Distributional Information: A Powerful Cue for Acquiring Syntactic Categories

Levindo Gabriel Taschetto Neto
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Probabilistic models of language and cognition
Universität Stuttgart

Agenda

1. Introduction.
2. Learning Syntactic Categories' Problem.
3. Available Information.
4. Utility of Information Sources' Access.
5. Relevant Distributional Approaches.
6. New Distributional Approaches.
7. Experiments.
8. Conclusion.

1. Introduction

- Distributional information is a potentially important source of data for identifying the syntactic categories of words.
- Distributional information provides a powerful cue for acquiring syntactic categories.

2. Learning Syntactic Categories' Problem

- A completely unconstrained search with *n* items and m syntactic categories (assuming, for simplicity, that each item has a single syntactic category), would involve considering *m* in the power of *n* possible mappings.

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- Given 3 syntactic categories and 15 different items.
  n = 15
  m = 3
  Possible mappings = 3^15 = 14.348.907

3. Available Information

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Example (Maratsos and Chalkley, 1980)

Words which take the suffix *-ed* typically also take the suffix -*s*, and are verbs. Also, words which take the suffix -*s*, but not the suffix -*ed*, are typically count-nouns.

3.2 Relation of the linguistic input to the situation

- A mechanism for the initial classification of words makes use of a correlation between prior semantic categories (such as object and action) in terms of which the child already perceives the world and syntactic categories.

3.3 Phonological cues to syntactic category

- Myriad regularities between the phonology of words and their syntactic categories may be utilized in order to acquire these categories (Kelly, 1992).

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Example:

English disyllabic nouns tend to have stress on the initial syllable, while verbs have final syllable stress.

3.4 Analysis of prosody

- Learners exploit the mutual predictability between the syntactic phrasing of a sentence, and the way it is said (Morgan and Newport, 1981).

3.5 Natural knowledge of syntactic categories

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2. Innate knowledge or constraints may specify, for instance, the number of syntactic categories or the relationships between them.

4. Utility of Information Sources' Access

- Distributional analysis can be conducted over electronically stored texts, represented purely as sequences of distinct words, and these are (at least for English) available to researchers in almost unlimited supply.

5. Relevant Distributional Approaches

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- They conceived of language as an external cultural product, and <u>did not</u> consider it in a psychological or computational context.
- They were <u>unable to test</u> their methods except with very small samples of language.

5.2 Neural Networks

- The most influential for learning the structure of a sequential material uses SRNs.

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Simple Recurrent Networks

Assign similar hidden unit patterns to items which have the same syntactic category in a simple grammar.

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  Results

  The results show that items with the same linguistic category tend to lie in neighboring regions of the space.

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Limitations (SRNs and Competitive Networks)

- Scaling up still not being possible from very small artificial data sets in order to deal with real linguistic data.

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- The linguistic categories can only be revealed using a subsequent cluster analysis.

5.3 Statistical Approaches to Language Learning

Main aim:

- Practical utility.

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Problem:

- It has not demonstrated utility of distributional information concerning syntactic categories for a very large and rich corpora.

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Measurements' Records

- A record of such statistics can be viewed as a contingency table.

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- **Target:** *jumped*.

Indexed cells which would be incremented in the contingency table:

(jumped, the), (jumped, cow), (jumped, over), (jumped, the), (jumped, moon).

6.2 Comparing the Distributions of Pairs of Words

- The more similar the words' distributions, the more likely that they are members of the same category.

6.3 Grouping Together Words with Similar Distributions

Goal due to the syntactic categories' boundaries:

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- Assigning words to discrete categories.

Requirement for it:

- Identifying clusters of similarly distributed target words.

7. Experiments

1. Corpus
2. Benchmark Classification
3. Scoring
4. Qualitative Description of Results
5. Experiment 1
6. Experiment 2
7. Experiment 3
8. Experiment 4
9. Experiment 5
10. Experiment 6
11. Experiment 7
12. Experiment 8
13. Experiment 9

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- CHILDES is a machine-readable collection of corpora of child and child-related speech, transcribed by a number of investigators, and largely recorded in informal North American domestic settings.
- The resultant corpus contained several million words of speech, from approximately 6,000 speakers.

