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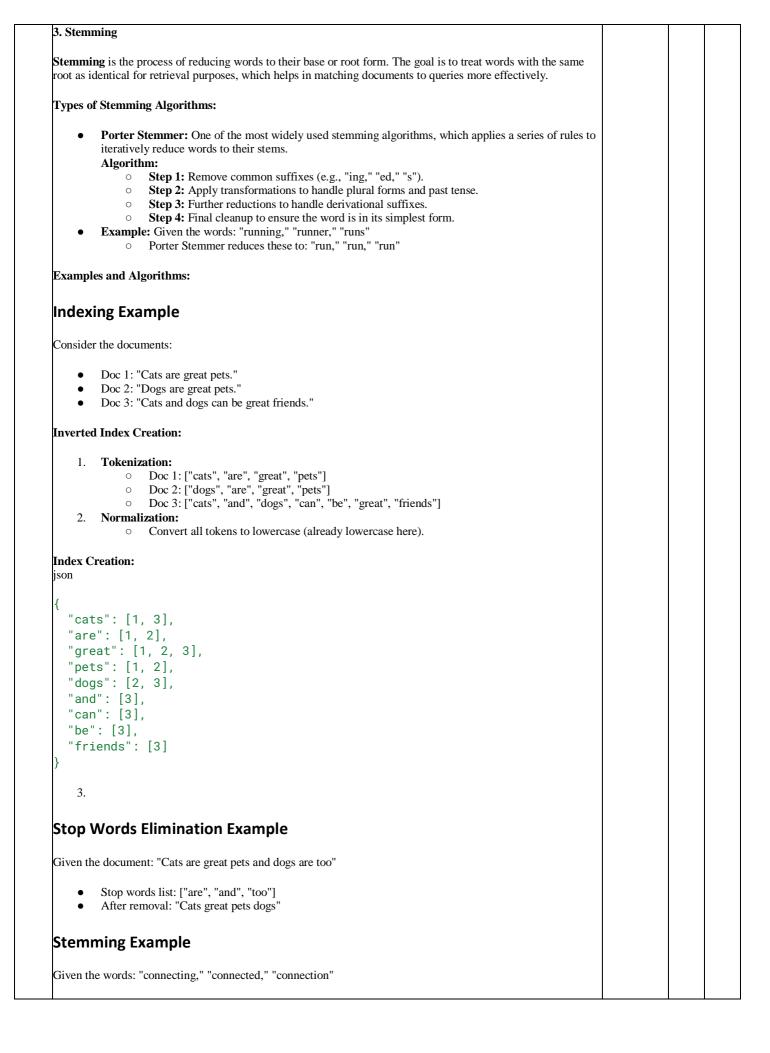
Internal Assessment Test 3 – JULY 2024

0.1	NL ( 1 L	D	Inte	rnal Assessment T	est 5 –	Sub Code:	21AI643	D 1			
Sub:	Natural Language				50			Branch:	AIM	1	
Date:	30/07/2024	Duration:	90 mins	Max Marks:	50	Sem / Sec:		/I/ A	ADIZO	OB	
1	Describe the follow a) Topic mo b) Cohesion	/ing:	·	<u>VE FULL Questio</u>	<u>ns</u>			I	ARKS 5+5] Des-5 eg-2	CO CO4	RBT L2
	○ 2. Non-Neg ○ 3. Latent S ○ ○	<pre>imments. It helps in topic modeling a itopic modeling a itopic modeling a itopics are mixtu Example: Give technology, and</pre>	n understandin, lgorithms: ion (LDA): ative probabilis tres of words. I n a set of news l health, with e cs: election, go s: game, team, nology: softwar h: doctor, diser <b>tetorization (N</b> the term-docu opic distributio collection of re- cience, and bio ine Learning: a Science: data, a gy: cell, DNA, is (LSA): lar value decon nt relationships yzing custome e, and delivery tot Quality: dur mer Service: h	g the structure and stic model that assu [t helps in discover s articles, LDA mig ach topic represent overnment, policy, player, match re, computer, intern ase, treatment, med	theme umes d ing hid ght ide ed by vote net, de licine wo nor present IF mig pic cha training , visua o decor d docu ght rev each to ellent, sponse	s present in larg ocuments are n lden topics in a ntify topics such a set of words l vice n-negative matr ing the topic-wo ht identify topic racterized by sp g, neural lization mpose the term ments. real topics such pic identified b value friendly	e text datasets. H nixtures of topics set of documents h as politics, spor ike: ices: one represen ord distribution. cs like machine becific terms: -document matri: as product qualit	ere are , and , ts, ts, nting x and			
	<b>Cohesion</b> <b>Cohesion</b> refers to in a meaningful way Higher cohesion in interpretable.	y. In topic model	ing, cohesion u	sually pertains to the	he sem	antic similarity	of words within	ogether a topic.	lec-3 eg-2		
	Example:										
	<ul><li>related to</li><li>A topic v</li></ul>	the theme of he	althcare. 1 might include	e words like "docto e unrelated words l t the theme.		-	-	all			
	Cohesion Ma	trix									
	A <b>cohesion matrix</b> It provides a nume										
	Types of Cohesion	Measures:									
	1. Pointwis	e Mutual Inform	nation (PMI):								

