Errors in word meaning acquisition
as explained by semantic typology and computational modeling

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Joint work with Afsaneh Fazly and Suzanne Stevenson
1 Introduction
- Errors in word meaning acquisition
- Outline of our approach

2 The approach
- Representing word meanings
- Simulating a learner
- Evaluating the model’s predictions
Issue 1: Errors in lexical semantic acquisition

- Word meaning acquisition is not flawless
  - Calling all round things *ball*,
  - Mixing up first and second person pronouns,
  - Using one preposition where another would be ‘correct’

- Errors display patterns

- Asymmetries!

- Why do children make these errors?
Typology!
Typological Prevalence Hypothesis

- Explanation: **cognitive accessibility** of a meaning concept.
- Bowerman & Gentner (2009): **Typological prevalence reflects cognitive accessibility** (simplicity, salience)
  - Many languages will use a particular meaning concept if it is easily accessible
  - Reversed: if a meaning concept is widespread, it must be cognitively accessible (all other things being equal)
- And: low cognitive accessibility leads to **errors**.
- In particular: **overextension** of high-accessible meaning concepts to words signifying low-accessible ones.
- Case study: Dutch *op* ‘surface support’ overextended to ‘tenuous support’ situations (expressed with *aan*)
Our approach

- Use crosslinguistic elicitation data to represent word meaning
- Train a computational word learning model to associate word forms with these representations.
- See if the developmental pattern of the model is similar to that of children
  - If this is indeed due to the representations used, this supports the Typological Prevalence Hypothesis
1 Introduction
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2 The approach
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Figure: Dutch divisions of SPACE
Figure: Swahili divisions of SPACE
Figure: Thai divisions of SPACE
Step 1: gather count matrices

For every language, count number of labels per situation

<table>
<thead>
<tr>
<th>situation</th>
<th>op</th>
<th>in</th>
<th>aan</th>
<th>onder</th>
<th>over</th>
</tr>
</thead>
<tbody>
<tr>
<td>cup on table</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>apple in bowl</td>
<td></td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>coat on hook</td>
<td></td>
<td></td>
<td></td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>ball under chair</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>10</td>
</tr>
<tr>
<td>tablecloth on table</td>
<td>4</td>
<td></td>
<td></td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>cat on mat</td>
<td></td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table**: Counts of Dutch terms
**Step 2: extract distances between situations**

Per language, for every pair of situations, calculate Euclidean distance between counts. Then normalize to $[0, 1]$.

<table>
<thead>
<tr>
<th></th>
<th>cup</th>
<th>apple</th>
<th>coat</th>
<th>ball</th>
<th>cloth</th>
<th>cat</th>
</tr>
</thead>
<tbody>
<tr>
<td>cup on table</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.85</td>
<td>0</td>
</tr>
<tr>
<td>apple in bowl</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>coat on hook</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>ball under chair</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>tablecloth on table</td>
<td>0</td>
<td>0.85</td>
<td>0</td>
<td>0</td>
<td>0.85</td>
<td>0</td>
</tr>
<tr>
<td>cat on mat</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0</td>
</tr>
</tbody>
</table>

**Table:** Distance matrix of situations for Dutch
Step 3: Global distance matrix

Sum all distance matrices. Then normalize to $[0, 1]$ again.

<table>
<thead>
<tr>
<th></th>
<th>cup</th>
<th>apple</th>
<th>coat</th>
<th>ball</th>
<th>cloth</th>
<th>cat</th>
</tr>
</thead>
<tbody>
<tr>
<td>cup on table</td>
<td>0</td>
<td>0.97</td>
<td>0.70</td>
<td>0.98</td>
<td>0.22</td>
<td>0.07</td>
</tr>
<tr>
<td>apple in bowl</td>
<td>0</td>
<td>0.79</td>
<td>0.97</td>
<td>0.90</td>
<td>0.97</td>
<td></td>
</tr>
<tr>
<td>coat on hook</td>
<td></td>
<td>0.80</td>
<td>0.60</td>
<td>0.69</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ball under chair</td>
<td></td>
<td>0.92</td>
<td>0.98</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>tablecloth on table</td>
<td></td>
<td>0.22</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cat on mat</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0</td>
</tr>
</tbody>
</table>

Table: Distance matrix of situations in 15 languages
### Step 4: PCA

Apply PCA to matrix; extract coordinates per situation.

