Computational Cognitive Science

Lecture 15: Language Acquisition

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Overview

Reading: Frank et al. (2009).

Background

Word Learning

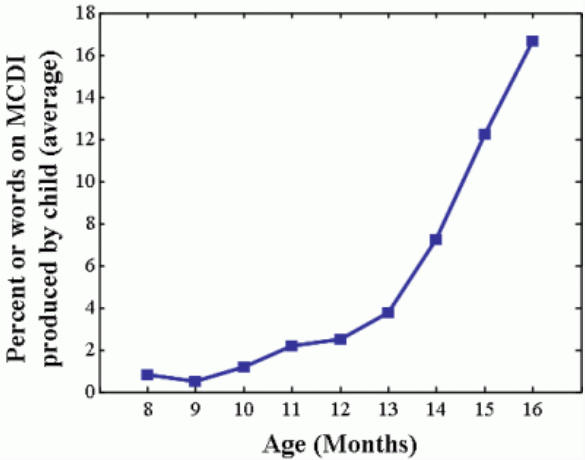
In the last lecture, we discussed how words are processed (word recognition). But these models can't explain how words are learned, i.e., lexicon acquisition:

- between birth and adulthood, children learn about 60,000 words (8–10 words per day on average);
- during the second postnatal year, word learning accelerates dramatically: vocabulary explosion;
- often children learn a new word based on a single example of its use: one-trial learning.

How is this possible?

Word Learning

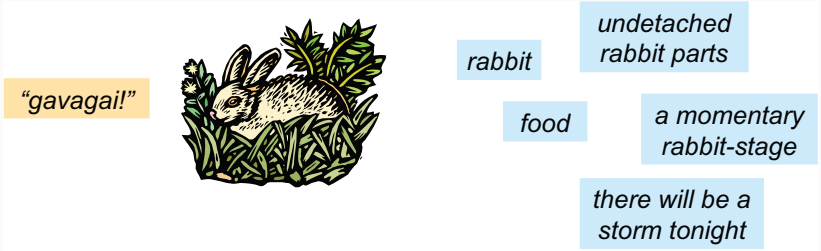
Growth curve from the MacArthur-Bates Communicative Development Inventory (MCDI):



http://www2.psychology.uiowa.edu/faculty/mcmurray/recent/science/

Referential Ambiguity

Philosophers think this should be impossible (Quine 1960):



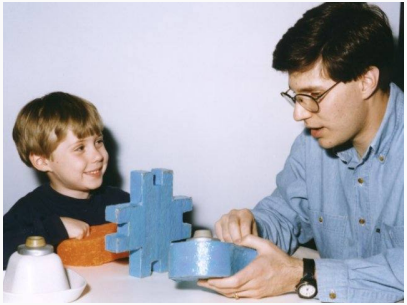
Developmental psychologists think:

- referential ambiguity is a serious problem, but:
- concrete nouns are learned first, then verbs, adjectives, abstract nouns follow;
- coincides with the development of syntax (two-word stage);
- one-trial learning happens when a new word is encountered in a context in which the other objects are familiar.

Social Learning

Crucially, children rely on social context to learn words. They infer other peoples' intentions based on:

- eye gaze;
- body position;
- pragmatics/saliency.



Evidence for this comes from:

- apparent lack of learning from video;
- tracking of others' gaze at six months;
- learning new words using gaze at 18 months.

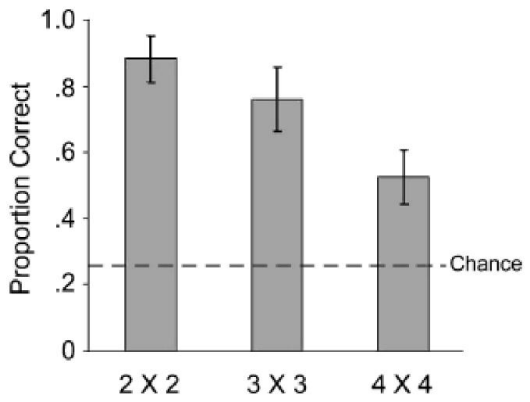
Image: http://www-cogsci.ucsd.edu/~deak/cdlab/research.html

Cross-situational Learning

Cross-situational learning resolves referential ambiguity over time:

Cross-situational Learning

Evidence: both adults and infants can learn word meanings from cross-situational experience in the lab (Yu and Smith 2007):



$n \times n$ condition: trial presented n words and n possible referents.

