

# *Distributional Semantics - Introduction*

Pawan Goyal

CSE, IIT Kharagpur

Week 7, Lecture 1

*What is Semantics?*

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John told Mary that the train moved out of the station at 3 o'clock.

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- **Formal Semantics:** Construction of precise mathematical models of the relations between expressions in a natural language and the world.  
*John chases a bat*  $\rightarrow \exists x[bat(x) \wedge chase(john, x)]$
- **Distributional Semantics:** The study of statistical patterns of human word usage to extract semantics.

# *Distributional Hypothesis*

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## *Distributional Hypothesis: Basic Intuition*

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*“You know a word by the company it keeps.” (Firth, 1957)*

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*“Words that occur in the same contexts tend to have similar meanings.” (Zellig Harris, 1968)*

→ Semantically similar words tend to have similar distributional patterns.

# *Distributional Semantics: a linguistic perspective*

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**Differential** and not *referential*

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He filled the **wampimuk** with the substance, passed it around and we all drunk some.

We found a little **wampimuk** sleeping behind the tree.

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- Computational models that build contextual semantic representations from corpus data

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- DSMs are models for semantic representations
  - ▶ The semantic content is represented by a vector
  - ▶ Vectors are obtained through the statistical analysis of the linguistic contexts of a word

# *Distributional Semantic Models (DSMs)*

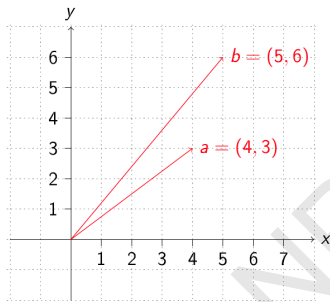
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- Alternative names
  - ▶ corpus-based semantics
  - ▶ statistical semantics
  - ▶ geometrical models of meaning
  - ▶ vector semantics
  - ▶ word space models



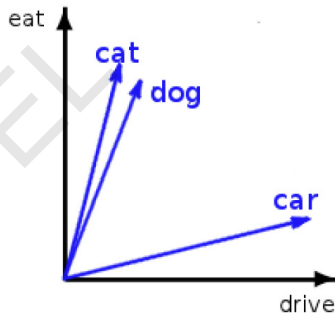
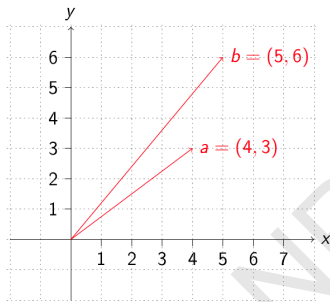
# *Distributional Semantics: The general intuition*

- **Distributions** are vectors in a multidimensional semantic space, that is, objects with a magnitude and a direction.
- The **semantic space** has dimensions which correspond to possible contexts, as gathered from a given corpus.

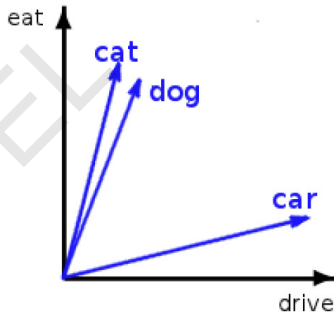
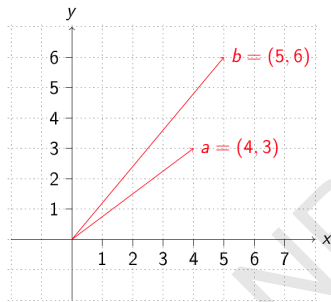
# Vector Space



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In practice, many more dimensions are used.

$cat = [...dog\ 0.8, eat\ 0.7, joke\ 0.01, mansion\ 0.2, ...]$

## *Small Dataset*

*An automobile is a wheeled motor vehicle used for transporting passengers .*

*A car is a form of transport , usually with four wheels and the capacity to carry around five passengers .*

*Transport for the London games is limited , with spectators strongly advised to avoid the use of cars .*

*The London 2012 soccer tournament began yesterday , with plenty of goals in the opening matches .*

*Giggs scored the first goal of the football tournament at Wembley , North London .*

*Bellamy was largely a passenger in the football match , playing no part in either goal .*

*Target words: 〈automobile, car, soccer, football〉*

*Term vocabulary: 〈wheel, transport, passenger, tournament, London, goal, match〉*