<table>
<thead>
<tr>
<th></th>
<th>PC 1</th>
<th>PC 2</th>
<th>PC 3</th>
<th>PC 4</th>
<th>PC 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>cup on table</td>
<td>-0.74</td>
<td>-0.01</td>
<td>-0.12</td>
<td>-0.09</td>
<td>-0.05</td>
</tr>
<tr>
<td>apple in bowl</td>
<td>0.88</td>
<td>0.70</td>
<td>-0.19</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>coat on hook</td>
<td>0.27</td>
<td>0</td>
<td>0.62</td>
<td>-0.04</td>
<td>0</td>
</tr>
<tr>
<td>ball under chair</td>
<td>0.93</td>
<td>-0.68</td>
<td>-0.19</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>tablecloth on table</td>
<td>-0.6</td>
<td>0.01</td>
<td>0</td>
<td>0.22</td>
<td>0</td>
</tr>
<tr>
<td>cat on mat</td>
<td>-0.74</td>
<td>-0.01</td>
<td>-0.12</td>
<td>-0.10</td>
<td>0.05</td>
</tr>
</tbody>
</table>

**Table:** Values on 5 principal components for the situations
Step 4: PCA

Apply PCA to matrix; extract coordinates per situation.

Figure: Situations in first two components, with Dutch divisions of *SPACE*
Learning word meanings

- Every situation is represented as a coordinate in the PCA space.
- Learning a word meaning is learning what subspace of this space should be associated with a word form.
- Note: simplistic vision of meaning – purely extensional, no distinction semantics/pragmatics, etc.
**Input items**

- Model learns by integrating input items in a **Self-Organizing Map**
- Input item consists of **two parts**: word form and the representation of the situation
  - Word form: array of zeros with a one for the used label
    - E.g. for Dutch: \([1, 0, 0, 0, 0]\) for *op*, \([0, 1, 0, 0, 0]\) for *in*, etc.
  - Situation: PCA coordinates of situation
- So: term *op* referring to situation 'cat on mat' is represented as: \([1, 0, 0, 0, 0, -0.74, -0.01, -0.12, -0.10, 0.05]\)
Learning in SOM

- SOM is a grid of $m \times n$ cells.
- Each cell has the same number of values as input items.
- For every input item: find cell that is most similar to input item.
- Most similar cell and neighbors are then updated so that they resemble the input item more closely.
- Cells start out with random values.
- Over time, map comes to reflect categories of learned language.
- Cells function as summary representations of input items.
Figure: A trained SOM for English color terms
Where do input items come from?

- Children hear words with varying frequencies
- So, training data should reflect that
- At every turn, the model integrates a sampled input item (term-situation pair) into the SOM:
  - Sample term $t$ with probability $P(t)$: the relative frequency of $t$ in a corpus
  - Sample situation $s$ given a term $t$ with a probability $P(s|t)$ as observed in the elicitation data
- Possibility of controlling for frequency effects! Setting $P(t)$ to a uniform distribution does that.
Testing the model: situations without terms

- Give model a situation without term and ask it to predict the label
- 'cat on mat': [0.74, -0.01, -0.12, -0.10, 0.05]
- Again, find most similar cell for input item (only using PCA features)
- Then: read off the term values for that cell
- E.g.: [0.62, 0.07, 0.28, 0.02, 0.01]
- So: *op* has a probability of 0.62, *in* of 0.07, etc.
Evaluation 1: Convergence with adult behavior

- **Sanity check**: does model end up behaving like adult language users?
- For all situations, **predict most-likely term** on basis of situation
- See how often predicted term is the same as the term most adult language users use
Evaluation 2: Matching developmental pattern

Few data points in observed data, many in model predictions

(a) Observed

(b) Predicted (avg. distribution over 30 simulations)
Aligning observed and predicted test moments

- Dynamic Time Warping: Contiguous series of bins of predicted test moments
- **Bin** is summary over all simulations in certain time interval
- Find bins maximizing similarity for all situations: global score of goodness of prediction
Figure: A possible alignment between predicted and observed data
Evaluation

(a) Observed

(b) Predicted, binned
Recap: modeling error patterns

- Obtain **semantic representations** with PCA over cross-linguistic data,
- Train a **category learning model** (Self-Organizing Map) on pairs of a word and a semantic representation,
- **Evaluate** match with (1) adult production, (2) observed developmental path.