Lexical Chains (for Summmarization)

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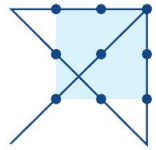
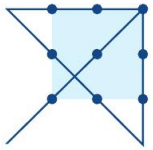
Lexical Cohesion



A text or discourse is not just a set of sentences, each on some random topic. Rather, the sentences and phrases of any sensible text will each tend to be about the same things – that is, the text will have a quality of unity. This is the property of cohesion. . . .
Lexical cohesion is the cohesion that arises from semantic relationships between words. All that is required is that there be some recognizable relation between the words.

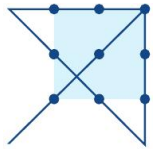
Source: Morris & Hirst (1991)

Lexical Chains



- lexical cohesion occurs not only between pairs of words (in pairs of sentences)
- lexical cohesion occurs also over a sequences of semantically related words (in sequences of sentences) – lexical chains

Lexical Chains



Why?

- to provide context for word sense disambiguation
  - {hair, comb, curl, *wave*} – the word sense of *wave* is narrowed down to *hair wave*
  - {gin, alcohol, sober, *drink*} – the word sense of *drink* is narrowed down to *alcoholic drink*

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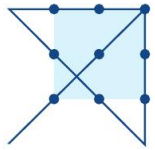

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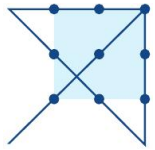

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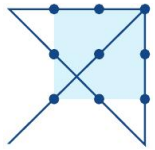
- to provide information for determining coherence and discourse structure – when a new lexical chain begins there is a high probability that a new discourse segment begins also
- to provide information about important entities in a document and which can be used for automatic summarization

Lexical Chains

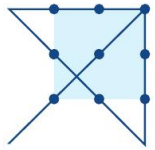


require *lexical knowledge*

e.g.:

- thesauri (Roget's thesaurus (4th ed., 1977) – this is a book, but an electronic version is commercially available)
  - a *dictionary* explains the meaning of words
  - a *thesaurus* aids in finding words that best express an idea or meaning
- lexical databases (WordNet, GermaNet)
- taxonomies, ontologies (e.g. ontologies derived from Wikipedia)
- …

Roget's Thesaurus



Class 1 ···

⋮

Class 4: Matter

I ···

⋮

III Organic Matter

A ···

⋮

B Vitality

⋮

407 Life

1. NOUNS life, living, vitality, being alive, having life, animation, animate existence; liveliness, animal spirits, vivacity, spriteliness; long life, longevity; viability; lifetime 110.5; immortality 112.3; birth 167; existence 1; bio-, organ-; -biosis.

⋮

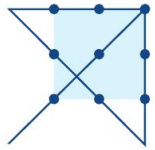
2. ···

⋮

408 Death ···

- 1042 basic categories which group words by *idea*
- eight major semantic abstract classes on top
- related words are physically close

Determining Discourse Structure



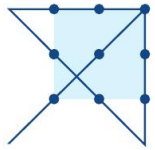
(Morris & Hirst, 1991)

- can be applied to any domain
- computationally feasible

parameters:

- thesaural relations
- transitivity of word relations
- distance (in sentences) between words in a chain

Forming Lexical Chains



- candidate words:
  - remove closed class words
  - remove high-frequency words (such as *good, do, taking, . . .*)
- types of relations:
  1. words have common category (e.g. *apartment* and *residentialness* share category *189*)
  2. a word's category has a pointer to the other word's category (*car* has category *273* which points to category *276*, the category of *driving*)
  3. a word is either a label in the other word's index entry, or is in a category of the other word, e.g, *blind* has category *442* in its index entry, which contains the word *see*
  4. two words are in the same group, and hence are semantically related, e.g., *blind* has category *442 blindness*, in its index entry and *see* has category *441*, *vision*, in its index entry
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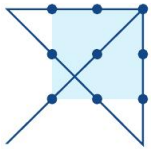

