

# Modelling the acquisition of lexical meaning from caregiver-child interaction

## Getting the semantics straight

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# Goals

## Topic

Cognitive models of acquiring word-meaning mappings

## Goal #1

Discuss **sources of semantic data** for models and present a new one

## Goal #2

Show how this data can be used to **re-evaluate old claims**

# Data?

- Cross-situational models of acquiring word meanings<sup>1</sup>
- Source of meaning: situational context.
- Your average CHILDES corpus **does not contain** that.

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- So: method of **synthesizing semantics**.
  - Every word is a semantic symbol (Fazly, Alishahi & Stevenson 2010)
  - Obtain lexical semantics from WordNet (id., 2008)
- Allows you to make large quantities of data.

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  - **Cognitive** availability of meaning?
  - **Situational** availability? (noise, referential uncertainty)

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- But: quality of data?
  - Cognitive availability of meaning?
  - Situational availability? (noise, referential uncertainty)
- Recent method: **annotating video material** (Yu, Roy, Frank)
- But: either **limited** to basic-level objects or in the pragmatic realism (explicit labeling task).

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- Some desiderata:
  - Children should be **young enough** not to know too much already.
  - Coded descriptions should be **cognitively available**.
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- Realizations:
  - High-quality data can **only complement** high-quantity data, not replace it.
  - Little earlier work: the specifics may contain **serious methodological flaws** (more than happy to find out!)

# The block game corpus

- $\pm$  120 90-min videos of **mother-daughter** (16mo) **interaction**, gathered by Child Studies in Leiden
- Every dyad played a game of putting differently-shaped blocks in a bucket through corresponding holes
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- **175 minutes** of material, **7842 word tokens**, **2492 utterances**.
- **Situational coding**. For every interval of 3 seconds, code:
  - simple behavior (grab,move,position,letgo),
  - changes in spatial relations (in,on,out,off,match),
  - objects (block,bucket,mother,table)
  - properties (triangular,square,red,blue)
- **Structured**: grab(mother,(red,square,block))
- **High** intra- & interannotator **agreement** (almost all  $\kappa > 0.8$ )

# Example

**Table:** A sample of the dataset. The dash-separated abbreviations denote blocks and holes and their properties (colors & shapes)

| time | type               | coding/transcription  |
|------|--------------------|---|
| 0m0s | <b>situation</b>   |   |
|      | <b>language</b>    | een. nou jij een.   |
|      | <b>translation</b> | “One. Now you try one.”   |
| 0m3s | <b>situation</b>   | position(mother, toy, on(toy, floor)) grab(child, b-ye-tr) move(child, b-ye-tr, on(b-ye-tr, floor), near(b-ye-tr, ho-ro)), mismatch(b-ye-tr, ho-ro) |
|      | <b>language</b>    | nee daar.   |
|      | <b>translation</b> | “No, there.”  |
| 0m6s | <b>situation</b>   | point(mother, ho-tr, child) position(child, b-ye-tr, near(b-ye-tr, ho-ro)) mismatch(b-ye-tr, ho-ro)   |
|      | <b>language</b>    | nee lieverd hier past ie niet.  |
|      | <b>translation</b> | “No sweetie, it won’t fit in here.”   |

# Acquiring lexical meaning

- **How** to learn the meaning of a word?
  - **Cross-situationally observing** objects, relations, events, properties.
  - Seems **insufficient** (esp. for relational terms; verbs, prepositions)
    - Number of possibilities is vast (Gentner 1978)
    - Many actions and relations do not take place at the moment of utterance (Gleitman 1990)
  - Bootstrapping by using linguistic structure (Gleitman 1990), intentionality (Tomasello 2003), ...

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## Goal #2

Using this data set to **re-evaluate the claim** that relational terms are more difficult than non-relational terms.

# The model

- Fazly, Alishahi & Stevenson (2010) **incremental** model of **aligning words** in utterance  $U = \{w_1, \dots, w_n\}$  **with features** in situation  $S = \{f_1, \dots, f_n\}$ .

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- Calculating alignment** on the basis of conditional probabilities:

$$a(w|f, U^{(t)}, S^{(t)}) = \frac{p^{(t-1)}(f|w)}{\sum_{w' \in U^{(t)}} p^{(t-1)}(f|w')} \quad (1)$$



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$$\text{assoc}^{(t)}(w, f) = \text{assoc}^{(t-1)}(w, f) + a(w|f, U^{(t)}, S^{(t)}) \quad (2)$$

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$$\text{assoc}^{(t)}(w, f) = \text{assoc}^{(t-1)}(w, f) + a(w|f, U^{(t)}, S^{(t)}) \quad (2)$$

