Discourse coherence

Ted Gibson, courtesy of Florian Wolf March 15, 2005

- 1. Bill hid John's car keys. He was drunk. It was not the first time that John got that drunk.
- 2. ?Bill hid John's car keys. He likes spinach. She said it works well.

What makes (1) coherent and (2) incoherent?

Overview

- 1. Coherence relations basics / working vocabulary
 - What is the informational structure of a discourse? (discourse = collection of sentences that are in some relation to each other)

2. Implications of coherence – pronoun resolution

- How does discourse structure influence other aspects of language processing? Example: pronoun resolution
- 3. Current theories of discourse coherence
 - How can we represent discourse structure? (cf. lecture on sentence structure)
- 4. Constraints on building discourse structures
 - How can we determine discourse structure? (cf. lecture on parsing)

1.) Coherence relations – basics / working vocabulary

Coherence relations in their basic form have a long history:

Aristotle (4th cent. BC)

Hume (18th cent.) Boccaccio (14th cent.)

1. Causal relations:

Cause-Effect:

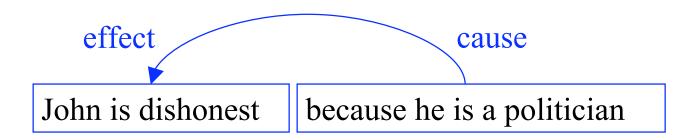
1. Causal relations:

Cause-Effect:

John is dishonest because he is a politician

1. Causal relations:

Cause-Effect:



1. Causal relations:

Violated Expectation:

John is honest although he is a politician

1. Causal relations:

Violated Expectation:

John is honest although he is a politician

1. Causal relations:

Violated Expectation:

John is honest although he is a politician

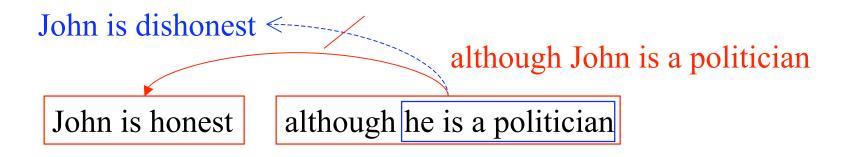
1. Causal relations:

Violated Expectation:

John is dishonest John is a politician John is honest although he is a politician

1. Causal relations:

Violated Expectation:



1. Causal relations:

Condition:

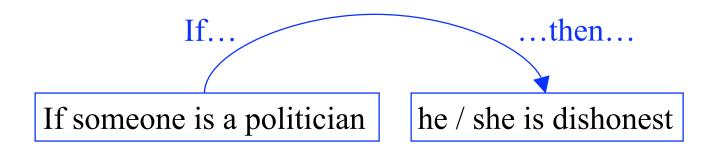
1. Causal relations:

Condition:

If someone is a politician he / she is dishonest

1. Causal relations:

Condition:



2. Resemblance relations:

Parallel:

2. Resemblance relations:

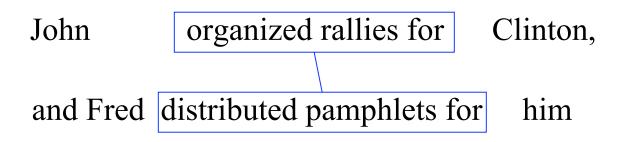
Parallel:

John organized rallies for Clinton,

and Fred distributed pamphlets for him

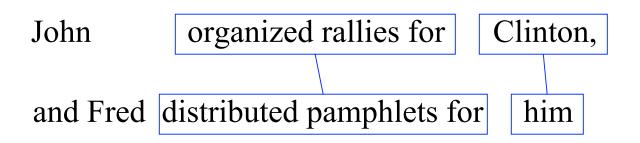
2. Resemblance relations:

Parallel:



2. Resemblance relations:

Parallel:



2. Resemblance relations:

Contrast:

2. Resemblance relations:

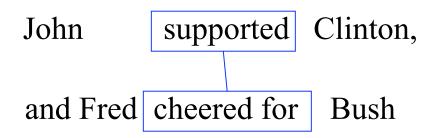
Contrast:

John supported Clinton,

and Fred cheered for Bush

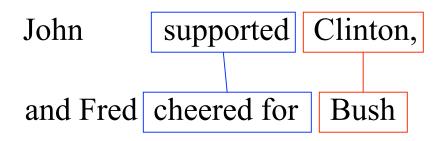
2. Resemblance relations:

Contrast:



2. Resemblance relations:

Contrast:



3. Elaboration relations:

3. Elaboration relations:

A political heavyweight resigned in Washington today. D. Rumpsteak's resignation came as no surprise.

