How math helps us better understand language

Linguistics Studies Lecture Series College of Charleston February 18, 2021

Lisa S. Pearl Professor Department of Language Science SSPB 2219 University of California, Irvine lpearl@uci.edu



Computation of Language Laboratory UC Irvine





Language is a uniquely human ability.

We can investigate many things about language, including

what we know when we know language





We can investigate many things about language, including

how language knowledge develops







We can investigate many things about language, including





how we use language to communicate different information







So what kinds of things do we know when we know language?



how to identify words in fluent speech (speech segmentation)



wлrəpлrikıri wлr ə pлri kıri what a pretty kitty!









what a pretty kitty!
speech segmentation



how to pronounce words (phonology)

KI tty ki TTY







how to interpret words in context (syntax, semantics)

"Oh look — a pretty kitty!" "Look — there's another one!"









how to put words together to ask questions (syntax)

This kitty was bought as a present for someone.



Lily thinks this kitty is pretty.







how to identify the right interpretation in context (pragmatics)



"Every kitty didn't sit on the stairs"



No kitties sat on the stairs.

Not all kitties sat on the stairs.





"Who does Lily think the kitty for is pretty?"

syntax









Children are amazing at learning language





Much of the linguistic system is already known by age 4.











Also, children figure language out mostly without explicit instruction.









What they're doing: Extracting patterns and making generalizations from the surrounding data mostly just by hearing examples of what's allowed in the language.

What's so hard about that?





There are often many ways to generalize beyond the input, and most of them aren't right.







There are often many ways to generalize beyond the input, and most of them aren't right.

??? "birdie"



"What a pretty birdie!"







There are often many ways to generalize beyond the input, and most of them aren't right.



??? "birdie"



"Look - a birdie!"







There are often many ways to generalize beyond the input, and most of them aren't right.



??? "birdie"





"Look at that birdie!"







There are often many ways to generalize beyond the input, and most of them aren't right.



??? "birdie"



What generalization to make?







There are often many ways to generalize beyond the input, and most of them aren't right.



??? "birdie"

= blue creature











There are often many ways to generalize beyond the input, and most of them aren't right.



??? "birdie"

= creature on branch













There are often many ways to generalize beyond the input, and most of them aren't right.



??? "birdie"

= [whatever makes something a bird]















These kinds of induction problems are everywhere in cognitive development, including language development.





These kinds of induction problems are everywhere in cognitive development, including language development.



phonolo	ogy	syntax, semantics
speech segmentation	syntactic	categorization
pra	gmatics	syntax

Language development = Solving a lot of induction problems.



Solving a lot of induction problems.







How do we use language knowledge to communicate?







How do we use language knowledge to communicate?



And can we help machines do it too?









something salient in the context









"C'mon — don't you think this is awesome?"







But more subtle information is communicated too.

"C'mon — don't you think this is awesome?"










The speaker likely has a persuasive intention.

"C'mon - don't you think this is awesome?"

core information











"C'mon — don't you think this is awesome?"

core information



If the speaker actually doesn't like penguins, he could be intending to ingratiate himself with the addressee (using deception).







"C'mon — don't you think this is awesome?"

core information

At face value, the speaker seems to have a good feeling about penguins (positive sentiment).



subtle information











"C'mon — don't you think this is awesome?"

The casual style of speaking suggests familiarity with the addressee, and may indicate something about the speaker's identity.

subtle information



emotions/attitudes





So, our knowledge of language use involves communicating both core and subtle information.







My research focuses on understanding development and use.



And I use math to do it!







Quantitative techniques = techniques that rely on math

One main part: Counting things







Quantitative techniques = counting things

(sometimes we count a lot of things)



About math





Quantitative techniques = counting things

Another part: principled reasoning based on those counts



Bayesian inference

 $p(Generalization | Data) \propto p(Generalization) \cdot p(Data | Generalization)$

Tolerance & Sufficiency Principles

 $exceptions < = \frac{\# items}{ln(\# items)}$





Quantitative techniques = counting things + principled reasoning



Then we use these quantitative techniques to help us understand how little humans develop language knowledge and how adult humans and machines use language knowledge





Quantitative techniques = counting things + principled reasoning



But what do we count and reason over? How do we connect that information to language development and use?