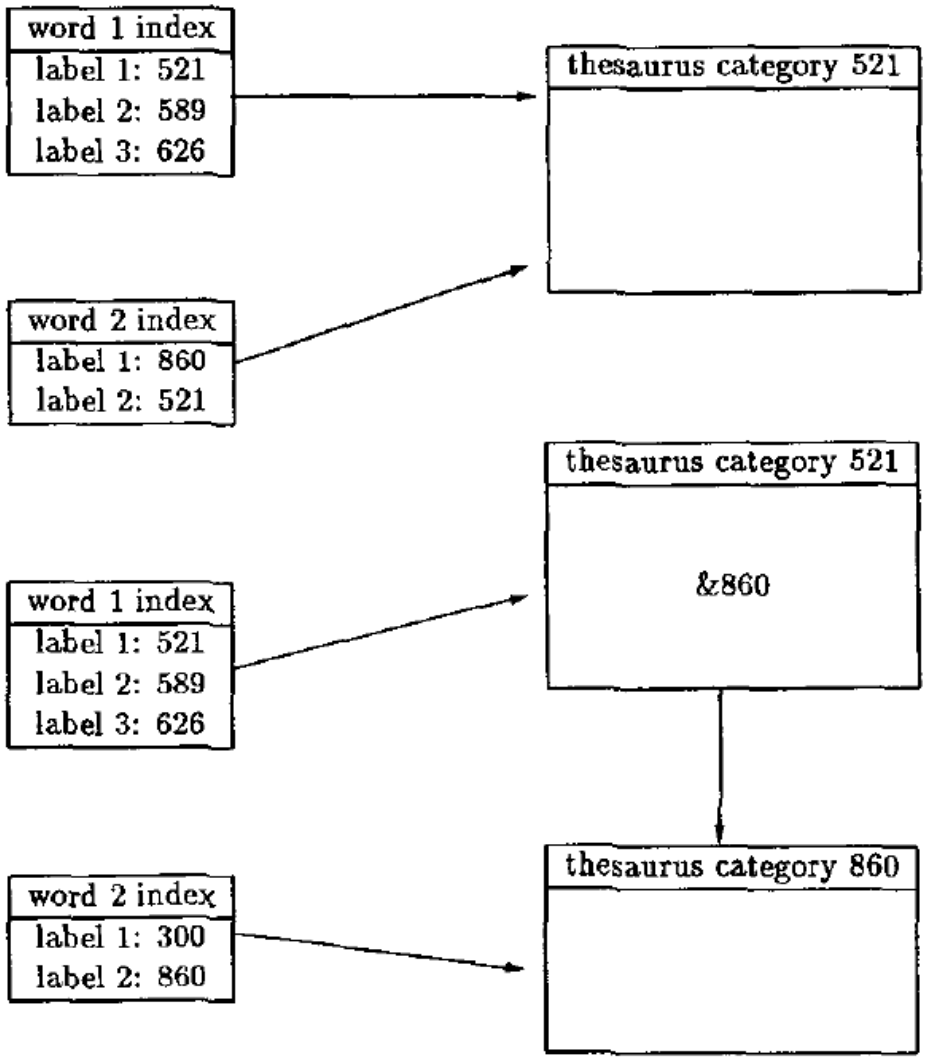

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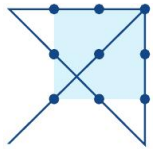

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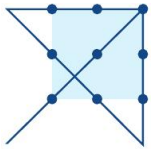
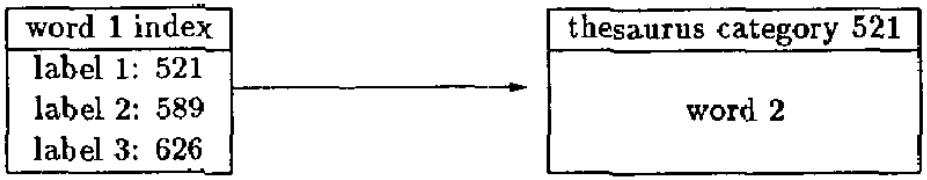




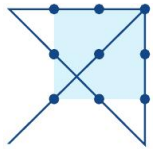
(b)

word 1 index
label 1: 521
word 2: 589
label 3: 626

word 1 index
label 1: x
word 2: 589
label 3: 626

word 2 index
label 1: x+1
label 2: 860

Forming Lexical Chains



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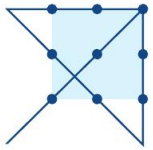