3. Elaboration relations:

A political heavyweight resigned in Washington today.

details D. Rumpsteak's resignation came as no surprise.

2.) Implications of coherence – pronoun resolution

Pronoun resolution

- Pronouns = expressions that depend on something that is mentioned elsewhere
- Cannot be looked up in a dictionary
- Pronouns get their meaning from context pronouns and coherence?
- Three accounts
 - Centering Theory
 - Parallel Preference
 - Causality-based
- Unifying account and experiment
 - How we interpret pronouns falls out our attempt to make a discourse coherent

Centering (Grosz et al 1995)

First, John met Susan. Then he met Fred.

#First, John met Susan. Then she met Fred.

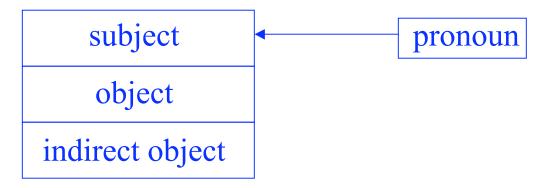
(Under normal declarative intonation, no stress on the pronouns.)



How Centering explains the contrast:

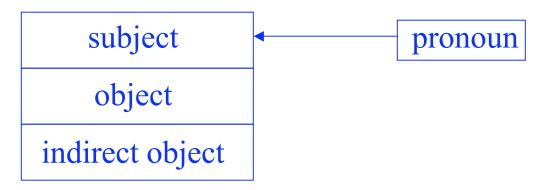


How Centering explains the contrast:





How Centering explains the contrast:



- implemented: Lappin & Leass 1994
- (somewhat) tested behaviorally: Gordon et al 1993
- Also: Wundt 1911

Centering

But:

John complimented Susan, and Fred congratulated her.

#John complimented Susan, and Fred congratulated him.

Parallel Preference (Smyth 1994)

- Subject pronoun \rightarrow subject antecedent
- Object pronoun \rightarrow object antecedent
- Implemented: Kameyama 1986
- Tested behaviorally: Chambers & Smyth 1998

Parallel Preference

John complimented Susan, and

Fred congratulated her.

John complimented Susan, and

Fred congratulated her.

John complimented Susan, and Fred

congratulated him.

John complimented Susan, and

Fred congratulated her.

John complimented Susan, and Fred

congratulated him.

First, John met Susan.

Then he met Fred.

Gibson lab, MIT

John complimented Susan, and

Fred congratulated her.

John complimented Susan, and Fred

congratulated him.

First, John met Susan.

First, John met Susan.

Then he met Fred.

Then she met Fred.

Gibson lab, MIT

But:

The **city council** denied the demonstrators the permit because **they** feared violence.

The city council denied the **demonstrators** the permit because **they** advocated violence.

(Winograd 1972)

Gibson lab, MIT -

Causality-based approach

- establish causal inference path to resolve the pronoun
- implemented: Hobbs et al 1990; Appelt et al 1993
- tested behaviorally: Wolf, Gibson & Desmet (2004) – details later

Causality-based approach

• Limitation of causality-based approach: does not apply to parallelism contrast:

Susan complimented John and similarly Fred congratulated him.

Susan complimented John and similarly Fred congratulated her.

