Perceptual, Conceptual, and Frequency Effects on Error Patterns in English Color Term Acquisition

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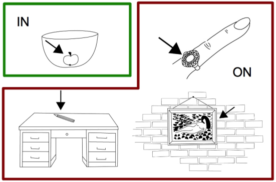
Overview

- What causes children to make errors in word-meaning acquisition?
- Typological Prevalence Hypothesis
- Earlier work for space
- Extension to color

Typological Prevalence Hypothesis

- [?]:The more languages group two situations under the same linguistic label, the more cognitively natural that grouping is and hence, the easier to acquire for children



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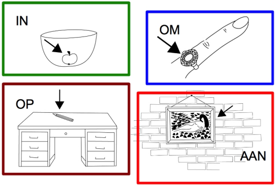

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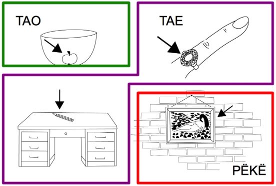

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- This hypothesis in a computational model
- Extract semantic space from linguistic elicitations
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- Follows from semantic space

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	English		Dutch				Tiriyo		
	on	in	op	aan	om	in	tao	tae	pëkë
apple in bowl	0	1	0	0	0	1	1	0	0
ring on finger	1	0	0	0	1	0	0	1	0
pen on table	1	0	1	0	0	0	0	1	0
painting on wall	1	0	0	1	0	0	0	0	1

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	ring on finger	pen on table	painting on wall
apple in bowl	1	1	1
ring on finger		0.5	0.25
pen on table			0.4

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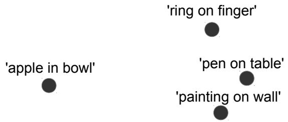

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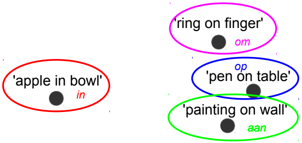

- Study effect of typological prevalence in other domains
- Here : Color
- Our focus: many overextensions: why?
    - Overextension = use of word to express a meaning for which adult speakers have another word (e.g., *op* for *aan*).
- Explanation in terms of typological prevalence?

[?]

- 591 English-speaking children, age 6-12.
- Shown 8 color chips each, for colors BLACK, WHITE, RED, YELLOW, GREEN, BLUE, ORANGE, and PURPLE
- Results:
  - BLACK, WHITE, RED, and BLUE: hardly any errors;
  - GREEN and YELLOW: a few early errors;
  - ORANGE: somewhat haphazard, persistent errors;
  - PURPLE: persistent errors, mostly *blue* (but not *purple* for BLUE!)

- What causes this error pattern?
  - Usual suspect #1: color term frequency
  - Usual suspect #2: perceptual features of colors [**?**]
  - New: Typological prevalence of color groupings?
- Approach:
  - Cognitive model parametrizing these possible factors
    - perceptual features $\rightarrow$ part of meaning space,
    - typological prevalence $\rightarrow$ part of meaning space,
    - frequency $\rightarrow$ part of input-item sampling procedure.
  - Give model Bateman's color chips and ask for most likely color term.
  - Evaluate fit with Bateman's observed error pattern given various parameter settings.

- Do the perceptual features of the colors play a role?
- CIELab space
- If `+perc`, every exemplar has as a coordinate in this space

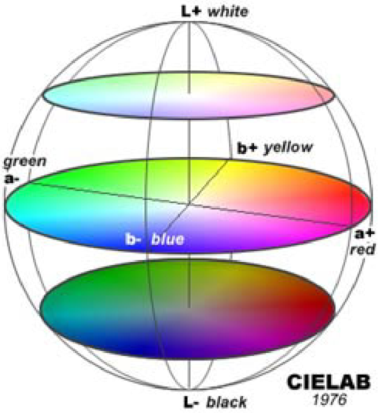

Figure: CIELab space

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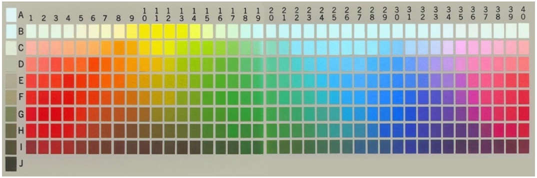