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Category	Example	n
noun	truck, card, hand	407
adjective	little, favorite, white	81
numeral	two, ten, twelve	10
verb	could, hope, empty	239
article	the, a, an	3
pronoun	you, whose, more	52
adverb	rather, always, softly	60
preposition	in, around, between	21
conjunction	cos, while, and	9
interjection	oh, huh, wow	16
simple contraction		0
complex contraction	I'll, can't, there's	58

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- Proportion of pairs of items which are grouped by the benchmark that are also grouped together in the derived groupings.

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$$Completeness = \frac{hits}{hits + misses}$$

7.4 Qualitative Description of Results

- **Target words:** Most frequent 1000 ones.
- **Context words:** Most frequent 150 ones.

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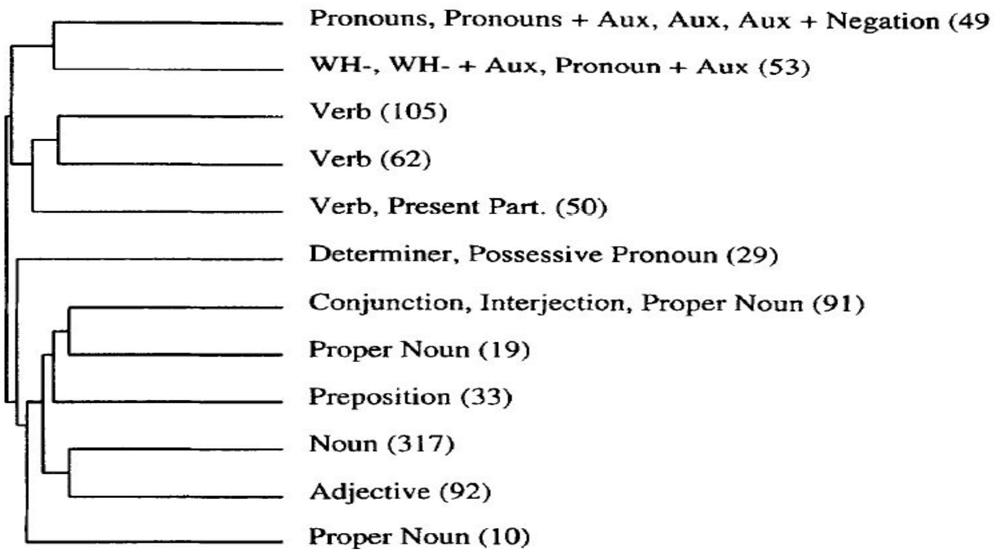
- **The discrete clusters at a similarity level of 0.8 from the CHILDES corpus' analysis**



7.5 Experiment 1: Different Contexts

- How the <u>informativeness of context</u> words changes with distance from the target word, in order to determine which contextual information would be useful to the child.

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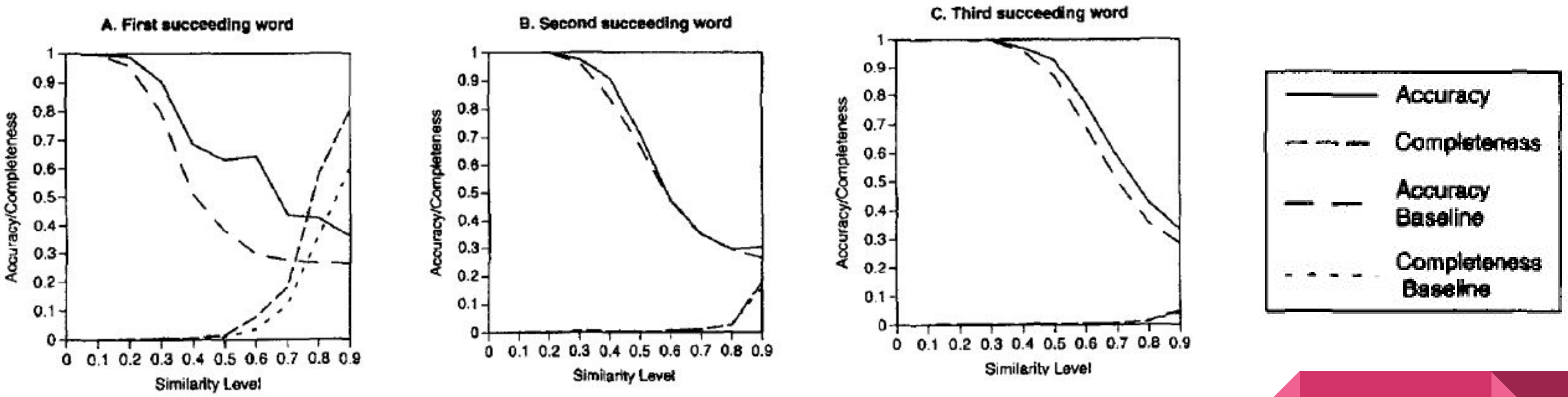
Accuracy and completeness when the 1st (A), 2nd (B) and 3rd (C) succeeding words are used as contexts:



7.6 Experiment 2: Varying the Number of Target and Context Words

- What number of target (and context) words is required for the distributional method to be effective, and is this number realistic for the child?

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- Decreasing between 1000 and 2.000 target words.

7.7 Experiment 3: For Which Classes is Distributional Information of Value?

- The major open classes (noun and verb) are more likely to be acquired first (Tomasello, 1992).

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The major categories from the Collins Cobuild Lexical Database:

		Observed		Baseline	
Class	n	Accuracy	Completeness	Accuracy	Completeness
noun	407	.90	.53	.43	.14
adjective	81	.38	.45	.09	.16
numeral	10	.09	.82	.02	.27
verb	239	.72	.24	.25	.14
article	3	.10	1.00	.01	.51
pronoun	52	.25	.24	.06	.14
adverb	60	.17	.18	.07	.16
preposition	21	.33	.53	.03	.16
conjunction	9	.06	.33	.02	.24
interjection	16	.18	.67	.02	.20
complex contraction	58	.55	.47	.07	.17
Overall	956	.72	.47	.27	.17

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- More given input → Moderate increase in performance.

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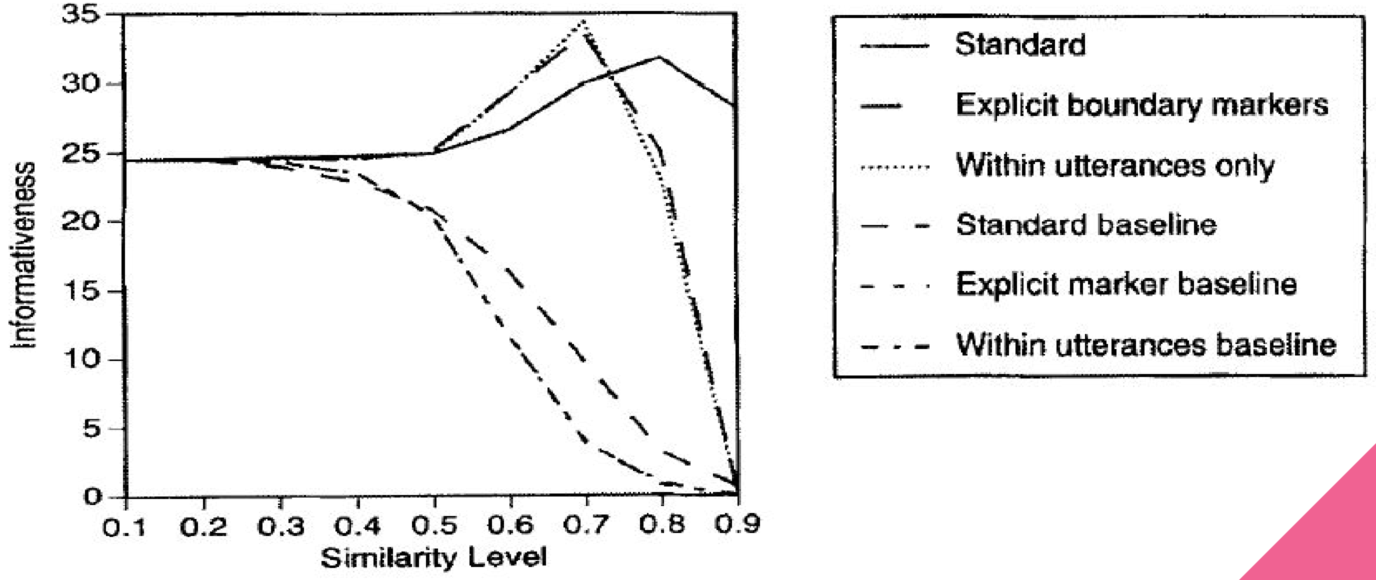