Modeling Word Learning

Bayesian Formulation

Frank et al. (2009) propose a Bayesian model of word learning:

- combines cross-situational learning and inferring speaker's intention;
- learns a lexicon L from a video corpus C annotated with objects present and words spoken.

Goal: infer a lexicon given a corpus:

$$P(L|C) \propto P(C|L)P(L)$$

Here, L is a set of word-object pairs. $P(C|L)$ is defined using generative model, and $P(L)$ favors smaller L:

$$P(L) \propto e^{-\alpha|L|}$$

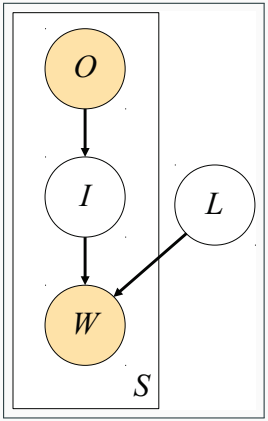
Generative Model

The corpus consists of independent situations. For each situation $s \in C$:

- O is the set of objects present in the situation;
- chose $I \subseteq O$, the set of intended referents (objects the speakers wants to talk about);
- chose $W \subseteq L$, the words the speaker utters (the lexicon L includes referential and non-referential words).

In practice, situation = utterance.

Graphical model notation: empty circle: observed random variable; shaded circle: hidden random variable; arrow: conditional dependence; plate: replicated S times.



Generative Model

$$
\begin{aligned}
P(C|L) &= \prod_{s \in C} P(O_s, W_s|L) \\
&= \prod_{s \in C} \sum_{I_s \subseteq O_s} P(O_s, I_s, W_s|L) \\
&= \prod_{s \in C} \sum_{I_s \subseteq O_s} P(O_s) P(I_s|O_s) P(W_s|I_s, L) \\
&\propto \prod_{s \in C} \sum_{I_s \subseteq O_s} P(I_s|O_s) P(W_s|I_s, L)
\end{aligned}
$$

Generative Model

Generate intentions from objects: uniform distribution:

$$P(I_s|O_s) \propto 1$$

Generate words from intentions and lexicon: words are independent. For each word w in W_s:

- choose referential ($p = \gamma$) or non-referential ($p = 1 - \gamma$):

$$P(W_s|I_s, L) = \prod_{w \in W_s} \left[\gamma \sum_{o \in I_s} \frac{1}{|I_s|} P_R(w|o, L) + (1 - \gamma) P_{NR}(w|L) \right]$$

- $P_R(w|o, L)$: choose uniformly from lexical items that refer to correct object;
- $P_{NR}(w|L)$: choose uniformly from all words in corpus.

Data

Small hand-annotated corpus:

- two 10-minute videos of mothers playing with preverbal infants using a small number of toys;
- speech is transcribed;
- each line of transcription is annotated with all visible mid-size objects, and true intention (for evaluation only).

words	"do bunnies go jumping through the forest?"
objects	BOOK, BIRD, RATTLE, MIRROR, BUNNY
intention	BUNNY

Evaluation

Evaluate model predictions against:

- gold-standard lexicon (word-object pairings);
- gold-standard intentions for each utterance (coded manually).

Compute precision (proportion of pairings that were correct) and recall (proportion of total correct pairings that were found).

Compare against related models:

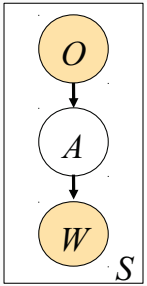
- simple statistics (co-occurrence frequency, conditional probability, mutual information);
- cross-situational model without intentions: IBM Machine Translation Model 1 (associative model).

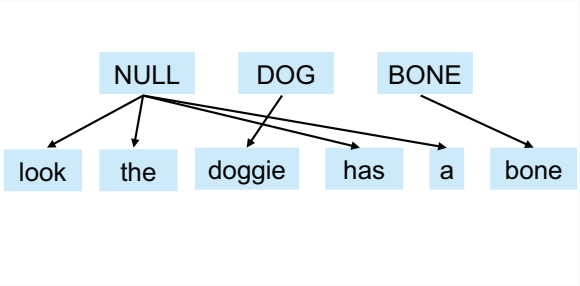
Machine Translation Model

Given objects $O = o_1 \dots o_J$ in current situation:

- choose number of words K;
- choose an alignment $a_1 \dots a_K$ between objects and words (including special NULL object);
- for each k, choose w_k given object that is aligned to it.

