Cognition

PSYC 2040

L10: Language

Part 2

today's agenda

- Saffran study review
- co-occurrence
- error-free vs. error-driven learning
- language models

Saffran, Aslin & Newport (1996)

example speech heard:

prettybabyatepotatoprett
yfloweryummypotatobaby
lovemamapotatoisbrown

tracking co-occurring sounds:

prettybabyatepotatoprett
yfloweryummypotatobaby
lovemamapotatoisbrown

E1: words vs. novel items

words	part-words	novel items
pre-tty	tty-ba	re-ly
ba-by	by-a	ca-so
a-te	te-po	mo-du
po-ta-to	to-ba	si-ma

heard sounds

never heard sounds

E2: words vs. part-words

Saffran, Aslin & Newport (1996)

<u>example speech heard:</u>

buladobigokudatibatadup
abigokubuladodatibabula
dobigokudatibatadupabig
okubuladodatiba

E1: words vs. novel items

words	part-words	novel items
bu-la-do bi-go-ku	do-bi-go ti-ba-ta	re-ly ca-so mo-du si-ma
heard sounds		never heard sounds

E2: words vs. part-words

Saffran, Aslin & Newport (1996)

- sounds played in the artificial language had different transition probabilities
    - “**words**”: pre – tty
    - “**part words**”: tty – ba
    - “**novel items**”: mo-du
- E1: testing words vs. novel items
- E2: more difficult test, comparing words (higher transition probabilities) and part-words (lower but non-zero transition probabilities)

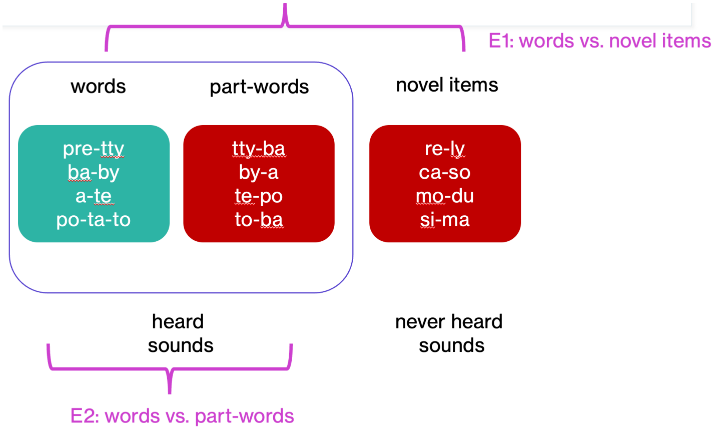


Table 1. Mean time spent listening to the familiar and novel stimuli for experiment 1 (words versus nonwords) and experiment 2 (words versus part-words) and significance tests comparing the listening times.

Experiment	Mean listening times (s)		Matched-pairs t test
	Familiar items	Novel items	
1	7.97 (SE = 0.41)	8.85 (SE = 0.45)	$t(23) = 2.3, P < 0.04$
2	6.77 (SE = 0.44)	7.60 (SE = 0.42)	$t(23) = 2.4, P < 0.03$

from artificial to natural language

- Pelucchi, Hay, & Saffran (2009) tested English-learning 8-month-old infants with Italian speech
- familiarization followed by test trials

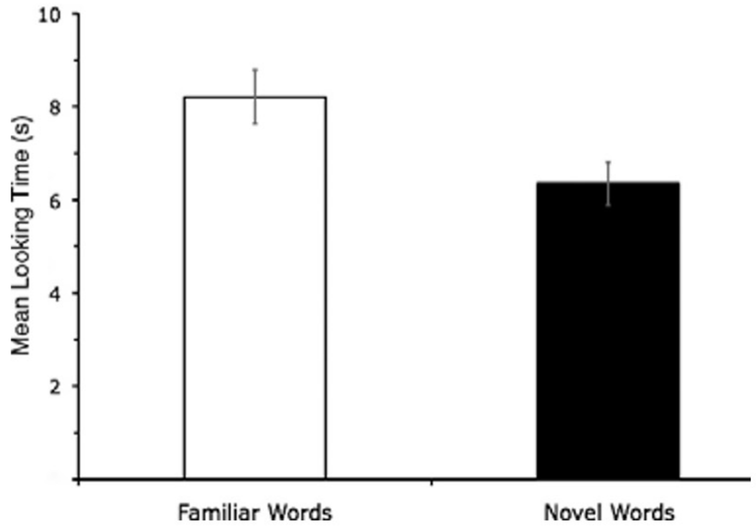
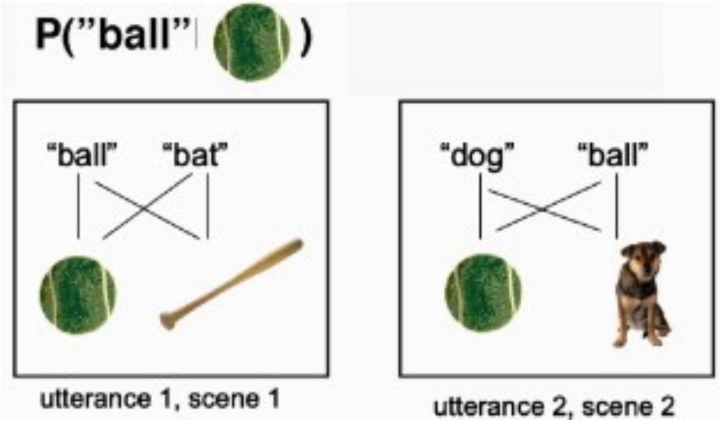


Figure 1. Results of Experiment 1: Mean looking times (±1 *SE*) to familiar words and novel words.