Existing accounts - summary

| sentence / judgment | Cent. Theory | Par. Pref. | Causality- based |
|---|-----------------|---------------|---------------------|
| John complimented Susan and Fred congratulated her. | no | yes | no |
| #John complimented Susan and Fred congratulated him. | no | yes | no |
| First, John met Susan. Then he met Fred. | yes | yes | no |
| #First, John met Susan. Then she met Fred. | yes | yes | no |
| The city council denied the demonstrators the permit because they advocated violence. | no | yes | yes |
| The city council denied the demonstrators the permit because they feared violence. | yes | no | yes |

Existing accounts - summary

No earlier account can explain full range of data

 \rightarrow how can we bring the accounts together?



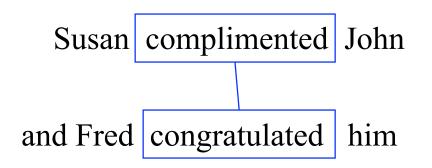
Use different approaches to pronoun processing under different coherence relations



Susan complimented John

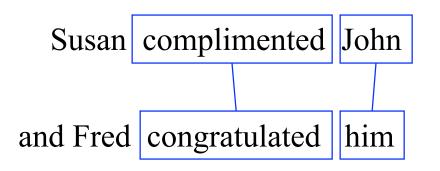
and Fred congratulated him





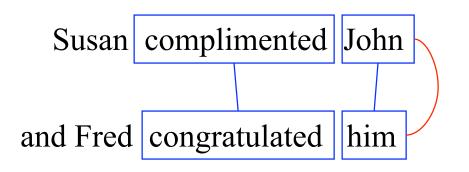
• Supported by semantic and structural similarities





• Supported by semantic and structural similarities





• Supported by semantic and structural similarities



- **Cause-Effect** establish causal inference path between utterances
- Sentence structure does not help here

Susan defeated John and so Fred congratulated her.

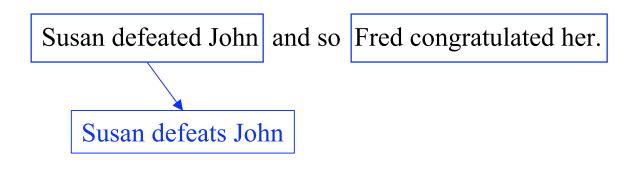


- **Cause-Effect** establish causal inference path between utterances
- Sentence structure does not help here

Susan defeated John and so Fred congratulated her.

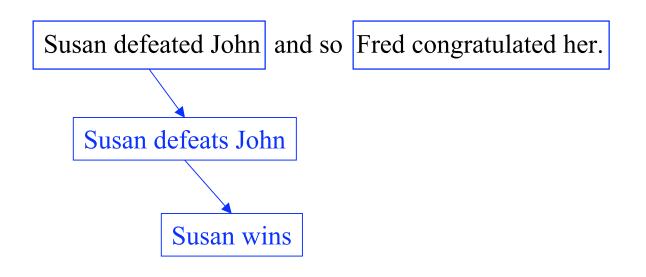


- **Cause-Effect** establish causal inference path between utterances
- Sentence structure does not help here



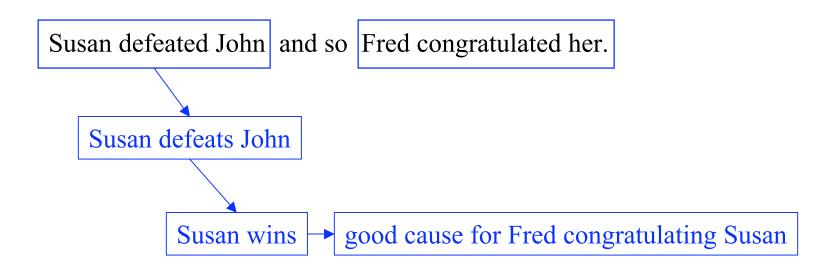


- **Cause-Effect** establish causal inference path between utterances
- Sentence structure does not help here



