Inspire...Educate...Transform.

Inspire…Educate…Transform.

8. Summarization

Dr. Manish Gupta

Sr. Mentor – Academics, INSOFE

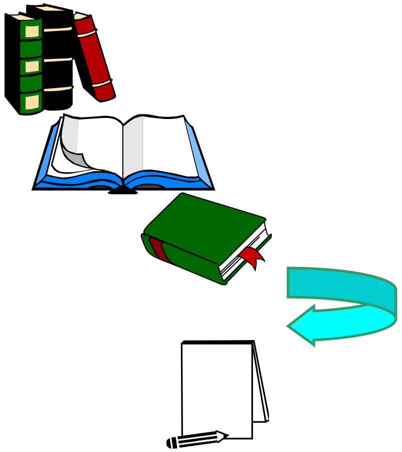
Course Content

- Collection of three main topics of high recent interest.
  - Search engines (Crawling, Indexing, Ranking)
    - Language Modeling
    - Text Indexing and Crawling
    - Relevance Ranking
    - Link Analysis Algorithms
  - Text Processing (NLP, NER, Sentiments)
    - Natural Language Processing
    - Named Entity Recognition
    - Sentiment Analysis
    - **Summarization**
  - Social networks (Properties, Influence Propagation)
    - Social Network Analysis
    - Influence Propagation in Social Networks

What is summarization?

...put a book on the scanner, turn the dial to ‘2 pages’, and read the result...

...download 1000 documents from the web, send them to the summarizer, and select the best ones by reading the summaries of the clusters...



Summarization System:
An information access technology that given a document or sets of *related* documents, extracts the most important content from the source(s) taking into account the user or task at hand, and presents this content in a well formed and concise text

Agenda

- **Applications of text summarization**
- Genres and types of summaries
- Extraction based Summarization methods
- Evaluating summaries

Headline news — informing

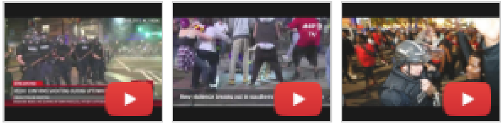
Washington Post

See realtime coverage

NC governor declares state of emergency after another night of violence in Charlotte
Washington Post - 2 hours ago
CHARLOTTE - After a second night of violent demonstrations here that left one man clinging to life and several businesses damaged, North Carolina Gov.

One person critically wounded during Keith Scott protests New York Daily News
OpEd: Charlotte Is Burning: Waking up From the American Dream... Finally? NBCNews.com

Highly Cited: Charlotte faces aftermath of protests ignited by fatal police shooting; 16 officers injured Charlotte Observer
Local Source: Charlotte police shooting: State of emergency declared during 2nd night of violent protests WSOC Charlotte
Featured: Who is Keith Lamont Scott? Fusion
Trending: NC Gov. declares state of emergency following violent Charlotte protests USA TODAY


USA TODAY TODAYonline CNN


Newsweek

Trump calls for nationwide 'stop-and-frisk' policy
Politico - 12 hours ago
KING'S SPEECH: DONALD TRUMP's coalition assembled in Cleveland today to push back on the idea that his campaign espouses racist ideas - and that effort included boxing promoter Don King.


CNN

US fighter jet crashes off Japanese island of Okinawa
CNN - 1 hour ago
Tokyo (CNN) A US Marine Corps pilot ejected safely when his fighter jet crashed into the waters east of the Japanese island of Okinawa, officials said.

TV-GUIDES — decision making

2:30am **VC2 – 76**

The Jackal

Movie: Bruce Willis excels as "The Jackal," a cunning assassin who uses many disguises in this 1997 thriller. Richard Gere and Sidney Poitier costar as players from different sides of the law who unite to stop him.