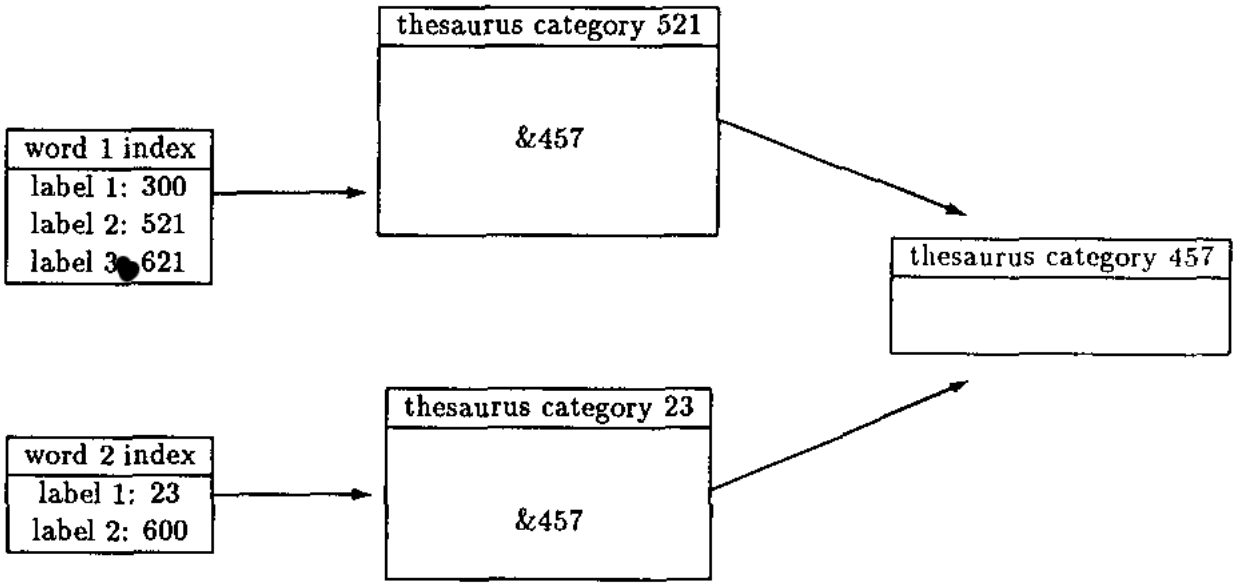

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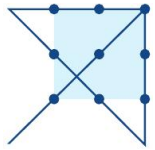
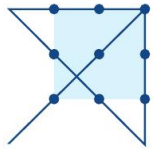


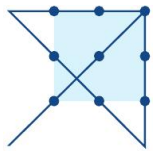
- transitivity:
  - limits on transitivity – if *a* is related to *b*, and *b* to *c*, then *a* is also related to *c*
  - to avoid chains like: {cow, sheep, wool, scarf, boots, hat, snow}, only one transitive link is allowed

Forming Lexical Chains



- how many sentences can separate two words in a chain:
  - at most three sentences distance
  - four and more sentences distance indicates return to a previous chain
- chain strength (helps to identify whether it is possible to return to a previous chain):
  1. reiteration: the more repetitions, the stronger the chain
  2. densitiy: the denser the chain, the stronger it is
  3. length: the longer the chain, the stronger it is

Computing Lexical Chains



keep for each word in a chain:

- word id
- sentence id
- complete chain created up to that point

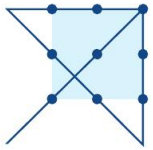
lexical relationship in a chain is represented as $(u, v)_x^y$:

- u: current word id
- v: id of related word
- x: transitive distance – 0, 1
- y: identifies thesaural relationship

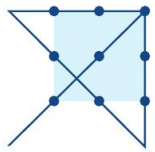
Chain 1

Word	Sentence	Lexical Chain
1. evade	15	
2. feigning	15	$(2,1)_0^2$
3. escaped	16	$(3,1)_1^0$ $(3,2)_1^{T1}$

Algorithm Outline



1. select a set of candidate words
2. for each candidate word, find an appropriate chain relying on a relatedness criterion among members of the chains
3. if it is found, insert the word in the chain and update it accordingly



Lexical Chains and Text Structure

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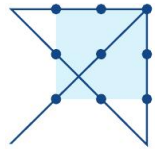
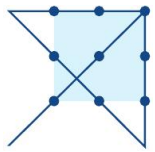


(Morris & Hirst, 1991)

- correspondence between chain boundaries and text segment boundaries
  - chain strength
  - chain length
- returns to existing chains and their correspondency to returns to previous segments

- manual application of algorithm
- results:
  - lexical chains provide a good clue for determining text structure
  - lexical chains on their own are not sufficient for determing text structure
  - chain returns are important and occur frequently
- see also (Galley et al., 2003)



Using Lexical Chains for Text Summarization

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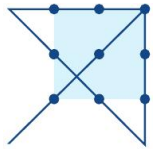


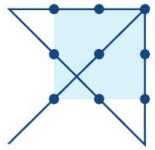
(Barzilay & Elhadad, 1997), (Barzilay & Elhadad, 1999)
contributions:

- new algorithm
- WordNet, POS tagger, NP chunker
- text segmentation algorithm

text summarization:

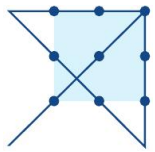
1. segment text
2. construct lexical chains
3. determine strong chains
4. extract significant sentences

Automatic Sumarization



- *extractive summarization* extracts important sentences from a document and concatenates them to produce a summary
- earlier work relied on:
  1. word frequency
  2. cue phrases (*in conclusion*)
  3. location of sentences
  4. length of sentences
- problems: how many sentences to include? which notion of importance? what to do with pronouns? location relies pretty much on domain. . . .

Lexical Chains



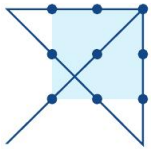
problem with earlier work (Morris & Hirst, 1991):

- algorithm did not distinguish between different senses of a word

hence

- lexical chain computing can be interpreted as word sense disambiguation
- greedy disambiguation (Hirst & St-Onge, 1998) apparently does not work well
- main idea here: all words in lexical chains consider all possible word senses and then choose the best global interpretation

Relevant Wordnet Relations



Two noun instances are identical, and are used in the same sense.
(*The house on the hill is large. The house is made of wood.*)

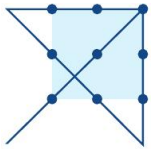
Two noun instances are used in the same sense (i.e., are synonyms).
(*The car is fast. My automobile is faster.*)

The senses of two noun instances have a hypernym/hyponym relation between them. (*John owns a car. It is a Toyota.*)