with the word1 = word2	newspapers. That is, cohesion is not present or absent in a binary or optional sense. Instead, cohesion in text exists on a continuum of presence, which is sometimes indicative of the text-type in question and sometimes indicative of the audience for which the text was written. In this paper, we discuss the nature and importance of cohesion; we demonstrate a computational tool that measures cohesion; and, most importantly, we demonstrate a novel approach to identifying text-types by incorporating contrasting rates of cohesion. Iteral word matching and Soundex word matching approaches. Apply the word matching algorithms e given string below: "example" "example"	[10] dec-5 sol-5	CO4	L3
Explain with the word1 =	newspapers. That is, cohesion is not present or absent in a binary or optional sense. Instead, cohesion in text exists on a continuum of presence, which is sometimes indicative of the text-type in question and sometimes indicative of the audience for which the text was written. In this paper, we discuss the nature and importance of cohesion; we demonstrate a computational tool that measures cohesion; and, most importantly, we demonstrate a novel approach to identifying text-types by incorporating contrasting rates of cohesion. In Literal word matching and Soundex word matching approaches. Apply the word matching algorithms e given string below: = "example"		CO4	L3
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٨	newspapers.			
1	But cohesive elements, and by consequence cohesion, does not simply feature in a text as dialogues tend to feature in narratives, or as cartoons tend to feature in			
_	English! we that red lever? It will slow the rotors down long enough for me to get out. Stand by it. Wait word.			
	tator control unit can reverse the polarity long enough to disengage maglev and that could			
co ar th For exa	exts contain pertinent information that co-refers across sentences and paragraphs,texts ontain relations between phrases, clauses, and sentences that are often causally linked; nd texts that depend on relating a series of chronological events contain temporal features nat help the reader to build a coherent representation of the text. mple in the movie "The Avengers", when the helicarrier is attacked and one of its engine is broken, and n and captain america are trying to fix it, the conversation between them goes like this:			
• • •	<ul> <li>Model Evaluation: Assessing the quality and interpretability of the topics generated by a topic model.</li> <li>Parameter Tuning: Helping in the selection of optimal parameters for topic modeling algorithms, such as the number of topics.</li> <li>Comparison of Models: Comparing different topic modeling approaches or algorithms to determine which provides more coherent and meaningful topics.</li> </ul>			
Applica	ations of Cohesion and Cohesion Matrix:			
3.	<ul> <li>Word Co-occurrence:         <ul> <li>This measures how often words appear together within a certain context window in the text. High co-occurrence rates indicate strong cohesion.</li> <li>Example: In a collection of articles about technology, the words "internet" and "browser" might frequently appear together, indicating a cohesive topic.</li> </ul> </li> </ul>			
	<ul> <li>Cosine similarly inclusives the cosine of the angle between two vectors in a mature dimensional space, indicating how similar the vectors are.</li> <li>Example: In a vector space model, if the word vectors for "computer" and "software" are close to each other, their cosine similarity would be high, suggesting they belong to a cohesive topic.</li> </ul>			
2.	<ul> <li>healthcare, their PMI would be high, indicating strong cohesion.</li> <li>Cosine Similarity:         <ul> <li>Cosine similarity measures the cosine of the angle between two vectors in a multi-</li> </ul> </li> </ul>			