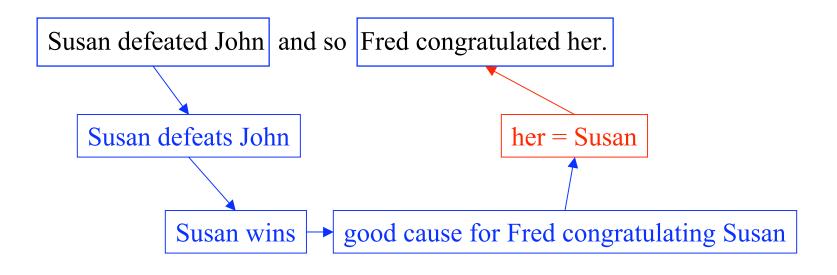


- **Cause-Effect** establish causal inference path between utterances
- Sentence structure does not help here





- **Cause-Effect** establish causal inference path between utterances
- Sentence structure does not help here



Kehler 2002

Resemblance

- look at sentence structure
- parallel preference approach for pronouns

Kehler 2002

Resemblance

- look at sentence structure
- parallel preference approach for pronouns

Cause-Effect

- do not look at sentence structure
- causality-based approach for pronouns

Reading time experiment

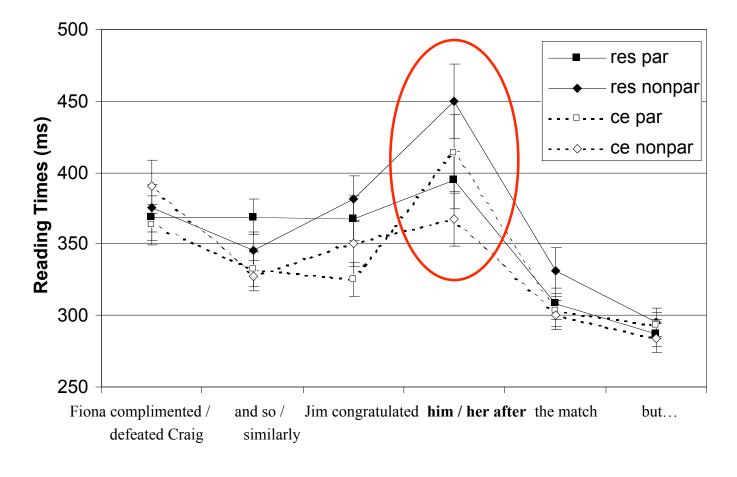
Resemblance, parallel: Susan complimented John and similarly Fred congratulated him.

Resemblance, non-parallel: Susan complimented John and similarly Fred congratulated her.

Cause-Effect, parallel (hard): Susan defeated John and so Fred congratulated him.

Cause-Effect, non-parallel (easy): Susan defeated John and so Fred congratulated her.

Reading time data



Gibson lab, MIT

Pronouns - summary

- Purely structural approaches to pronoun resolution are not enough
- Coherence is an important factor in pronoun resolution:
 - Resemblance \rightarrow parallel preference
 - Cause-Effect \rightarrow causal inference

3.) Current theories of discourse coherence

Gibson lab, MIT ——

Basic considerations

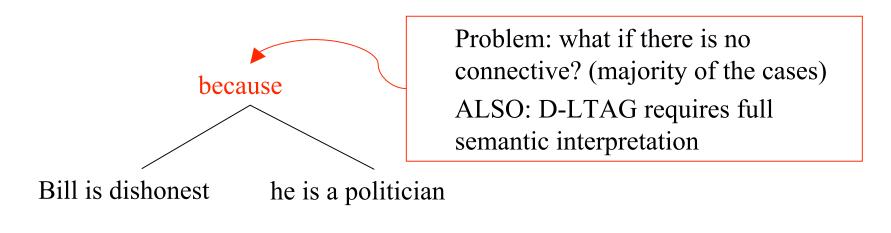
- What kind of discourse do we want to account for?
 - Conversations
 - Task-oriented dialogs
 - Monologues
- Basic considerations for an account of discourse coherence
 - Intention of the discourse or informational structure?
 - How many different coherence relations does one need? (cf. parts of speech)
 - Appropriate data structure for representing discourse coherence?
 - Is there something like a "discourse grammar"?