To understand language development, we're typically using computational cognitive modeling to encode a child's learning process very precisely.





We think the child is learning by counting different parts of her input and reasoning over those counts in a sensible way. So, the model will count those same things and learn about language by doing principled reasoning over those counts.



Let's think about this for speech segmentation.





whataprettykitty!



Let's think about this for speech segmentation.





what a pretty kitty!



These are the kinds of utterances infants hear.



what a pretty kitty!

what a cute penguin!

look at the pretty birdie! the kitty is very cute!

do you see the kitty?







But they're more like this before infants know where the words are.







whataprettykitty whatacutepenguin lookattheprettybirdie thekittyisverycute doyouseethekitty But they're more like this before infants know where the words are.



One idea is that children initially perceive syllables.

whataprettykitty

whatacutepenguin

lookattheprettybirdie thekittyisverycute doyouseethekitty





One idea is that children initially perceive syllables.

what a pre tty ki tty

what a cute pen guin



look at the pre tty bir die the ki tty is ve ry cute do you see the ki tty



what a pre tty ki tty what a cute pen guin look at the pre tty bir die the ki tty is ve ry cute do you see the ki tty One learning theory is that infants count syllables and where they occur.





what a pre tty ki tty what a cute pen guin look at the pre tty bir die the ki tty is ve ry cute do you see the ki tty Then, infants can reason about those counts to figure out where words are.





what a pre tty kitty what a cute pen guin look at the pre tty bir die the kitty is ve ry cute do you see the kitty Then, infants can reason about those counts to figure out where words are.





what a pre tty kitty what a cute pen guin look at the pre tty bir die the kitty is ve ry cute do you see the kitty So this is what our computational cognitive model can do.



what a pre tty kitty what a cute pen guin look at the pre tty bir die the kitty is ve ry cute do you see the kitty Example model from my research group: Use Bayesian inference to reason about counts of syllables in a child's input.

Bayesian inference

Phillips & Pearl 2012, 2014a, 2014b, 2015a, 2015b, Pearl & Phillips 2018



what a pre tty ki tty what a cute pen guin look at the pre tty bir die the ki tty is ve ry cute do you see the ki tty This learning strategy involves the child imagining what collection of words (a lexicon) could be used to create the utterances she hears.





Some possible lexicons a child might consider for the first utterance:

what a pre tty ki tty

	whata			what		whatanre			s
	pre			а	what	ttv		whatapretty	1
	tty	i ub	oto	pretty	a	ki	whatapre	kitty	:
	ki	• WII		kitty	pre	· • • • • • • • • • • • • • • • • • • •	tty		·····
			tty i		tty		kitty	wł	nataprettykitty
		KIL	ty		ki				
					1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.1.				





Each possible lexicon could be used to generate the observed utterance.

what a pre tty ki tty

ļ	whata		what		whatapre			4 - C
	pre tty ki	whata	a pretty kitty	what a pre	tty ki	whatapre tty	whatapretty kitty	
•		pretty kitty	integ	tty ki		kitty	wh	ataprettykitty
				rxi				





Each possible lexicon could be used to generate the observed utterance.

		what	a pre tt	y ki tty			
whata		what	,	whatapre			
pre tty	whata	a pretty	what a	tty ki	whatapre	whatapretty kitty	
ki :	pretty kitty	kitty	pre tty		tty kitty	w	hataprettykitty
	·····		KI				





Each possible lexicon could be used to generate the observed utterance. what a pre tty ki tty

whata pre tty ki tty







Each possible lexicon could be used to generate the observed utterance. what a pre tty ki tty whata pretty kitty







Each possible lexicon could be used to generate the observed utterance. what a pre tty ki tty whatapretty kitty







The child tries to identify the most probable one. what a pre tty ki tty

		a general services and a service of the service of					
whata		what		whatapre		***********	
pre		а	what	tty		whatapretty	
tty		pretty	i a i		whatapre	: kitty	
ki	whata	kitty	nre	NI	tty :		•
· · · · · · · · · ·	pretty	racey	±11		kitty	wh	ataprottykitty
	kitty		tty			VVII	αιαρισιιγκιιγ
	· · · · · · · · · · · · · · · · · · ·		KI				





The modeled child in the computational cognitive model chooses the most probable one using Bayesian inference.