3:00am **KCOP – 13**

The Untouchables

Movie: Eliot Ness (Kevin Costner) and ‘‘The Untouchables’’ take on Robert De Niro’s flamboyant Al Capone in the pulse–pounding 1987 adaptation of the popular TV series.\Sean Connery won an Oscar as the Irish beat cop who shows Ness ‘‘the Chicago way.’’\ Brian De Palma directed the feature;\David Mamet wrote the script.\And yes, film majors, the scene at Union Station was lifted directly from the

3:05am **STARZ – 25**

Grosse Pointe Blank

Movie: A razor–sharp script and a fine turn by John Cusack as a troubled hit man mark 1997’s "Grosse Pointe Blank," a dark comedy in which the assassin encounters his old flame (Minnie Driver of "Good Will Hunting") at a high–school reunion. Cusack’s sister Joan ("In and Out") is hilarious as the killer’s devoted assistant, and Alan Arkin makes the most of his small role as Cusack’s terrified the

CSE 7306c

Examples of summaries – sports results

New Zealand tour of India, 1st Test: India v New Zealand at Kanpur, Sep 22-26, 2016

Summary | Full scorecard | Commentary | Statistics

India **318**
New Zealand **89/1 (27.0 ov)**

New Zealand trail by 229 runs with 9 wickets remaining in the 1st innings

New Zealand RR 3.29
Last 10 ovs 33/0 **RR** 3.30
Min overs remaining 54

Day 2 — **Current time** 12:37 local, 07:07 GMT — **Test Career**

Batsmen	R	B	4s	6s	SR	This bowler	Mat	Runs	HS	Ave
Kane Williamson (rhb)	**31**	45	4	0	68.88	8 (20b)	53	4424	242*	51.44
Tom Latham (lhb)	**33**	86	4	0	38.37	13 (28b)	23	1587	137	39.67

Bowlers	O	M	R	W	Econ	0s	4s	6s	Mat	Wkts	BBI	Ave
Ravindra Jadeja (sla)	11.0	0	32	0	2.90	48	4	0	18	71	6/138	23.87
Mohammed Shami (rfm)	7.0	1	22	0	3.14	33	4	0	17	58	5/47	34.56

Recent overs • 1 • • • 4 | • • • 1 4 • | 4 • • • • •

Current partnership 54 runs, 17.3 overs, RR: 3.08

Last bat MJ Guptill lbw b Yadav 21 (31b 3x4 0x6) SR: 67.74
Fall of wicket 35/1 (9.3 ov); Partnership: 35 runs, 9.3 overs, RR: 3.68

End of over 27 (4 runs) **New Zealand 89/1**

TWM Latham	33 (86b 4x4 0x6)	**Mohammed Shami**	7-1-22-0
KS Williamson	31 (45b 4x4 0x6)	**RA Jadeja**	11-0-32-0

Abhishek Jain: "You guys are going way over board to describe KANE. Just relax. Never saw you describing Indian batsmen in such a manner."

26.6 Mohammed Shami to Latham, no run, shortish on middle and off, Latham wanted to nudge it through square leg but the ball held on the pitch and forces the ball to pop up towards midwicket

26.5 Mohammed Shami to Latham, no run, back of a length on off stump, defended

Abstracts of papers — time saving

An Incremental Interpreter for High-Level Programs with Sensing

Giuseppe De Giacomo
Dipartimento di Informatica e Sistemistica
Universita di Roma "La Sapienza"
Via Salaria 113, 00198 Rome, Italy
degiacomo@dis.uniroma1.it

Hector Levesque
Department of Computer Science
University of Toronto
Toronto, Canada M5S 3H5
hector@cs.toronto.edu

Abstract

Like classical planning, the execution of high-level agent programs requires a reasoner to look all the way to a final goal state before even a single action can be taken in the world. This deferral is a serious problem in practice for large programs. Furthermore, the problem is compounded in the presence of sensing actions which provide necessary information, but only after they are executed in the world. To deal with this, we propose (characterize formally in the situation calculus, and implement in Prolog) a new incremental way of interpreting such high-level programs and a new high-level language construct, which together, and without loss of generality, allow much more control to be exercised over when actions can be executed. We argue that such a scheme is the only practical way to deal with large agent programs containing both nondeterminism and sensing.

Introduction

In [4] it was argued that when it comes to providing high level control to autonomous agents or robots, the notion of *high-level program execution* offers an alternative to classical planning that may be more practical in many applications. Briefly, instead of looking for a sequence of actions $\vec{a}$ such that

$$Axioms \models Legal(do(\vec{a}, S_0)) \wedge \phi(do(\vec{a}, S_0))$$

where ϕ is the goal being planned for, we look for a sequence $\vec{a}$ such that

$$Axioms \models Do(\delta, S_0, do(\vec{a}, S_0))$$

to find a sequence with the right properties. This can involve considerable search when δ is very nondeterministic, but much less search when δ is more deterministic. The feasibility of this approach for AI purposes clearly depends on the expressive power of the programming language in question. In [4], a language called ConGolog is presented, which in addition to nondeterminism, contains facilities for sequence, iteration, conditionals, concurrency, and prioritized interrupts. In this paper, we extend the expressive power of this language by providing much finer control over the nondeterminism, and by making provisions for sensing actions. To do so in a way that will be practical even for very large programs requires introducing a different style of on-line program execution.