- Recalculating the conditional probabilities** on the basis of the association scores:

$$p^{(t)}(f|w) = \frac{\text{assoc}^{(t)}(w, f) + \lambda}{\sum_{f' \in F} \text{assoc}^{(t)}(w, f') + \beta \times \lambda} \quad (3)$$

# Data preparation

- Representations are structured, so **flatten** them:  
`grab(mother, (red, square, block)) →`  
`{grab, mother, red, square, block}`
- Take the **set** of all flattened representations of the situation taking place **in the interval** in which the utterance was beginning to be produced.
- We used **lemma** representations for the words

# Evaluation

- **No golden lexicon**, so **hand-built** one for 'meaningful' words ( $n = 41$ ):
  - Object labels: *blok* meaning block
  - Properties: *rood* meaning red
  - Spatial relations: *op* meaning on
  - Actions: *passen* meaning match, *stoppen* meaning {move, in}

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- Two (partially complementary) measures:
  - Summed Conditional Probability (*SCP*): how much probability mass is assigned to the true meanings given a word?
  - Average Precision (*AP*): how are the true meanings ranked (on conditional probability) w.r.t. the other meanings.

# Results

**Table:** Results of experiment 1. Given are mean *SCP* and *AP* values per class

|            | property | object | spatial | action | <b>total</b> |
|------------|----------|--------|---------|--------|--------------|
| <i>SCP</i> | 0.10     | 0.05   | 0.09    | 0.07   | <b>0.08</b>  |
| <i>AP</i>  | 0.81     | 0.25   | 0.19    | 0.15   | <b>0.31</b>  |

- Conditional probability distributions do **not** get **very peaky** in general
- Ranking is **good for properties** (colors, shapes), but **rather bad for other** classes.

# Model dependence?

- Compared with one other model: Jon Stevens (2011)' hypothesis testing model.
- **Same direction of results:** properties > objects > spatial relations > actions

Table: Results of experiment 1

|       |            | property | object | spatial | action | <b>total</b> |
|-------|------------|----------|--------|---------|--------|--------------|
| FAS10 | <i>SCP</i> | 0.10     | 0.05   | 0.09    | 0.07   | <b>0.08</b>  |
|       | <i>AP</i>  | 0.81     | 0.25   | 0.19    | 0.15   | <b>0.31</b>  |
| S11   | <i>SCP</i> | 0.09     | 0.06   | 0.06    | 0.02   | <b>0.05</b>  |
|       | <i>AP</i>  | 0.28     | 0.20   | 0.13    | 0.09   | <b>0.17</b>  |

# Interpretation

|            | property | object | spatial | action | <b>total</b> |
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- Re-evaluation **corroborates** Gleitman's finding:  
Properties > object labels > spatial relations and actions
- Why are the latter three harder to learn?
  - 1 True meaning is **absent** from *S*
  - 2 Foil features are structurally **present** in *S*
  - 3 True meaning is also **present** in many **other** *Ss*
- Combination of these! For **properties**, 2) and 3) hold as well.



- Focussing on **absent true meanings**
- Perhaps the temporal scope is **too narrow?**
- Learners may focus on situations slightly temporally displaced
- **Pragmatically defined window**:  $S$  = all coded material in intervals between the previous utterance,  $U^{(t-1)}$ , and the next one,  $U^{(t+1)}$ .
- Variable: sometimes a large window of situations, sometimes just the time of the utterance itself.

| $W$                     |            | prop. | object | spatial | action | <b>total</b> |
|-------------------------|------------|-------|--------|---------|--------|--------------|
| $0 : 0$                 | <i>SCP</i> | 0.10  | 0.05   | 0.09    | 0.07   | <b>0.08</b>  |
|                         | <i>AP</i>  | 0.81  | 0.25   | 0.19    | 0.15   | <b>0.31</b>  |
| $U^{(t-1)} : U^{(t+1)}$ | <i>SCP</i> | 0.08  | 0.05   | 0.10    | 0.08   | <b>0.07</b>  |
|                         | <i>AP</i>  | 0.79  | 0.41   | 0.22    | 0.20   | <b>0.39</b>  |

- **Slight increase** for three less-learned categories:
  - wider context is informative, more true meanings found
  - while not producing more referential uncertainty (as expected).
- **Pragmatics**: people talk about what should happen, or what has happened.

- Difficulty of getting **good data**; perhaps more tedious than developing a realistic model.
- Manual coding of situational contexts can be done
  - to complement synthesization methods (how much noise and uncertainty is realistic for which meaning category?)
  - to perform small-scale evaluations experiments
- However, ideally: **wider situational contexts**

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- Verbs and Prepositions are **harder to learn** than Nouns, which are harder than Color & Shape terms
- A wider scope **helps a bit**
- Structured learning? (Bootstrapping on syntax, using structure of semantics)

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- Structured learning? (Bootstrapping on syntax, using structure of semantics)
- **Realistic data is important!**