Bayesian inference



 $p(lexicon | utterances) \propto$

 $p(lexicon) \cdot p(utterances | lexicon)$

We want to figure out the lexicon with the highest probability, given the utterances the child encounters (and the syllables in them).


Bayesian inference

 $p(lexicon | utterances) \propto$

 $p(lexicon) \cdot p(utterances | lexicon)$



The model reasons about this by considering two other probabilities.





$p(lexicon | utterances) \propto$

 $p(lexicon) \cdot p(utterances | lexicon)$



The prior probability of the lexicon captures any preferences the modeled child has (which we think real children would have too).



Bayesian inference

$p(lexicon | utterances) \propto$

 $p(lexicon) \cdot p(utterances | lexicon)$



One preference: Prefer lexicons with fewer words.



Bayesian inference

$p(lexicon | utterances) \propto$

 $p(lexicon) \cdot p(utterances | lexicon)$



Another preference: Prefer lexicons with shorter words.



Bayesian inference

 $p(lexicon | utterances) \propto$

 $p(lexicon) \cdot p(utterances | lexicon)$



These preferences compete with each other.

shorter words fewer words



Bayesian inference



$p(lexicon | utterances) \propto$

 $p(lexicon) \cdot p(utterances | lexicon)$

The modeled child uses Bayesian inference to reason about the lexicon that's the best balance between these preferences...





Bayesian inference

$p(lexicon | utterances) \propto$

 $p(lexicon) \cdot p(utterances | lexicon)$



...that also has a high probability of generating the observed utterances = a high likelihood.





what a pre tty ki tty

what a pretty kitty



Bayesian inference



We can then see if the lexicon the modeled child identifies has the right kind of things in it (like real words).

Phillips & Pearl 2012, 2014a, 2014b, 2015a, 2015b, Pearl & Phillips 2018





what a pre tty ki tty

what a pretty kitty

Bayesian inference



If so, then the computational cognitive model has captured (using this math) how a child could identify words in fluent speech.





Phillips & Pearl 2012, 2014a, 2014b, 2015a, 2015b, Pearl & Phillips 2018



It turns out this learning strategy for speech segmentation is useful.





what a pre tty ki tty

useful





It can segment realistic English input to children fairly well...though the inferred lexicons aren't perfect.



Phillips & Pearl 2012, 2014a, 2014b, 2015a, 2015b, Pearl & Phillips 2018

Bayesian inference



But it turns out these imperfect lexicons are very useful for subsequent stages of language development, like learning what a word form refers to.



This was true for idealized modeled children, with perfect memory and perfect processing abilities.





But what about modeled children with more realistic constraints on their memory and processing abilities?



Is this segmentation strategy useable by children, who have these kinds of cognitive limitations?







Yes! Modeled children with cognitive constraints on their memory and processing abilities can still use this strategy to segment English quite well.





Does it work for different languages (besides English)?







Yes! It segments well for languages with different properties: Spanish, Italian, German, Hungarian, Japanese, Farsi

different languages





language

segmentation strategy is by using computational cognitive modeling.



Some general questions about language development that my research has tried to answer this way



Which learning strategies could children be using?

(Bayes & Pearl under review, Pearl 2021, Forsythe & Pearl 2019, Bates & Pearl 2019, Nguyen & Pearl 2019, Phillips & Pearl 2018, Pearl 2017, Bar-Sever & Pearl 2016, Phillips & Pearl 2015a, 2015b, 2014a, 2014b, 2012; Pearl 2014, Pearl et al. 2011, Pearl et al. 2010)



Which learning strategies could children be using?

Which learning biases are necessary?