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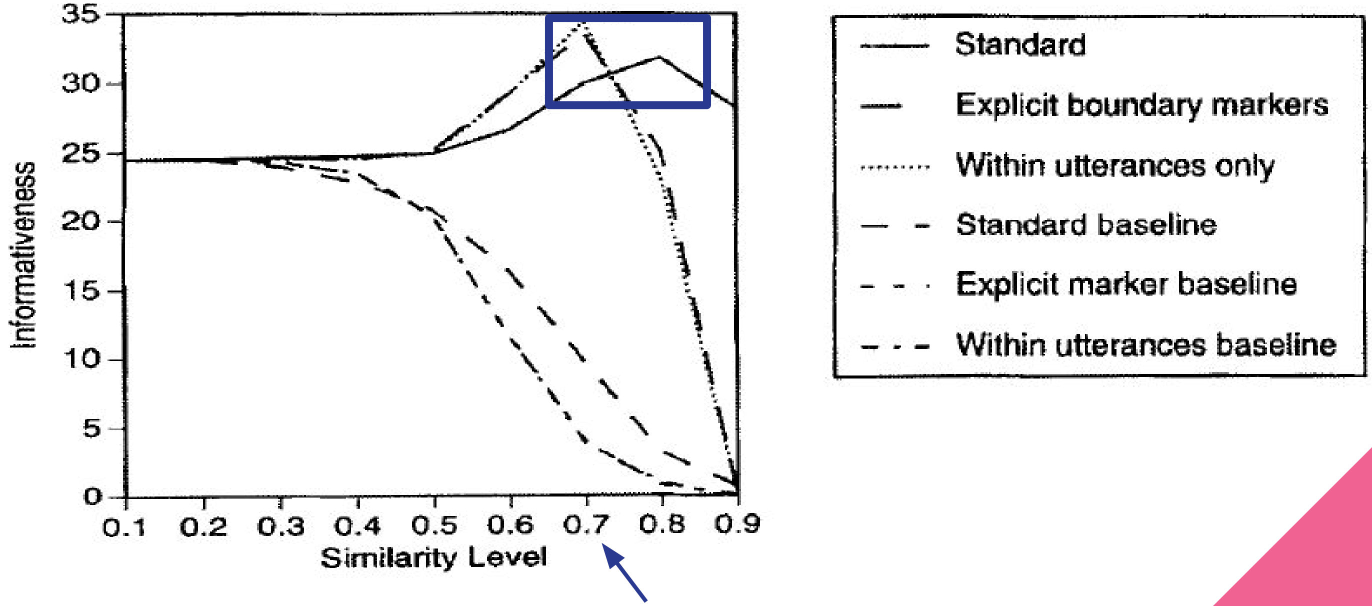

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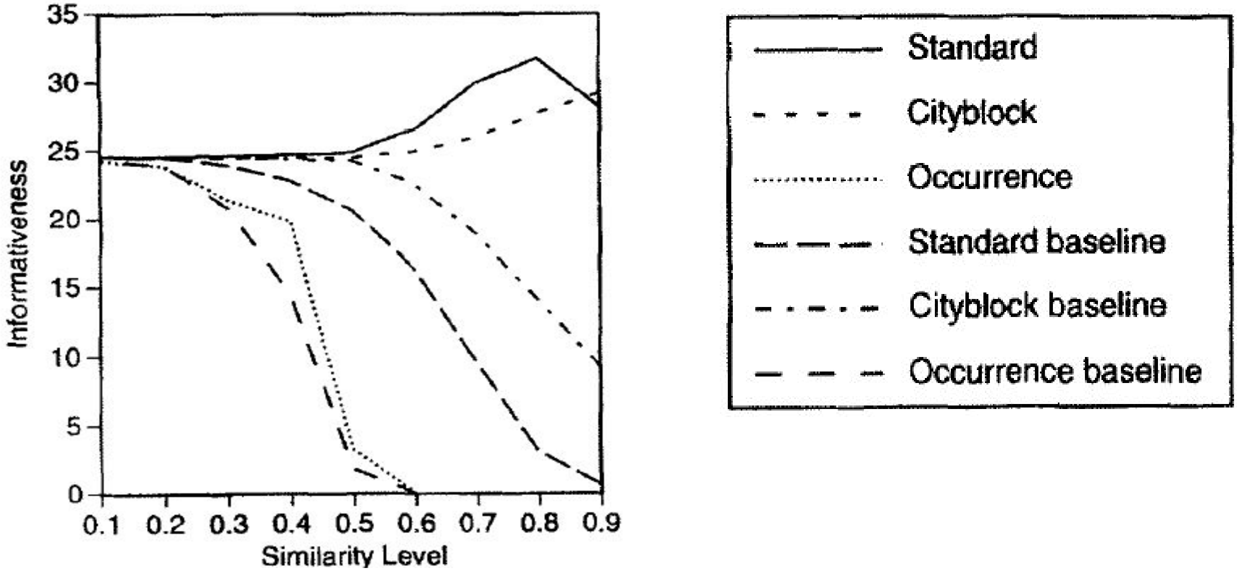