In the rest of this section, we discuss on-line and off-line execution informally, and show why sensing actions and nondeterminism together can be problematic. In the following section, we formally characterize program execution in the language of the situation calculus. Next, we describe an incremental interpreter in Prolog that is correct with respect to this specification. The final section contains discussion and conclusions.

Off-line and On-line execution

To be compatible with planning, the ConGolog interpreter presented in [4] executes in an *off-line* manner, in the sense that it must find a sequence of actions constituting an entire legal execution of a program *before* actually executing any of them in the world.[1] Consider, for example, the following program:

Summly News summarization

Yahoo Paid $30 Million in Cash for 18 Months of Young Summly Entrepreneur's Time

MARCH 25, 2013 AT 8:35 AM PT | Tweet | Share | G+1 | in Share | Share | Print

Earlier today, Yahoo said it had acquired the trendy and decidedly stylish news reading app Summly, along with its telegenic and very young entrepreneur Nick D'Aloisio.

Yahoo said it plans to close down the actual app and use the algorithmic summation technology that the 17-year-old D'Aloisio built with a small team of five, along with a major assist from Silicon Valley research institute SRI International, throughout its products.

Summarization Startups
https://angel.co/content-summarization

Content Summarization Startups

18 COMPANIES 21,431 INVESTORS 224,071 FOLLOWERS

◂ All Markets

PARENTS
- Digital Media

SIBLINGS
- Blogging Platforms
- Content Farms
- Content Syndication
- E-Books
- Email Newsletters

VIEW MORE ▾

Company	Joined	Followers	Signal
tldr.io Human-written summaries Paris · Crowdsourcing	Nov '12	69	
Agolo Summarizations as a service New York City · Content Summarization	Feb '13	40	
Clipped Text Summarization Cupertino · Algorithms	Dec '12	15	
ThisIs.Me Profile 3.0 Content Summarization	Mar '12	15	
Wondren Discover the full story New York City · Content Summarization	Mar '12	26	
Deck Book Recreate the book summary ... lik... Presentations	Oct '12	5	
Skim.it Summarize the web for easy shar... London · Algorithms	Jan '14	15	
Jotup All your knowledge, organised on... London · Content Summarization	Nov '15	12	

Debate.fm A simple platform to start a side b... Kolkata · Content Summarization	Jan '12	17
Voxini The easiest way to share your so... Washington · Content Summarization	Apr '12	12
Precily Precily takes great works of non-fi... New Delhi · Content Summarization	Jul '16	4
Summaritan Intelligent News Reporting portal India · Content Summarization	Mar '14	9
Riyarchy Outlining & concluding debates. Visualization	Aug '12	5
Smmry Crowdsourced Book Summaries Romania · Content Summarization	Jun '16	2
Gajere Nigerian News summary site Kaduna · Content Summarization	Oct '15	1
Brieflet Save time reading the news London · Content Summarization	Jun '15	1
AutoSummarizer AutoSummarizer is a service for s... New York · Content Summarization	Jul '14	1
Newspeye Personalised news search (Goog... Lincoln · Content Summarization	May '14	1

CSE 7306c

Agenda

- Applications of text summarization
- **Genres and types of summaries**
- Extraction based Summarization methods
- Evaluating summaries

‘Genres’ of Summary?