The senses of two noun instances are siblings in the hypernym/hyponyn tree. (*The truck is fast. The car is faster.*)

Source: Silber & McCoy (2002)

Illustration



Mr. *Kenny is the* **person** *that invented an anesthetic* **machine** *which uses* **micro-computers** *to control the rate at which an anesthetic is pumped into the blood. Such* **machines** *are nothing new. But his* **device** *uses two* **micro-computers** *to achieve much closer monitoring of the* **pump** *feeding the anesthetic into the patient.*

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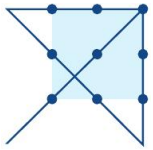

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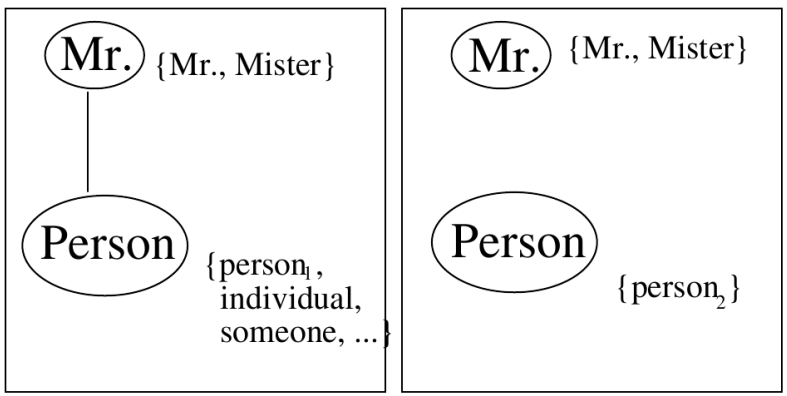

Figure 1: Step 1, Interpretations 1 and 2

Illustration

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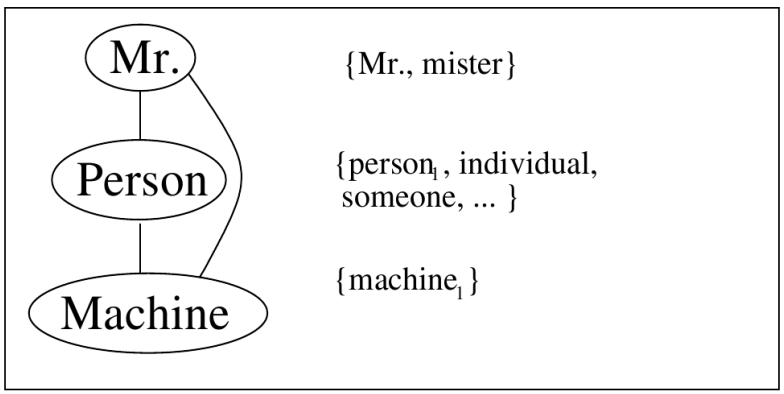