# Constructing Word spaces

Informal algorithm for constructing word spaces

- Pick the words you are interested in: **target words**

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**co-occurrence matrix**

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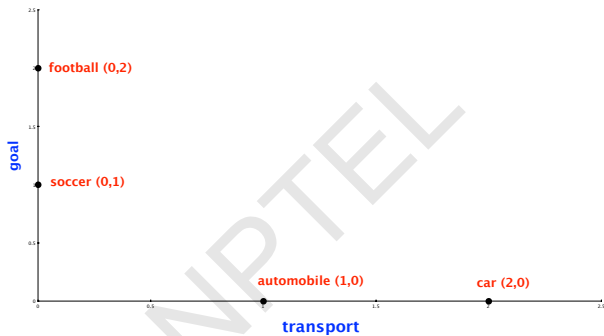
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- Count number of times the target word co-occurs with the context words:  
**co-occurrence matrix**
- Build vectors out of (a function of) these co-occurrence counts

# Constructing Word spaces: distributional vectors

distributional matrix = targets X contexts

	wheel	transport	passenger	tournament	London	goal	match
automobile	1	1	1	0	0	0	0
car	1	2	1	0	1	0	0
soccer	0	0	0	1	1	1	1
football	0	0	1	1	1	2	1



# Computing similarity

	wheel	transport	passenger	tournament	London	goal	match
automobile	1	1	1	0	0	0	0
car	1	2	1	0	1	0	0
soccer	0	0	0	1	1	1	1
football	0	0	1	1	1	2	1

## Using simple vector product

automobile . car = 4

automobile . soccer = 0

automobile . football = 1

car . soccer = 1

car . football = 2

soccer . football = 5

# *Distributional Models of Semantics*

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Week 7, Lecture 2

# *Vector Space Model without distributional similarity*

Words are treated as atomic symbols

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# Vector Space Model without distributional similarity

Words are treated as atomic symbols

*One-hot representation*

motel [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0] AND  
hotel [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0] = 0



# *Distributional Similarity Based Representations*

*You know a word by the company it keeps*

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*You know a word by the company it keeps*

government debt problems turning into banking crises as has happened in  
saying that Europe needs unified banking regulation to replace the hodgepodge

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*You know a word by the company it keeps*

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*These words will represent banking*

# Building a DSM step-by-step

## *The “linguistic” steps*

Pre-process a corpus (to define targets and contexts)



Select the targets and the contexts

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# Building a DSM step-by-step

## The “linguistic” steps

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Select the targets and the contexts

## The “mathematical” steps

Count the target-context co-occurrences



Weight the contexts (optional)



Build the distributional matrix



Reduce the matrix dimensions (optional)



Compute the vector distances on the (reduced) matrix

# Many design choices

Matrix type		Weighting		Dimensionality reduction		Vector comparison
word $\times$ document		probabilities		LSA		Euclidean
word $\times$ word		length normalization		PLSA		Cosine
word $\times$ search proximity	$\times$	TF-IDF	$\times$	LDA	$\times$	Dice
adj. $\times$ modified noun		PMI		PCA		Jaccard
word $\times$ dependency rel.		Positive PMI		IS		KL
verb $\times$ arguments		PPMI with discounting		DCA		KL with skew
$\vdots$		$\vdots$		$\vdots$		$\vdots$

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## General Questions

- How do the rows (words, ...) relate to each other?
- How do the columns (contexts, documents, ...) relate to each other?

# The parameter space

## *A number of parameters to be fixed*

- Which type of context?
- Which weighting scheme?
- Which similarity measure?
- ...

A specific parameter setting determines a particular type of DSM (e.g. LSA, HAL, etc.)



## *Documents as context: Word $\times$ document*

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
against	0	0	0	1	0	0	3	2	3	0
age	0	0	0	1	0	3	1	0	4	0
agent	0	0	0	0	0	0	0	0	0	0
ages	0	0	0	0	0	2	0	0	0	0
ago	0	0	0	2	0	0	0	0	3	0
agree	0	1	0	0	0	0	0	0	0	0
ahead	0	0	0	1	0	0	0	0	0	0
ain't	0	0	0	0	0	0	0	0	0	0
air	0	0	0	0	0	0	0	0	0	0
aka	0	0	0	1	0	0	0	0	0	0

# Words as context: Word $\times$ Word

	against	age	agent	ages	ago	agree	ahead	ain.t	air	aka	al
against	2003	90	39	20	88	57	33	15	58	22	24
age	90	1492	14	39	71	38	12	4	18	4	39
agent	39	14	507	2	21	5	10	3	9	8	25
ages	20	39	2	290	32	5	4	3	6	1	6
ago	88	71	21	32	1164	37	25	11	34	11	38
agree	57	38	5	5	37	627	12	2	16	19	14
ahead	33	12	10	4	25	12	429	4	12	10	7
ain't	15	4	3	3	11	2	4	166	0	3	3
air	58	18	9	6	34	16	12	0	746	5	11
aka	22	4	8	1	11	19	10	3	5	261	9
al	24	39	25	6	38	14	7	3	11	9	861

## Parameters

- Window size
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## Consider the following passage

*Suspected communist rebels on 4 July 1989 killed Col. Herminio Taylo, police chief of Makati, the Philippines major financial center, in an escalation of street violence sweeping the Capitol area. The gunmen shouted references to the rebel New People's Army. They fled in a commandeered passenger jeep. The military says communist rebels have killed up to 65 soldiers and police in the Capitol region since January.*

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## Indexing function $F$ : Essential factors

- **Word frequency ( $f_{ij}$ ):** How many times a word appears in the document?

$$F \propto f_{ij}$$

- **Document length ( $|D_i|$ ):** How many words appear in the document?