- extract vs abstract
  - fragments from the document
  - newly re-written text
- generic vs query-based vs user-focused
  - all major topics equal coverage
  - based on a question “what are the causes of the war?”
  - users interested in chemistry
- for novice vs for expert
  - background
  - Just the new information

- single-document vs multi-document
  - research paper
  - proceedings of a conference
- in textual form vs items vs tabular vs structured
  - paragraph
  - list of main points
  - numeric information in a table
- in the language of the document vs in other language
  - monolingual
  - cross-lingual

Agenda

- Applications of text summarization
- Genres and types of summaries
- **Extraction based Summarization methods**
- Evaluating summaries

Overview of Extraction Methods

- Position in the text
  - lead method; optimal position policy
  - title/heading method
- Cue phrases in sentences
- Word frequencies throughout the text
- Cohesion: links among words
  - word co-occurrence
  - coreference
  - lexical chains

Position-based method

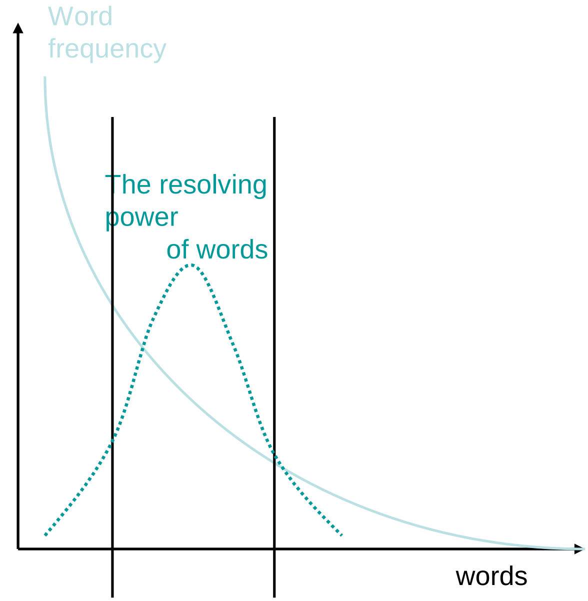
- Claim: Important sentences occur at the beginning (and/or end) of texts.
  - paragraph#: 1,2, ..., 10, last, last-1, ..., last-4
  - in paragraph: initial, middle, final
  - First sentence of document, first sentence of paragraph, last sentence of document, etc.
- Lead method: just take first sentence(s)!
- Optimum Position Policy (OPP)
  - Important sentences are located at positions that are genre-dependent; these positions can be determined automatically through training (Lin and Hovy, 97).
    - Corpus: 13000 newspaper articles (ZIFF corpus).
    - Step 1: For each article, determine overlap between sentences and the index terms for the article.
    - Step 2: Determine a partial ordering over the locations where sentences containing important words occur
    - OPP for ZIFF corpus: (T) > (P2,S1) > (P3,S1) > (P2,S2) > {(P4,S1),(P5,S1),(P3,S2)} >… (where T=title; P=paragraph; S=sentence)
    - 10%-extracts cover 91% of the salient words.
- Title-based method
  - Words in titles and headings are positively relevant to summarization.

CSE 7306c

Cue-Phrase method

- **Claim 1**: Important sentences contain 'bonus phrases', such as *significantly, In this paper we show,* and *In conclusion*, while non-important sentences contain 'stigma phrases' such as *hardly* and *impossible*.
- Cue = a predefined list of words with associated weights
- **Method**: Add to sentence score if it contains a bonus phrase, penalize if it contains a stigma phrase.

Word-frequency-based method



(Luhn, 59)

- **Claim**: Important sentences contain words that occur “somewhat” frequently.
- **Method**: Increase sentence score for each frequent word.
- Stemming should be used
- “stop words” (i.e.”the”, “a”, “for”, “is”) are ignord

LexRank

- LexRank does document summarization by estimating sentence importance using random walks and eigenvector centrality.
- A graph is constructed by creating a vertex for each sentence in the document.
- The edges between sentences are based on some form of semantic similarity or content overlap. While LexRank uses cosine similarity of TF-IDF vectors, TextRank uses a very similar measure based on the number of words two sentences have in common (normalized by the sentences' lengths).
- Sentences are ranked by applying PageRank to the resulting graph. A summary is formed by combining the top ranking sentences, using a threshold or length cutoff to limit the size of the summary.
- LexRank was used as part of a larger summarization system (MEAD) that combines the LexRank score (stationary probability) with other features like sentence position and length using a linear combination with either user-specified or automatically tuned weights.
- For multi-document summarization, to avoid duplicate sentences, LexRank applies a heuristic post-processing step that builds up a summary by adding sentences in rank order, but discards any sentences that are too similar to ones already placed in the summary. The method used is called Cross-Sentence Information Subsumption (CSIS).

Problems with extracts

- Lack of cohesion

source

A single-engine airplane crashed Tuesday into a ditch beside a dirt road on the outskirts of Albuquerque, killing all five people aboard, authorities said.

