Chapter 16: Discourse

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A Definition of Discourse

A discourse is a sequence of sentences: a text or a conversation

A discourse is made of words or phrases that refer to things: the **discourse entities**

A discourse normally links the entities together to address topics

Within a single sentence, grammatical structures provide with a model of relations between entities.

Discourse models extend relations to more sentences

Reference

Discourse entities – or discourse referents – are the real, abstract, or imaginary objects introduced by the discourse. **Referring expressions** are mentions of the discourse entities through the text

1. *Susan drives a Ferrari*
2. *She drives too fast*
3. *Lyn races her on weekends*
4. *She often beats her*
5. *She wins a lot of trophies*

Discourse Entities

Mentions (or referring expressions)	Discourse entities (or referents)	Logic properties
Susan, she, her	`'Susan'`	`'Susan'`
Lyn, she	`'Lyn'`	`'Lyn'`
A Ferrari	`X`	`ferrari(X)`
A lot of trophies	`E`	$E \subset \{X \mid trophy(X)\}$

Reference and Named Entities

Named entities are entities uniquely identifiable by their name.

Some definitions/ clarifications:

- Named entity recognition (NER): a partial parsing task, see Chap. 10;
- Reference resolution for named entities: find the entity behind a mention, here a name.

Words	POS	Groups	Named entities
U.N.	NNP	I-NP	I-ORG
official	NN	I-NP	O
Ekeus	NNP	I-NP	I-PER
heads	VBZ	I-VP	O
for	IN	I-PP	O
Baghdad	NNP	I-NP	I-LOC
.	.	O	O

As it is impossible to set a physical link between a real-life object and its mention, we use unique identifiers or tags in the form of URIs instead (from Wikidata,DBpedia, Yago).

Mentions of Named Entities are Ambiguous

Cambridge: England, Massachusetts, or Ontario?
Saussure has 11 entries in Wikipedia. Given the text (from Wikipedia):

> *One of his translators, Roy Harris, summarized* ***Saussure****'s contribution to linguistics and the study of language in the following way...*

Which Saussure?

- *Ferdinand de Saussure*:
  - Wikidata: `http://www.wikidata.org/wiki/Q13230`
  - DBpedia: `http://dbpedia.org/resource/Ferdinand_de_Saussure`
- *Henri de Saussure*: `http://www.wikidata.org/wiki/Q123776`
- *René de Saussure*: `http://www.wikidata.org/wiki/Q13237`

Disambiguation of Named Entities

Given:

> *One of his translators, Roy Harris, summarized **Saussure**'s contribution to linguistics and the study of language...*

Disambiguation is a classification problem dealing with mention-entity pairs:

Mention	Entity	Q number	T/F
Saussure	Ferdinand de Saussure	Q13230	1
Saussure	Henri de Saussure	Q123776	0
Saussure	René de Saussure	Q13237	0
...			

Feature vectors represent pair of mentions and entities:

- Cosine similarity between the mention context and the named entity page in Wikipedia and bag-of-word vectors of the mention context
- Training set built from Wikipedia markup: `[[Ferdinand_de_Saussure|Saussure]]`

Named Entities and Linked Data

Graph databases are popular devices used to represent named entities, especially the resource description framework (RDF).

Entities are assigned unique resource identifiers (URIs) similar to URLs (as in HTTP addresses) and can be linked to other data sources (Linked data)

Examples of databases using the RDF format:

DBpedia: A database of persons, organizations, locations, etc. DBpedia is automatically extracted from Wikipedia semi-structured data (info boxes)

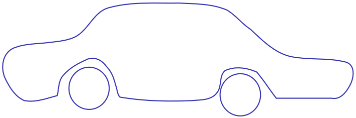
Geonames: A database of geographical names (a gazetteer).

SPARQL is a database query language that enables a programmer to extract data from a graph database (similar to Prolog or SQL).

