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16 - Distributional Semantics

Information Retrieval

by

Dr. Rajendra Prasath

Indian Institute of Information Technology, Sri City, Chittoor

Sri City – 517 646, Andhra Pradesh, India

Topics Covered So Far

- Term Weighting
- Vector Space Models
- Evaluation Metrics
- Relevance Feedback / Pseudo Relevance Feedback
- Query Expansion appoaches
  - Dictionary Based Approach
  - Co-occurrence Based approach
  - Tag-Cloud Based Approach
  - Pseudo Relevance Based Approaches

Now:

Distributional Semantics

Recap: Overview

- Why Ranked Retrieval?
- Term Frequency
- Term Weighting
- TF-IDF Weighting
- The Vector Space Model
- Relevance Feedback
- Pseudo Relevance Feedback

Query Expansion

Query expansion

- Another Way to increase recall
- Global query expansion

  ⇒ global methods for query reformulation
- In global query expansion, the query is modified based on some global resource, i.e. a resource that is not query-dependent.
- Main information we use: (near-)synonymy
- A publication or database that collects (near-)synonyms is called a thesaurus.
- We will look at two types of thesauri: manually created and automatically created

Query expansion at search engines

- Main source of query expansion at search engines: query logs
- **Example 1:**
  After issuing the query [herbs], users frequently search for [herbal remedies].
  - "herbal remedies" is potential expansion of "herb"
- **Example 2:**
  a) Users searching for [flower pix] frequently click on: photobucket.com/flower
  b) Users searching for [flower clipart] frequently click on the same URL.
  - "flower clipart" and "flower pix" are potential expansions of each other.

Word Space Models

- How do we identify semantically related information that improves documents retrieval better

- User query terms are expanded based on terms with similar word senses that are discovered by the "**associatedness**" of the document context with that of the given query

- Can we capture the term contexts using higher order term associations and assists the effective retrieval of news documents

Motivations

- **Associatedness** - guided by word space models (Kanerva et al 2000)
- The word-space model computes the meaning of terms by implicitly utilizing the contexts of words collected over large text data
- The distributional patterns represent semantic similarity between words in terms of their spatial proximity in the context space
  - Words □ context vectors whose relative directions are assumed to indicate semantic similarity
- **Distributional hypothesis:**
  - words with similar meanings are assumed to have similar contexts
  - word space methodology makes semantics computable
  - Underlying models do not require linguistic or semantic expertise

Interesting Contributions

- Similarity assessment is conjectured to involve higher-order relationships, particularly in the models of analogical reasoning (Gentner and Forbus, 1991)
- Discovered higher-order distributional relations for textual CBR (Chakraborti et al., 2007; Deerwester et al., 1990)
- RI is an alternative to **Latent Semantic Indexing (LSI)** that reduces dimensionality (Kanerva et al., 2000; Sahlgren, 2005)
- Semantic behavior, word order information can be learned in an unsupervised way, using **Holographic Reduced Representations(HRR)** (Plate, 1995; Jones and Mewhort, 2007)
- We follow the evaluation measures proposed for the standard IR systems (Singhal et al., 1996; Raghunathan et al., 2008)

Interesting Contributions (contd)

- Bruninghaus et al. [5] NLP & IE methods to automatically extract relevant factual information without converting into structured documents.
- Harman [12] - Abductive inference reasons upon incomplete or inconsistent information
- Baddeley [3] - find context relationship between documents
- Kanerva [18, 17] - scalable distributional model – meaningful implicit relationships between terms in queries and documents
- Harris [13] - semantically similar terms occur in similar contexts □ semantically similar docs (no topic info)
- Johnson - Lindenstrauss Lemma [16] - a way of encoding textual information in the form of random projections.