Literal word matching refers to comparing two words character by character to check if they are exactly the same. This is a straightforward method and does not account for minor spelling errors or variations. Example: Given words: word1 = "example" and word2 = "exampel" Literal matching will compare each character in both words. 0 e vs e 0 x vs x 0 a vs a 0 m vs m 0 p vs p l vs e (mismatch) 0 e vs l (mismatch) 0 Since there are mismatches, word1 and word2 do not match literally. Soundex Word Matching Soundex is a phonetic algorithm used to index words by their sound when pronounced in English. It maps words to a four-character code based on their pronunciation. Words that sound similar should have the same Soundex code, even if they are spelled differently. Soundex Algorithm Steps: Retain the first letter of the word. 1. Replace the remaining letters with numbers based on the Soundex table. 2. 3. Remove all occurrences of a, e, i, o, u, y, h, w (except the first letter). 4. Replace consecutive duplicate numbers with a single number. 5. Truncate or pad the result to ensure it is four characters long. Example: Given words: word1 = "example" and word2 = "exampel" Convert each word to its Soundex code: For word1 = "example": • E (retain first letter) 0 x = 2 0 a (ignore) m = 5 0 0 p = 1  $\circ$  l = 4 • e (ignore) Resulting code: E251 0 For word2 = "exampel": 0 E (retain first letter) 0  $\mathbf{x} = 2$ a (ignore) 0 m = 5 0 p = 1 0 0 e (ignore) 0 1 = 4Resulting code: E251 0 Both words have the same Soundex code E251, indicating they sound similar. Applying the Algorithms to the Given Strings Literal Word Matching: word1 = "example" . word2 = "exampel" . Literal match result: No match (since there are mismatches at the 6th and 7th positions).

Soundex Word Matching:			
<ul> <li>word1 = "example"</li> </ul>			
<ul> <li>word2 = "exampel"</li> </ul>			
<ul> <li>Soundex codes: Both are E251.</li> <li>Soundex match result: Match (since both words have the same Soundex code).</li> </ul>			
• Soundex match result: <b>Match</b> (since both words have the same Soundex code).			
In summary, while literal word matching identifies word1 and word2 as different, Soundex word matching identifies them as similar based on their phonetic representation.			
Describe the following approaches used in Information Retrieval with suitable examples and algorithms. a) Indexing b) Stop words elimination c) Stemming	[10]	CO5	
1. Indexing	des-7 example-3		
<b>Indexing</b> is the process of creating data structures that allow for efficient retrieval of information from a large dataset. In the context of information retrieval, indexing involves organizing documents or data in a way that makes it easier and faster to search and retrieve relevant information.			
Types of Indexing:			
• Inverted Index: An inverted index maps terms to the documents that contain them. This allows for			
quick lookup of documents based on the presence of specific terms. Algorithm:			
• <b>Tokenization:</b> Break down documents into individual terms or tokens.			
• <b>Normalization:</b> Convert tokens to a standard form (e.g., lowercase).			
• <b>Index Creation:</b> Create a dictionary where each term points to a list of documents (and optionally, positions within the documents) that contain the term.			
• Example: Consider the following documents:			
• Document 1: "Information retrieval is fun"			
• Document 2: "Retrieval of information is important"			
The inverted index would be: json			
8			
"information": [1, 2],			
"retrieval": [1, 2],			
"is": [1, 2],			
"fun": [1], "of": [2],			
or : [2], "important": [2]			
}			
2. Stop Words Elimination			
<b>Stop words elimination</b> is the process of removing common words that are unlikely to be useful in retrieving relevant documents. These words (e.g., "the," "is," "in," "and") occur frequently but do not carry significant meaning in the context of a search query.			
Algorithm:			
1. <b>Create a List of Stop Words:</b> This list contains words to be removed during preprocessing.			
<ol> <li>Contract a last of btop words. This list contains words to be removed during proprocessing.</li> <li>Tokenization: Break down documents into individual terms.</li> <li>Stop Words Removal: Remove terms that are present in the stop words list.</li> </ol>			
Example: Given the document: "Information retrieval is fun and important"			
• Stop words list: ["is", "and"]			
• After removal: "Information retrieval fun important"			