Coreference

[$_{\text{entity1}}$ Garcia Alvarado], 56, was killed when [$_{\text{entity2}}$ a bomb] placed by [$_{\text{entity3}}$ urban guerrillas] on [$_{\text{entity4}}$ his vehicle] exploded as [$_{\text{entity5}}$ it] came to [$_{\text{entity6}}$ a halt] at [$_{\text{entity7}}$ an intersection] in [$_{\text{entity8}}$ downtown] [$_{\text{entity9}}$ San Salvador].

*on **his vehicle** exploded as **it** came to a halt*



Anaphora

Anaphora, often pronouns

Pronouns: it, she, he, this, that

Cataphora

I just wanted to touch ***it****, this stupid animal.*
They *have stolen my bicycle.*

Antecedents
Ellipsis is the absence of certain referents

I want to have information on caterpillars. And also on hedgehogs.

Coreference Annotation

The MU Conferences have defined a standard annotation for noun phrases
It uses the COREF element with five possible attributes: ID, REF, TYPE, MIN, and STAT.

- <COREF ID="100">Lawson Mardon Group Ltd.</COREF> said <COREF ID="101" TYPE="IDENT" REF="100">it</COREF>
- <COREF ID="100" MIN="Haden MacLellan PLC">Haden MacLellan PLC of Surrey, England</COREF> ...
  <COREF ID="101" TYPE="IDENT" REF="100">Haden MacLellan</COREF>

Coreference Annotation: CoNLL 2011 simplified

0	"	"	...	-
1	Vandenberg	NNP		(8 |(0)
2	and	CC		-
3	Rayburn	NNP		(23) |8)
4	are	VBP		-
5	heroes	NNS		-
6	of	IN		-
7	mine	NN		(15)
8	,	,		-
9	"	"		-
10	Mr.	NNP		(15
11	Boren	NNP		15)
12	says	VBZ		-
13	,	,		-
14	referring	VBG		-
15	as	RB		-
16	well	RB		-
17	to	IN		-
18	Sam	NNP		(23
19	Rayburn	NNP		-
20	,	,		-
21	the	DT		-
22	Democratic	JJ		-
23	House	NNP		-
24	speaker	NN		-
25	who	WP		-
26	cooperated	VBD		-
27	with	IN		-
28	President	NNP		-
29	Eisenhower	NNP		23)
30	.	.		-

Entities and mentions:

$e_0 = \{Vandenberg\}$

$e_8 = \{Vandenberg\ and\ Rayburn\}$

$e_{15} = \{mine, Mr.\ Boren\}$

$e_{23} = \{Rayburn, Sam\ Rayburn\ `,'\ the\ Democratic\ House\ speaker\ who\ cooperated\ with\ President\ Eisenhower\}$

Coreference Chains

In the MUC competitions, coreference is defined as symmetric and transitive:

- If A is coreferential with B, the reverse is also true.
- If A is coreferential with B, and B is coreferential with C, then A is coreferential with C.

It forms an equivalence class called a **coreference chain**.
The `TYPE` attribute specifies the link between the anaphor and its antecedent.
`IDENT` is the only possible value of the attribute
Other types are possible such as part, subset, etc.

Solving Coreferences

Coreferences define a class of equivalent references
Backward search with a compatible gender and number
98% of the antecedents are in the current or previous sentence
Focus: an integer attached to all objects, incremented when:

- It is mentioned: subject, object, adjunct
- It is visible or pointed at.

The focus is decremented over time
Constraints are also applied: subject $\neq$ object, grammatical role
Anaphora is resolved by taking the highest focus

A Simplistic Method

Garcia Alvarado, 56, was killed when ***a bomb*** *placed by urban guerrillas*

$\boxed{2}$

on ***his vehicle*** *exploded as* ***it*** *came to a halt at an intersection in*

$\boxed{1}$

downtown San Salvador

Machine Learning to Solve Coreferences

Instead of manually engineered rules, machine learning uses an annotated corpus and trains the rules automatically.

The coreference solver is a decision tree. It considers pairs of noun phrases (NP_i, NP_j).

Each pair is represented by a feature vector of 12 parameters.

The tree takes the set of NP pairs as input and decides for each pair whether it corefers or not.