Four adults and one child died in the crash, which witnesses said occurred about 5 p.m., when it was raining, Albuquerque police Sgt. R.C. Porter said.

The airplane was attempting to land at nearby Coronado Airport, Porter said.

It aborted its first attempt and was coming in for a second try when it crashed, he said…

extract

Four adults and one child died in <u>the crash</u>, which witnesses said occurred about 5 p.m., when it was raining, Albuquerque police Sgt. R.C. Porter said.

<u>It</u> aborted <u>its</u> first attempt and was coming in for a second try when <u>it</u> crashed, he said.

CSE 7306c

Problems with extracts

- Lack of coherence

source

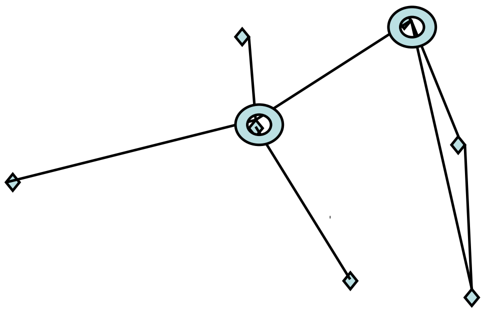
Supermarket A announced a big profit for the third quarter of the year. The directory studies the creation of new jobs. Meanwhile, B's supermarket sales drop by 10% last month. The company is studying closing down some of its stores.

extract

Supermarket A announced a big profit for the third quarter of the year. The company is studying closing down some of its stores.

Cohesion-based methods

- **Claim**: Important sentences/paragraphs are the highest connected entities in more or less elaborate semantic structures.
- Classes of approaches
  - word co-occurrences;
  - co-reference;
  - lexical similarity (WordNet, lexical chains);
  - combinations of the above.



Cohesion: Lexical chains method

But Mr. Kenny's move speeded up work on a **machine** which uses **micro-computers** to control the rate at which an *anaesthetic* is pumped into the blood of *patients* undergoing *surgery*. Such **machines** are nothing new. But Mr. Kenny's **device** uses two **personal-computers** to achieve much closer monitoring of the **pump** feeding the *anaesthetic* into the *patient*. Extensive testing of the **equipment** has sufficiently impressed the authorities which regulate *medical* **equipment** in Britain, and, so far, four other countries, to make this the first such **machine** to be licensed for commercial sale to *hospitals*.

- Lexical chain: word sequence in a text where the words are related by repetition, synonymy, class/superclass (hypernymy), paraphrase
- A chain C represents a "concept" in WordNet
  - *Financial institution* "bank"
  - *Side of the river* "bank"

- Method for creating chain:
  - Select a set of candidate words from the text.
  - For each of the candidate words, find an appropriate chain, relying on a relatedness criterion among members of the chains and the candidate words.
  - If such a chain is found, insert the word in this chain and update it accordingly; else create a new chain.

Cohesion: Lexical chains method

- Scoring the chains
  - Length of chain
  - the kind of relation between their words (same word, antonym, synonym, meronym, hyper/hyponyms)
  - their starting position within the text
- Strong chain must be selected
- Sentence selection for summary
  - H1: select the first sentence that contains a member of a strong chain
  - H2: select the first sentence that contains a "representative" (frequency) member of the chain
  - H3: identify a text segment where the chain is highly dense (density is the proportion of words in the segment that belong to the chain)

Take-aways

- We discussed various applications where text summarization is useful.
- We looked at various genres and types of summaries
- We talked about three types of summarization methods: Topic extraction, Interpretation, Multi-document summarization
- Finally, we discussed various metrics for summarization evaluation.

References (1)

Aone, C., M.E. Okurowski, J. Gorlinsky, B. Larsen. 1997. A Scalable Summarization System using Robust NLP. *Proceedings of the Workshop on Intelligent Scalable Text Summarization*, 66–73. ACL/EACL Conference, Madrid, Spain.

Baldwin, B. and T. Morton. 1998. Coreference-Based Summarization. In T. Firmin Hand and B. Sundheim (eds). TIPSTER-SUMMAC Summarization Evaluation. *Proceedings of the TIPSTER Text Phase III Workshop*. Washington.

