Modeling developmental and linguistic relativity effects in color term acquisition

Barend Beekhuizen & Suzanne Stevenson

University of Toronto

CogSci 2016

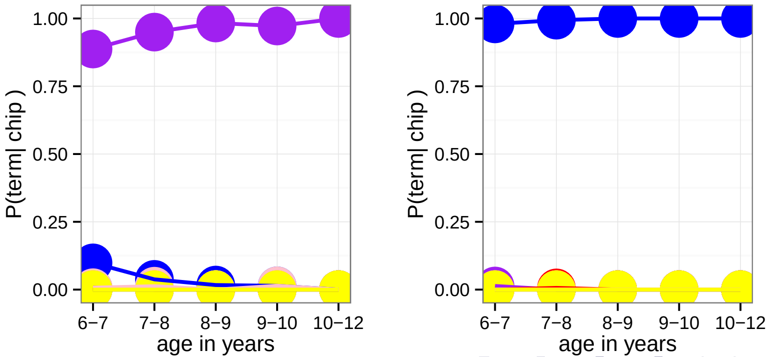
Color terms as a window into cognition

- Acquisition: it's hard
- Consequences of acquisition

Acquisition

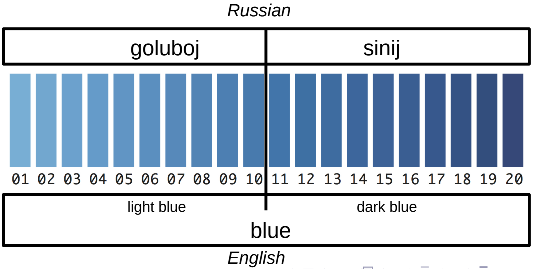
- Studied for many languages
- Asymmetrical overextension errors
- E.g., English: *blue* for PURPLE but not *purple* for BLUE.

Bateman (1915):



Consequences of acquisition

- Languages vary in number & boundaries of color term categories (Berlin & Kay 1969)
- Speakers sensitive to language-specific boundaries (linguistic relativity)
- Winawer et al. (2006):
  - Russian: two primary terms for 'blue'
  - Russian speakers discriminate faster across boundary than English speakers



Our goal

Explain both phenomena with a unified computational model and understand why

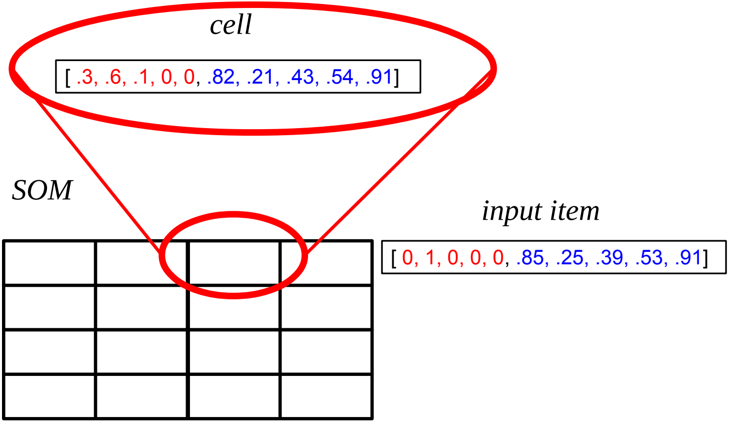
Training the model: input items

- Training input items: term-referent pair (i.c., a color term and a color chip)
- Input items are feature vectors:
  - [0, 1, 0, 0,.85, .25, .39, .53, .91]
  - Linguistic term: vector of possible terms; 1 for present term, 0 for others
  - Properties of color chip as point in geometrical space.