Intentional or informational structure

- Intentional structure
 - Grosz & Sidner 1986; cf Centering Theory
 - speaker intentions determine discourse structure
 - speaker intentions = key to discourse understanding
 - Problem: determining intention: **Too hard**
- Informational structure
 - cf. slides in the beginning: *cause-effect*, *resemblance*, *elaboration*, etc
 - Some real-time evidence for validity: pronoun experiments (difference *cause-effect / resemblance*)

Informational structure accounts

- D-LTAG (<u>Discourse Lexicalized Tree</u> <u>Adjoining Grammar</u>) – Forbes et al 2001
 - Coherence structure tree
 - Uses connectives (because, although, while, etc)



Informational structure accounts

- RST (<u>R</u>hetorical <u>Structure Theory</u>) Mann & Thompson 1988; Marcu 2000
 - Tree structure
 - Large number of coherence relations (some versions of RST accounts have more than 400):
 - Cause-Effect:
 - volitional
 - non-volitional
 - Elaboration:
 - object-attribute
 - whole-part
 - process-step

Informational structure accounts

• Hobbs 1985

- No tree structure
- Small number of coherence relations cf. slides in the beginning

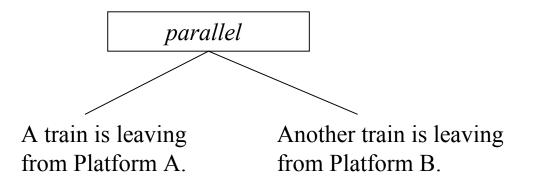
Still open questions

• Large or small number of coherence relations?

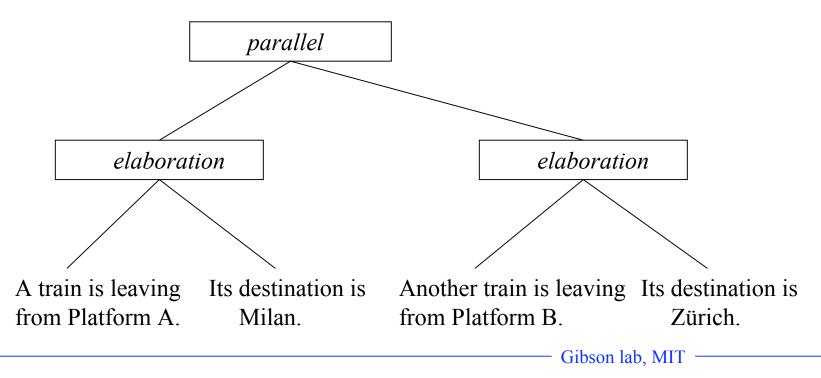
- Hovy & Maier 1998: small sets include large sets
- Use small set
 - more abstract and generalizable
 - easier to code
- Hobbs, not RST
- Trees or no trees?

- 1. A train is leaving from Platform A.
- 2. Its destination is Milan.
- 3. Another train is leaving from Platform B.
- 4. Its destination is Zürich.

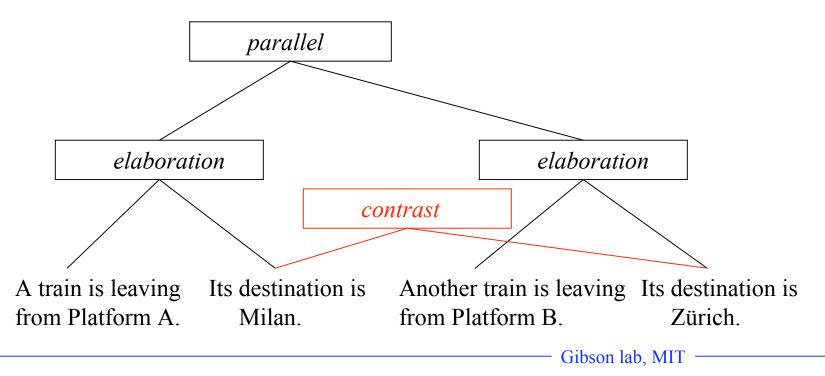
- 1. A train is leaving from Platform A.
- 2. Its destination is Milan.
- 3. Another train is leaving from Platform B.
- 4. Its destination is Zürich.



- 1. A train is leaving from Platform A.
- 2. Its destination is Milan.
- 3. Another train is leaving from Platform B.
- 4. Its destination is Zürich.