Barzilay, R. and M. Elhadad. 1997. Using Lexical Chains for Text Summarization. In *Proceedings of the Workshop on Intelligent Scalable Text Summarization* at the ACL/EACL Conference, 10–17. Madrid, Spain.

Baxendale, P.B. 1958. Machine-Made Index for Technical Literature—An Experiment. *IBM Journal* (October) 354–361.

Boguraev B. and C. Kennedy, 1997. Salience-based Content Characterization of Text Documents. In *Proceedings of the Workshop on Intelligent Scalable Text Summarization* at the ACL/EACL Conference, 2–9. Madrid, Spain.

Buckley, C. and C. Cardie. 1997. SMART Summarization System. In T. Firmin Hand and B. Sundheim (eds). TIPSTER-SUMMAC Summarization Evaluation. *Proceedings of the TIPSTER Text Phase III Workshop*. Washington.

DeJong, G. 1978. Fast Skimming of News Stories: The FRUMP System. Ph.D. diss. Yale University.

Donlan, D. 1980. Locating Main Ideas in History Textbooks. *Journal of Reading*, 24, 135–140.

Edmundson, H.P. 1968. New Methods in Automatic Extraction. *Journal of the ACM* 16(2), 264–285.

Elhadad, M. 1992. Using Argumentation to Control Lexical Choice: A Functional Unification-Based Approach. Ph.D. diss, Columbia University.

Endres-Niggemeyer, B. 1998. Summarizing Information. New York: Springer-Verlag.

Hovy, E.H. and L. Wanner. 1996. Managing Sentence Planning Requirements. In *Proceedings of the Workshop on Gaps and Bridges in NL Planning and Generation*, 53–58. ECAI Conference. Budapest, Hungary.

Hovy, E.H. and Lin, C-Y. 1998. Automated Text Summarization in SUMMARIST. In M. Maybury and I. Mani (eds), *Intelligent Scalable Summarization Text Summarization*. Forthcoming.

Hovy, E.H. 1998. Experiments in Evaluating Summarization. In prep.

References (2)

Jing, H., R. Barzilay, K. McKeown, and M. Elhadad. 1998. Summarization Evaluation Methods: Experiments and Analysis. *In Working Notes of the AAAI'98 Spring Symposium on Intelligent Text Summarization*, 60–68. Stanford, CA.

Kintsch, W. and T.A. van Dijk. 1978. Toward a Model of Text Comprehension and Production. *Psychological Review*, 85, 363–394.

Knight, K. and V. Hatzivassiloglou. 1995. Two-Level Many-Paths Generation. In *Proceedings of the Thirty-third Conference of the Association of Computational Linguistics (ACL-95)*, 252–260. Boston, MA.

Kupiec, J., J. Pedersen, and F. Chen. 1995. A Trainable Document Summarizer. In *Proceedings of the Eighteenth Annual International ACM Conference on Research and Development in Information Retrieval* (SIGIR), 68–73. Seattle, WA.

Lehnert, W.G. 1983. Narrative complexity based on summarization algorithms. In *Proceedings of the Eighth International Joint Conference of Artificial Intelligence (IJCAI-83)*, 713–716. Karlsruhe, Germany.

Lin, C-Y. 1995. Topic Identification by Concept Generalization. In *Proceedings of the Thirty-third Conference of the Association of Computational Linguistics (ACL-95)*, 308–310. Boston, MA.

Lin, C-Y. 1997. Robust Automated Topic Identification. Ph.D. diss., University of Southern California.

Lin, C-Y. and E.H. Hovy. 1997. Identifying Topics by Position. In *Proceedings of the Applied Natural Language Processing Conference (ANLP-97),* 283–290. Washington.

Luhn, H.P. 1959. The Automatic Creation of Literature Abstracts. *IBM Journal of Research and Development*, 159–165.

Mani, I., E. Bloedorn, and B. Gates. 1998. Using Cohesion and Coherence Models for Text Summarization. *In Working Notes of the AAAI'98 Spring Symposium on Intelligent Text Summarization*, 69–76. Stanford, CA.

Mani I. And E. Bloedorn. 1998. Machine Learning of Generic and User-Focused Summarization. *Proceedings of the National Conference on Artificial Intelligence, (AAAI).* Madison, WI.

Mann, W.C. and S.A. Thompson. 1988. Rhetorical Structure Theory: Toward a Functional Theory of Text Organization. *Text* 8(3), 243–281. Also available as USC/Information Sciences Institute Research Report RR-87-190.