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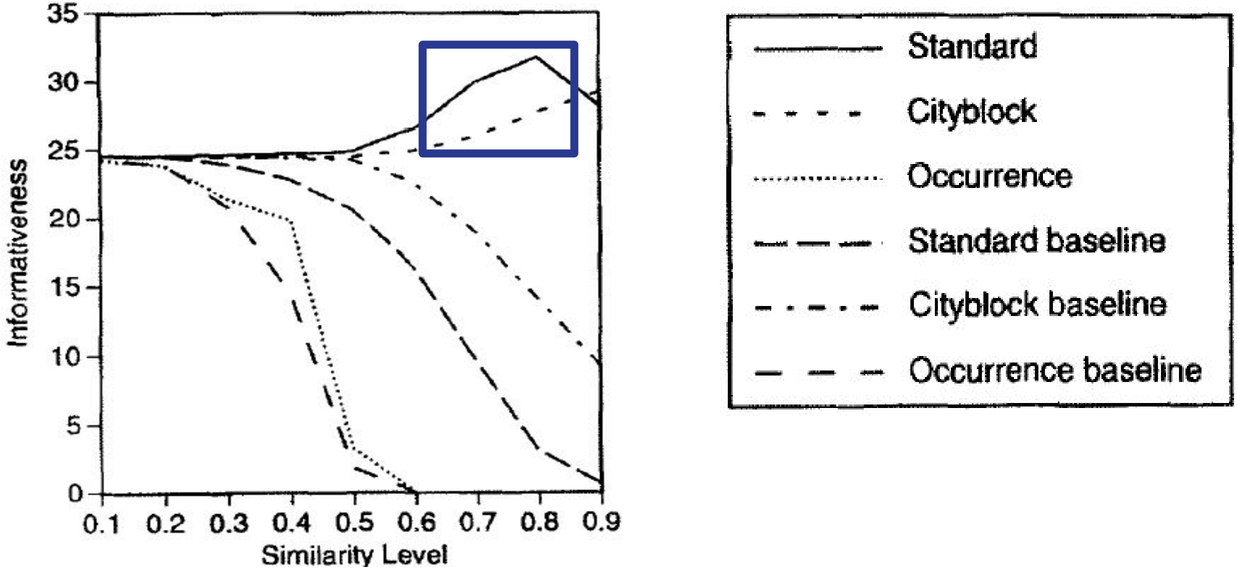