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## Indexing Weight: $tf$ - $Idf$

- $f_{ij} * \log(\frac{N}{N_j})$  for each term, normalize the weight in a document with respect to  $L_2$ -norm.

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## *basic intuition*

word1	word2	freq(1,2)	freq(1)	freq(2)
dog	small	855	33,338	490,580
dog	domesticated	29	33,338	918

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- different measures - e.g., Mutual information, Log-likelihood ratio

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$$P_{corpus}(w_1, w_2) = \frac{freq(w_1, w_2)}{N}$$

$$P_{corpus}(w) = \frac{freq(w)}{N}$$

# *PMI: Issues and Variations*

## *Positive PMI*

All PMI values less than zero are replaced with zero.

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## Bias towards infrequent events

Consider  $w_j$  having the maximum association with  $w_i$ ,

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PMI increases as the probability of  $w_i$  decreases.

Also, consider a word  $w_j$  that occurs once in the corpus, also in the context of  $w_i$ . A discounting factor proposed by Pantel and Lin:

$$\delta_{ij} = \frac{f_{ij}}{f_{ij} + 1} \frac{\min(f_i, f_j)}{\min(f_i, f_j) + 1}$$

$$PMI_{\text{new}}(w_i, w_j) = \delta_{ij} PMI(w_i, w_j)$$

# Distributional Vectors: Example

## Normalized Distributional Vectors using Pointwise Mutual Information

<b>petroleum</b>	oil:0.032 gas:0.029 crude:0.029 barrels:0.028 exploration:0.027 barrel:0.026 opec:0.026 refining:0.026 gasoline:0.026 fuel:0.025 natural:0.025 exporting:0.025
<b>drug</b>	trafficking:0.029 cocaine:0.028 narcotics:0.027 fda:0.026 police:0.026 abuse:0.026 marijuana:0.025 crime:0.025 colombian:0.025 arrested:0.025 addicts:0.024
<b>insurance</b>	insurers:0.028 premiums:0.028 lloyds:0.026 reinsurance:0.026 underwriting:0.025 pension:0.025 mortgage:0.025 credit:0.025 investors:0.024 claims:0.024 benefits:0.024
<b>forest</b>	timber:0.028 trees:0.027 land:0.027 forestry:0.026 environmental:0.026 species:0.026 wildlife:0.026 habitat:0.025 tree:0.025 mountain:0.025 river:0.025 lake:0.025
<b>robotics</b>	robots:0.032 automation:0.029 technology:0.028 engineering:0.026 systems:0.026 sensors:0.025 welding:0.025 computer:0.025 manufacturing:0.025 automated:0.025



# *Distributional Semantics: Applications, Structured Models*

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Week 7, Lecture 3

# Application to Query Expansion: Addressing Term Mismatch

## Term Mismatch Problem in Information Retrieval

- Stems from the word independence assumption during document indexing.
- User query: *insurance cover which pays for long term care*.
- A relevant document may contain terms different from the actual user query.
- Some relevant words concerning this query:  $\{\text{medicare, premiums, insurers}\}$

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## Using DSMs for Query Expansion

Given a user query, reformulate it using related terms to enhance the retrieval performance.

- The distributional vectors for the query terms are computed.
- Expanded query is obtained by a linear combination or a functional combination of these vectors.

# Query Expansion using Unstructured DSMs

## *TREC Topic 104: catastrophic health insurance*

**Query Representation:** surtax:1.0 hcfa:0.97 medicare:0.93 hmos:0.83  
medicaid:0.8 hmo:0.78 beneficiaries:0.75 ambulatory:0.72 premiums:0.72  
hospitalization:0.71 hhs:0.7 reimbursable:0.7 deductible:0.69

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- Broad expansion terms: **medicare, beneficiaries, premiums** ...
- Specific domain terms: **HCFA** (Health Care Financing Administration), **HMO** (Health Maintenance Organization), **HHS** (Health and Human Services)

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- Specific domain terms: **HCFA** (Health Care Financing Administration), **HMO** (Health Maintenance Organization), **HHS** (Health and Human Services)