	Porter Stemmer reduces these to: "connect," "connect," "connect"			
	Summary			I
	<ul> <li>Indexing enables efficient search by creating structures like inverted indices that map terms to documents.</li> <li>Stop words elimination improves relevance by removing common words that do not add meaningful value.</li> <li>Stemming enhances retrieval by reducing words to their base form, thus treating related words as equivalent.</li> </ul>			
4	Explain basic Information Retrieval process with a neat diagram.	[5+5]	CO5	L2
	State and explain the importance of Zip's law related to word distribution in NLP. The Information Retrieval (IR) process involves several steps to fetch relevant information from a large collection of data based on a user's query. Here's a step-by-step explanation along with a diagram to illustrate the process. <b>Steps in the Information Retrieval Process:</b>	des-3 eg-2		
	1. Document Collection: The collection of documents that will be searched. These documents can be any form of text, such as web pages, articles, books, etc. 2. Preprocessing: This step involves preparing the text for indexing and retrieval. It includes several substeps: <ul> <li>Tokenization: Splitting text into individual words or tokens.</li> <li>Stop Words Removal: Eliminating common words that do not carry significant meaning (e.g., "the", "is", "in").</li> <li>Stemming/Lemmatization: Reducing words to their base or root form.</li> </ul> <li>JIndexing: Creating an index to enable efficient search. An inverted index is commonly used, which maps each term to the documents in which it appears.</li> <li>Query Processing: Similar to document preprocessing, the user's query is processed to prepare it for searching.</li> <li>Stop Words Removal: Removing common words.</li> <li>Stemming/Lemmatization: Reducing query terms to their base form.</li> <li>Sternhing: Matching the processed query against the index to retrieve relevant documents.</li> <li>Ranking: Ordering the retrieved documents based on relevance to the query. This can be done using various ranking algorithms, such as TF-IDF (Term Frequency-Inverse Document Frequency) or BM25.</li> <li>Results Presentation: Displaying the ranked list of documents to the user.</li> Document   Preprocessing   Indexing   <ul> <li>Collection +&gt;   Index  </li> <li> </li> <li< th=""><th></th><th></th><th></th></li<></ul>			

	<b>Zipf's Law in NLP</b> <b>Zipf's Law</b> states that in a given corpus of natural language, the frequency of any word is inversely proportional to its rank in the frequency table. Specifically, the second most frequent word occurs approximately half as often as the most frequent word, the third most frequent word occurs about one-third as often, and so on.	des-3 eg-2		
	Formal Expression of Zipf's Law:			
	$f(r) \approx Craf(r) \operatorname{approx} (r^a) f(r) \approx raC$			
	<ul> <li>f(r)f(r)f(r): Frequency of the word with rank rrr</li> <li>CCC: Constant</li> <li>rrr: Rank of the word</li> <li>aaa: Exponent close to 1 (typically around 1)</li> </ul>			
	Importance of Zipf's Law in NLP:			
	<ol> <li>Understanding Vocabulary Distribution: Zipf's Law helps in understanding the distribution of words in a language, which is crucial for tasks like corpus analysis, language modeling, and lexicon building.</li> <li>Efficient Indexing: By recognizing that a small number of words appear very frequently while the majority appear rarely. IR systems can optimize indexing and storage. For example, stop words can be identified and handled differently to improve search efficiency.</li> <li>Compression and Storage: Zipf's Law is used in text compression algorithms because it reveals patterns in word frequency that can be exploited to reduce the size of stored text data.</li> <li>Improving Search Performance: Understanding word frequency distribution helps in designing better ranking algorithms. For instance, frequent words might be given less weight in relevance scoring.</li> <li>Handling Rare Words: Zipf's Law indicates that most words in a large corpus are rare. Techniques like smoothing in language models are used to address the issue of rare words.</li> <li>Resource Allocation: Helps in allocating computational resources effectively by focusing more on processing frequent terms that contribute most to the information content.</li> </ol> Example: Consider a corpus with the following word frequencies: <ul> <li>"the": 5000 times (rank 1)</li> <li>"is": 2500 times (rank 4)</li> <li>"of": 1000 times (rank 4)</li> <li>"of": 1000 times (rank 5)</li> </ul> According to Zipf's Law, the word ranked 2 should appear about half as frequently as the word ranked 1, the word ranked 3 about one-third as frequently, and so on. This distribution helps in understanding the redundancy and importance of different words in text processing tasks.			
5	Explain the Cluster and fuzzy models of information retrieval systems with suitable examples.	[10] Desc-5 examples-5	CO5	L2
	The cluster model attempts to reduce the number of matches during retrieval.			
	The cluster hypothesis that explains why clustering could prove efficient in IR states that			
	"Closely associated documents tend to be relevant to the same clusters."			
	The hypothesis suggests that closely associated documents are likely to be retrieved together.			
	By forming groups or classes or clusters of related documents, the search time reduces considerably.			
	Instead of matching a query with every document in the collection, it is matched with representatives of the cluster (class), and only documents from a class whose representative is close to query, are considered for individual match.			