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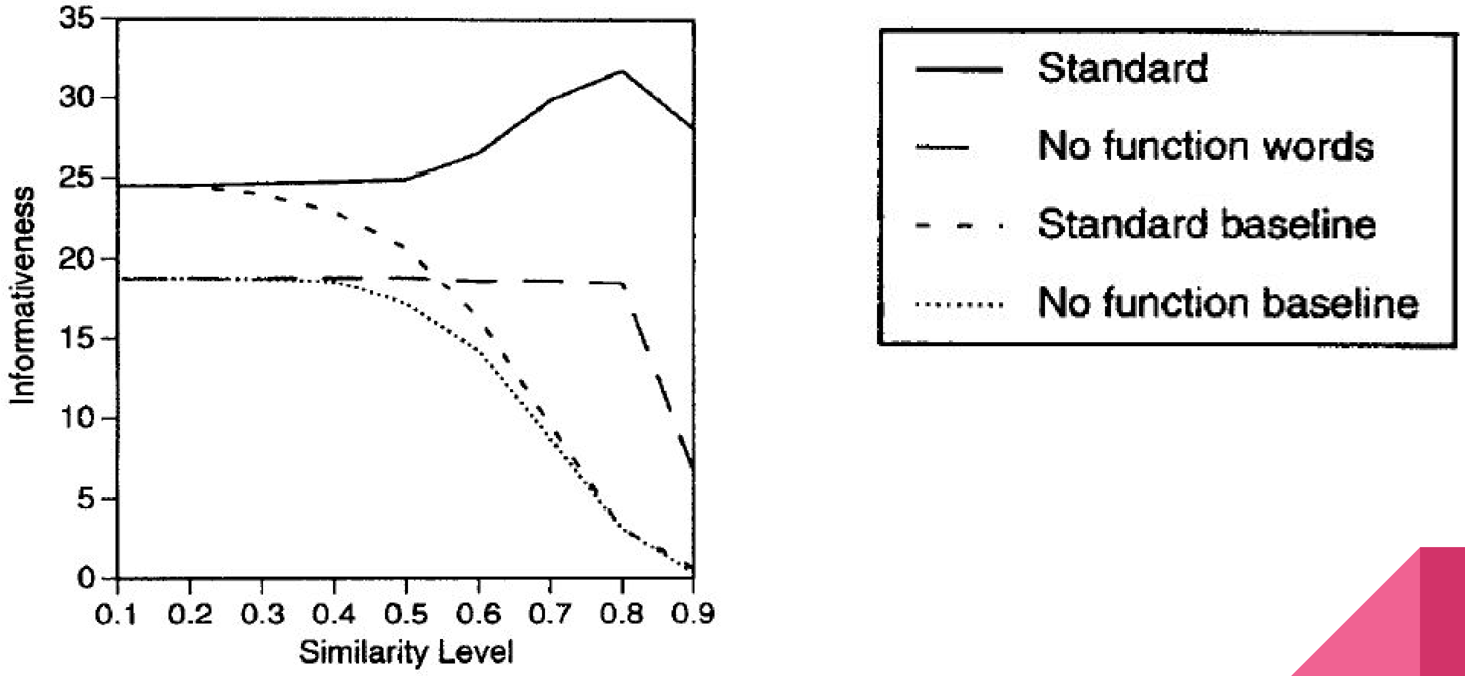

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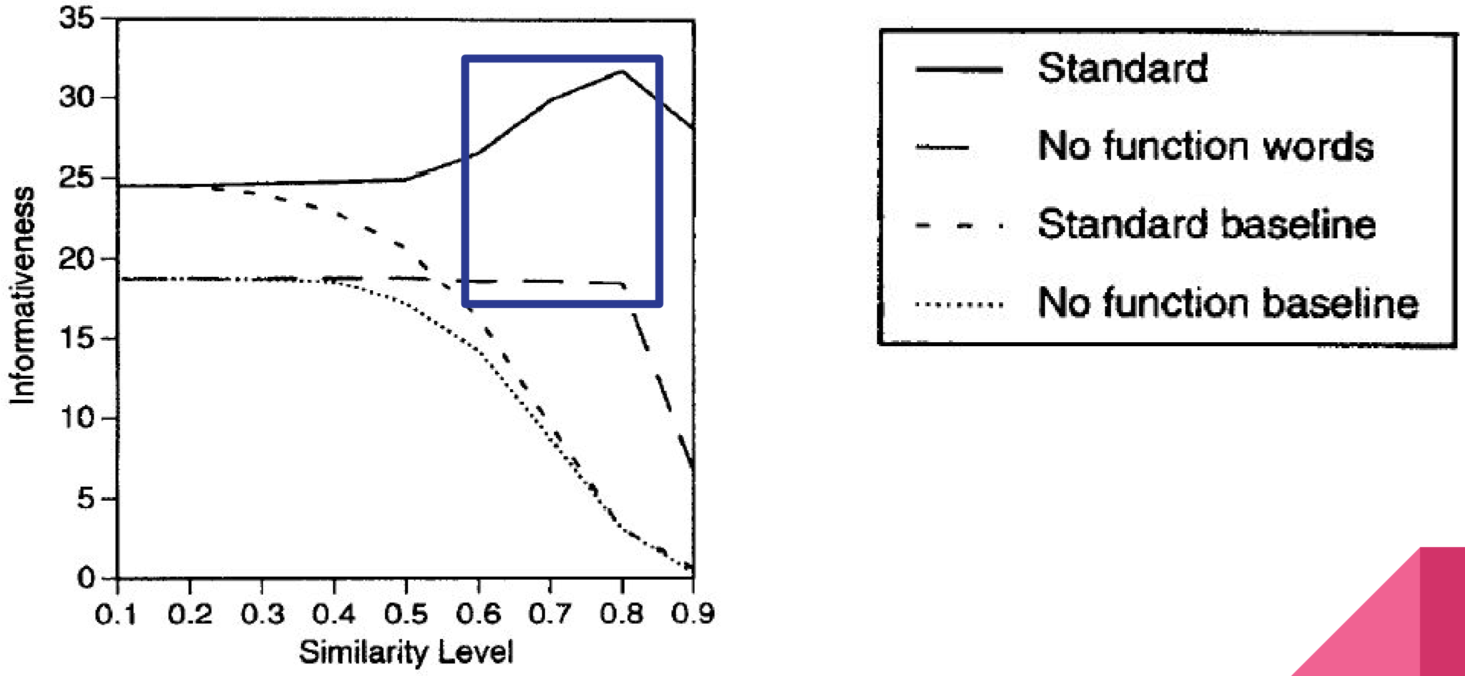