(Pearl 2021, Pearl & Sprouse 2019, Nguyen & Pearl 2019, Pearl, Ho, & Detrano 2017, 2014; Pearl & Mis 2016, Pearl & Sprouse 2015, 2013a, 2013b, Pearl & Mis 2011, Pearl & Lidz 2009, Pearl 2008, Pearl & Weinberg 2007)



Which learning strategies could children be using? Which learning biases are necessary?

Which knowledge representations are learnable — and which aren't?

(Pearl & Sprouse in press, Bates & Pearl 2019, Pearl, Ho, & Detrano 2017, 2014; Pearl 2017, Pearl 2011, Pearl 2009)



Which learning strategies could children be using?

Which learning biases are necessary?

Which knowledge representations are learnable — and which aren't?

When do children learn different aspects of the linguistic system?

(Nguyen & Pearl under review, Bates, Pearl, & Braunwald 2018, Savinelli, Scontras, & Pearl 2018, Bar-Sever, Lee, Scontras, & Pearl 2018, Savinelli, Scontras, & Pearl 2017, Nguyen & Pearl 2018, Caponigro, Pearl et al. 2012, Caponigro, Pearl et al. 2011)



Which learning strategies could children be using?Which learning biases are necessary?Which knowledge representations are learnable — and which aren't?When do children learn different aspects of the linguistic system?

What factors affect children's observable behavior?

(Scontras & Pearl under review, Nguyen & Pearl under review, Forsythe & Pearl 2019, Nguyen & Pearl 2019, Nguyen & Pearl 2018, Savinelli, Scontras, & Pearl 2018, Nguyen & Pearl 2017, Savinelli, Scontras, & Pearl 2017)



Quantitative techniques for language use



What about using math to help us understand how humans use language and how machines could learn to do the same thing?



Let's focus on subtle information that can be expressed in language.





Quantitative techniques for language use



Math is again at the heart of the techniques researchers use.





Quantitative techniques for language use









So, we're counting things and reasoning about those counts in principled ways.









Psychological: "specific details" in a description









 $log(\frac{p(f_v|T)}{p(f_v|D)})$

Quantitative techniques for language use

The counts of these features are used in mathematical equations that underlie machine learning techniques available in common computational tools.




10:30 AM

 \uparrow \uparrow \uparrow

Some discoveries from CoLaLab about subtle information in language text alone

electronic (more conversational)

written text





Detecting emotions, attitudes, and intentions in short messages



Pearl & Steyvers 2013, Pearl & Enverga 2015: Detecting emotions, attitudes, and intentions in short messages



What features we counted: n-grams (strings of n units) that abstracted across linguistic constructs

the+best the+brightest ···· the+most+fantastic the+most+fun

the+Positive-Adjective-In-The-Superlative









> Answer: Yes and no. The features the author manipulated (which did create several fairly distinct characters) weren't the ones that signified his own style. His own style features were still present.





What features we counted: character-level (like punctuation)





What features we counted: word-level (like total words)





What features we counted: syntactic (like first person pronouns)





What features we counted: semantic (like endearments)





What features we counted: formatting (like all capitals)



> We then used standard computational tools to determine the stylistic components that were distinct from the author's own style vs. those that were alike.



Vogler & Pearl 2019: Can we more accurately detect deception across different content domains, like online product reviews, short opinion essays, and transcripts of job interviews?





Vogler & Pearl 2019: Can we more accurately detect deception across different content domains, like online product reviews, short opinion essays, and transcripts of job interviews?

Answer: Yes. When the content (and form) of the language text changes a lot from sample to sample, we can do much better if we use features that are linguistically-defined and also capture the psychological idea of "specific details".



constructions like exact numbers and prepositional phrases.

from Hyde Park.



Math is at the heart of quantitative techniques, where we count things and reason about those counts.



We can use quantitative techniques to better understand many different questions about the utterly human capacity of language.



In language development, quantitative techniques are used in computational cognitive modeling.



In language use, quantitative techniques underlie common computational tools that are used in combination with insights from psychology and linguistics.



So let's keep using math to help us better understand language!





Thank you!

Lisa S. Pearl Professor Department of Language Science SSPB 2219 University of California, Irvine lpearl@uci.edu