Using the transitivity property, it identifies all the coreference chains in the text.

The ID3 learning algorithm automatically induces the decision tree from texts annotated with the MUC annotation standard.

Architecture

Text → Tokenizer → Morphology → POS tagging → Noun phrases → Named entities → Nested NPs → Semantic classes → **Mentions**

The coreference engine takes a pair of extracted noun phrases (NP_i, NP_j)
For a given index j, the engine considers from right to left, NP_i as a potential antecedent and NP_j as an anaphor.
It classifies the pair as positive if both NPs corefer or negative if they don't.

Some Features

- Positional feature:
    1. Distance (DIST): This feature is the distance between the two noun phrases measured in sentences: 0, 1, 2, 3, ... The distance is 0 when the noun phrases are in the same sentence.
- Grammatical features:
    2. *i*-Pronoun (I_PRONOUN): Is NP_i a pronoun i.e. personal, reflexive, or possessive pronoun? Possible values are true or false.
    3. *j*-Pronoun (J_PRONOUN): Is NP_j a pronoun? Possible values are true or false.
- Lexical feature:
    12. String match (STR_MATCH): Are NP_i and NP_j equal after removing articles and demonstratives from both noun phrases? Possible values are true or false.

Training Examples: The Positive Examples

The classifier can be a decision tree or logistic regression.
It is trained from positive and negative examples extracted from the annotated corpus
The positive examples use pairs of adjacent coreferring noun phrases.
If $NP_{a1} - NP_{a2} - NP_{a3} - NP_{a4}$ is a coreference chain in a text, we have

Noun phrases	Coreference chains
NP_{a1}	Chain 22
...	
NP_{a2}	Chain 22
...	
NP_{a3}	Chain 22
...	
NP_{a4}	Chain 22
...	

The positive examples correspond to the pairs: (NP_{a1}, NP_{a2}), (NP_{a2}, NP_{a3}), (NP_{a3}, NP_{a4})

Training Examples: The Negative Examples

The negative examples consider the noun phrases NP_{i+1}, NP_{i+2},..., NP_{j-1} intervening between adjacent pairs (NP_i, NP_j).

Noun phrases	Coreference chains	Relation
NP_i	Chain 22	Antecedent
NP_{i+1}	Not part of Chain 22	
NP_{i+2}	Not part of Chain 22	
...		
NP_{j-1}	Not part of Chain 22	
NP_j	Chain 22	Anaphor

For each positive pair (NP_i, NP_j), the training procedure generates negative pairs:

- They consist of one intervening NP and the anaphor NP_j: (NP_{i+1}, NP_j), (NP_{i+2}, NP_j), . . . , and (NP_{j-1}, NP_j).
- The intervening noun phrases can either be part of another coreference chain or not.

Performances

At this point, it is useful to have the current performances in mind

- Morphological parsing can parse correctly 99 % of the words in many languages (Koskenniemi 1984)
  Bilolyckorna `"bil#olycka" N UTR DEF PL NOM`
- Part-of-tagging reaches and exceeds 97 % (Church 1991)

  En bilolycka med tre bilar

  En/`dt_utr_sin_ind` bilolycka/`nn_utr_sin_ind_nom` med/`pp` tre/`rg_nom` bilar/`nn_utr_plu_ind_nom`
- Sentence parsing reaches 85% in Swedish (Nivre 2006) – labeled dependencies.

Performances (II)

- Conversion of a sentence into a predicate–argument structure. The F-measure reaches about 80 (CONLL 2009).
  [$_{Judge}$ She] blames [$_{Evaluee}$ the Government] [$_{Reason}$ for failing to do enough to help]
  ```
  blames(judge, evaluee, reason)
  blames('She', 'The Government',
    'for failing to do enough to help').
  ```
- Coreference solving reaches a MUC F-measure of ∼60. Latest figures from CoNLL, Pradhan et al. (2011)