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Count matrix for English

	white	*pink*	*orange*	...	*purple*
chip A1	15	0	0	...	0
chip A2	2	13	0	...	0
⋮					
chip I40	0	0	0	...	15

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Distance matrix for English

	chip B1	chip C1	chip D1	...	chip I40
chip A1	0.81	0.87	0.98	...	1
chip B1		0.26	0.42	...	0.96
⋮					
chip H40				...	0.81

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Distance matrix for all languages

	chip B1	chip C1	chip D1	...	chip I40
chip A1	120.4	122.1	136.8	...	142.0
chip B1		73.6	82.1	...	128.1
⋮					
chip H40				...	112.6

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  - apply PCA, use components with Eigenvalue > 1,

PCA coordinates for all color chips

	PCA1	PCA2	PCA3	...	PCA330
chip A1	2.4	-4.2	3.8	...	0.0
chip B1	2.7	-1.9	1.0	...	0.0
⋮					
chip H40	-4.2	2.2	3.2	...	0.0

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- If $+\texttt{conc}$, all exemplars have a coordinate in this space.

- Does frequency in CDS play a role?

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- Sampling procedure: we sample iteratively pairs of a color term t and a situation s,
  - where s is the vector of the `perceptual` and/or `conceptual` coordinates.
- $P(s, t) = P(s|t)P(t)$
  - $P(s|t) = \frac{n(t,s)}{\sum_{s' \in S} n(t,s')}$

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- Two conditions:
  - `relative`: $P(t)$ is relative frequency of color terms in CDS, [**?**],
  - `uniform`: $P(t)$ is uniform.

Overview

- Train learning model on iteratively sampled t, s pairs

t	s
red	$\underbrace{52.4, 0.8, 0.2,}_{\texttt{perc}} \underbrace{0.83, 0.23, 0.41, 0.03}_{\texttt{conc}}$

- Every 10 input items (test moment)
  - give model the 8 colors of [?] (using focal colors [?] represented as an s)
  - ask model for most likely color term t
- Evaluate fit between predicted responses and observed responses

Gaussian Naive Bayes (GNB)

- Centroid learner
- Learns Gaussians over the dimensions of the situations (perceptual and conceptual) from available data
- Categorizes test item on the basis of Maximum A Posteriori probability

Generalized Context Model (GCM)

- Exemplar learner [**?**]
- Categorizes test item on the basis of similarity to all stored exemplars

- Simulation runs for 1000 input items
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- I.e. 100 test moments for the 8 color chips
- 30 simulations per combination of parameter settings:
  - `features = {perc&conc, perc, conc}` $\times$
  - `frequency = {relative, uniform}` $\times$
  - `model = {GNB, GCM}`

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  - 30 simulations: distribution over color terms
  - *n* children: distribution over color terms
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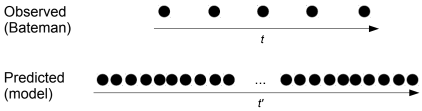

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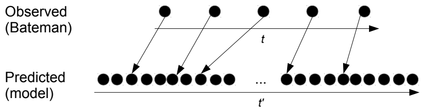
- Solution: 5 test moments that have lowest distance to 5 age bins (over all 8 colors)
- Constraint: linearly ordered



parameter	setting	mean error
features ***	perc&conc	$\mu = 0.015$
	perc	$\mu = 0.020$
	conc	$\mu = 0.354$
frequency	relative	$\mu = 0.130$
	uniform	$\mu = 0.130$
model *	GCM	$\mu = 0.120$
	GNB	$\mu = 0.139$

Interpretation

- No effect of frequency: cf. [?]?
- Small effect of model
- Effect of features: perc, perc&conc $>$ conc:
  - English is natural
  - Children too old
  - Color is easier domain then space

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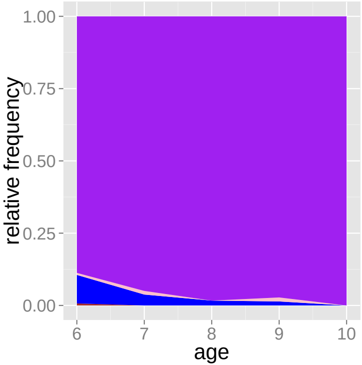
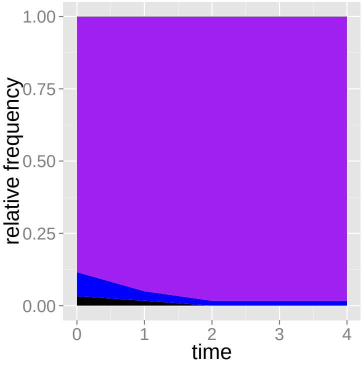
  → see following slides . . .