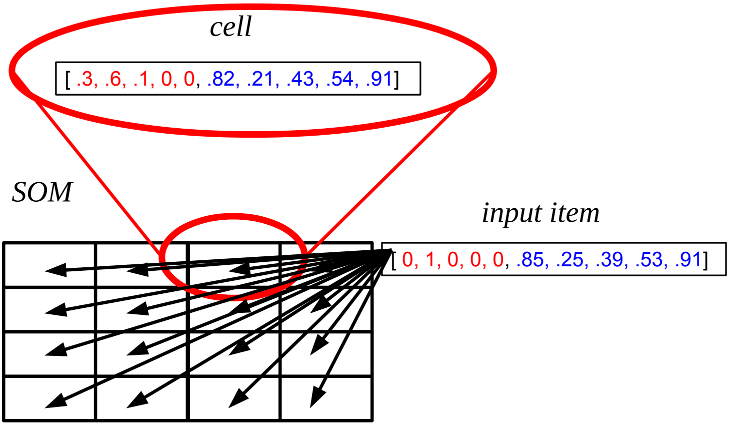
Training the model: input items

- Training input items: term-referent pair (i.c., a color term and a color chip)
- Input items are feature vectors:
  - $[0, 1, 0, 0, .85, .25, .39, .53, .91]$
  - Linguistic term: vector of possible terms; 1 for present term, 0 for others
  - Properties of color chip as point in geometrical space.
- Naturalistic input: vectors are sampled on the basis of term frequency and probability of chip given term

- Self-Organizing Map (SOM; Kohonen & Ritter 1989)
- Applied by Li and colleagues for language acquisition
- grid of cells with vectors

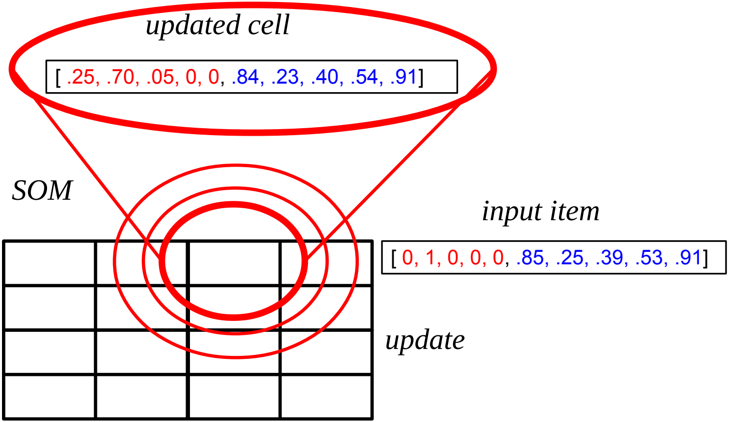


Step I – find Best Matching Unit (BMU)



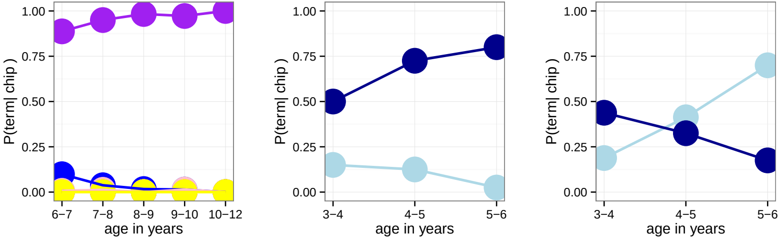
Step II – Update BMU and neighboring cells

Step II – update neighborhood of BMU



Case #1: Color term acquisition

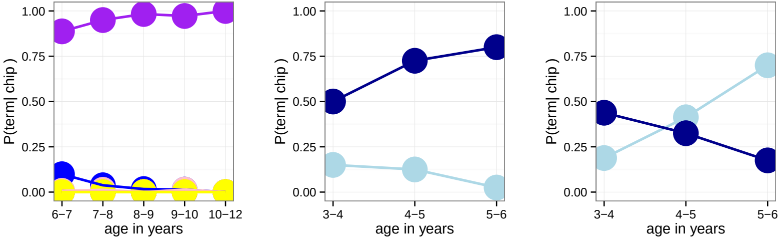
- Color naming: present chip, elicit term
  - Bateman (1915): English-speaking 6-12yos; 8 color chips
  - Davies et al. (1998): Russian-speaking 3-5yos; 12 color chips



Eng. PURPLE Rus. DARK BLUE Rus. LIGHT BLUE

Case #1: Color term acquisition

- Color naming: present chip, elicit term
  - Bateman (1915): English-speaking 6-12yos; 8 color chips
  - Davies et al. (1998): Russian-speaking 3-5yos; 12 color chips
- Why do (asymmetrical) overextension errors occur?
  Nature of property features or frequency effects?



