Psych 229: Language Acquisition

Lecture 7 Categories & Models

Gómez & Lakusta 2004: Categorization

Category abstraction task

Learners a those device	paradigm re exposed i ted by emp generalize o cells)	to the pair ty cells. L	ings shown tarners are	below exc then tested	ept fo to ser
	\mathbf{X}_{i}	\mathbf{X}_{2}	\mathbf{X}_{1}	X.,	X
$a_1 = the$ $a_2 = a$	boy boy	girl girl	bali ball	dog dog	cal
	Yi	Y;	Y.	Υ.	Y
b ₁ = will b ₂ = can	jump jump	run run	play play	sleep sleep	cal

Previous work (aX, bY paradigm)

i second (Smith, 1969), categories and the mahips (i.e. that words belong to particular a, b classes, and that a-words go with Xs and not tually impossible to acourie unless some subse Virtually imposite X- and Y-category members

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What's going on (aX, bY paradigm) - a 2 step process

The US going of the (A), or particulty (III) -According the Brains (13%), we ado by figure (schemal, 1998), there are two ensemial steps in axi-tatory abstraction. Learners must first associate a-bedments with cuss differentiating X and Y cat-tions. They can then categories as and bedients based that co-occurrence (or distributional) relationships associated and the steps of the step of the step bedients of the step of the step of the step of cations with particular distinguishing cuss. Once a statistication of the step of the step of the step pair they have based (a₂, who cat is likely 1) and the step of the step o

Initial Association a --> X (with cue), b --> Y (with cue)

Category Membership (abstract) D1 is type a since it goes with X - how is D1 like other as? D2 is type b since it goes with Y - how is D2 like other bs?

coome fongle klory lega peyilg wazil

hevit merper packle roosa navba himure

words.

2

2

deech ghope jic skipe sabe tam

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17-month olds can do both steps

What about younger children?

7- 12 month abilities: previous work

the kind of ab

So let's look at 12-month olds.

Gómez & Lakusta 2004: Categorization Novel "vocabulary"

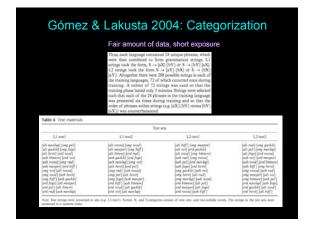
General procedure

ιX. of bY pairings. The other of aY and bX pairs. Xs w c words and Ys were mor

Basic (Example) Task:

Data alt, ush --> 2-syllable words ong, erd --> 1-syllable words

- Notice correlation.
- Realize *n*-syllable abstraction. Form new rules: e.g. alt/ush --> 2-syllable word Apply new rule to new items.



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Expt 1: infants make the association (familiarity preference) A Wilcourn Signed Ranks Test showed that infants listened significantly longer to howed that infants listened significantly longer to s from their training language than to strings from her language (T = 251, p = .004). Eighteen out of ants showed this pattern, suggesting that they had ed some sensitivity to the category-based structure

Infants can make abstract rule and apply it new items. But what's the relationship of this to "real" categorization?

to discriminate legal from illegal market s, despite the fact that X- and Y-element est, reflects sensitivity to the co-occurrence erem markers and X- and Y-categoric distinguishing features. Such learning its complexity: – infants had to track for ng markers, associate them with particula ing markers, associate them with particular f features and generalize to pairings con-words. The fact that infants were able to novel X- and Y-elements suggests that to some degree abstract (involving grouping ing feat

Does such grouping count as categorization? argue 'yes' to the extent that categorization in tinguishing elements according to some feat of features. When individuals treat elements they are responding to these elements as if members of the same category.	volves dis- are or set similarly,
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Expt 2: Noisy data (more like real life)

in Experiment 2 we investigated wi are able to separate more probab structure by exposing them to artific ying degrees of probabilistic s 83/17, approximately 83% of the tr n the infants' 'predominant' trainin 17% of the strings were from the oth tion 67/33, the split between the p-predominant training languages een the p or of 35, the spin between the periodin predominant training languages was 67% sectively. Infants who are able to disting sable from less probable structure should s non-pr