## *TREC Topic 355: ocean remote sensing*

**Query Representation:** radiometer:1.0 landsat:0.97 ionosphere:0.94  
cnes:0.84 altimeter:0.83 nasda:0.81 meterology:0.81 cartography:0.78  
geostationary:0.78 doppler:0.78 oceanographic:0.76

# Query Expansion using Unstructured DSMs

## TREC Topic 104: catastrophic health insurance

**Query Representation:** surtax:1.0 hcfa:0.97 medicare:0.93 hmos:0.83  
medicaid:0.8 hmo:0.78 beneficiaries:0.75 ambulatory:0.72 premiums:0.72  
hospitalization:0.71 hhs:0.7 reimbursable:0.7 deductible:0.69

- Broad expansion terms: **medicare**, **beneficiaries**, **premiums** ...
- Specific domain terms: **HCFA** (Health Care Financing Administration), **HMO** (Health Maintenance Organization), **HHS** (Health and Human Services)

## TREC Topic 355: ocean remote sensing

**Query Representation:** radiometer:1.0 landsat:0.97 ionosphere:0.94  
cnes:0.84 altimeter:0.83 nasda:0.81 meterology:0.81 cartography:0.78  
geostationary:0.78 doppler:0.78 oceanographic:0.76

- Broad expansion terms: **radiometer**, **landsat**, **ionosphere** ...
- Specific domain terms: **CNES** (Centre National d'Études Spatiales) and **NASDA** (National Space Development Agency of Japan)

# Similarity Measures for Binary Vectors

Let  $X$  and  $Y$  denote the binary distributional vectors for words  $X$  and  $Y$ .

## Similarity Measures

$$\text{Dice coefficient} : \frac{2|X \cap Y|}{|X| + |Y|}$$



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*Jaccard coefficient penalizes small number of shared entries, while Overlap coefficient uses the concept of inclusion.*

# Similarity Measures for Vector Spaces

Let  $\vec{X}$  and  $\vec{Y}$  denote the distributional vectors for words  $X$  and  $Y$ .  
 $\vec{X} = [x_1, x_2, \dots, x_n]$ ,  $\vec{Y} = [y_1, y_2, \dots, y_n]$

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$$\text{Euclidean distance : } |\vec{X} - \vec{Y}| = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

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Let  $p$  and  $q$  denote the probability distributions corresponding to two distributional vectors.

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## Similarity Measures

$$\text{KL-divergence : } D(p||q) = \sum_i p_i \log \frac{p_i}{q_i}$$

$$\text{Information Radius : } D(p||\frac{p+q}{2}) + D(q||\frac{p+q}{2})$$

$$L_1\text{-norm : } \sum_i |p_i - q_i|$$



# Attributional Similarity vs. Relational Similarity

## Attributional Similarity

The attributional similarity between two words  $a$  and  $b$  depends on the degree of correspondence between the properties of  $a$  and  $b$ .

Ex: *dog and wolf*

## Relational Similarity

Two pairs  $(a, b)$  and  $(c, d)$  are relationally similar if they have many similar relations.

Ex: *dog: bark and cat: meow*

# Relational Similarity: Pair-pattern matrix

## Pair-pattern matrix

- Row vectors correspond to pairs of words, such as *mason: stone* and *carpenter: wood*
- Column vectors correspond to the patterns in which the pairs occur, e.g. *X cuts Y* and *X works with Y*
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## Extended Distributional Hypothesis; Lin and Pantel

Patterns that co-occur with similar pairs tend to have similar meanings.

This matrix can also be used to measure the semantic similarity of patterns.

Given a pattern such as “X solves Y”, you can use this matrix to find similar patterns, such as “Y is solved by X”, “Y is resolved in X”, “X resolves Y”.

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- Words may not be the basic context units anymore
- How to capture and represent syntactic information?  
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Use Dependency grammar framework

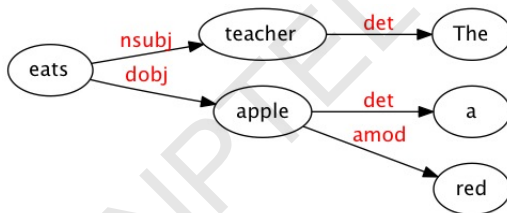


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# Structured DSMs

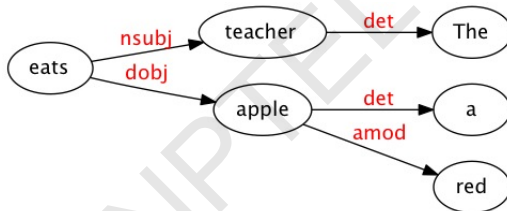
*Using Dependency Structure: How does it help?*