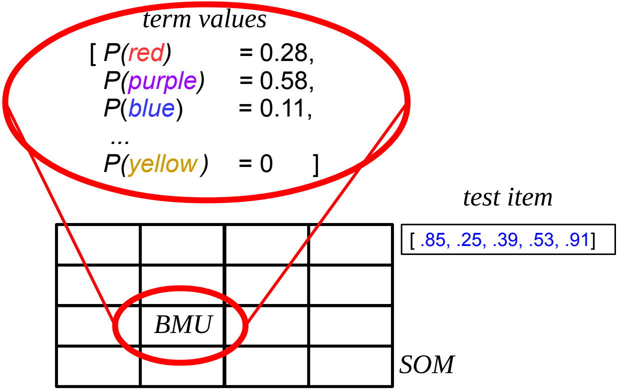
Eng. PURPLE

Rus. DARK BLUE

Rus. LIGHT BLUE

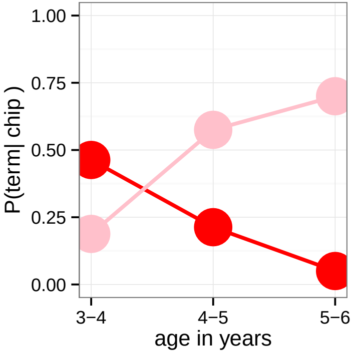
Evaluating developmental pattern

- Every 100 training input items ...
- ...present model with all color chips in the experiment
- ...property features w/out term features

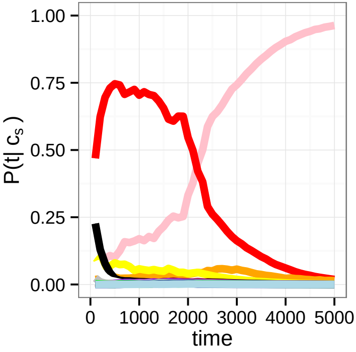


Evaluating fit with developmental pattern

- Evaluate fit of the model predictions with child data:
- Predicting the ranking of terms (Kendall τ_b)



Child data (Russian) for PINK



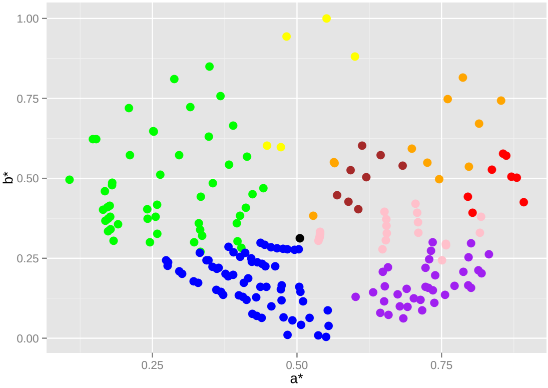
Model data

Condition #1: Frequency effects

- Asymmetrical overextension because one term is more frequent than the other?
- Two settings:
  - `corpus`: relative frequency of each label in training data given by relative frequency of the labels in child-directed or naturally occurring speech
  - `uniform`: all labels occur with same relative frequency in training data

Condition #2: Nature of property features

- Feature set 1 (`perc`)
- Locations of color chips in $L^*a^*b^*$ space
- Thought to reflect perceptual distance (Fairchild 1998)



Condition #2: Nature of property features

- Feature set 2 (`conc`): Closeness in space given by crosslinguistic agreement in labeling of color chips

color chip	English	Dutch	Russian
PURPLE	*purple*	*paars*	*fioletovyj*
BLUE 1	*blue*	*blauw*	*sinij*
BLUE 2	*blue*	*blauw*	*goluboj*

Condition #2: Nature of property features

- Feature set 2 (conc): Closeness in space given by crosslinguistic agreement in labeling of color chips

color chip	English	Dutch	Russian
PURPLE	*purple*	*paars*	*fioletovyj*
BLUE 1	*blue*	*blauw*	*sinij*
BLUE 2	*blue*	*blauw*	*goluboj*

  - PCA over WCS (Kay et al. 2009; 330 chips, 110 languages)

Condition #2: Nature of property features

- Feature set 2 (conc): Closeness in space given by crosslinguistic agreement in labeling of color chips

color chip	English	Dutch	Russian
PURPLE	*purple*	*paars*	*fioletovyj*
BLUE 1	*blue*	*blauw*	*sinij*
BLUE 2	*blue*	*blauw*	*goluboj*