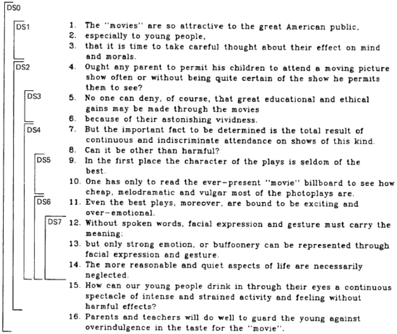
Discourse Theories and Models

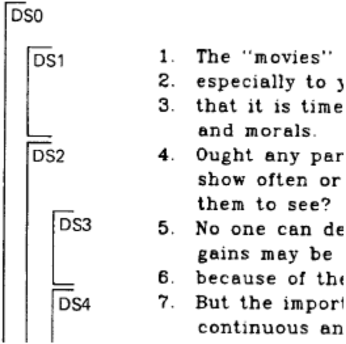
Discourse theories are used to develop organization models of texts
They have three objectives: **represent**, **parse automatically**, and **generate** a discourse.
There are many ways to represent a text and competing theories.
In 1992, Mann and Thompson compared 12 different representations obtained from experts in the field. The most significant are:

- Grosz and Sidner's theory (1986) and Centering (1995)
- Rhetorical structure theory (RST) (Mann and Thompson 1988)

Grosz and Sidner's Theory

Discourse is describes a hierarchical tree


DS0
DS1
1. The "movies" are so attractive to the great American public,
2. especially to young people,
3. that it is time to take careful thought about their effect on mind and morals.
DS2
4. Ought any parent to permit his children to attend a moving picture show often or without being quite certain of the show he permits them to see?
DS3
5. No one can deny, of course, that great educational and ethical gains may be made through the movies
6. because of their astonishing vividness.
DS4
7. But the important fact to be determined is the total result of continuous and indiscriminate attendance on shows of this kind.
8. Can it be other than harmful?
DS5
9. In the first place the character of the plays is seldom of the best.
10. One has only to read the ever-present "movie" billboard to see how cheap, melodramatic and vulgar most of the photoplays are.
DS6
11. Even the best plays, moreover, are bound to be exciting and over-emotional.
DS7
12. Without spoken words, facial expression and gesture must carry the meaning:
13. but only strong emotion, or buffoonery can be represented through facial expression and gesture.
14. The more reasonable and quiet aspects of life are necessarily neglected.
15. How can our young people drink in through their eyes a continuous spectacle of intense and strained activity and feeling without harmful effects?
16. Parents and teachers will do well to guard the young against overindulgence in the taste for the "movie".



Centers

Centers are entities that link one a sentence to another one.
Grosz divides centers in a unique **backward-looking center** that is the most important entity in the segment and others **forward-looking** centers.
Two relations link segments: dominance and satisfaction-precedence.

Rhetoric

- Invention (*Inventio*).
- Arrangement (*Dispositio*): introduction (*exordium*), a narrative (*narratio*), a proposition (*propositio*), a refutation (*refutatio*), a confirmation (*confirmatio*), and finally a conclusion (*peroratio*).
- Style (*Elocutio*): emote (*movere*), explain (*docere*), or please (*delectare*).
- Memory (*Memoria*)
- Delivery (*Actio*).

Rhetorical Structure Theory

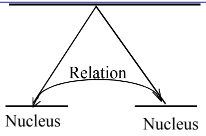
The rhetorical structure theory is a text grammar that analyzes argumentation: A text consists of:

- **Text spans** that can be sentences or clauses
- **Rhetorical relations** that link the text spans

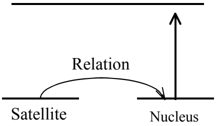
Relations are richer than with Grosz and Sidner.

Relations

Relations between segments can be symmetrical when spans have the same importance: Both spans are **nuclei**.



When relations are asymmetrical, we have a **nucleus** and a **satellite** where the nucleus is the most important

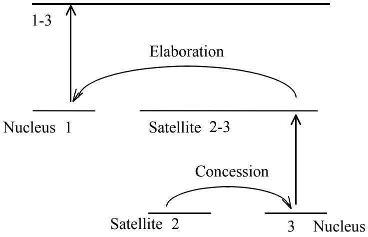


The text analysis produces a tree of text spans that are linked by different relation types.