7.12 Experiment 8: Does Information About One Category Help the Acquisition of the Others?

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All the nouns → NOUN
All the verbs → VERB
… → …

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Disadvantage:

- Information about differences between nouns is lost.

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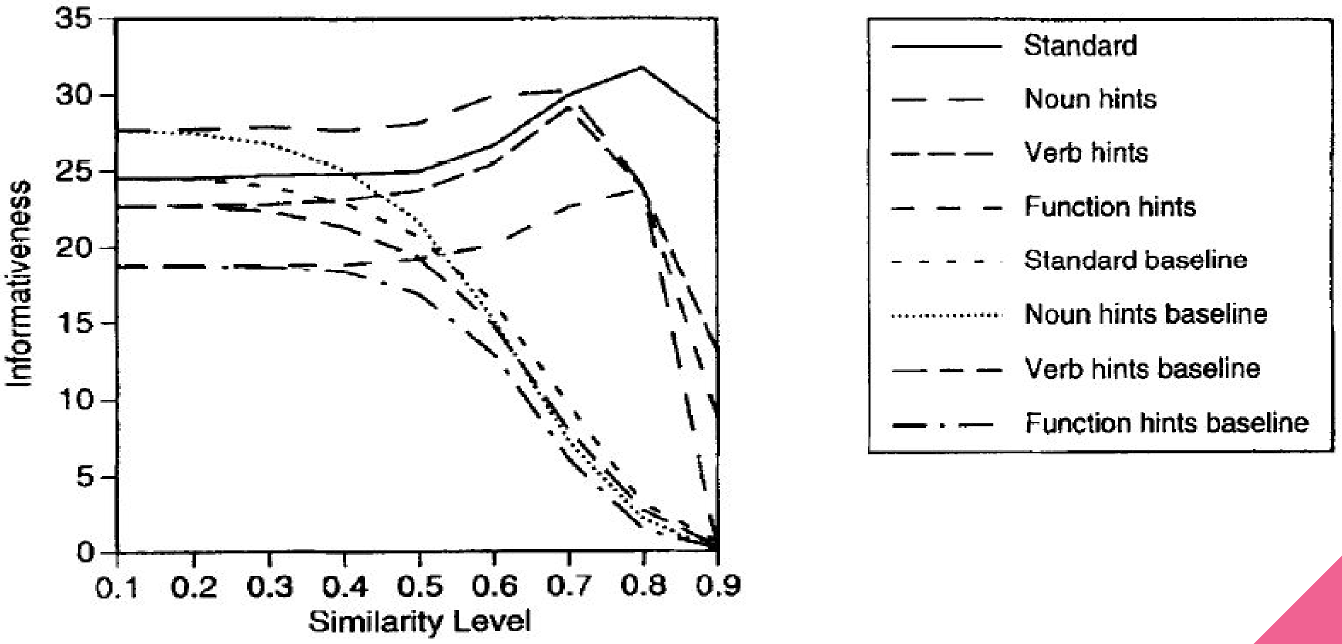