-		
	Clustering is applied on terms instead of documents. Terms can be grouped to form classes of co-occurrence terms.	
	A number of methods are used to group documents. One of the method is based on similarity matrix.	
	Cluster Generation method based on Similarity Matrix	
]	Let $D = \{ d_1, d_2, d_3, \dots, d_m \}$ be set of documents.	
]	Let $E = (e_{ij})_{n,n}$ be the similarity matrix.	
ŗ	The element $E_{i,j}$ in this matrix, denotes a similarity between document $d_i$ and $d_j$ .	
]	Let T be the threshold value.	
	Any pair of documents $d_i$ and $d_j$ (i != j) whose similarity measure exceeds threshold ( $e_{ij} >=$ T) is grouped to form a cluster.	
ŗ	The remaining documents form a single cluster.	
	The set of clusters thus obtained is	
	$C = \{ C_1, C_2,, C_k,, C_p \}$	
	A representative vector of each cluster is constructed by computing the centroid of the document vectors belonging to that class.	
]	Representation vector for a cluster $C_k$ is $r_k = \{a_{1k}, a_{2k},, a_{ik},, a_{mk}\}$	
	An element $a_{ik}$ in this vector is computed as $a_{ik} = \frac{\sum_{\substack{d_j \in C_k}} a_{ij}}{ C_k }$	
	Where $a_{ij}$ is weight of the term $t_i$ , of the document $d_j$ , in cluster $C_k$ .	
]	During retrieval, the query is compared with the cluster vectors	
	$(r_1, r_2,, r_k,, r_p)$	
	This comparison is carried out by computing the similarity between the query vector q and the representative vector r, as	
	$s_{ik} = \sum_{i=1}^{m} a_{ik} q_i,  k = 1, 2,, p$	
	A cluster C, whose similarity s, exceeds a threshold is returned and the search proceeds in that cluster.	
	Example 9.4 Let $A = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix}$	

be the term-by-document matrix. The similarity matrix corresponding to these documents is

1.0 0.9 1.0

0.4 0.4 1.0

Using a threshold of 0.7, we get the following two clusters:

 $C_1 = \{d_1, d_2\}$  $C_2 = \{d_3\}$ The cluster vectors (representatives) for  $C_1$  and  $C_2$  are  $r_1 = (1 \ 0.5 \ 1 \ 0 \ 1)$ 

$$r_0 = (0 \ 0 \ 1 \ 1 \ 0)$$

Retrieval is performed by matching the query vector with  $r_1$  and  $r_2$ .

- In the **fuzzy model**, the document is represented as a fuzzy set of terms, i.e., a set of pairs [ $\mathbf{t}_i, \boldsymbol{\mu}(\mathbf{t}_i)$ ] Where  $\boldsymbol{\mu}$  is the membership function.
- The membership function assigns to each term of the document a numeric membership degree.
- The membership degree expresses the significance of term to the information contained in the document.
- Significance values (weights) are assigned based on the number of occurrences of the term in the document and in the entire document collection.

Each document in the collection -

 $D = \{ d_1, d_2, ..., d_i, ..., d_n \}$ 

Can thus be represented as a vector of term weights,

 $(W_{ij}, W_{2j}, W_{3j}, ..., W_{ij}, ..., W_{mj})^t$ 

Where  $w_{ij}$  is the degree to which term  $t_i$  belongs to document  $d_i$ .

- Each term in the document is considered a representative of a subject area and wij is the membership function of document dj to the subject area represented by term ti.
- Each term ti is represented by a fuzzy set fi in the domain of documents given by

 $f_i = \{ (d_i, w_{ij}) \} | i = 1, ..., m; j = 1, ..., n$ 

- This weighted representation makes it possible to rank the retrieved documents in decreasing order of their relevance to the user's query.
- Queries are Boolean queries.
- For each term that appears in the query, a set of documents is retrieved.
- Fuzzy set operations are then applied to obtain the desired result.