Graphical Representation

Example cited by Mann and Thompson (1987):

1. *Concern that this material is harmful to health or the environment may be misplaced.*
2. *Although it is toxic to certain animals,*
3. *evidence is lacking that it has any serious long-term effect on human beings.*

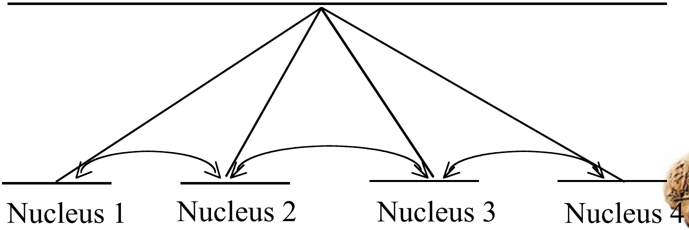


Links Between Nuclei

Spans can have a same importance and are linked by a sequence relation:

1. *Napoleon met defeat in 1814 by a coalition of major powers, notably Prussia, Russia, Great Britain, and Austria.*
2. *Napoleon was then deposed*
3. *and exiled to the island of Elba*
4. *and Louis XVIII was made ruler of France.*

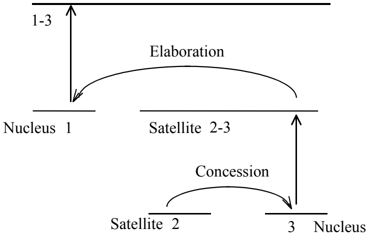
Microsoft Encarta, cited from Simon Corston-Oliver (1998)



Attempt to Formalize Structure

Mann and Thompson gave a formal structure to the graph that correspond to a parse tree:

1. The tree extends over the whole text;
2. Each text span part of the text analysis is either a terminal symbol or a node constituent;
3. A span has a unique parent;
4. Relations bind adjacent spans.



RST Relations

The original relations in RST are:

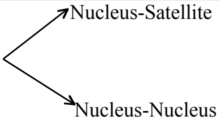
Nucleus-satellite relations		
Circumstance	Evidence	Otherwise
Solutionhood	Justify	Interpretation
Elaboration	Cause	Evaluation
Background	Antithesis	Restatement
Enablement	Concession	Summary
Motivation	Condition	

Multi-nucleus relations		
Sequence	Contrast	Joint

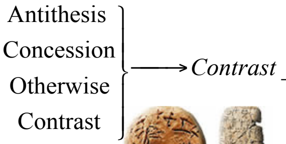
Relation Number

The number of relations is somewhat arbitrary.
Mann and Thompson first proposed 15 relations, then 23.
It is possible to group and simplify them.

Symmetrical (nucleus-nucleus) and asymmetrical relations (nucleus-satellite)



Group classes in a superclass



Definition of the Relations

The following text corresponds to an **evidence** relation that links a nucleus (segment 1) and a satellite (segment 2):

1. *The program as published for calendar year 1980 really works.*
2. *In only a few minutes, I entered all the figures from my 1980 tax return and got a result which agreed with my hand calculations to the penny.*

Mann and Thompson defined each relation in the RST model using a set of "constraints".

Definition of the Relations (II)

Relation name	EVIDENCE
Constraints on the nucleus N	The reader R might not believe to a degree satisfactory to the writer W
Constraints on the satellite S	The reader believes S or will find it credible
Constraints on the $N+S$ **combination**	
	R's comprehending S increases R's belief of N
The effect	R's belief of N is increased
Locus of the effect	N

Automatic Processing of Discourse

Is it possible to process automatically texts with these definitions?
And how can we do?
The description of an evidence relation is:

> *Reader believes Satellite or finds it credible*

How can we measure this?

Cues in Text

The idea is to map a certain relation to certain words.

Words like *and*, *so*, *but*, *although*, and commas denote frontiers and ideas in a text.