Figure 2: Step 2, Interpretation 1

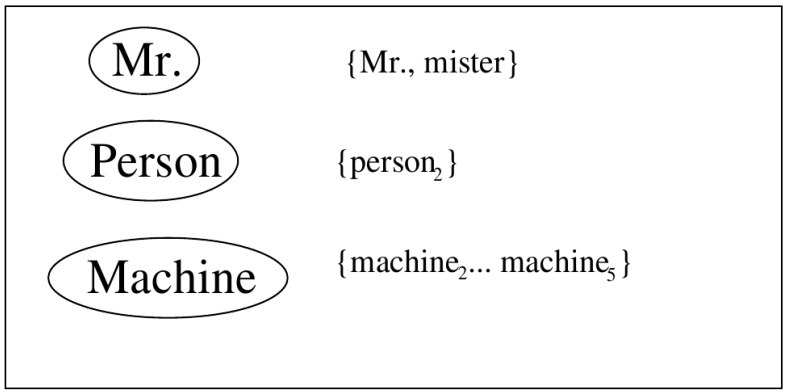


Figure 3: Step 2, Interpretation 2

Illustration

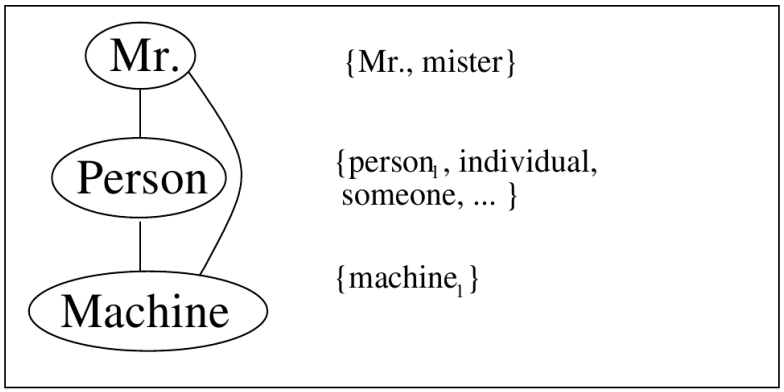


Figure 2: Step 2, Interpretation 1

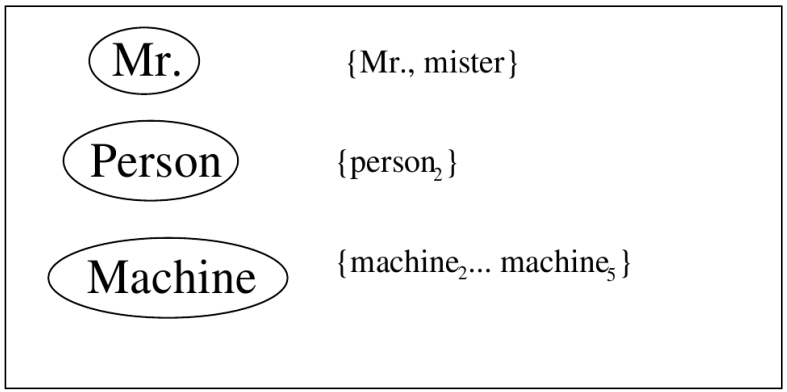


Figure 3: Step 2, Interpretation 2

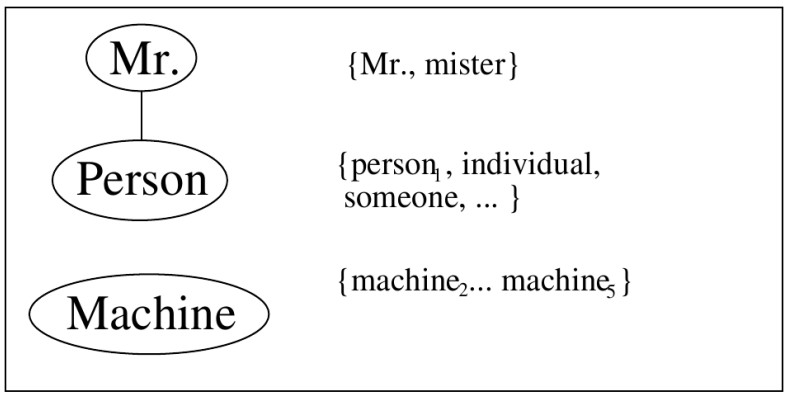


Figure 4: Step 2, Interpretation 3

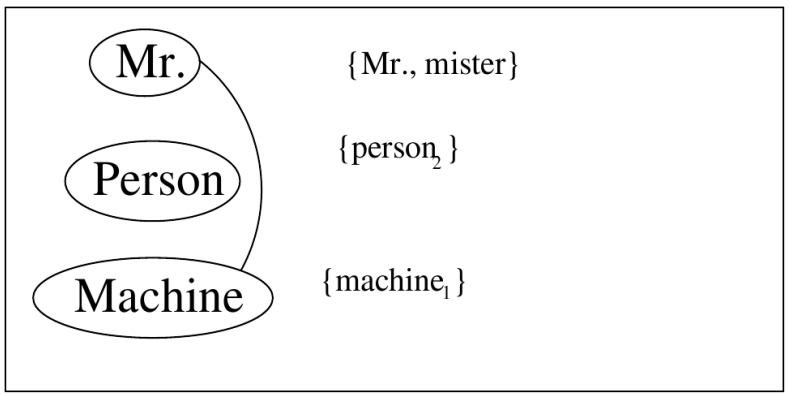


Figure 5: Step 2, Interpretation 4

Illustration

Mr. *Kenny is the* **person** *that invented an anesthetic* **machine** *which uses* **micro-computers** *to control the rate at which an anesthetic is pumped into the blood. Such* **machines** *are nothing new. But his* **device** *uses two* **micro-computers** *to achieve much closer monitoring of the* **pump** *feeding the anesthetic into the patient.*