LSI vs Random Indexing

- Latent Semantic Indexing (LSI) :
  - Sparse term - document matrix and Singular Value
  - Decomposition (SVD)
  - Not incremental
  - Dimensionality reduction

- Random Indexing (RI): uses distributional statistics for identifying the semantic similarity
  - Random index and context vectors - one for each term /
  - sentence / para - of fixed size
  - Incremental
  - Identifies implicit semantic relations

Distributional Hypothesis

Johnson-Lindenstrauss Lemma [1984]:

- A set of points in a high dimensional vector space can be mapped down into a reduced dimensional space such that the distance between any two points changes but not significantly

- This inherently leads to:
  - Dimensionality Reduction
  - Random Projections

Word Relations

- Associative relations - immediate relations to adjacent words:

  eat → food

- Synonymy relations - second order relations to words that share contexts:

  eat

  ↓

  drink

- word space methodology makes semantics computable and constitutes a purely descriptive approach to semantic modeling

Random Indexing

- **Index Vectors:**
  - each context (e.g. each document or each word) is assigned a unique and randomly generated representation
  - index vectors are sparse, high-dimensional, and ternary
  - their dimensionality (d) is in the order of thousands, and that they consist of a small number of randomly distributed +1s and -1s, with the rest of the elements of the vectors set to 0.
- **Context Vectors:**
  - context vectors are produced by scanning through the text
  - each time a word occurs in a context (within a sliding context window), that context's d-dimensional index vector is added to the context vector for the word in question.
  - Words are thus represented by d-dimensional context vectors that are effectively the sum of the words' contexts

Random Indexing (contd)

Context Vectors:

- For each occurrence of a given feature in all cases, we focus on a fixed window of size (2 × k) + 1 centered at the given feature [suggested window size is 5 (= term + / - k terms)]
- Then feature context vector for featurei is computed using the following equation:

$$C_{feature_i} = C_{feature_i} + \sum_{j=-k;j\neq 0}^{+k} I_{feature_{(i+j)}} \times \frac{1}{d^{|j|}}$$

- where 1/d|j| is the weight proportion w.r.to size j of window (d=2)

- Superposition is used while updating the context vector
- Adding two vectors x and y yields a vector z where z = x + y & the cosine similarities between x & z, and y & z will be high

RI – An Example

New Case: "The fisherman caught a big salmon today"
window size k = 2 , and we are training the feature **big**

The windowed sentence for the feature big looks like this:
The, [fisherman, caught, big, salmon, today].
The feature-context-vector Cbig for big becomes now:

$$C_{big} = C_{big} + (0.25 \times I_{fisherman}) + (0.5 \times I_{caught}) + (0.5 \times I_{salmon}) + (0.25 \times I_{today})$$

Meaning of a case is captured in the collective representation of the constituent features

Case Context Vectors:

- Case context vector = a weighted superposition of context vectors of features that occur in the case, as follows:

$$C_{case} = \sum_{i=1} f_i \times C_{feature_i}$$

where f_i is the number of occurrences of $feature_i$ in case.

Example: Consider 2 Sentences

Two sample sentences:

the weather is **fine** in Hong Kong

the weather is **nice** in Hong Kong

Generate random keys for each word within some context

Window:

weather	{ 0	-1	+1	0 }
is	{ 0	0	+1	-1 }
in	{ +1	0	0	-1 }
hong	{ +1	-1	0	0 }

Collect sums for words of interest:

	d1	d2	d3	d4
weather	{ 0	-1	+1	0 }
is	{ 0	0	+1	-1 }
in	{ +1	0	0	1 }
hong	{ +1	1	0	0 }
				+
fine	{ +2	2	+2	2 }
nice	{ +2	2	+2	2 }

Advantages of RI

- **RI is an incremental method**
  - Similarity computation even with a few examples

- Dimensionality d of the vectors is a parameter

- Random Indexing uses “implicit” dimension reduction
  - [Constant (much lower) dimensionality]

- Random Indexing can be used with any type of context
  - Other word space models typically use either documents or words as contexts

Summary

In this class, we focused on:

(a) Query Expansion

i. Thesaurus based Approach
ii. Co-occurrence Based Approach

(b) Distributional Semantics

i. Word Space Models
ii. Distributional Hypothesis
iii. Random Indexing
iv. Advantages of RI in IR

Acknowledgements

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1. Introduction to Information Retrieval Manning, Raghavan and Schutze, Cambridge University Press, 2008.
2. Search Engines Information Retrieval in Practice W. Bruce Croft, D. Metzler, T. Strohman, Pearson, 2009.
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4. Modern Information Retrieval Baeza-Yates and Ribeiro-Neto, Addison Wesley, 1999.
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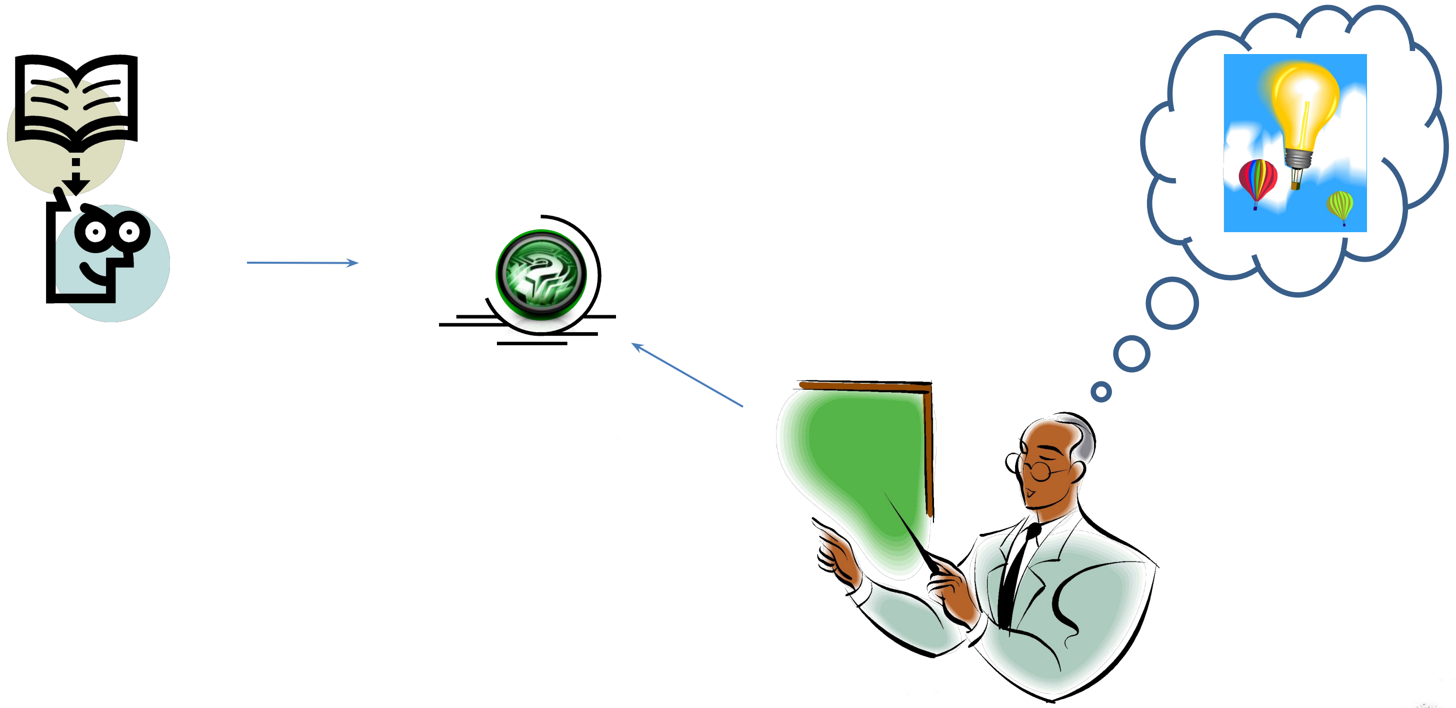

… Questions ???