Marcu, D. 1997. The Rhetorical Parsing, Summarization, and Generation of Natural Language Texts. Ph.D. diss. University of Toronto.

CSE 7306c

References (3)

Marcu, D. 1998. Improving Summarization Through Rhetorical Parsing Tuning. *Proceedings of the Workshop on Very Large Corpora*. Montreal, Canada.

Marcu, D. 1998. The Automatic Construction of Large-Scale Corpora for Summarization Research. In prep.

Mauldin, M.L. 1991. *Conceptual Information Retrieval—A Case Study in Adaptive Partial Parsing*. Boston, MA: Kluwer Academic Publishers.

McKeown, K.R. and D.R. Radev. 1995. Generating Summaries of Multiple News Articles. In *Proceedings of the Eighteenth Annual International ACM Conference on Research and Development in Information Retrieval* (SIGIR), 74–82. Seattle, WA.

Mitra M., A. Singhal, and C. Buckley. 1997. Automatic Text Summarization by Paragraph Extraction. In *Proceedings of the Workshop on Intelligent Scalable Summarization* at the ACL/EACL Conference, 39–46. Madrid, Spain.

Morris J. and G. Hirst. 1991. Lexical Cohesion Computed by Thesaural Relations as an Indicator of the Structure of Text. *Computational Linguistics* 17(1), 21–48.

MUC conference series. 1989–1997. Sundheim, B. (ed.) *Proceedings of the Message Understanding Conferences, I–VI*. Morgan Kaufman.

Ono K., K. Sumita, and S. Miike. Abstract Generation Based on Rhetorical Structure Extraction. *In Proceedings of the International Conference on Computational Linguistics (Coling),* 344–348. Japan.

Paice, C.D. 1990. Constructing Literature Abstracts by Computer: Techniques and Prospects. *Information Processing and Management* 26(1): 171–186.

Rau, L.S. and P.S. Jacobs. 1991. Creating Segmented Databases from Free Text for Text Retrieval. In *Proceedings of the Fourteenth Annual International ACM Conference on Research and Development in Information Retrieval* (SIGIR), 337–346. New York, NY.

Reimer U. and U. Hahn. 1997. A Formal Model of Text Summarization Based on Condensation Operators of a Terminological Logic. In *Proceedings of the Workshop on Intelligent Scalable Summarization* at the ACL/EACL Conference, 97–104. Madrid, Spain.

CSE 7306c

References (4)

Salton, G., J. Allen, C. Buckley, and A. Singhal. 1994. Automatic Analysis, Theme Generation, and Summarization of Machine-Readable Texts. Science 264: 1421–1426.

Schank, R.C. and R.P. Abelson. 1977. Scripts, Plans, Goals, and Understanding. Hillsdale, NJ: Lawrence Erlbaum Associates.

Spark Jones, K. 1997. Invited keynote address, Workshop on Intelligent Scalable Text Summarization. ACL/EACL Conference. Madrid, Spain.

SUMMAC, 1998. Firmin Hand, T. and B. Sundheim (eds). TIPSTER-SUMMAC Summarization Evaluation. Proceedings of the TIPSTER Text Phase III Workshop. Washington.

Teufel, S. and M. Moens. 1997. Sentence Extraction as a Classification Task. In Proceedings of the Workshop on Intelligent Scalable Summarization. ACL/EACL Conference, 58–65. Madrid, Spain.

Online bibliographies:

http://www.cs.columbia.edu/~radev/summarization/

http://www.cs.columbia.edu/~jing/summarization.html

http://www.dcs.shef.ac.uk/~gael/alphalist.html

A list of text summarization projects

http://web.science.mq.edu.au/~swan/summarization/projects_full.htm

International School of Engineering

Plot 63/A, 1st Floor, Road # 13, Film Nagar, Jubilee Hills, Hyderabad - 500 033

For Individuals: +91-9502334561/63 or 040-65743991

For Corporates: +91-9618483483

Web: http://www.insofe.edu.in

Facebook: https://www.facebook.com/insofe

Twitter: https://twitter.com/Insofeedu

YouTube: http://www.youtube.com/InsofeVideos

SlideShare: http://www.slideshare.net/INSOFE

LinkedIn: http://www.linkedin.com/company/international-school-of-engineering