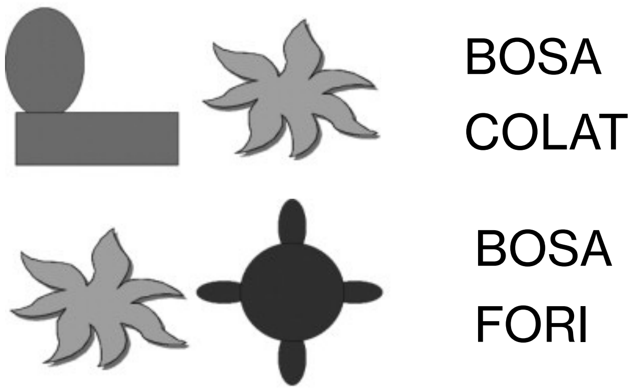
labels to referents: cross-situational statistics

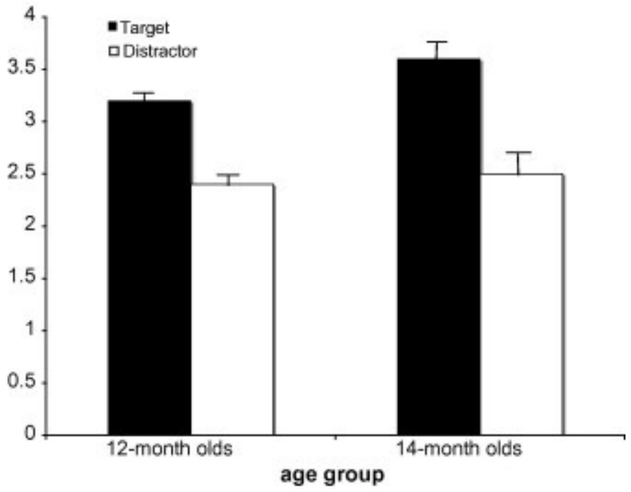
- mapping labels (“ball”) to the object is difficult as multiple objects may be in view when the label is used
- Smith and Yu (2008) showed that 12- and 14-month-old infants resolve this uncertainly by combining statistics across situations



labels to referents: cross-situational statistics

- infants first "studied" referents and novel word labels
- infants were tested by playing a sound and then displaying the target referent and a distractor 4 times and recording looking times
- key finding: infants looked reliably longer to the target than to the distractor
- inference: infants were able to identify label to referent mappings by tracking cross situational statistics





revisiting innateness vs. learning

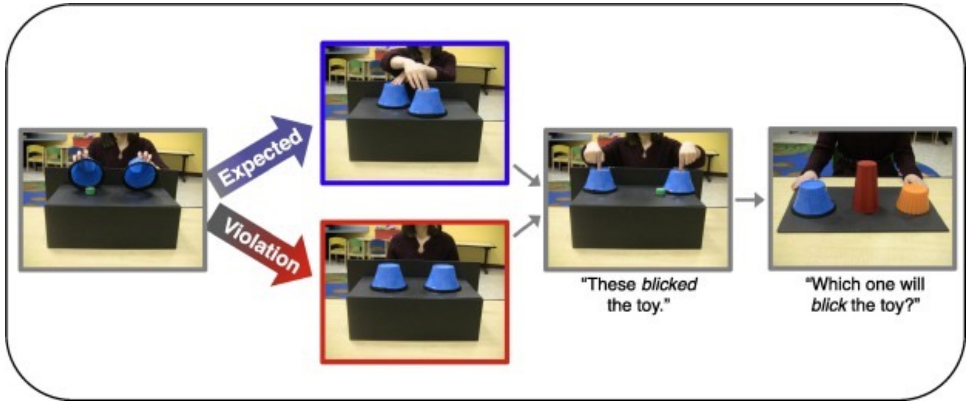
- statistical learning studies show that infants are able to extract regularities from environmental input
- suggestion: some aspect of language learning is *innate*
  - Chomsky's "poverty of the stimulus" argument
- but….
  - you only need *one example* to falsify a theory! (next time)
  - OR: there is enough structure in the language itself

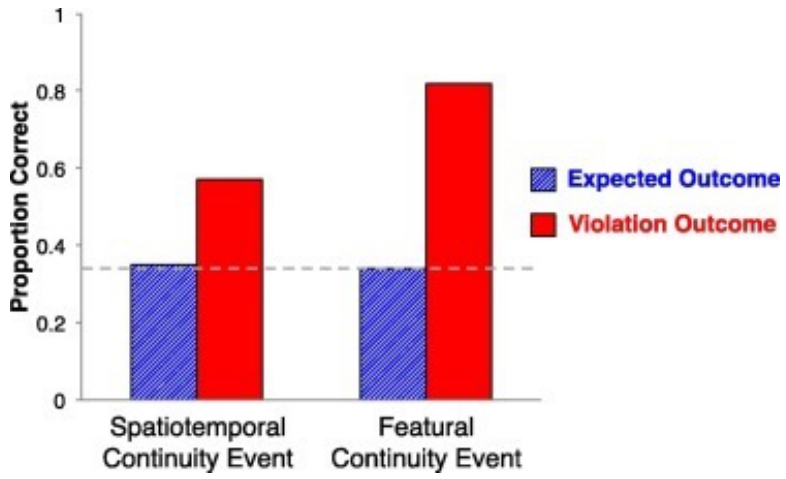
why track statistics?

- infants are not required to or motivated by reward to track statistics, so why do they do it?
- possible hypotheses:
  - infants want to communicate with their caregivers
  - infants want to generate predictions about the environment

statistical learning and prediction

- Stahl & Feigenson (2017) tested 3- to 6-year-old children in an experiment where novel labels (blick) were mapped to actions in expected or violation conditions
  - expected : toy in the <u>expected</u> location
  - violated: toy in the <u>unexpected</u> location
- learning was maximized when children were surprised by the outcomes