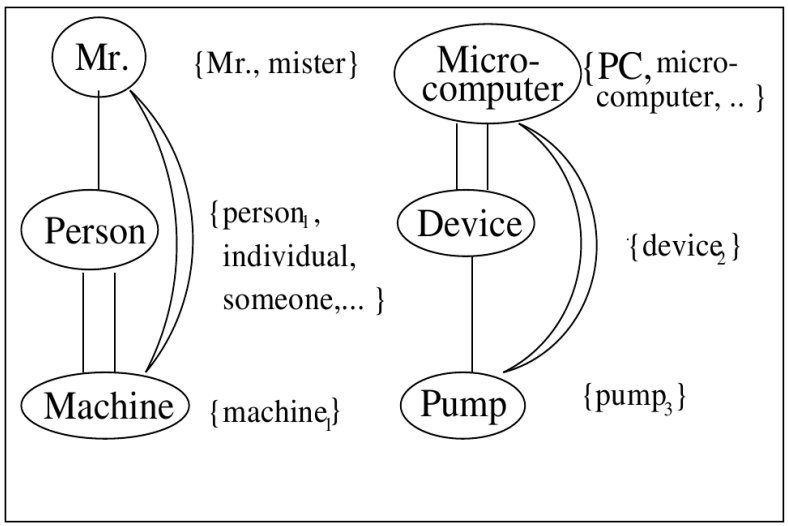


Figure 6: Step 3, Interpretation 1

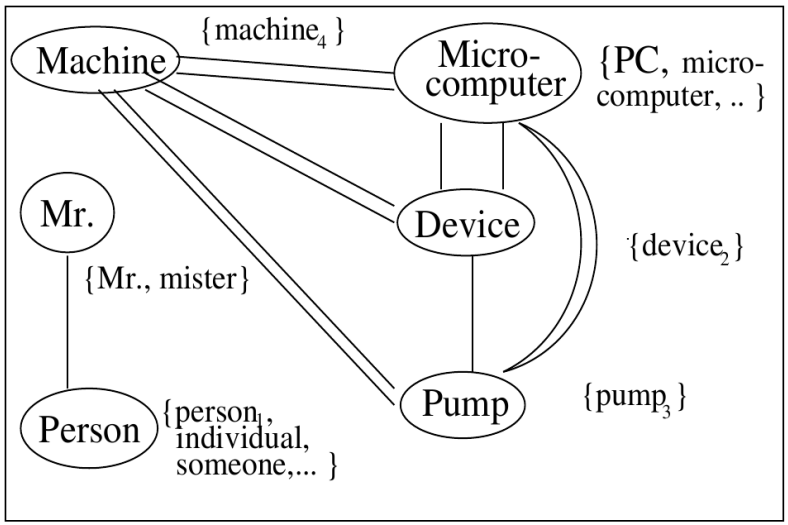
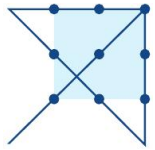


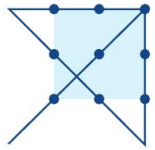
Figure 7: Step 3, Interpretation 2

Algorithm Details



- algorithm chooses the *strongest* interpretation eventually
  - strong: sum of the chain scores
  - chain scores: number and weight of the relations between chain members
  - reiteration and synonym: 10; antonym: 7; hypernym: 4
- algorithm computes *all* possible interpretations
- if there are too many interpretations, weak (i.e. the least strongest) interpretations are pruned
- algorithm divides document into discourse segments (Hearst, 1997) and extends chains over a segment boundary only if both segments have a common word with the same word sense

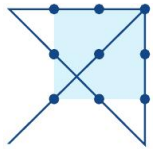
Summarization Using Lexical Chains



hypotheses:

- the most important topic in a document plays an important role in its summary
- strong lexical chains help to identify the most important topic
- advantage: words get mapped to *concepts* (chains) thus overcoming artefacts of concepts with many different realizations

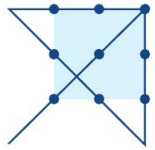
Strength of a Chain



- length: number of mentions in a chain
- homogeneity index:
  1 - the number of distinct occurrences divided by the length

- $Score(Chain) = Length * HomogeneityIndex$
- strength criterion:
  $Score(Chain) > Average(Scores) + 2 * StandardDeviation(Scores)$

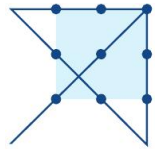
Extracting Significant Sentences



extract one sentence for each chain from the text based on the chain distribution:

- heuristic 1: for each chain choose the sentence which starts the chain
  (selects sometimes not the strongest representative sentences for a chain)
- heuristic 2: for each chain choose the sentence containing the most representative chain member
- heuristic 3: identify the (successive) text segment(s) where the chain represents the central topic
  number of chain mentions in segment(s) divided by number of all nouns in segment(s)

Extracting Significant Sentences



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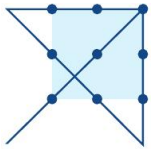
  number of chain mentions in segment(s) divided by number of all nouns in segment(s)

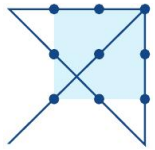
- heuristic 1 and heuristic 2 produce very similar results
- heuristic 2 gives the best results
- heuristic 3 often selects sentences from the middle of the document

Evaluation



- to evaluate automatic summarization is extremely difficult
- here:
  - 40 documents (news articles, TREC collection, avg. length 30 sentences)
  - for each document 10 summaries constructed by 5 humans (10% and 20% document length in terms of sentences)
  - 10% and 20% summaries generated with Mircosoft Word 97 summarizer
  - agreement between human subjects: 96% for 10% summaries, 90% for 20% summaries – relatively high

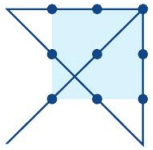
Evaluation



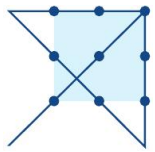
- construct ideal summaries by taking majority opinion among human subjects

	Microsoft		Lexical Chain	
	Prec	Recall	Prec	Recall
10%	33	37	61	67
20%	32	39	47	64

Limitations

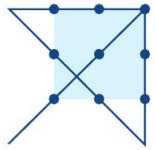


- long sentences are much more likely to be extracted
- extracted sentences contain pronouns
- method does not have the means to change the length of the summary (one sentence per chain selected)
- computational complexity of chain buidling algorithm: exponential