Model is asymmetric; try both $O|W$ and $W|O$.





Results

Results: Lexicon Accuracy

Model	Precision	Recall	F score
Association frequency	.06	.26	.10
Conditional probability (object|word)	.07	.21	.10
Conditional probability (word|object)	.07	.32	.11
Mutual information	.06	.47	.11
Translation model (object|word)	.07	.32	.12
Translation model (word|object)	.15	.38	.22
Intentional model	**.67**	**.47**	**.55**
Intentional model (one parameter)	.57	.38	.46

Results: Lexicon Accuracy

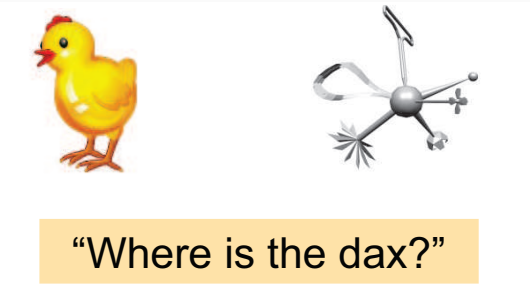
Word	Object
bear	**bear**
bigbird	**bird**
bird	**duck**
birdie	**duck**
book	**book**
bottle	bear
bunnies	**bunny**
bunnyrabbit	**bunny**
hand	**hand**
hat	**hat**
hiphop	mirror
kittycat	**kitty**
lamb	**lamb**
laugh	cow
meow	baby
mhmm	hand
mirror	**mirror**
moocow	**cow**
oink	pig
on	ring
pig	**pig**

Results: Referent Accuracy

Model	Precision	Recall	F score
Association frequency	.27	**.81**	.40
Conditional probability (object|word)	.59	.36	.45
Conditional probability (word|object)	.32	.79	.46
Mutual information	.36	.37	.37
Translation model (object|word)	.57	.41	.48
Translation model (word|object)	.40	.57	.47
Intentional model	**.83**	.45	**.58**
Intentional model (one parameter)	.77	.36	.50

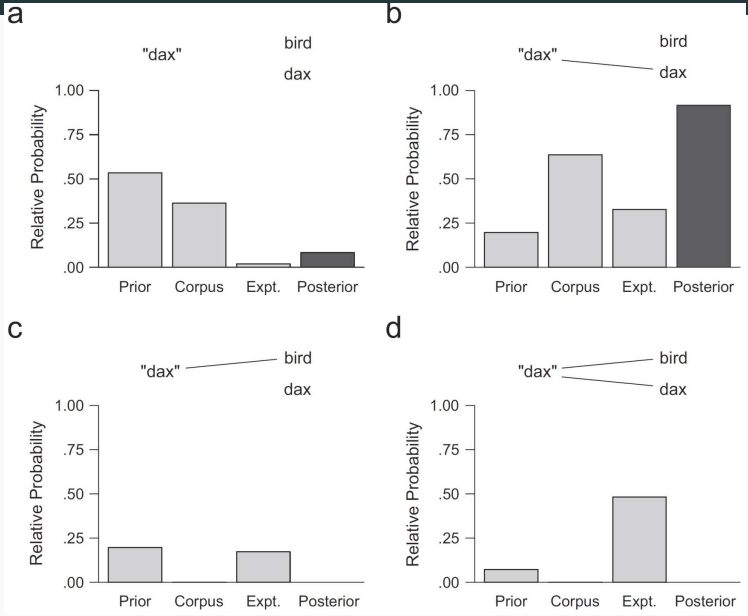
Results: Mutual Exclusivity

Children as young as 16 months map novel words to novel objects:



- some researchers have postulated a principle of mutual exclusivity to account for this;
- but it could also be general pragmatic principles at work;
- is mutual exclusivity learned or innate?