- 1. A train is leaving from Platform A.
- 2. Its destination is Milan.
- 3. Another train is leaving from Platform B.
- 4. Its destination is Zürich.



(20) Example text (modified from SAT practicing materials)

- 0. Schools tried to teach students history of science.
- 1. At the same time they tried to teach them hwo to think logically and inductively.
- 2. Some success has been reached in the first of these aims.
- 3. However, none at all has been reached in the second.

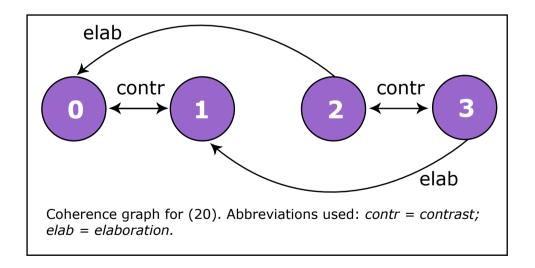


Figure by MIT OCW.

- (21) Example test (constructed)
 - 0. Susan wanted to buy some tomatoes
 - 1. and she also tried to find some basil
 - 2. because her recipe asked for these ingredients.
 - 3. The basil would probably be quite expensive at this time of the year.

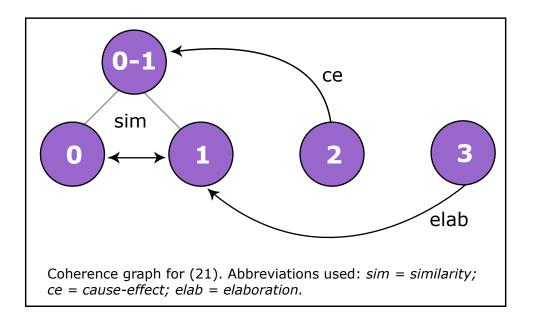


Figure by MIT OCW.

- (25) Example test (from ap890103-0014; AP Newswire 1989 corpus; Harman & Liberman (1993))
 - 0. "Sure I'll be polite,"
 - 1. promised one BMW driver
 - 2. who gave his name only as Rudolf.
 - 3. "As long as the trucks and the timid stay out of the left lane."

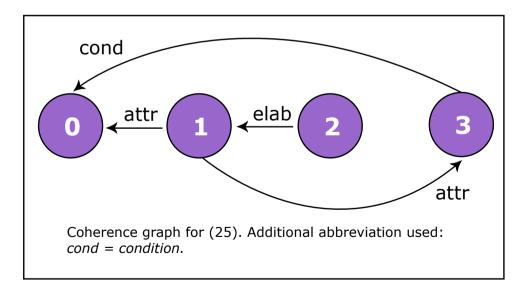


Figure by MIT OCW.

No trees: Lots of crossed dependencies

Correlation between text length, and number of crossed dependencies, from 135 texts (Wolf & Gibson, in press)

Graph removed for copyright reasons.

No trees: Lots of nodes with multiple parents Correlation between text length, and number of nodes with multiple parents, from 135 texts (Wolf & Gibson, in press)

Graph removed for copyright reasons.

No trees...

Images of tree and chainsaw removed for copyright reasons.

Discourse grammar?

- No trees (Wolf & Gibson, in press)
 - Lots of crossed dependencies: On average, 12.5% of the arcs need to be deleted in order to form graphs without crossed dependencies
 - Lots of nodes have multiple parents: 41.2% on average.
 - − No context-free phrase structure grammar (VP \rightarrow V NP, NP \rightarrow Det N, etc)
- Are there other constraints?
 - Linguistic constraints
 - Signal phrases / connectives
 - Anaphoric relations
 - Lexical chains
 - Discourse graph patterns
 - Connect any node with any other node?
 - Certain sub-patterns more likely than others?