Efficiently Computing Lexical Chains

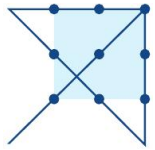
Efficiently Computing Lexical Chains



(Silber & McCoy, 2002)
contributions:

- efficient algorithm for computing lexical chains: linear in space and time
- evaluation of the quality of lexical chains

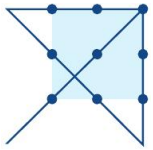
Problem Outline



- (Barzilay & Elhadad, 1999) define an interpretation as a mapping of noun instances to specific senses and then of these senses to specific lexical chains
- they essentially compute every possible combination between lexical chains and word senses and evaluate the strongest interpretation only at the end of the document
- this has exponential complexity and requires heuristic pruning

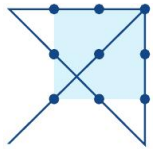
- (Silber & McCoy, 2002) create a structure that *implicitly* stores every interpretation without actually creating it
- they then provide a method for finding the best interpretation
- they recompile WordNet into a binary format to make access to it faster

Chain Computation



- create array of *metachains*: number of noun senses in WordNet plus number of nouns in document (this is the maximum size which possibly would be needed)
- when a noun in document is encountered each sense is placed in every metachain for which it has an identity, synonym, or hypernym relation with that sense
- metachains represent every possible interpretation
- metachains are indexed with WordNet synset ids

Chain Computation

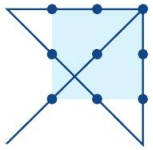


Index	Meaning	Chain		
0	person	John	Machine	
1	unit	Computer	IBM	
2	device	Computer	Machine	IBM
3	organization	Machine	IBM	
4	unknown	IBM		
⋮				
N				

Note: Assume the sentences "John has a computer. The machine is an IBM." and that the nouns have the following senses (meanings): John (0), computer (1,2), machine (0,2,3), IBM (1,2,3,4), and that words are put in a chain if they have an identity relation. This table then depicts the metachains after the first step.

Source: Silber & McCoy (2002)

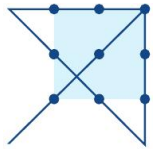
Finding the Best Interpretation



2nd pass through document:

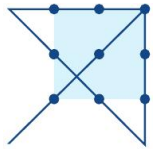
- for each noun, determine to which metachain it contributes most – based on the type of the relation and distance factors
- delete the noun from all other metachains
- after processing of document, only the interpretation with the highest scoring chains is left
- select best (highest scoring) chains from this interpretation for further processing, e.g. summarization

Finding the Best Interpretation



Step 1	For each noun instance For each sense of the noun instance Compute all scored metachains
Step 2	For each noun instance For each metachain to which the noun belongs Keep word instance in the metachain to which it contributes most Update the scores of each other metachain

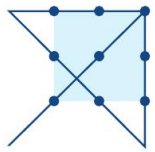
Scoring System



	One Sentence	Three Sentences	Same Paragraph	Default
Identical word	1	1	1	1
Synonym	1	1	1	1
Hypernym	1	.5	.5	.5
Sibling	1	.3	.2	0

- for scoring chains (Silber & McCoy, 2002) use (Barzilay & Elhadad, 1999)'s method (2 standard deviations above the average)

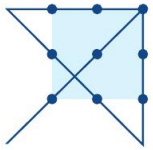
Runtime of the Algorithm



Value	Worst Case	Average Case
C_1 = # of senses for a given word	30	2
C_2 = parent/child "is a" relations of a word sense	45,147	14
C_3 = # of nouns in WordNet	94,474	94,474
C_4 = # of synsets in WordNet	66,025	66,025
C_5 = # of siblings of a word sense	397	39
C_6 = # of chains to which a word instance can belong	45,474	55

- collection of WordNet information:
  $n * (log_2(C_3) + C_1 * C_2 + C_1 * C_5)$
- building the graph:
  $n * C_6 * 4$
- extracting the best information:
  $n * C_6 * 4$
- overall runtime performance:
  $n * (1,548,216 + log_2(94,474) + 45,474 * 4)$ (worst case)
  $n * (326 + log_2(94,474) + 55 * 4)$ (average case)

Evaluation

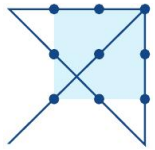


- linear runtime makes evaluation on larger documents possible
- evaluation question: are the lexical chains identified the concepts which humans identify as important for summaries?
- documents from different domains (10 scientific articles along with their abstracts, 10 textbook chapters along with their chapter summaries)
- length of documents between 2,200 and 26,500 words