Results: Mutual Exclusivity



Results: Mutual Exclusivity

The model is able to capture mutual exclusivity:

- mapping "dax" to BIRD is unlikely:
  - highly coincidental that no other BIRDs are "dax";
  - likelihood is low;
- prior favors not mapping "dax" to anything, but this lowers the probability of the corpus;
- many of the other models also predict mutual exclusivity, suggesting no special principle is needed.

This example also shows that the model captures one-trial learning.

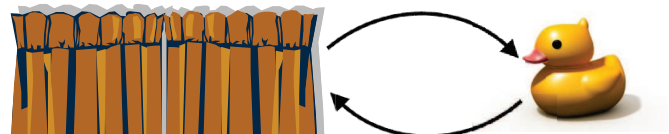
Results: Object Individuation

Infants as young as 12 months can use words to individuate objects. Experiment (Xu 2002):

1. an object emerges behind a screen, they hear a word, the object disappears again;
2. a different object emerges and disappears, they either hear the same word or a different word;
3. the screen disappears revealing either one or two objects.

Children show longer looking times when the number of objects in step 3 mismatches the number of words in steps 1 and 2.

Results: Object Individuation

1. 

“Look, a toy!”

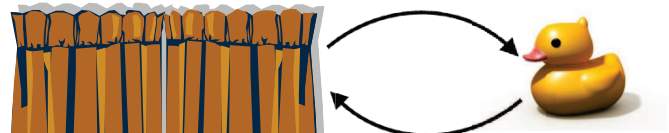
2.

“Look, a toy!”

3. 

vs. 

Results: Object Individuation

1. 

"Look, a duck!"

2.

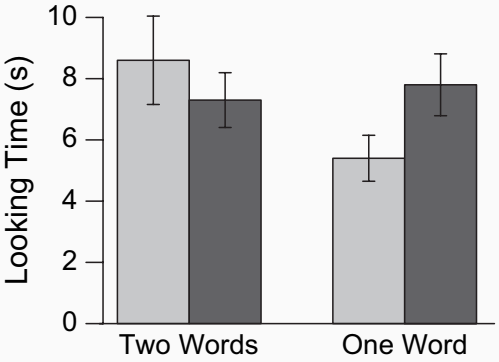
"Look, a ball!"

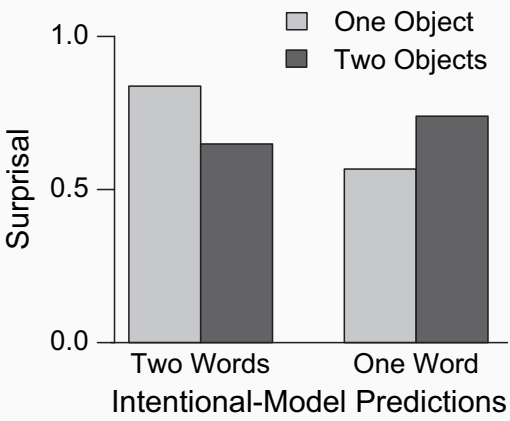
3. 

vs. 

Results: Object Individuation

This can be captured by the model in terms of surprisal (more on surprisal in lecture 13):





Discussion

Strengths:

- model combines cross-situational and social/intentional learning;
- more accurate learning of lexicon and referents than previous models;
- explains various experimental phenomena without special principles.

Weaknesses:

- only tested on very small corpus;
- only deals with concrete nouns;
- no model of syntax.

Summary

- Infants learn words based on multiple cues (eye gaze, body position, pragmatics/salience);
- encountering a word in multiple situations is crucial for word learning;
- the model of Frank et al. (2009) combines visual information (objects) and gaze (intended referents) to infer a mapping from words to meanings;
- it aggregates information across situations;
- it outperforms a simple translation (alignment) model and captures mutual exclusivity and object individuation.

References

Frank, Michael C., Noah D. Goodman, and Joshua B. Tenenbaum. 2009. Using speakers' referential intentions to model early cross-situational word learning. *Psychological Science* 20(5):578–585.

Quine, Willard. 1960. *Word and Object*. MIT Press, Cambridge, MA.

Xu, F. 2002. The role of language in acquiring object concepts in infancy. *Cognition* 85:223–250.

Yu, Chen and Linda B. Smith. 2007. Rapid word learning under uncertainty via cross-situational statistics. *Psychological Science* 18(5):414–420.