed co-occurrence counts for a single word pair (w_t, w_n)
4. The accumulation of values is direction sensitive

   The count of sequence "$w_1 w_2$" and count for the sequence "$w_2 w_1$" are different
5. For every word, there is both a row and a column containing relevant co-occurrence values, each one representing its concept axis

HAL SCANNING

Corpus: the horse raced past the barn fell

Left2Right Scanning

the	horse	raced	past	the	barn	fell
K	5	4	3	2	1	0

	horse	raced	past	the	barn	fell
	K	5	4	3	2	1

Right2Left Scanning

fell	barn	the	past	raced	horse	the
K	5	4	3	2	1	0

	barn	the	past	raced	horse	the
	K	5	4	3	2	1

Incidence Matrix

	the	horse	raced	past	barn	fell
the	2	3				
horse	5					
raced	4	5				
past	3	4				
barn	1	2				
fell		1				

	the	horse	raced	past	barn	fell
the						
horse						
raced						
past						
barn						
fell	4	1	2	3	5	

HAL ALGORITHM

Require a big corpus $>$5 GB for a reasonable similarity measures

1. Preprocess to limit the vocabulary size
2. Perform two scans using a ramping window of size 11 - first $\longrightarrow$ direction and later in the $\longleftarrow$ direction
3. Use the first word as the key word and the rest as context words
4. Use the last word as the key and rest as the context words, during the $\longleftarrow$ scanning
5. The nearest neighbor of the key gets the weight 10 and the 10th word gets the weight 1
6. Construct an incidence matrix using the co-occurrence values
7. Concatenate two word vectors found for every word (row and column) in the matrix Concatenate them to get the word vectors for all the words in the vocabulary.
8. The number of elements in the word vector will be $2||V|$

HAL EXPERIMENT

160 million words from Usenet news groups

Window size $= 10$

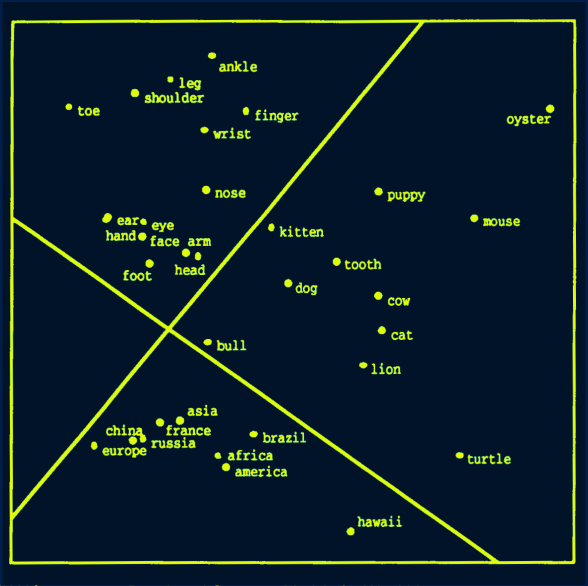
- Vocabulary - Words with a frequency > 50
- Zipf's law is used to eliminate most common and rare words
- Minkowski distance measure is used for computing word similarities

  $$d_{x_i y_j} = \sqrt[r]{|x_i - y_i|^r}$$
- The word vectors produce high dimensional semantic space - associative
- This is an unsupervised analysis of text
- Demonstrated sizable correlation between vector similarity and basic cognitive effects

RESULTS

Target	n1	n2	n3	n4	n5
jugs	juice	butter	vinegar	bottles	cans
leningrad	rome	iran	dresdan	azerbaijan	tibet
lipstick	lace	pink	cream	purple	soft
triumph	beauty	prime	grand	former	rolling
cardboard	plastic	rubber	glass	thin	tiny
monopoly	threat	huge	moral	gun	large

HAL WORD VECTORS - SIMILARITY CHART



CONCLUDING REMARKS - HAL

- HAL acquires contextual understanding of words by using the moving window and weighting co-occurrence distance.
- Using a large corpus, the co-occurrence matrix carries the history of this contextual experience
- The semantic vectors are representations that are essentially measures of context

IMPACT OF FREQUENCY MEASURE ON SIMILARITY

- Even if t_1 and t_2 are unrelated, if $p(t_1) \approx p(t_2)$, then their vectors will contain elements with similar magnitudes.

  $\implies$ any similarity measure

  For example, words a, an, the co-occur with many words in the vocabulary
- Conversely if they are related but $p(t_1) \ll p(t_2)$ then their vectors will contain elements with widely differing magnitudes, simply due to their differing co-occurrence probability.

In general, relative frequency does not imply semantic similarity. Hence we require normalized measures ro build word vectors.

REFERENCES

[1] Kevin Lund and Curt Burgess. "Producing high-dimensional semantic spaces from lexical co-occurrence". en. In: *Behavior Research Methods, Instruments, & Computers* 28.2 (1996), pp. 203–208. ISSN: 0743-3808, 1532-5970. DOI: 10.3758/BF03204766. URL: http://link.springer.com/article/10.3758/BF03204766 (visited on 09/09/2015).