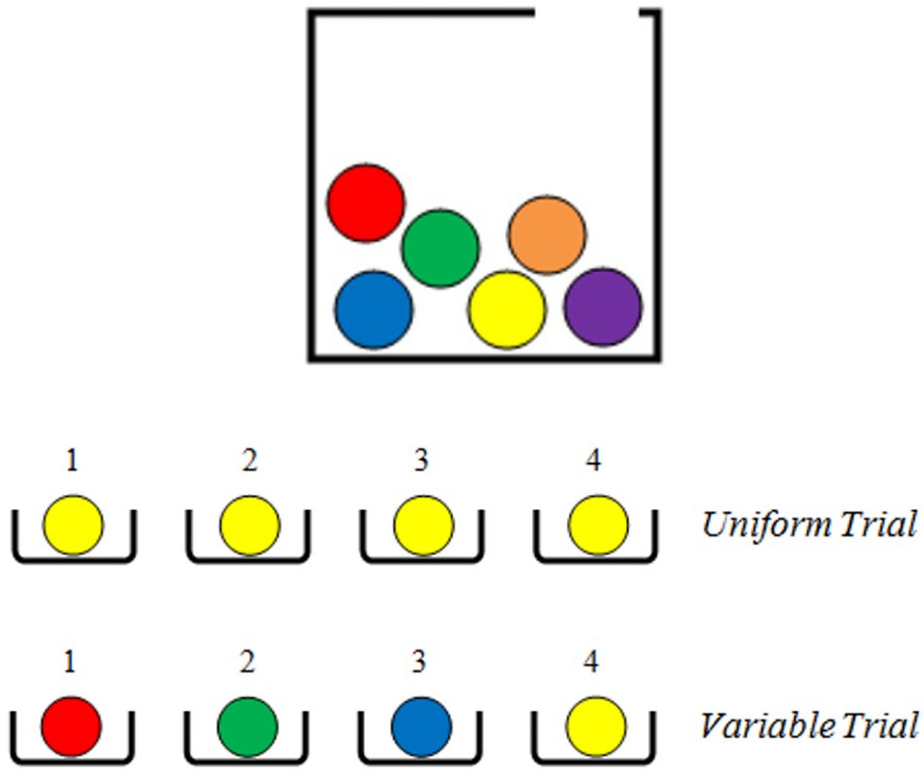


statistical learning and curiosity

- statistical learning may also inform what to learn about in the first place
- curiosity may be particularly important in creating learning opportunities and minimizing uncertainty in the environment

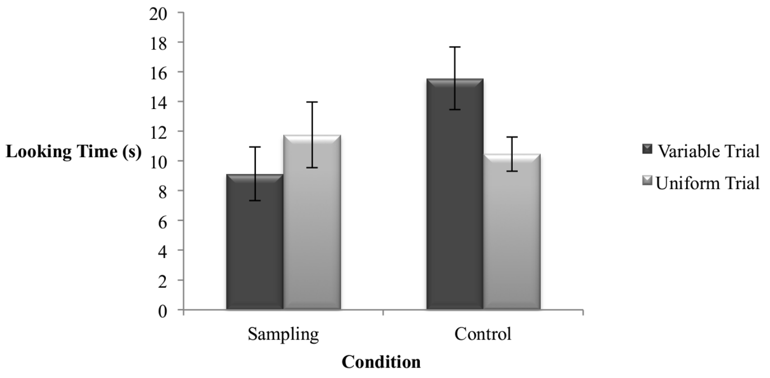
statistical learning and curiosity

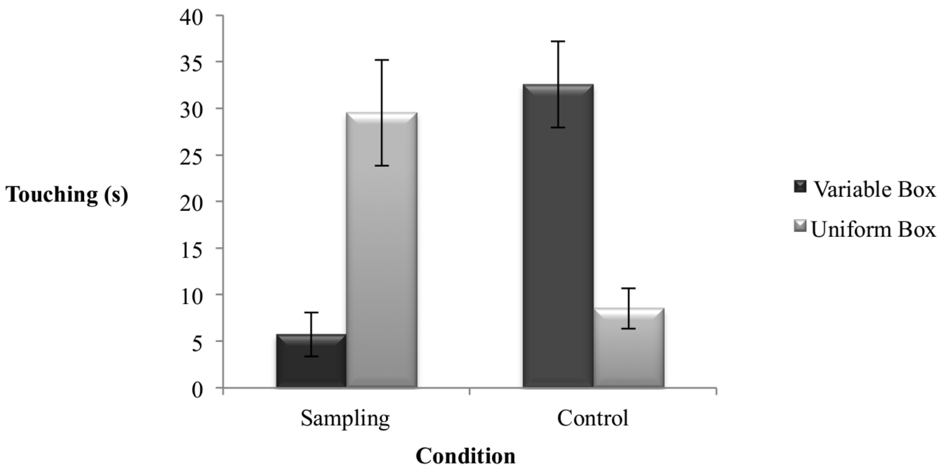
- Sim & Xu (2017) tested 13-month-old infants in a violation of expectation (VOE) and crawling paradigm
  - draw: could be “uniform” or “variable”
  - conditions: control condition (experimenter looked into the box before drawing out the balls) or sampling (no looking)
- two experiments: looking time (VOE) vs. touching/reaching time (crawling)

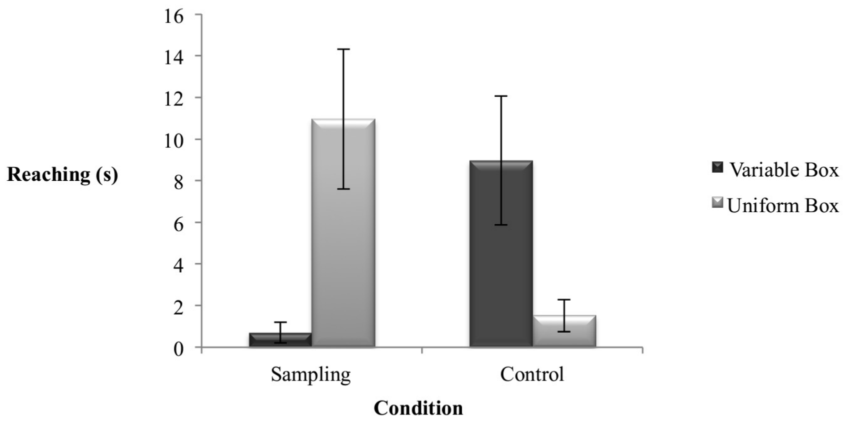


statistical learning and curiosity

- Sim & Xu (2017) showed that 13-month-old infants preferentially explore sources of unexpected events







review of findings/inferences

- infants track statistical regularities
- children learn from prediction error
- children are inherently curious and want to reduce uncertainty
- but.....
- how far can you take this idea of statistical learning?

statistical learning in animals

Segmentation of the speech stream in a non-human primate: statistical learning in cotton-top tamarins

Marc D Hauser [a], Elissa L Newport [b], Richard N Aslin [b]

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Abstract

Previous work has shown that human adults, children, and infants can rapidly compute sequential statistics from a stream of speech and then use these statistics to determine which syllable sequences form potential words. In the present paper we ask whether this ability reflects a mechanism unique to humans, or might be used by other species as well, to acquire serially organized patterns. In a series of four experimental conditions, we exposed a New World monkey, the cotton-top tamarin (*Saguinus oedipus*), to the same speech streams used by Saffran, Aslin, and Newport (Science 274 (1996) 1926) with human infants, and then tested their learning using similar methods to those used with infants. Like humans, tamarins showed clear evidence of discriminating between sequences of syllables that differed only in the frequency or probability with which they occurred in the input streams. These results suggest that both humans and non-human primates possess mechanisms capable of computing these particular aspects of serial order. Future work must now show where humans' (adults and infants) and non-human primates' abilities in these tasks diverge.