- PCA over WCS (Kay et al. 2009; 330 chips, 110 languages)
- Motivation: Typological Prevalence Hypothesis (Gentner & Bowerman 2009):
  - the more languages use a single label for 2 chips, the more similar they are
  - the more similar 2 chips, the easier it is to learn one category containing both

Condition #2: Nature of property features

- Feature set 2 (conc): Closeness in space given by crosslinguistic agreement in labeling of color chips

color chip	English	Dutch	Russian
PURPLE	*purple*	*paars*	*fioletovyj*
BLUE 1	*blue*	*blauw*	*sinij*
BLUE 2	*blue*	*blauw*	*goluboj*

- PCA over WCS (Kay et al. 2009; 330 chips, 110 languages)
- Motivation: Typological Prevalence Hypothesis (Gentner & Bowerman 2009):
  - the more languages use a single label for 2 chips, the more similar they are
  - the more similar 2 chips, the easier it is to learn one category containing both
- Previously: Beekhuizen, Fazly & Stevenson (2014) simulated acquisition errors for Dutch spatial prepositions w/ TPRS

Results

- baseline: the error-free learner

	Russian corpus	Russian uniform	English corpus	English uniform
perc	.91	.86	.96	.95
conc	.91	.89	.91	.90
perc+conc	.90	.89	.98	.96
error-free learner	.81	.81	.95	.95

Fit with child data.

Results

- baseline: the error-free learner
- conc for English: poor fit

	Russian		English	
	corpus	uniform	corpus	uniform
perc	.91	.86	.96	.95
conc	.91	.89	.91	.90
perc+conc	.90	.89	.98	.96
error-free learner	.81	.81	.95	.95

Fit with child data.

Results

- baseline: the error-free learner
- conc for English: poor fit
- `corpus` > `uniform`

	Russian		English	
	`corpus`	`uniform`	`corpus`	`uniform`
`perc`	.91	.86	.96	.95
`conc`	.91	.89	.91	.90
`perc+conc`	.90	.89	.98	.96
error-free learner	.81	.81	.95	.95

Fit with child data.

Results

- baseline: the error-free learner
- conc for English: poor fit
- corpus > uniform
- conc is complementary to perc for English!

	Russian		English	
	corpus	uniform	corpus	uniform
perc	.91	.86	.96	.95
conc	.91	.89	.91	.90
perc+conc	.90	.89	.98	.96
error-free learner	.81	.81	.95	.95

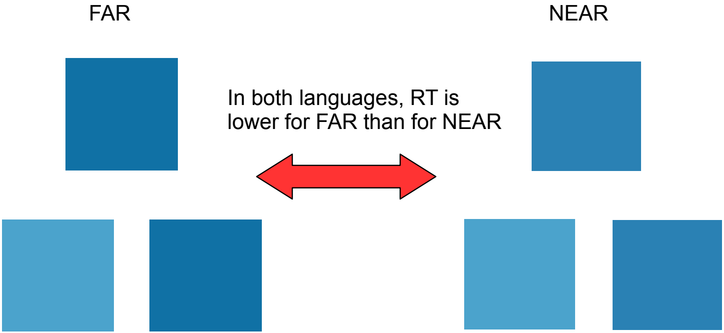
Fit with child data.

Case #2: Color discrimination

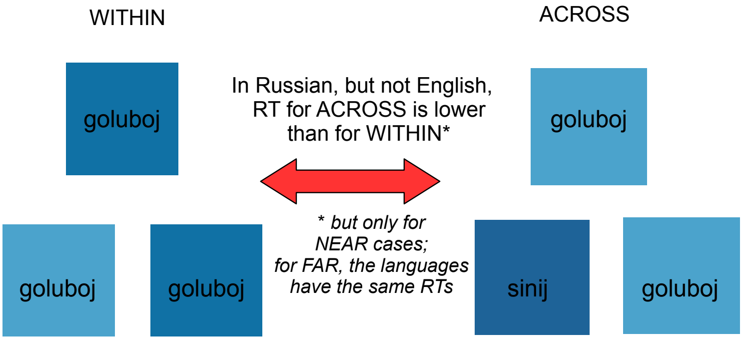
Russian speakers discriminate blue stimuli across the category boundary better than English speakers