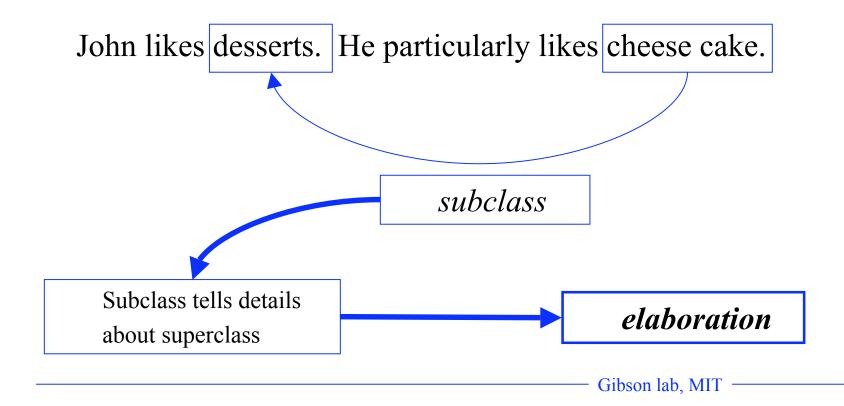
4.) Constraints on building discourse structures

Linguistic constraints

- Signal words / connectives
 - Because, although, while, since, etc
 - BUT: only about 15-20% of coherence relations are signaled by connectives (Schauer 2000)
- Anaphoric relations
 - IF anaphoric relation THEN coherence relation, and vice versa (Cristea et al 1999)

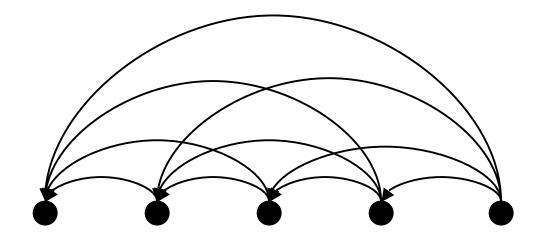
Linguistic constraints

• Lexical chains (Barzilay 1997)



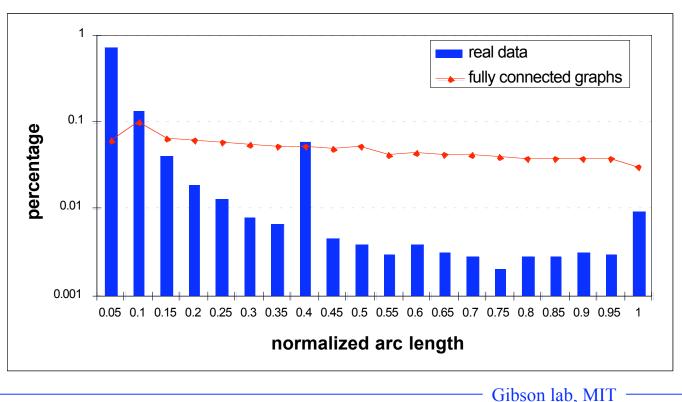
Graph structure patterns

• Connect any node with any other node?



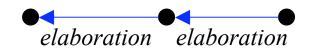
Graph structure patterns – arc length

- Short-distance relations are preferred
- Statistics from coherence structures of 135 texts
- Normalized arc length: divide absolute arc length by maximum possible arc length, given position in text



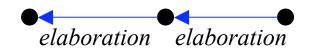
Graph structure sub-patterns

• Are there certain patterns that are more frequent than others?

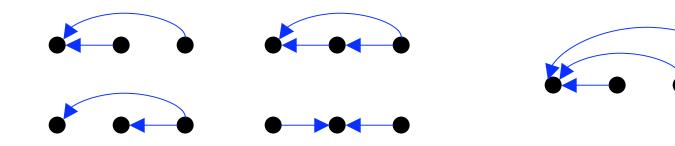


Graph structure sub-patterns

• Are there certain patterns that are more frequent than others?



• Not:



Summary

Gibson lab, MIT -----

Summary

- Coherence influences other linguistic processes (e.g. pronoun processing)
- Accounts of discourse structure
 - Informational structure of monologues
 - Small set of coherence relations
 - Data structures: directed graphs instead of trees
- Determining discourse structure
 - Linguistic cues
 - Connectives
 - Anaphoric links
 - Lexical chains
 - Structural patterns
 - Arc lengths
 - Frequent sub-patterns