Learning at a distance II. Statistical learning of non-adjacent dependencies in a non-human primate

Elissa L. Newport [a], Marc D. Hauser [b], Geertrui Spaepen [b], Richard N. Aslin [a]

Trends in Cognitive Sciences

Review

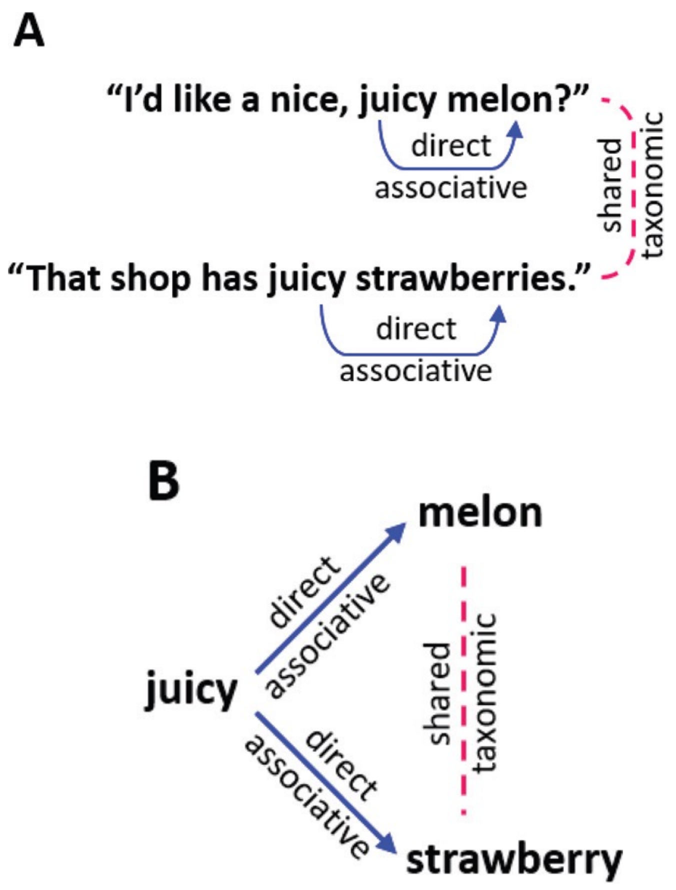
Constraints on Statistical Learning Across Species

Chiara Santolin[1,*] and Jenny R. Saffran[2]

Both human and nonhuman organisms are sensitive to statistical regularities in sensory inputs that support functions including communication, visual processing, and sequence learning. One of the issues faced by comparative research in this field is the lack of a comprehensive theory to explain the relevance of statistical learning across distinct ecological niches. In the current review we interpret cross-species research on statistical learning based on the perceptual and cognitive mechanisms that characterize the human and non-human models under investigation. Considering statistical learning as an essential part of the cognitive architecture of an animal will help to uncover the potential ecological functions of this powerful learning process.

learning from co-occurrence

- meaning of words is learned based on which words it co-occurs with in natural language
  - “you shall know a word by the company it keeps” (Firth, 1957)
- co-occurrence can be defined in two ways:
  - direct: if words occur together in the same context (e.g., eat-food, sit-chair, etc.)
  - indirect/shared: if words occur in similar contexts (e.g., strawberries are red, apples are red)
- co-occurrences = statistical regularities and can extend to any type of input (tones, figures, words, etc.)

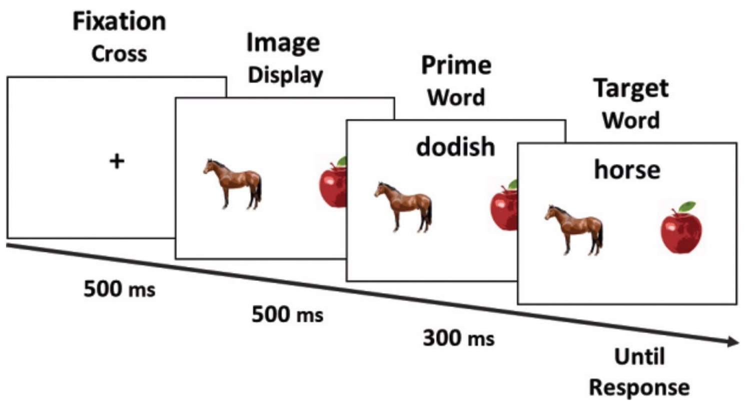


experiment review

- think back to the language experiment you did
- what kinds of tasks did you perform?
- what do you think the experiment was about?

learning new words

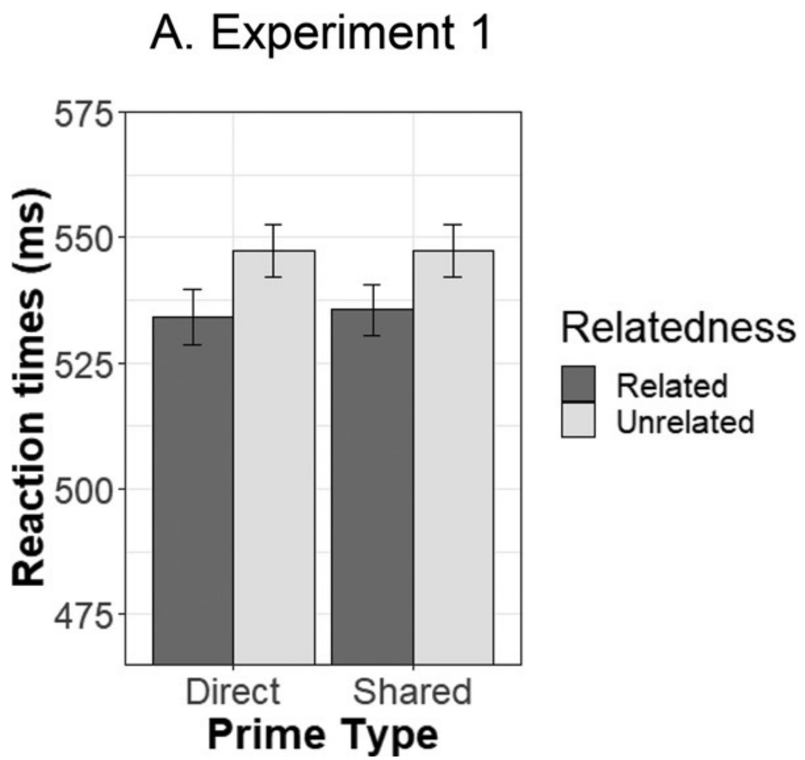
- Savic et al. (2022) had participants read sentences with novel and familiar words
  - novel words co-occurred with familiar words (direct or indirect)
- participants tested in a semantic priming experiment
- novel – familiar words were paired based on whether the pairs were related or unrelated and whether there was direct/indirect co-occurrence