# Single-term Query:

	۰	For a single-term query $q=t_q$ , those documents from the fuzzy set			
		$f_q = \{(d_j, w_{iq})\},\$			
	zero.	are retrieved for which wiq exceeds a given threshold. The threshold may also be			
	AND (	Query:			
	•	For an AND query $q = t_{q1} \wedge t_{q2}$ , the fuzzy sets fq1 and fq2 are obtained and then, their intersection is obtained, using the fuzzy intersection operator			
		$f_{q1} \wedge f_{q2} = min \{ (d_j, w_{iq1}), (d_j, w_{iq}) \}$			
		The documents in this set are returned.			
	OR Q	iery:			
	•	For an OR query $q = t_{q1} V t_{q2}$ , the union of fuzzy sets fq1 and fa2 is computed to retrieve documents as follows -			
		$f_{q1} V f_{q2} = max \{ (d_j, w_{iq1}), (d_j, w_{iq}) \}$			
	Consid	er the following 3 documents:			
		d <sub>1</sub> = { information, retrieval, query }			
		d <sub>2</sub> = { retrieval, query, model }			
		d <sub>3</sub> = { information, retrieval }			
	Where	the set of terms used to represent documents is			
		T = { information, model, query, retrieval }			
	Fuzzy	set for terms			
		$f_1 = \{ (d_1, 1/3), (d_2, 0), (d_3, 1/2) \} \rightarrow t_1 = information$			
		$f_2 = \{ (d_1, 0), (d_2, 1/3), (d_3, 0) \} \rightarrow t_2 = model$			
		$f_3 = \{ (d_1, 1/3), (d_2, 1/3), (d_3, 0) \} \rightarrow t_3 = query$			
		$f_4 = \{ (d_1, 1/3), (d_2, 1/3), (d_3, 1/2) \} \rightarrow t_4 = retrieval$			
	If the q	uery is $q = t_2 \wedge t_4$ , then document $d_2$ is returned.			
6 a)	wind} contair weight	virl $-> \log(n / ni) = \log (100 / 20) = 0.699$ Weight - tornado $-> tf x idf = 1 * 0.699$	Desc-3 calculator-2	CO5	L3
	= 0.09 idf - wi = 0.398	ind $-> \log(n / ni) = \log (100 / 40) = 0.398$ Weight - tornado $-> tf x idf = 1 * 0.398$			

Term	Frequency (tf)	Document frequency (n <sub>i</sub> )	idf [log(n/n <sub>i</sub> )]	Weight (tf × idf)		
Tornado	4	15	0.824	0.296		
	1	20	0.699	0.699		
Swirl Wind	n an tha an t	40	0.398	0.389		
				- of these		
	et and FrameNe ted from WordN	t with suitable examples and et 2.0	l write the hypernym	n chain for	[5] desc-3 eg:2	CO5
WordNet:						
theories, it was	developed and	base for the English languag is being maintained at the direction of George A. Miller.	Cognitive Science L			
•	One for nouns One for verbs	ases jectives and adverbs				
base concept. Th Lexical relations meanings. These / holonymy, trop	he synsets are lin s occur between e relations includ onymy, etc. A w The meaning of t	s of synonymous words called ked to each other by means o word forms (senses) and se le synonymy, hypernymy / hy yord may appear in more than the word is called sense. Wo ent synset.	f lexical and semantic mantic relations betw ponymy, antonymy, one synset and in more	c relations. ween word meronymy re than one		
	and examples de	of set synonyms and a gloss. emonstrating the use of a syr				
	-	elations in WordNet				
C		nto hierarchies based on the h	ypernymy/hyponymy	y relation.		
Relation	Definition		Example			
Hypernym Hyponym	n From con	cepts to super-ordinates	s $oak \rightarrow tree$ $oak \rightarrow white oa$	k		
Meronym	From who	oles to parts	tree $\rightarrow$ trunk			
Holonym	From par Opposites	ts to wholes	$\begin{array}{c} \text{trunk} \rightarrow \text{tree} \\ \text{victory} \rightarrow \text{defe} \end{array}$	at		
	Obbosites	5				
Antonym Figure 12.2		tions in WordNet				

