Scaling up to the rest of language without rules

March 3rd, 2025

adele@princeton.edu

What are people trying to do?

Understand messages, given forms (comprehension) &

Choose forms, given intended messages (production)

& Conform to the conventions of their communities



Need to learn and use form ~ function pairings:

CONSTRUCTIONS

People learn mappings that cluster together \rightarrow emergent generalizations (constructions)

>We avoid combining constructions with incompatible functions

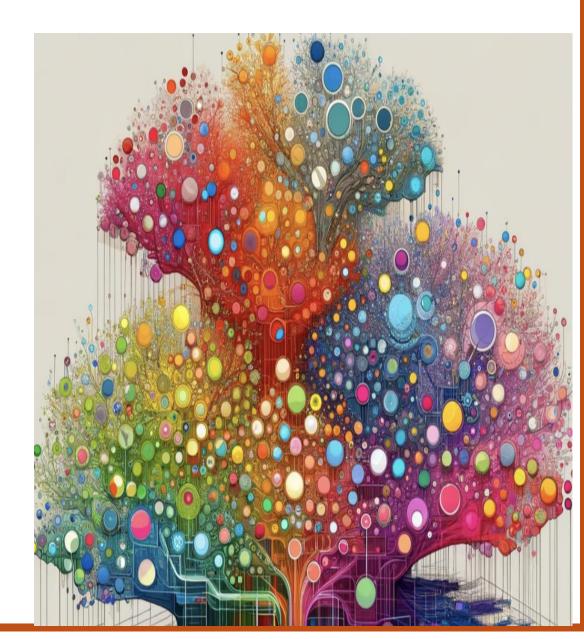
Context can influence degree of compatibility

➢We make our contributions helpful (not only efficient, but also expressive, appropriate, polite)

Current LMs do the same. Without rules

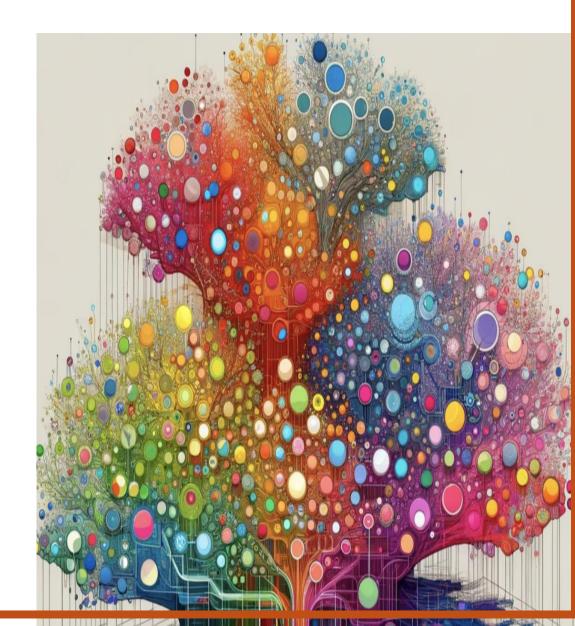
Our knowledge of language emerges from clusters of lossy (imperfect) memories that relate form and function;

combined on the fly as needed





The data is specific, the implications are not



Which order do you prefer?

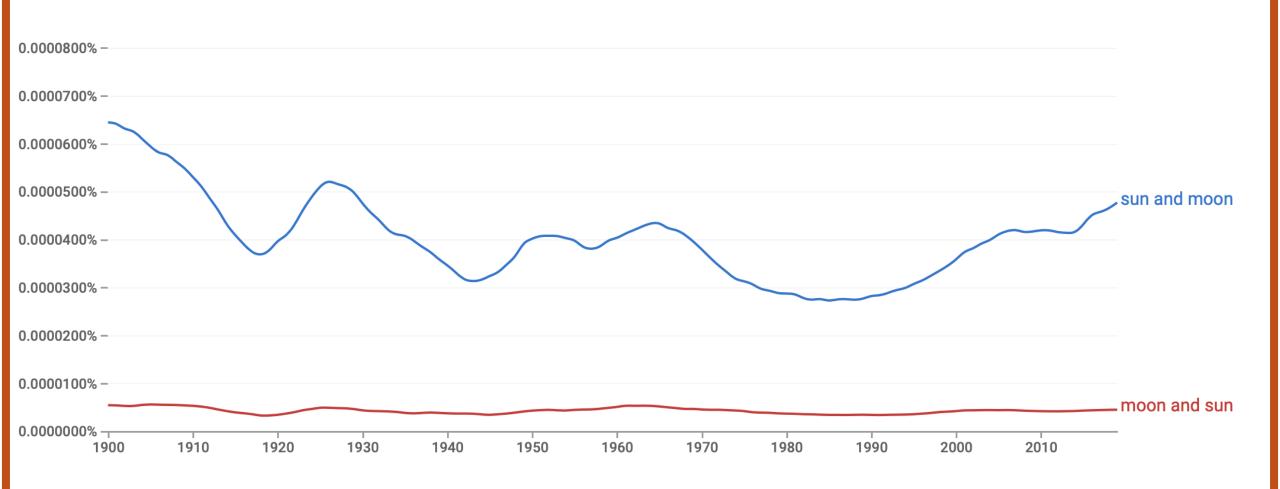
- a. table and chairsb. chairs and table
- a. sun and moonb. moon and sun