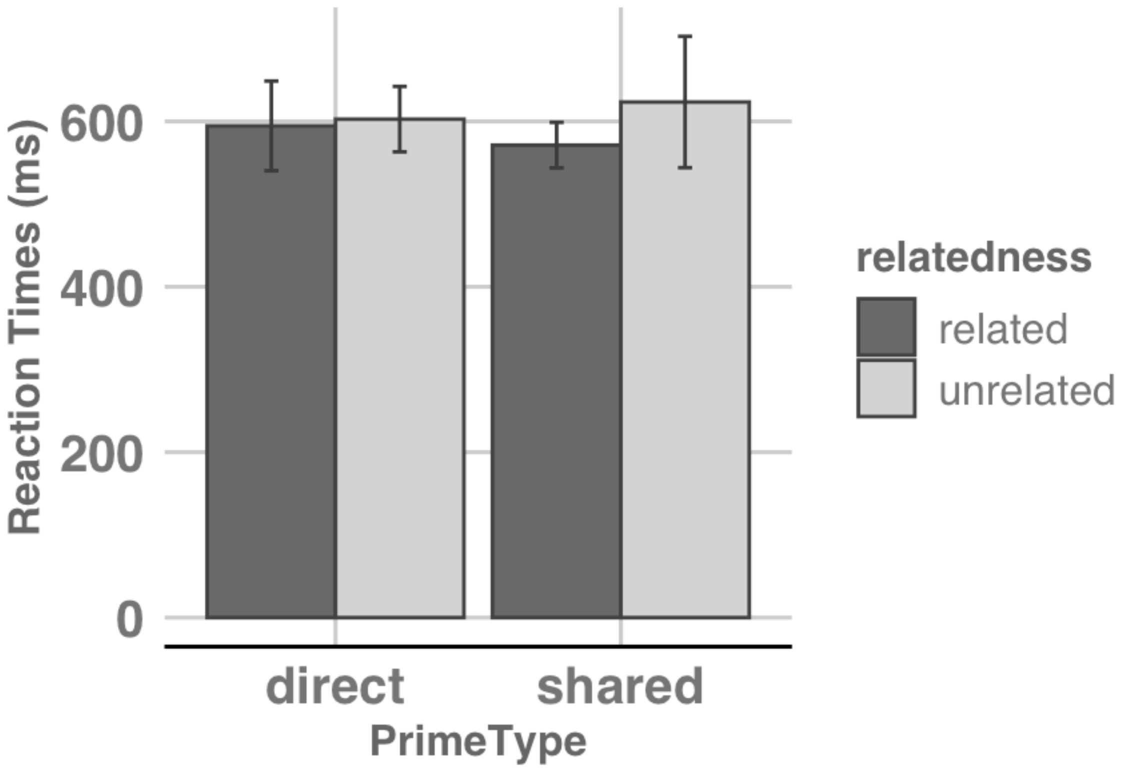
	related	unrelated
direct	dodish-horse	foobly-horse
indirect/shared	geck-horse	mipp-horse

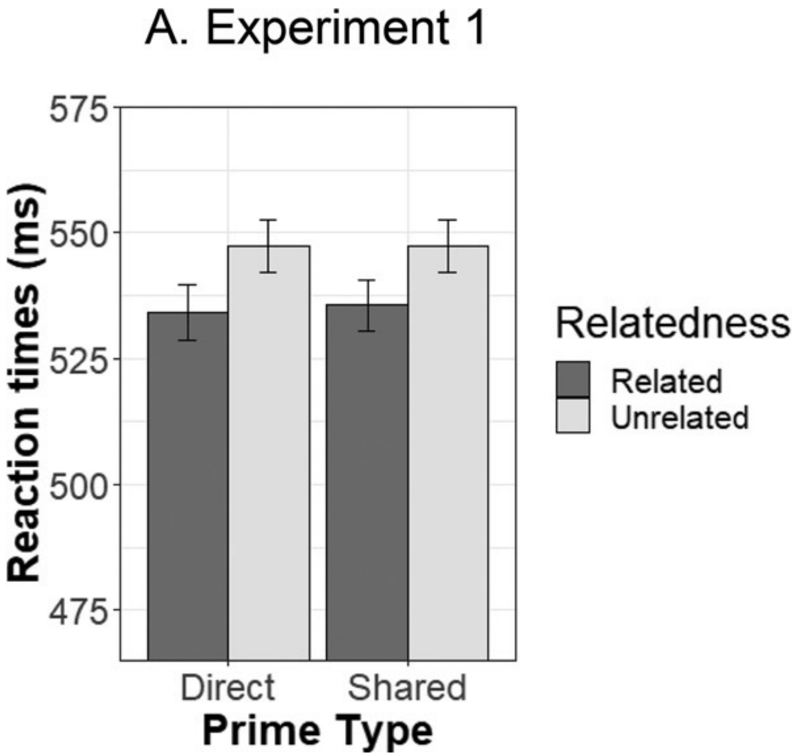
semantic priming and co-occurrences

- reaction time to identify targets was faster when they were preceded by novel pseudowords/primes with which they directly co-occurred or shared co-occurrence in training
- pattern did not differ for direct and indirect co-occurrences
- inference: co-occurrences in natural language can drive semantic integration of new words