*The teacher eats a red apple.*



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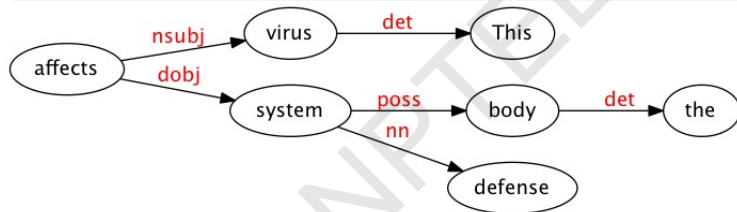
- 'eat' is not a legitimate context for 'red'.
- The 'object' relation connecting 'eat' and 'apple' is treated as a different type of co-occurrence from the 'modifier' relation linking 'red' and 'apple'.

## *Structured DSMs: Words as 'legitimate' contexts*

- Co-occurrence statistics are collected using parser-extracted relations.
- To qualify as context of a target item, a word must be linked to it by some (interesting) lexico-syntactic relation

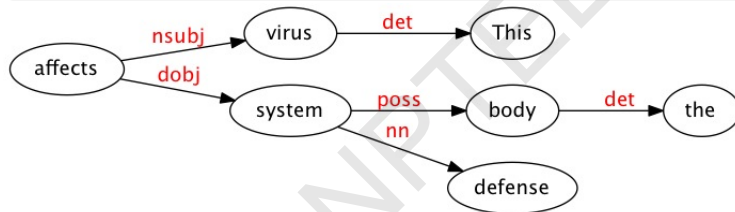
## *Distributional models, as guided by dependency*

Ex: For the sentence 'This virus affects the body's defense system.', the dependency parse is:



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## Word vectors

<system, dobj, affects> ...

Corpus-derived ternary data can also be mapped onto a 2-way matrix

## 2-way matrix

<system, dobj, affects>

<virus, nsubj, affects>

*The dependency information can be dropped*

- <system, dobj, affects>  $\Rightarrow$  <system, affects>
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- <system, dobj, affects>  $\Rightarrow$  <system, affects>
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*Link and one word can be concatenated and treated as attributes*

- virus={nsubj-affects:0.05,...},
- system={dobj-affects:0.03,...}



# Structured DSMs for Selectional Preferences

## *Selectional Preferences for Verbs*

Most verbs prefer arguments of a particular type. This regularity is known as selectional preference.

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	obj-carry	obj-buy	obj-drive	obj-eat	obj-store	sub-fly	...
car	0.1	0.4	0.8	0.02	0.2	0.05	...
vegetable	0.3	0.5	0	0.6	0.3	0.05	...
biscuit	0.4	0.4	0	0.5	0.4	0.02	...
...	...	...	...	...	...	...	...

# Structured DSMs for Selectional Preferences

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- The complete vectors of these  $n$  nouns are used to obtain an 'object prototype' of the verb.
- 'object prototype' will indicate various attributes such as these nouns can be consumed, bought, carried, stored etc.
- Similarity of a noun to this 'object prototype' is used to denote the plausibility of that noun being an object of verb 'eat'.



# *Word Embeddings - Part I*

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Week 7, Lecture 4

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- In a simple 1-of-N (or 'one-hot') encoding every element in the vector is associated with a word in the vocabulary.

# Word Vectors

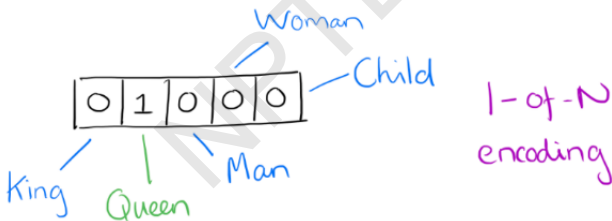
- At one level, it is simply a vector of weights.
- In a simple 1-of-N (or 'one-hot') encoding every element in the vector is associated with a word in the vocabulary.
- The encoding of a given word is simply the vector in which the corresponding element is set to one, and all other elements are zero.

## One-hot representation

motel [0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0] AND  
hotel [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0] = 0

# Word Vectors - One-hot Encoding

- Suppose our vocabulary has only five words: King, Queen, Man, Woman, and Child.
- We could encode the word 'Queen' as:



# Limitations of One-hot encoding

NPTTEL

# Limitations of One-hot encoding

## *Word vectors are not comparable*

Using such an encoding, there is no meaningful comparison we can make between word vectors other than equality testing.

# Word2Vec – A distributed representation

## *Distributional representation – word embedding?*

Any word  $w_i$  in the corpus is given a distributional representation by an embedding

$$w_i \in \mathbb{R}^d$$

i.e., a  $d$ –dimensional vector, which is mostly learnt!



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i.e., a  $d$ –dimensional vector, which is mostly learnt!