Hypernym	Definition		Example	
riypernym	From events events	to super-ordinate	wander $\rightarrow$ travel	
Troponym		to their subtypes	walk $\rightarrow$ stroll	
Entails		to the events they	snore $\rightarrow$ sleep	
	entail			
Antonym	Opposites		increase $\rightarrow$ decr	rease
Figure 12.3	Verb relations	in WordNet		
Relation		Definition	Example	
Antonym (ad	ljective)	Opposite	heavy $\rightarrow$ light	
Antonym (ad	lverb)	Opposite	quickly $\rightarrow$ slow	ly
oure 12.4	Adjective and	adverb relations in W	/ordNet	1000
		ed by CFILT (Resource		
chnology Solutio 928 Hindi words me Hindi-specifi RL <u>http://www.cf</u> FLIT has	ons), IIT Bombay . It is organized us c relations - causa filt.iitb.ac.in/word also	<ul> <li>Its database consists of sing the same principles ative relations. Hindi Work (Markov Markov)</li> <li>developed a</li> </ul>	of more than 26208 as English WordNet	synsets and but include
echnology Solutio 5928 Hindi words me Hindi-specifi RL <u>http://www.cf</u> FLIT has tp://www.cfilt.iith	ons), IIT Bombay . It is organized us c relations - causa filt.iitb.ac.in/word also o.ac.in/wordnet/wo	<ul> <li>Its database consists of sing the same principles ative relations. Hindi Work (Markov Markov)</li> <li>developed a</li> </ul>	of more than 26208 as English WordNet ordNet can be obtained	synsets and but include ed from the
echnology Solutio 5928 Hindi words me Hindi-specifi RL <u>http://www.cf</u> FLIT has tp://www.cfilt.iith <b>pplications of W</b>	ons), IIT Bombay . It is organized us c relations - causa filt.iitb.ac.in/word also o.ac.in/wordnet/we	7. Its database consists of sing the same principles ative relations. Hindi Wo net/webhwn/ developed a ebmwn/wn.php	of more than 26208 as English WordNet ordNet can be obtained	synsets and but include ed from the
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#### FrameNet:

- FrameNet is a large database of semantically annotated English sentences.
- It is based on principles of frame semantics.
- It defines a tagset of semantic roles called the **frame element**.
- Sentences from the British National Corpus are tagged with these frame elements.
- The basic philosophy involved is that each word evokes a particular situation with particular participants.
- FrameNet aims at capturing these situations through the case-frame representation of words (verbs, adjectives, and nouns).
- The word that invokes a frame is called the target word or predicate, and the participant entities are defined using semantic roles, which are called frame elements.
- The FrameNet ontology can be viewed as a semantic-level representation of the predicate-argument structure.
- Each frame contains a main lexical item as a predicate and associated frame-specific semantic roles, such as AUTHORITIES, TIME, AND SUSPECT in the ARREST frame, called frame elements.
- Example: The sentence below is annotated with semantic roles AUTHORITIES AND SUSPECT

### [Authorities The police] nabbed [suspect the snatcher].

- The COMMUNICATION frame has the semantic roles ADDRESSEE, COMMUNICATOR, TOPIC, and MEDIUM.
- A JUDGEMENT frame contains roles such as a JUDGE, EVALUEE, and REASON.
  Example:
  - [judge She] [Evaluee blames the police] [Reason for failing to provide enough protection].
- A frame may inherit roles from another frame. Eg., a STATEMENT frame may inherit from a COMMUNICATION frame, it contains roles such as SPEAKER, ADDRESSEE, and MESSAGE.
- Example:

## [Speaker She] told [Addressee me] [Message 'I'll return by 7:00 pm today'].

### **Applications of FrameNet:**

FrameNet data can be used for

- 1. Automatic semantic parsing
- 2. Information extraction
- 3. Question answering system
- 4. Information retrieval
- 5. Machine translation
- 6. Text summarization
- 7. Word sense disambiguation

<pre>ver was navigable for 50 miles') =&gt; stream, watercourse — (a natural body of running water owing on or under the earth) =&gt; body of water, water — (the part of the earth's surface vered with water (such as a river or lake or ocean); 'they invaded or territorial waters'; 'they were sitting by the water's edge') =&gt; thing — (a separate and self-contained entity) =&gt; entity — (that which is perceived or known or inferred to its own distinct existence (living or nonliving))</pre>	river — (a l	arge natural stream of water (larger than a cre	eek); 'the
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