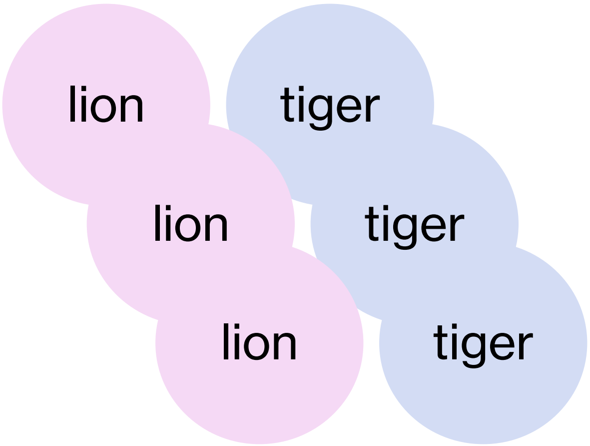
class data (N = 45) vs. Savic et al.'s data

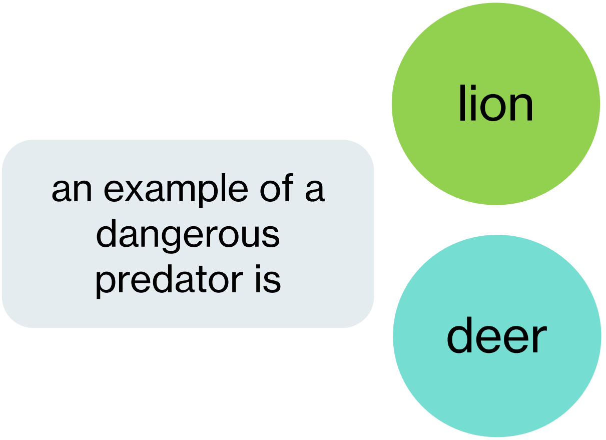




error-free vs. error-driven learning

- associative (error-free) learning
  - simply attending to statistical regularities/co-occurrence in the environment is sufficient to develop a conception of meaning
  - inspired by Hebbian learning within neurons
- predictive (error-driven) learning
  - use co-occurrence as a signal for word prediction at the sentence level
  - inspired by behaviorism/reinforcement learning



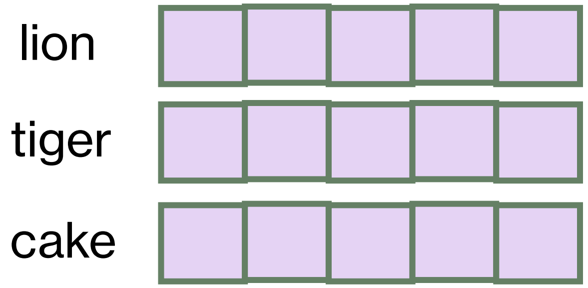


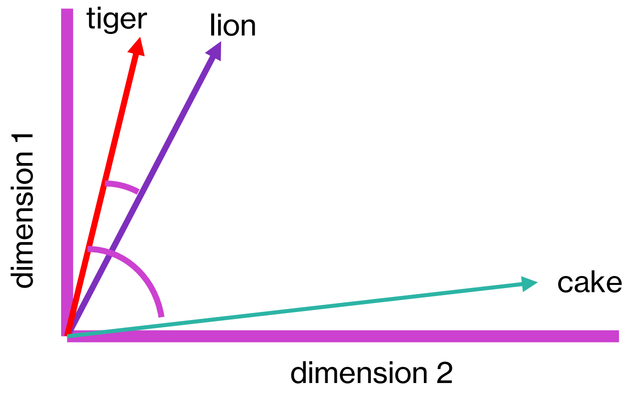
testing the claims

- how would you test whether learning is error-free or error-driven?
- one possible solution: model learning in both ways and compare!

what does it mean?

- **large** language models are typically “trained” on large databases of text (e.g., Wikipedia, Google News, etc.)
- algorithm: specific models prioritize creating a co-occurrence matrix or predicting the next word(s) in the sentence
- after training, we can look under the hood at what ‘representations’ the models have acquired
- these representations are usually a collection of numbers but they are meaningfully related to each other in a high-dimensional space

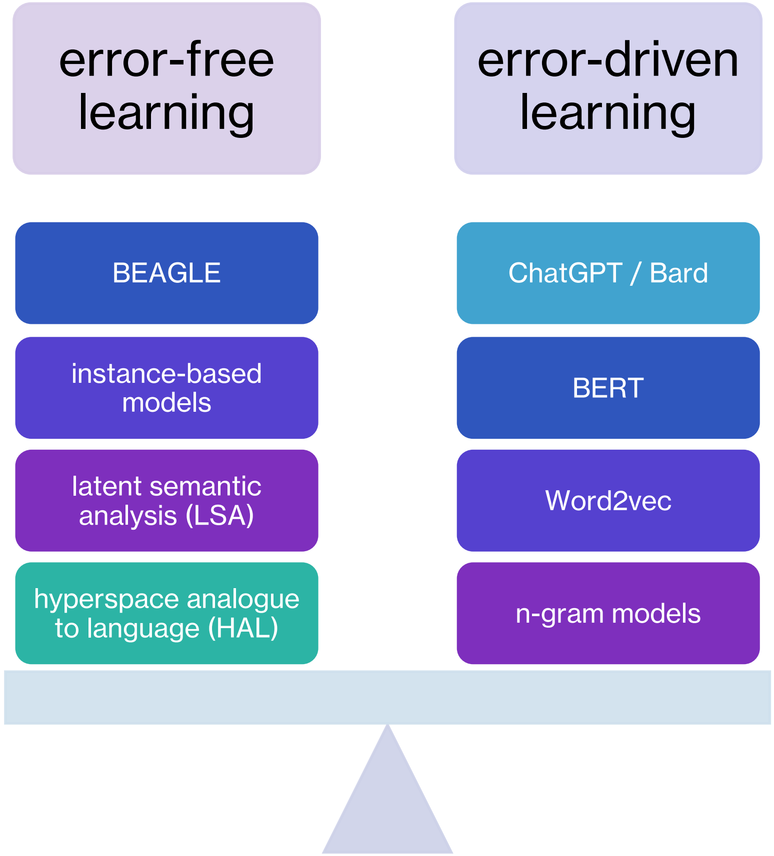




analogies with language models

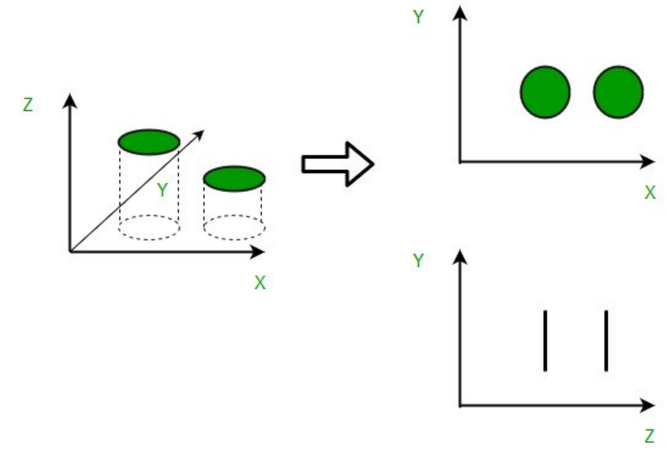
- king : queen :: man : ???
- [demo]
- try out different types of analogies!