The automatic text analysis uses these signs, *cues*, *cue phrases*, to segment a text and recognize relations

Ambiguity

Cues are often be ambiguous. Example:

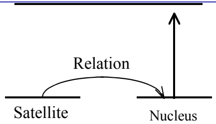
> *[Karl* ***and*** *Jan came to the lecture] [**and** asked questions]*

The first *and* has a syntactic role only. The second one defines a sequence
We must use supplementary constraints like position constraints between spans to carry out the analysis

Solving with Constraints

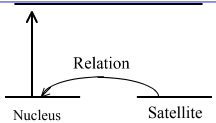
Mann and Thompson describe a typical ordering between relations

Satellite before nucleus



Antithesis	Condition
Background	Justify
Concession	Solutionhood

Nucleus before satellite



Elaboration	Evidence
Enablement	Statement

Corston-Oliver's Method

Corston-Oliver (1998) used such **position constraints** and **cues** as a strategy to analyze texts.

He recognizes an **elaboration** relation between two clauses where clause 1 is the nucleus and clause 2 the satellite using these constraints:

1. Clause 1 precedes Clause 2
2. Clause 1 is not subordinate to Clause 2
3. Clause 2 is not subordinate to Clause 1

and some **cues** that he ranks using heuristics

Heuristics for Elaboration

For elaboration, there are six heuristics. Two of them (simplified):

1. Clause 1 is the main clause of a sentence (sentence *k*) and Clause 2 is the main clause of a second one (sentence *l*). Sentence *k* immediately precedes sentence *l* and Clause 2 contains an elaboration conjunction (**also**, **for example**). (Heuristic 24, score 35)
2. Clause 2 contains a predicate nominal whose head is in the set {**portion**, **component**, **member**, **type**, **kind**, **example**, **instance**} or Clause 2 contains a predicate whose the main verb is in the set {**include**, **consist**} (Heuristic 41, score 35)

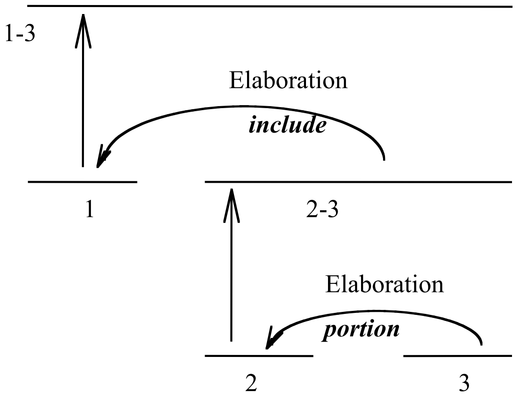
Analysis of Elaboration

Corston-Oliver applied this method to analyze the article stem in the Microsoft Encarta encyclopedia:

1. *A stem is a portion of a plant.*
2. *Subterranean stems* ***include*** *the rhizomes of the iris and the runners of the strawberry;*
3. *The potato is a* ***portion*** *of an underground stem.*

Analysis of Elaboration (II)

With heuristic 41 and because of words **include** and **portion**, he could find the following rhetorical structure:



Ambiguity

We saw that and can have a syntactic role and also a discourse role A discourse relation, here contrast, can use two or more cues:

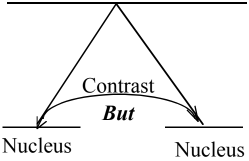
The driver died ***but*** *the passenger survived*
The driver died ***and*** *the passenger survived*

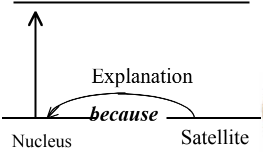
There can also be no cue to mark the relation

The driver died. The passenger survived

Learning Relations Automatically

	Contrast		Explanation
a	Such standards would preclude arms sales to states like Libya, which is also currently subject to a U.N. embargo.	a	South Africa can afford to forgo sales of guns and grenades
b	**But** states like Rwanda before its present crisis would still be able to legally buy arms.	b	**because** it actually makes most of its profits from the sale of expensive, high-technology systems like laser-designated missiles, aircraft electronic warfare systems, tactical radios, anti-radiation bombs and battlefield mobility systems.