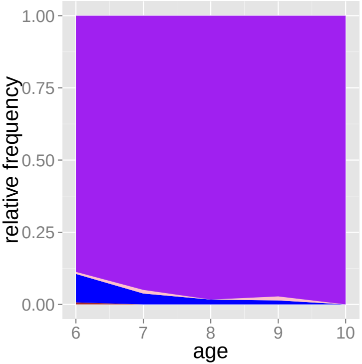
Best fit for PURPLE!



: In Bateman (1915)



: `perc, relative, gcm`



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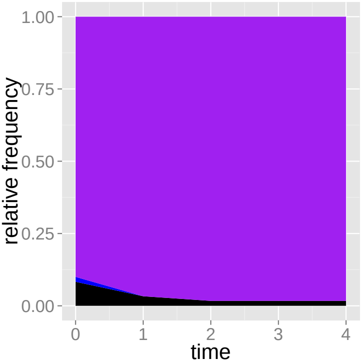

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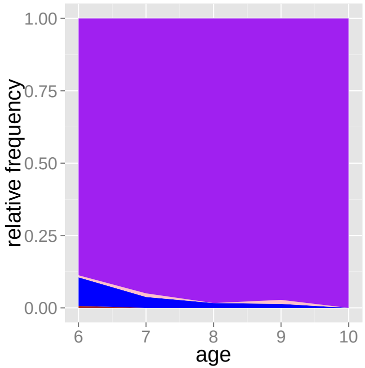

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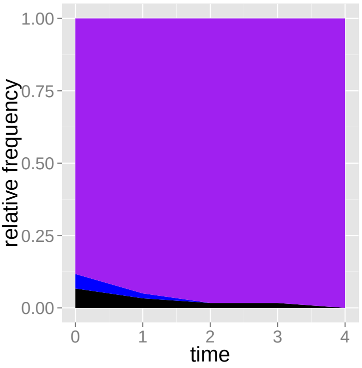
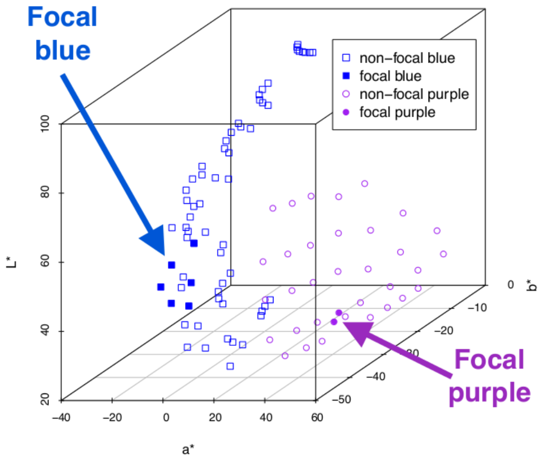


: `perc`, `uniform`, `gcm`


Focal blue
non–focal blue
focal blue
non–focal purple
focal purple
Focal purple
L*
100
80
60
40
20
–40
–20
0
20
40
60
a*
b*
0
–10
–20
–40
–50

- Conceptual dimensions don’t increase fit over perceptual

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- Reason: correlation with perceptual dimensions

	L^*	a^*	b^*
PCA1	-0.01	0.80^*	-0.01
PCA2	-0.97^{***}	0.40	-0.08
PCA3	0.16	-0.03	-0.88^{**}
PCA4	0.60	-0.86^*	0.70

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- However: why do they correlate strongly but perform much worse independently?

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- Main results:
  - Perceptual features predicted error pattern best.
  - Typological prevalence ('conceptual features') added no error-reduction and performed much worse without perceptual features.
  - Frequency matters for some colors (see PURPLE)

- Extend this approach to developmental data on more languages and younger children.
- Issue of model behaving too well (underestimating errors).

Thank you!