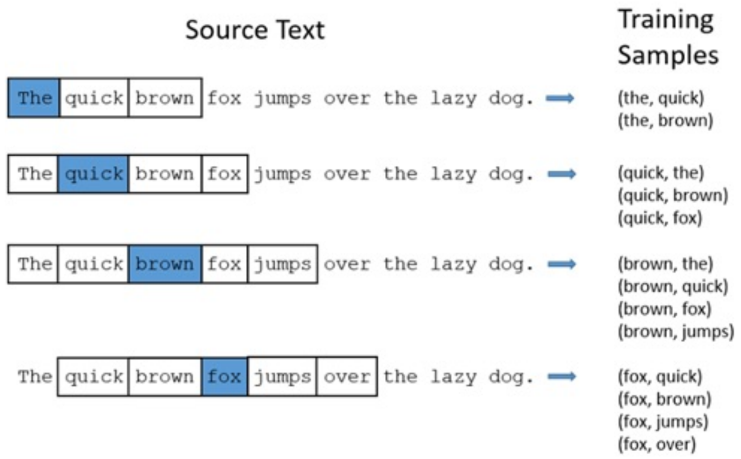
language models



error-free vs. error-driven models

- error-free models focus on the co-occurrence matrix
    - some models only emphasize direct co-occurrence (HAL), whereas others emphasize direct and indirect co-occurrence through some type of higher-level abstraction process (LSA, BEAGLE)
- error-driven models focus on prediction
    - prediction can occur at multiple levels and different models emphasize different aspects of the prediction process (n-word windows, attention-based, etc.)
    - neural networks are a family of models that can learn from prediction error





real empirical demonstrations

- word2vec and other prediction-based models, such as ChatGPT are extremely powerful when trained on large datasets with billions of parameters
- some work has shown that on smaller datasets (e.g., child-directed speech), error-free approaches may be more useful in predicting behavior (Asr, Willits, & Jones, 2016)

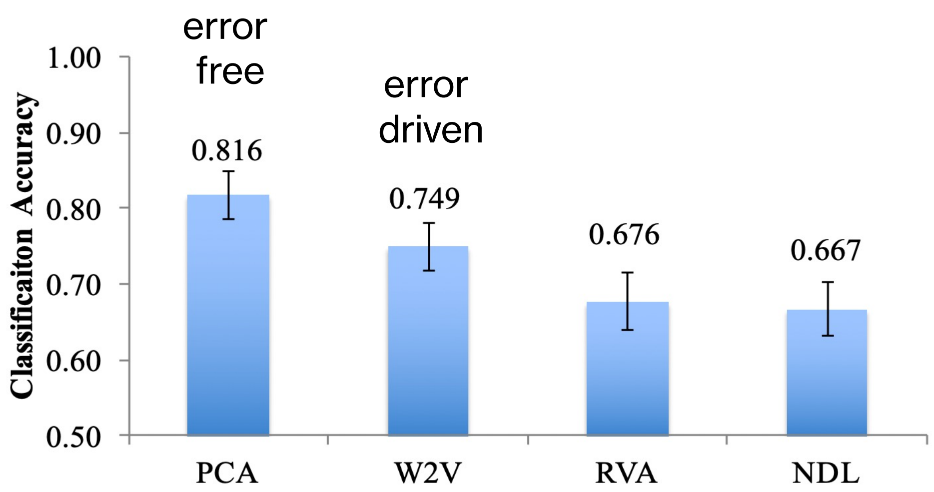


Figure 3. Mean classification accuracy (averaging across the 30 different categories and 95% CI) for the four DSMs.

the wins of language models

- truly start from “scratch”
- dispel the need for hard-wiring many abilities by showing “emergent” behavior
- have widespread applications

Modern language models refute Chomsky’s approach to language

Steven T. Piantadosi[a,b]

[a]UC Berkeley, Psychology [b]Helen Wills Neuroscience Institute

The rise and success of large language models undermines virtually every strong claim for the innateness of language that has been proposed by generative linguistics. Modern machine learning has subverted and bypassed the entire theoretical framework of Chomsky’s approach, including its core claims to particular insights, principles, structures, and processes. I describe the sense in which modern language models implement genuine *theories* of language, including representations of syntactic and semantic structure. I highlight the relationship between contemporary models and prior approaches in linguistics, namely those based on gradient computations and memorized constructions. I also respond to several critiques of large language models, including claims that they can’t answer “why” questions, and skepticism that they are informative about real life acquisition. Most notably, large language models have attained remarkable success at discovering grammar without using any of the methods that some in linguistics insisted were necessary for a science of language to progress.

potential concerns: thinking & reasoning

- the models often fail on logical reasoning and thinking tasks

Language and thought are not the same thing: evidence from neuroimaging and neurological patients

Evelina Fedorenko[1,2,3] and Rosemary Varley[4]

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Abstract Go to: ▸

Is thought possible without language? Individuals with global aphasia, who have almost no ability to understand or produce language, provide a powerful opportunity to find out. Astonishingly, despite their near-total loss of language, these individuals are nonetheless able to add and subtract, solve logic problems, think about another person's thoughts, appreciate music, and successfully navigate their environments. Further, neuroimaging studies show that healthy adults strongly engage the brain's language areas when they understand a sentence, but not when they perform other nonlinguistic tasks like arithmetic, storing information in working memory, inhibiting prepotent responses, or listening to music. Taken together, these two complementary lines of evidence provide a clear answer to the classic question: many aspects of thought engage distinct brain regions from, and do not depend on, language.

Prompt: Get your sofa onto the roof of your house.