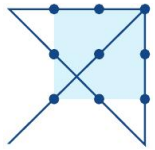
Document	Total Number of Strong Chains in Document	Total Number of Noun Instances in Summary	Strong Chains with Corresponding Noun Instances in Summary	Noun Instances with Corresponding Strong Chains in Document
CS Paper 1	10	22	7 (70.00%)	19 (86.36%)
CS Paper 2	7	19	6 (71.43%)	17 (89.47%)
CS Paper 3	5	31	4 (80.00%)	27 (87.19%)
CS Paper 4	6	25	5 (83.33%)	24 (96.00%)
CS Paper 5	8	16	6 (75.00%)	12 (75.00%)
ANTH Paper 1	7	20	7 (100.00%)	17 (85.00%)
ANTH Paper 2	5	17	4 (80.00%)	13 (76.47%)
ANTH Paper 3	7	21	6 (28.57%)	7 (33.33%)
BIO Paper 1	4	19	4 (100.00%)	17 (89.47%)
BIO Paper 2	5	31	5 (80.00%)	28 (90.32%)
CS Chapter 1	9	55	8 (88.89%)	49 (89.09%)
CS Chapter 2	7	49	6 (85.71%)	42 (85.71%)
CS Chapter 3	11	31	9 (81.82%)	25 (80.65%)
CS Chapter 4	14	47	5 (35.71%)	21 (44.68%)
ANTH Chapter 1	5	61	4 (80.00%)	47 (77.05%)
ANTH Chapter 2	8	74	7 (87.50%)	59 (79.73%)
ANTH Chapter 3	12	58	11 (91.67%)	48 (82.76%)
ANTH Chapter 4	13	49	11 (84.62%)	42 (85.71%)
ANTH Chapter 5	7	68	5 (71.43%)	60 (88.24%)
ANTH Chapter 6	9	59	8 (88.89%)	48 (81.36%)
HIST Chapter 1	12	71	10 (83.33%)	67 (94.37%)
HIST Chapter 2	8	65	7 (87.50%)	55 (84.62%)
ECON Chapter 1	14	68	12 (85.71%)	63 (92.65%)
ECON Chapter 2	9	51	7 (77.78%)	33 (64.71%)
Mean			79.12%	80.83%
Median			82.58%	85.35%

Note: ANTH—anthropology, BIO—biology, CS—computer science, ECON—economics, HIST—history.

Discussion

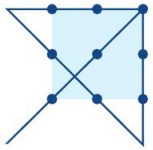


- pronouns and proper names cause problems
- WordNet does not have sufficient information on proper names
- coverage of WordNet – system defaults to word frequency if no WordNet entry is found
- lexical chains are based on nouns only; information on verbs (predicates) is disregarded



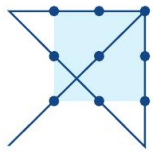
Further Applications

Further Applications



- spelling correction (Hirst & St-Onge, 1998)
- keyphrase indexing (Medelyan, 2007)
- keyword extraction (Erkan, 2007)
- more segmentation (Stokes et al., 2004)
- web directory construction (Stamou et al., 2005)
- question answering (Moldovan et al., 2002)
- . . . and many more

Homework



- read the paper on which you want to base your project (it would be preferable if this would coincide with your presentation)
- based on your knowledge of NLTK decide whether it is feasible (if you are in doubt, talk to me)
- write a specification (input, output, data structures, preprocessing tools needed, evaluation metric, data needed – I may be able to point you to or to provide you with the required data)
- send specification to me (michael.strube@h-its.org) by May 10, 2012, 1pm
- (later today) link to the slides at `http://michael.kimstrube.de/teaching.php`

References

Barzilay, Regina & Michael Elhadad (1997).
Using lexical chains for text summarization.
In *Proceedings of the ACL Workshop on Intelligent and Scalable Text Summarization, Madrid, Spain, July 1997*, pp. 10–17.

Barzilay, Regina & Michael Elhadad (1999).
Text summarization with lexical chains.
In Inderjeet Mani & Mark T. Maybury (Eds.), *Advances in Automatic Text Summarization*, pp. 111–121. Cambridge, Mass.: MIT Press.

Galley, Michel, Kathleen R. McKeown, Eric Fosler-Lussier & Hongyan Jing (2003).
Discourse segmentation of multi-party conversation.
In *Proceedings of the 41st Annual Meeting of the Association for Computational Linguistics,* Sapporo, Japan, 7–12 July 2003, pp. 562–569.

Hearst, Marti A. (1997).
TextTiling: Segmenting text into multi-paragraph subtopic passages.
Computational Linguistics, 23(1):33–64.

Hirst, Graeme & David St-Onge (1998).
Lexical chains as representations of context for the detection and correction of malapropisms.
In Christiane Fellbaum (Ed.), *WordNet: An Electronic Lexical Database*, pp. 305–332. Cambridge, Mass.: MIT Press.

Medelyan, Olena (2007).
Computing lexical chains with graph clustering.
In *Proceedings of the ACL 2007 Student Research Workshop,* Prague, Czech Republic, 25–26 June 2007, pp. 85–90.

Morris, Jane & Graeme Hirst (1991).
Lexical cohesion computed by thesaural relations as an indicator of the structure of text.
Computational Linguistics, 17(1):21–48.

Silber, Gregory H. & Kathleen F. McCoy (2002).
Efficiently computed lexical chains as an intermediate representation for automatic text summarization.
Computational Linguistics, 28(4):487–496.

Stokes, Nicola, Joe Carthy & Alan F. Smeaton (2004).
A lexical cohesion based news story segmentation system.
AI Communications, 17(1):3–12.