Learning Techniques

Marcu and Echihabi (2002) developed an unsupervised learning algorithm to identify rhetorical relations.
The idea is to use words like but as a strong sign of contrast and to find automatically other contrast conditions using a corpus of one billion words.

Contrast	Cause-evidence-explanation
[BOS. . . EOS] [But. . . EOS]	[BOS. . .] [because. . . EOS]
[BOS. . .] [but . . . EOS]	[BOS Because. . . ,] [. . . EOS]
[BOS. . .] [although. . . EOS]	[BOS. . . EOS] [BOS Thus. . . EOS]
[BOS Although. . . ,] [. . . EOS]	
Condition	**Elaboration**
[BOS If. . . ,] [. . . EOS]	[BOS. . . EOS] [BOS . . . for example. . . EOS
[BOS If. . . ,] [then. . . EOS]	[BOS. . .] [which. . . EOS]
[BOS . . .] [if . . . EOS]	

Determination of Discourse Relations

The goal of the analysis is to find systematically word pairs in relations.
First, build the Cartesian product of words $(o_m \times o_n) \in S_p \times S_q$ where S_p and S_q are two text segments.
Then, determine the discourse relation between two segments, S_1 and S_2 using the formula

$$\hat{r} = \arg\max_k P(r_k | S_1, S_2)$$

To simplify computation, use only nouns, verbs, and cue phrases.

Naïve Bayes

Bayes formula on conditional probabilities:

$$P(A|B)P(B) = P(B|A)P(A)$$

For the rhetorical relations, we compute

$$\hat{r} = \arg\max_{k} P(r_k)P(S_1, S_2|r_k)$$

The naïve application of Bayes' principle yields:

$$\hat{r} = \arg\max_{k}(P(r_k) \times \prod_{(o_m, o_n) \in S_1, S_2} P(r_k)P(S_1, S_2|r_k))$$

Cartesian Product

Left \ Right	aircraft	arms	bombs	crisis	legally
embargo		1 c		1 c	1 c
guns	1 e		1 e		
preclude		1 c		1 c	1 c
sales	1 e	1 c	1 e	1 c	1 c

Here pairs are unambiguous, but counts could be (sales, electronics): 19 contrasts, 23 explanations.

MLE

We estimate $P(o_1, o_2 | r_k)$ using the maximum likelihood estimate.
The estimation is done with automatically extracted word pairs that belong to a relation
Even with a corpus of one billion words, there are unseen pairs.
Marcu and Echihabi used the Laplace rule to handle them.

Results

When the program is compared with a manually annotated RST corpus, we have the results for two-way classifiers

	Contrast	CEV	Cond	Elab
#	238	307	125	1761
Contrast	–	63%	80 %	64 %
CEV			87 %	76 %
Cond				87 %

The classifier decides correctly in 63 % of the cases for the relations contrast and cause-evidence-explanation (CEV).
Only 26 % of the contrast relations are marked with an unambiguous cue like **but**. The rest is discovered using probabilities

Parsing Algorithm: An Overview

Parsing uses a bottom-up search strategy:

1. Identify segments
2. Generate all possible relations between segments
3. Order relations in increasing order using heuristics
4. For all segment pairs in increasing order, try to:
    1. Merge the highest pair that contains adjacent segments
    2. Replace the pair with the nucleus
5. Until all the segments are merged into the whole text

Perspectives

Results for whole texts are still preliminary
But we have seen that there are promising signs for a correct analysis
Improvements depend on models, formalisms, and use of gigantic corpora
Such text analysis should enable to turn computerized encyclopedia into knowledge bases and ask questions like:

- What are the causes of something?
- Are there contradictions in the text

Events

Research on the representation of time, events, and temporal relations dates back the beginning of logic.
It resulted in an impressive number of formulations and models.
A possible approach is to **reify** events: turn them into objects, quantify them existentially, and connect them using predicates

John saw Mary in London on Tuesday

$$\exists \varepsilon [saw(\varepsilon, John, Mary) \wedge place(\varepsilon, London) \wedge time(\varepsilon, Tuesday)],$$

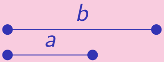
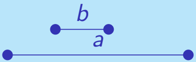
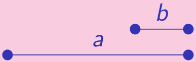
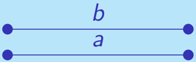
where ε represents the event.