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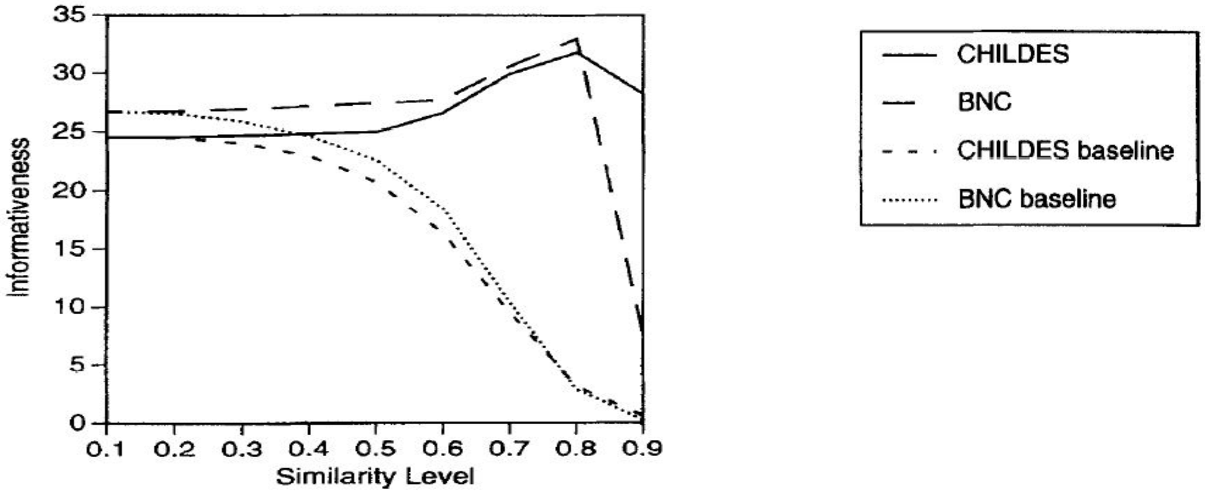

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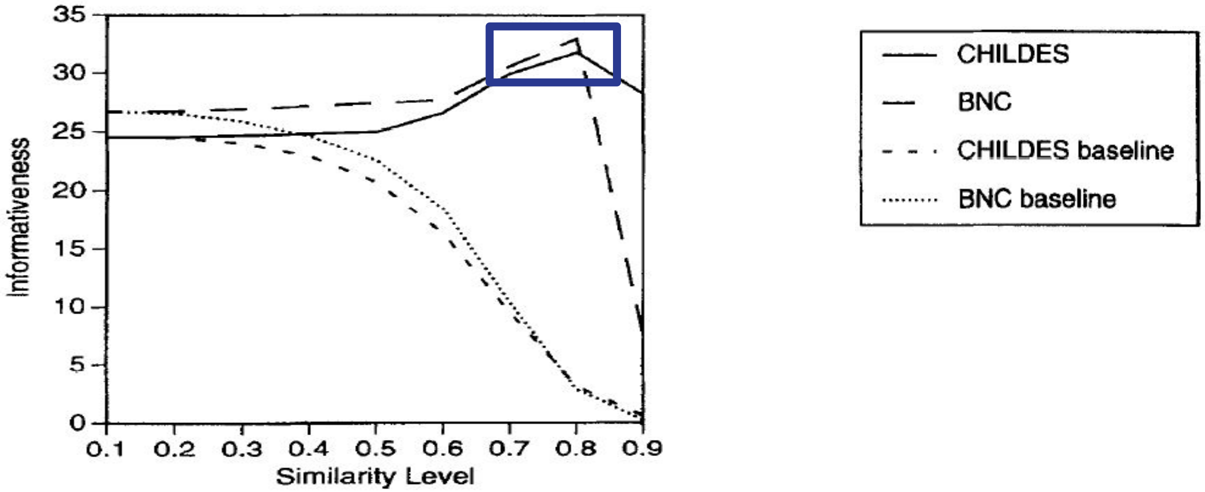

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- A model of how children may use distributional information in acquiring syntactic categories has been shown.
- Distributional information is a potentially powerful cue for learning syntactic categories.
- The use of distributional methods is often associated with empiricist approaches to language acquisition.

Thank you!

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