Winawer et al. (2006): task

Results in Winawer et al. (2006): FAR vs NEAR

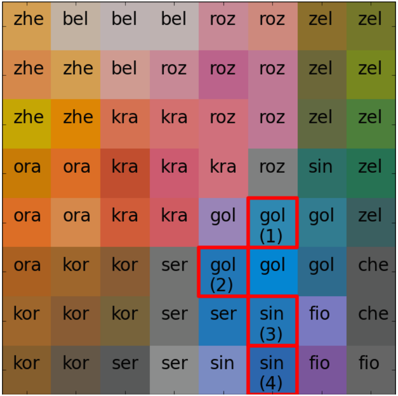


Results in Winawer et al. (2006): WITHIN vs ACROSS

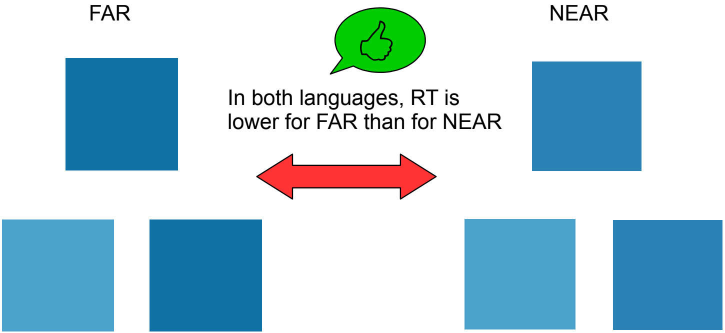


Evaluation

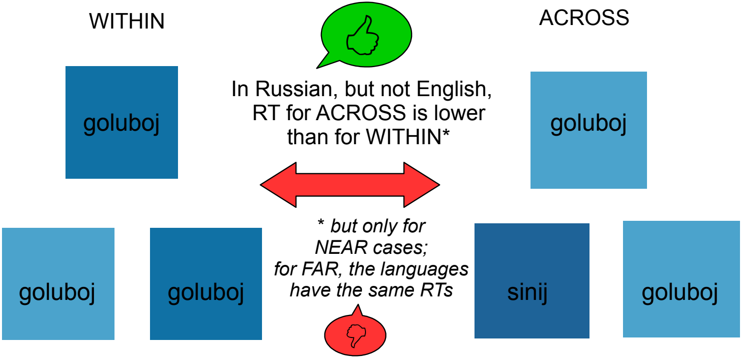
- Operationalize: the closer the BMUs of distracter and target, the harder, hence slower to discriminate
- Map distances of BMUs of stimuli in different conditions
- Same effects and non-effects as in Winawer et al.?



Model fit with Winawer et al. (2006): FAR vs NEAR

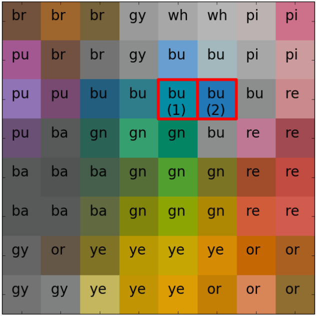


Model fit with Winawer et al. (2006) results: WITHIN vs ACROSS

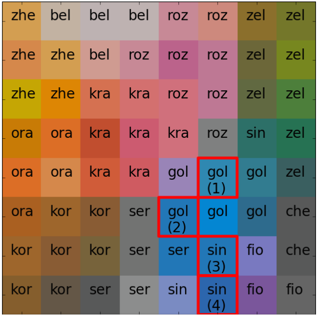


Interpretation

- Regardless of `feature` set and `sampling` method
- Primary reason: Eng. ‘blue’ more compressed than Rus. ‘light blue’+‘dark blue’



English



Russian

Final thoughts

- Unified model of development and linguistic relativity

Final thoughts

- Unified model of development and linguistic relativity

Overextensions

- Explanation: adjacent categories in feature space, aided by frequency (`corpus`)
- Complementary role of `conceptual` to `perceptual` features.
- Ecological validity: $P(\text{chip})$ unknown

Final thoughts

- Unified model of development and linguistic relativity

Overextensions

- Explanation: adjacent categories in feature space, aided by frequency (`corpus`)
- Complementary role of `conceptual` to `perceptual` features.
- Ecological validity: $P(\text{chip})$ unknown

Linguistic relativity

- Explanation color discrimination: Compression on the SOM drives linguistic relativity effect
- Linguistic relativity as language-specific compression?

Thank you!