Event Types

Events are closely related to sentence's main verbs Different classifications have been proposed to associate a verb with a type of event, Vendler (1967):

- A state – a permanent property or a usual situation (e.g. *be*, *have*, *know*, *think*);
- An achievement – a state change, a transition, occurring at single moment (e.g. *find*, *realize*, *learn*);
- An activity – a continuous process taking place over a period of time (e.g. *work*, *read*, *sleep*). In English, activities often use the present perfect *-ing*;
- An accomplishment – an activity with a definite endpoint completed by a result (e.g. *write a book, eat an apple*).

Temporal Representation of Events (Allen 1983)

#	Relations	#	Inverse relations	Graphical representations
1.	`before(a, b)`	2.	`after(b, a)`	
3.	`meets(a, b)`	4.	`met_by(b, a)`	
5.	`overlaps(a, b)`	6.	`overlapped_by(b, a)`	
7.	`starts(a, b)`	8.	`started_by(b, a)`	
9.	`during(b, a)`	10.	`contains(a, b)`	
11.	`finishes(b, a)`	12.	`finished_by(a, b)`	
13.	`equals(a, b)`			

TimeML, an Annotation Scheme for Time and Events

TimeML is an effort to unify temporal annotation, based on Allen's (1984) relations and inspired by Vendler's (1967) classification.
TimeML defines the XML elements:

- `TIMEX3` to annotate time expressions (at four o'clock),
- `EVENT`, to annotate the events (he slept),
- "signals".

The `SIGNAL` tag marks words or phrases indicating a temporal relation.

TimeML, an Annotation Scheme for Time and Events (II)

TimeML connects entities using different types of links

Temporal links, TLINKs, describe the temporal relation holding between events or between an event and a time.

TimeML elements have attributes. For instance, events have a tense, an aspect, and a class.

The 7 possible classes denote the type of event, whether it is a STATE, an instantaneous event (OCCURRENCE), etc.

TimeML Example

All 75 people on board the Aeroflot Airbus died when it ploughed into a Siberian mountain in March 1994

(Ingria and Pustejovsky 2004):

```
All 75 people
<EVENT eid="e7" class="STATE">on board</EVENT>
<MAKEINSTANCE eiid="ei7" eventID="e7" tense="NONE" aspect="NONE"/>
<TLINK eventInstanceID="ei7" relatedToEvent="ei5"
relType="INCLUDES"/>
the Aeroflot Airbus
<EVENT eid="e5" class="OCCURRENCE" >died</EVENT>
<MAKEINSTANCE eiid="ei5" eventID="e5" tense="PAST" aspect="NONE"/>
<TLINK eventInstanceID="ei5" signalID="s2" relatedToEvent="ei6"
relType="IAFTER"/>
```

TimeML Example

All 75 people on board the Aeroflot Airbus died when it ploughed into a Siberian mountain in March 1994

(Ingria and Pustejovsky 2004):

```
<SIGNAL sid="s2">when</SIGNAL>
it
<EVENT eid="e6" class="OCCURRENCE">ploughed</EVENT>
<MAKEINSTANCE eiid="ei6" eventID="e6" tense="PAST" aspect="NONE"/>
<TLINK eventInstanceID="ei6" signalID="s3" relatedToTime="t2"
relType="IS_INCLUDED"/>
<TLINK eventInstanceID="ei6" relatedToEvent="ei4"
relType="IDENTITY"/>
into a Siberian mountain
<SIGNAL sid="s3">in</SIGNAL>
<TIMEX3 tid="t2" type="DATE" value="1994-04">March 1994</TIMEX3>.
```