*linguistics* =

0.286  
0.792  
-0.177  
-0.107  
0.109  
-0.542  
0.349  
0.271

# Distributional Representation

- Take a vector with several hundred dimensions (say 1000).
- Each word is represented by a distribution of weights across those elements.
- So instead of a one-to-one mapping between an element in the vector and a word, the representation of a word is spread across all of the elements in the vector, and
- Each element in the vector contributes to the definition of many words.

# Distributional Representation: Illustration

If we label the dimensions in a hypothetical word vector (there are no such pre-assigned labels in the algorithm of course), it might look a bit like this:



*Such a vector comes to represent in some abstract way the 'meaning' of a word*

# Word Embeddings

- $d$  typically in the range 50 to 1000
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*SVD can also be thought of as an embedding method*

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## *Case of Singular-Plural Relations*

If we denote the vector for word  $i$  as  $x_i$ , and focus on the singular/plural relation, we observe that



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## Case of Singular-Plural Relations

If we denote the vector for word  $i$  as  $x_i$ , and focus on the singular/plural relation, we observe that

$$x_{apple} - x_{apples} \approx x_{car} - x_{cars} \approx x_{family} - x_{families} \approx x_{cat} - x_{cats}$$

and so on.

# Reasoning with Word Vectors

Perhaps more surprisingly, we find that this is also the case for a variety of semantic relations.

*Good at answering analogy questions*

a is to b, as c is to ?

man is to woman as uncle is to ? (aunt)

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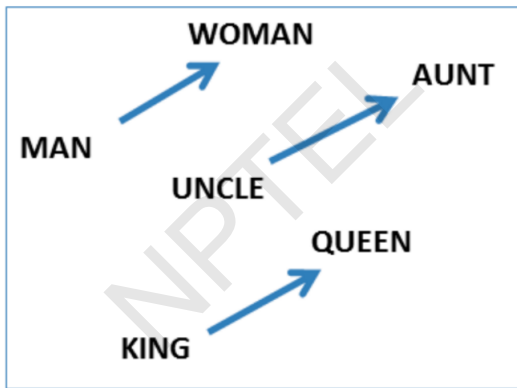
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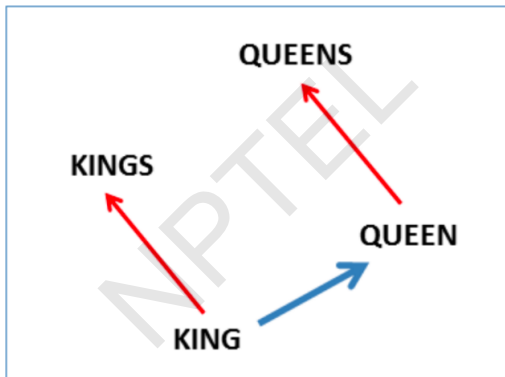
*man is to woman as uncle is to ? (aunt)*

*A simple vector offset method based on cosine distance shows the relation.*

# Vector Offset for Gender Relation



# Vector Offset for Singular-Plural Relation



# Encoding Other Dimensions of Similarity

## Analogy Testing

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

# Analogy Testing

a:b :: c:?



$$d = \arg \max_x \frac{(w_b - w_a + w_c)^T w_x}{||w_b - w_a + w_c||}$$

man:woman :: king:?

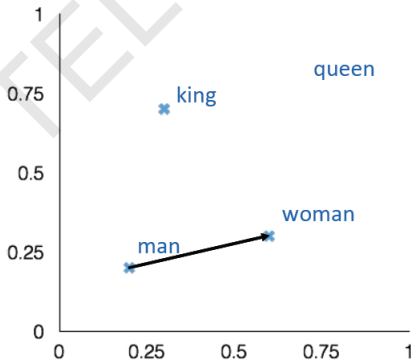
+ king [ 0.30 0.70 ]

- man [ 0.20 0.20 ]

+ woman [ 0.60 0.30 ]

---

queen [ 0.70 0.80 ]



# Country-capital city relationships

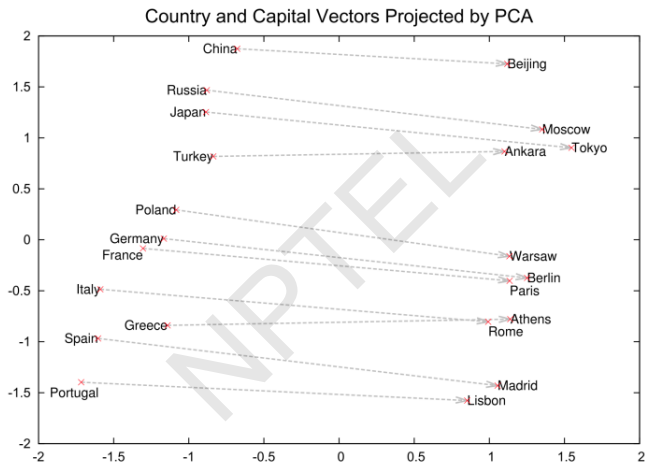


Figure 2: Two-dimensional PCA projection of the 1000-dimensional Skip-gram vectors of countries and their capital cities. The figure illustrates ability of the model to automatically organize concepts and learn implicitly the relationships between them, as during the training we did not provide any supervised information about what a capital city means.