83/17: ye	es! 67/33	: no
e listening time mus the non-p gnificant_discr	s (in seconds) to stri redominant training imination even wi ring training were in	.1% confidence intervals ngs from the predominant language. Infants showed sen 17% of the strings om the non-predominant
ohahility ratio	Median slifference	\$5.1% confidence interval
up. 1: 105/0 up. 2: 83/17 up. 2: 67/33	1.618* 1.248* -0.125	(0.665-2.605) (0.130-2.650) (-0.925-0.835)
or + Linesing term	differences in these could	tion were excisionly significant.

Question: How would adults do in these tasks? (ref: Hudson Kam & Newport 2005)

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So 12-month olds can make & apply this kind of rule (evidenced by novel test items)

ed whether 12-meeth-olds would learn the marker-relationships and generative these to new X and y and tures. The fact that in el X- and Y-elements ng to syllable n by me re. It i

Abstraction = # of syllables (how realistic is this?)

Importantly, we not simply vis and p hey were gene syllable most ring at it precursor to that sh Jerken et al. study, who by the ol

Threshold for generalization

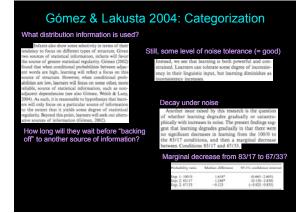
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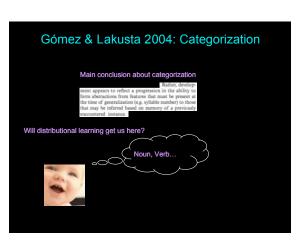
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Options for Learning:

- 1) Learn the rule for the more dominant data type, learn individual items for less dominant. (67/33 case: both "less" dominant)
- Ignore less dominant data as noise and learn nothing for those items.
- 2) Learn rules probabilistically? (67/33 case) - forced choice between two options might not reveal this level of probability distinction





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Discussion questions

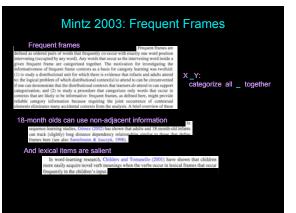
Relation to bilingual learning: if children are equipped to learn the predominant structure (assuming it's more than 83% of the data), what does this mean for bilingual children where the data distributions are far messier? (Related question: what if the two languages have different structures?)

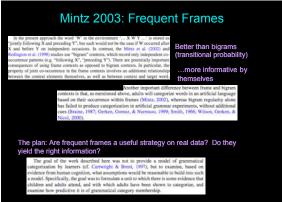
Artificial language vs. real language situations: How valid are artificial language results for explaining real language learning, especially since artificial languages are missing so much information available in real languages?

Related: Is distinguishing between one and two-syllable words a realistic analogy for categorization?

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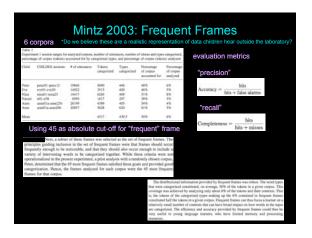


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Mintz 2003: Frequent Frames

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the -	0.96	0.51	0.91	0.25	0.42	0.50	11.89	0.40
Nina	0.96	0.48	0.98	0.29	0.95	0.46	0.94	0.36
Narmi	0.97	0.48	0.96	0.30	8:94	0.49	0.95	0.43
Anne	0.98	0.37	0.84	0.34	0.94	0.41	0.90	0.31
Ares	6.97	0.44	0.80	0.23	0.89	0.42	6.87	8.33
blown	2.04	0.46	0.91	0.27	0.93	0.47	0.91	0.38
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