GPT-3 response: I would start by getting a very strong ladder and a very strong friend... (goodness: 3.6 out of 7)

Human response: You may need to rent a Genie lift large enough to carry the sofa. You will need at least one other person... (goodness: 4.8 out of 7)

To manipulate how "out-of-distribution" the query is, the prompts get progressively more constrained:

Prompt: Get your sofa onto the roof of your house, without using a pulley.

GPT-3 response: Use a rope to tie around the sofa and connect it to a car. (goodness: 3.0 out of 7)

Human response: I would get a giant crane... and use the crane to lift it to the roof of my house. (goodness: 5.1 out of 7)

With more and more constraints, human responses remain at approximately the same level of goodness, whereas model performance breaks down completely:

Prompt: Get your sofa onto the roof of your house, without using a pulley, a ladder, a crane...

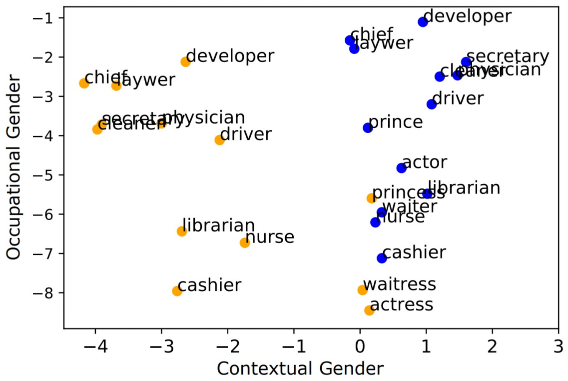
GPT-3 response: Cut the bottom of the sofa so that it would fit through the window...break the windows to make room for the sofa. (goodness: 2.7 out of 7)

Human response: I will build a large wooden ramp...on the side of my house with platforms every 5 feet... (goodness: 5.0 out of 7)

Mahowald, K., Ivanova, A. A., Blank, I. A., Kanwisher, N., Tenenbaum, J. B., & Fedorenko, E. (2023). Dissociating language and thought in large language models: a cognitive perspective. *arXiv preprint arXiv:2301.06627*.

potential concerns: biases and costs

- they learn stereotypes and biases
- there are sizeable costs to the environment and climate of training these models



Consumption	CO_2e (lbs)
Air travel, 1 passenger, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL)	39
w/ tuning & experimentation	78,468
Transformer (big)	192
w/ neural architecture search	626,155

Table 1: Estimated CO_2 emissions from training common NLP models, compared to familiar consumption.[1]

potential concerns: data

- the size of the corpora that models are trained on is 1000 times more than the input available to children
- most models are based on the English language (Bender rule)

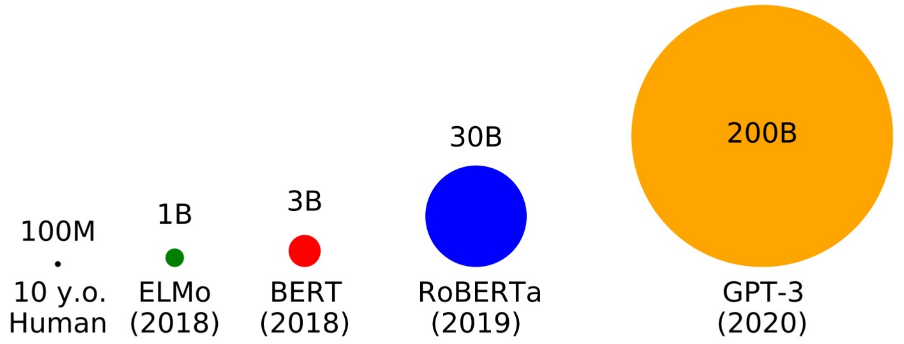


Figure 1: Comparison of human and model linguistic input (# of word tokens).

the path forward

- situating language within the broader conversation about human intelligence
- linguistic: sign language, prosody
- non-linguistic:
    - multimodal input
        - “intuitive physical reasoning”
    - interactive/social learning
        - “intuitive psychology”

Building machines that learn and think like people

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next class

- **before** class:
  - *finish:* L10 quiz/assignment
  - *work on:* QALMRI candidates
  - *read*: L11 reading
- **during** class:
  - judgment & decision making!

optional: bilingual brains

- early research suggested a bilingual advantage, i.e., improved executive functioning (Bialystok et al., 2004)
- recent meta-analyses appear to suggest otherwise; currently ongoing debate

The Bilingual Advantage in Children's Executive Functioning Is Not Related to Language Status: A Meta-Analytic Review

Psychological Science
2021, Vol. 32(7) 1115–1146

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Abstract
There is considerable debate about whether bilingual children have an advantage in executive functioning relative to monolingual children. In the current meta-analysis, we addressed this debate by comprehensively reviewing the available evidence. We synthesized data from published studies and unpublished data sets, which equated to 1,194 effect sizes from 10,937 bilingual and 12,477 monolingual participants between the ages of 3 and 17 years. Bilingual language status had a small overall effect on children's executive functioning (g = .08, 95% confidence interval = [.01, .14]). However, the effect of language status on children's executive functioning was indistinguishable from zero (g = −.04) after we adjusted for publication bias. Further, no significant effects were apparent within the executive-attention domain, in which the effects of language status have been hypothesized to be most pronounced (g = .06, 95% confidence interval = [−.02, .14]). Taken together, available evidence suggests that the bilingual advantage in children's executive functioning is small, variable, and potentially not attributable to the effect of language status.

Clear Theories Are Needed to Interpret Differences: Perspectives on the Bilingual Advantage Debate

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Keywords: bilingual advantage, executive control, bilingualism, inhibition, language control, brain plasticity

ABSTRACT
The heated debate regarding bilingual cognitive advantages remains ongoing. While there are many studies supporting positive cognitive effects of bilingualism, recent meta-analyses have concluded that there is no consistent evidence for a *bilingual advantage*. In this article we focus on several theoretical concerns. First, we discuss changes in theoretical frameworks, which have led to the development of insufficiently clear theories and hypotheses that are difficult to falsify. Next, we discuss the development of looking at bilingual experiences and the need to better understand *language* control. Last, we argue that the move from behavioural studies to a focus on brain plasticity is not going to solve the debate on cognitive effects, especially not when brain changes are interpreted in the absence of behavioural differences. Clearer theories on both behavioural and neural effects of bilingualism are needed. However, to achieve this, a solid understanding of both bilingualism and executive functions is needed first.