# More Analogy Questions

Newspapers			
New York San Jose	New York Times San Jose Mercury News	Baltimore Cincinnati	Baltimore Sun Cincinnati Enquirer
NHL Teams			
Boston Phoenix	Boston Bruins Phoenix Coyotes	Montreal Nashville	Montreal Canadiens Nashville Predators
NBA Teams			
Detroit Oakland	Detroit Pistons Golden State Warriors	Toronto Memphis	Toronto Raptors Memphis Grizzlies
Airlines			
Austria Belgium	Austrian Airlines Brussels Airlines	Spain Greece	Spainair Aegean Airlines
Company executives			
Steve Ballmer Samuel J. Palmisano	Microsoft IBM	Larry Page Werner Vogels	Google Amazon

Table 2: Examples of the analogical reasoning task for phrases (the full test set has 3218 examples). The goal is to compute the fourth phrase using the first three. Our best model achieved an accuracy of 72% on this dataset.

# Element Wise Addition

We can also use element-wise addition of vector elements to ask questions such as ‘German + airlines’ and by looking at the closest tokens to the composite vector come up with impressive answers:

Czech + currency	Vietnam + capital	German + airlines	Russian + river	French + actress
koruna	Hanoi	airline Lufthansa	Moscow	Juliette Binoche
Check crown	Ho Chi Minh City	carrier Lufthansa	Volga River	Vanessa Paradis
Polish zolty	Viet Nam	flag carrier Lufthansa	upriver	Charlotte Gainsbourg
CTK	Vietnamese	Lufthansa	Russia	Cecile De

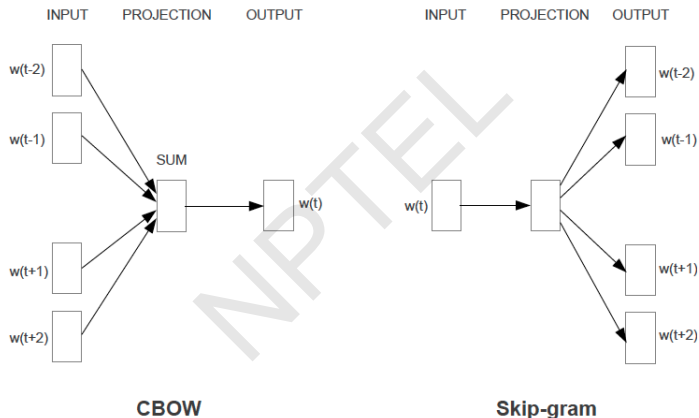
Table 5: Vector compositionality using element-wise addition. Four closest tokens to the sum of two vectors are shown, using the best Skip-gram model.

## Basic Idea

*Instead of capturing co-occurrence counts directly, predict (using) surrounding words of every word.*

Code as well as word-vectors: <https://code.google.com/p/word2vec/>

# Two Variations: CBOW and Skip-grams



# *Word Embeddings - Part II*

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CSE, IIT Kharagpur

Week 7, Lecture 5

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...an efficient method for learning high quality distributed vector ...

context

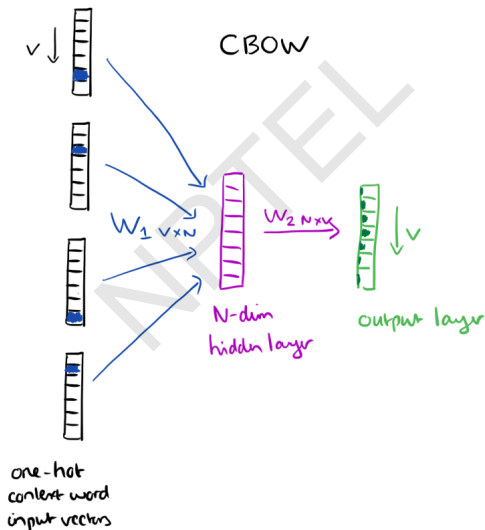
focus word

context



# CBOW

The context words form the input layer. Each word is encoded in one-hot form. A single hidden and output layer.



# CBOW: Training Objective

- The training objective is to maximize the conditional probability of observing the actual output word (the focus word) given the input context words, with regard to the weights.
- In our example, given the input (“an”, “efficient”, “method”, “for”, “high”, “quality”, “distributed”, “vector”), we want to maximize the probability of getting “learning” as the output.

## CBOW: Input to Hidden Layer

Since our input vectors are one-hot, multiplying an input vector by the weight matrix  $W_1$  amounts to simply selecting a row from  $W_1$ .

$$\begin{array}{c} \text{input} \\ 1 \times V \end{array} \begin{bmatrix} 0 & 1 & 0 \end{bmatrix} \begin{array}{c} W_1 \\ V \times N \end{array} \begin{bmatrix} a & b & c & d \\ e & f & g & h \\ i & j & k & l \end{bmatrix} = \begin{array}{c} \text{hidden} \\ 1 \times N \end{array} \begin{bmatrix} e & f & g & h \end{bmatrix}$$

$W_1$

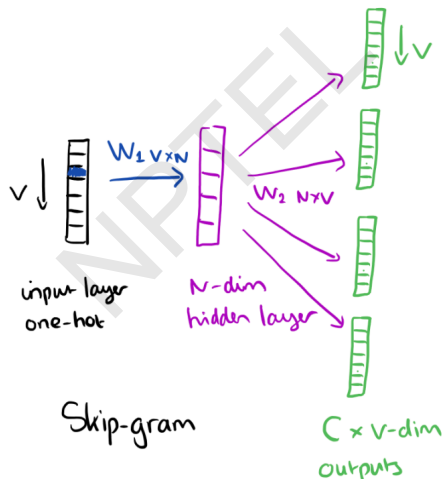
Given  $C$  input word vectors, the activation function for the hidden layer  $h$  amounts to simply summing the corresponding 'hot' rows in  $W_1$ , and dividing by  $C$  to take their average.

# CBOW: Hidden to Output Layer

From the hidden layer to the output layer, the second weight matrix  $W_2$  can be used to compute a score for each word in the vocabulary, and softmax can be used to obtain the posterior distribution of words.

# Skip-gram Model

The skip-gram model is the opposite of the CBOW model. It is constructed with the focus word as the single input vector, and the target context words are now at the output layer:



# Skip-gram Model: Training

- The activation function for the hidden layer simply amounts to copying the corresponding row from the weights matrix  $W_1$  (linear) as we saw before.
- At the output layer, we now output  $C$  multinomial distributions instead of just one.
- The training objective is to minimize the summed prediction error across all context words in the output layer. In our example, the input would be “learning”, and we hope to see (“an”, “efficient”, “method”, “for”, “high”, “quality”, “distributed”, “vector”) at the output layer.

# Skip-gram Model

## Details

Predict surrounding words in a window of length  $c$  of each word

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Predict surrounding words in a window of length  $c$  of each word

**Objective Function:** Maximize the log probability of any context word given the current center word:

$$J(\theta) = \frac{1}{T} \sum_{t=1}^T \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j} | w_t)$$



For  $p(w_{t+j}|w_t)$  the simplest first formulation is

$$p(w_O|w_I) = \frac{\exp(v'_{w_O} v_{w_I})}{\sum_{w=1}^W \exp(v'_w v_{w_I})}$$

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where  $v$  and  $v'$  are “input” and “output” vector representations of  $w$  (so every word has two vectors)

With  $d$ —dimensional words and  $V$  many words:

$$\theta = \begin{bmatrix} v_{aardvark} \\ v_a \\ \vdots \\ v_{zebra} \\ v'_{aardvark} \\ v'_a \\ \vdots \\ v'_{zebra} \end{bmatrix} \in \mathbb{R}^{2dV}$$

# Gradient Descent for Parameter Updates

$$\theta_j^{new} = \theta_j^{old} - \alpha \frac{\partial}{\partial \theta_j^{old}} J(\theta)$$

## Two sets of vectors

Best solution is to sum these up

$$L_{final} = L + L'$$

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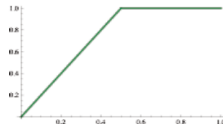
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*An interactive Demo*

<https://ronxin.github.io/wevi/>

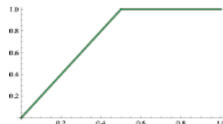
$$J = \frac{1}{2} \sum_{ij} f(P_{ij}) (w_i \cdot \tilde{w}_j - \log P_{ij})^2 \quad f \sim$$



*Combine the best of both worlds – count based methods as well as direct prediction methods*



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*Combine the best of both worlds – count based methods as well as direct prediction methods*

- Fast training
- Scalable to huge corpora
- Good performance even with small corpus, and small vectors

Code and vectors: <http://nlp.stanford.edu/projects/glove/>