Benor & Levy 2006; Cooper & Ross 1975; Fenk-Oczlon 1989; Iliev & Smirnova 2016; Lohmann & Takada 2014; Malkiel 1959; Mollin 2014; Morgan & Levy 2016; Onishi, Murphy, & Bock, 2008; Wright, Hay, & Bent, 2005 Binomial preferences tend to be stable across people

Benor & Levy 2006; Cooper & Ross 1975; Fenk-Oczlon 1989; Iliev & Smirnova 2016; Lohmann & Takada 2014; Malkiel 1959; Mollin 2014: Morgan & Levy 2016: Onishi, Murphy, & Bock, 2008; Wright, Hay, & Bent, 2005 Binomial preference tends to remain stable across people

And across time

Google Books Ngram Viewer : table and chairs,chairs and table Q X 2 1900 - 2019 -English (2019) -Case-Insensitive Smoothing -0.0000300% -0.0000280% -0.0000260% -0.0000240% table and chairs 0.0000220% -0.0000200% -0.0000180% -0.0000160% -0.0000140% -0.0000120% -0.0000100% -0.0000080% -0.0000060% -0.0000040% chairs and table 0.0000020% -1980 1910 1920 1930 1940 1950 1960 1970 1990 2000 2010 1900



Phrases are conventional (are learned)

day and night

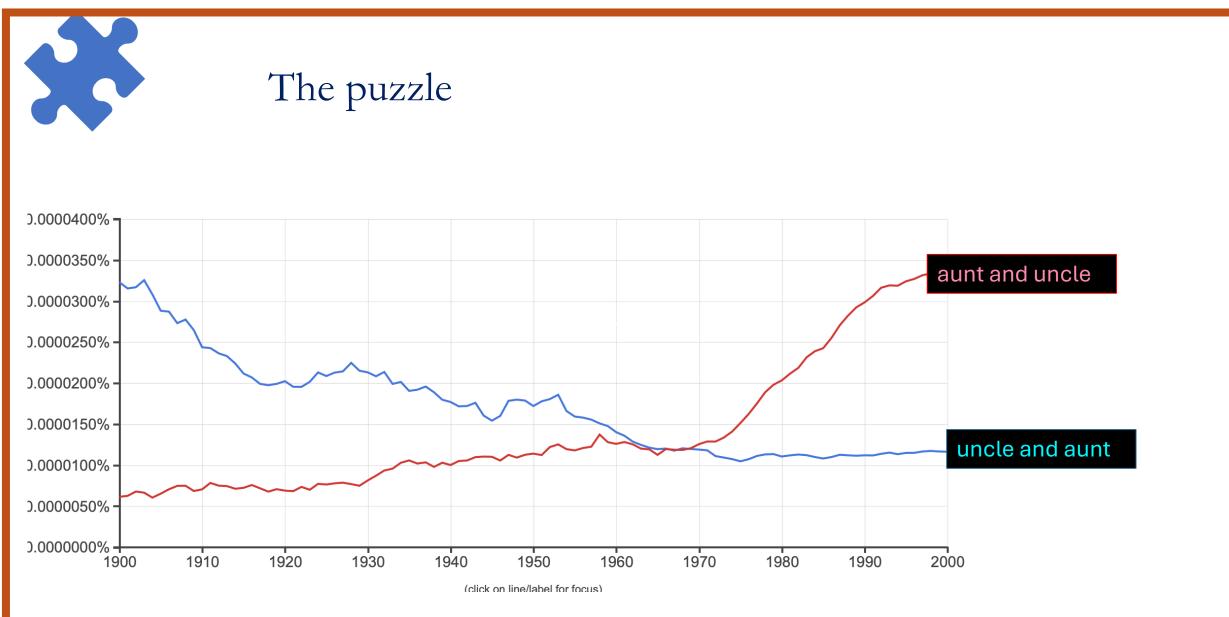
night and day

Phrases are conventional (are learned)

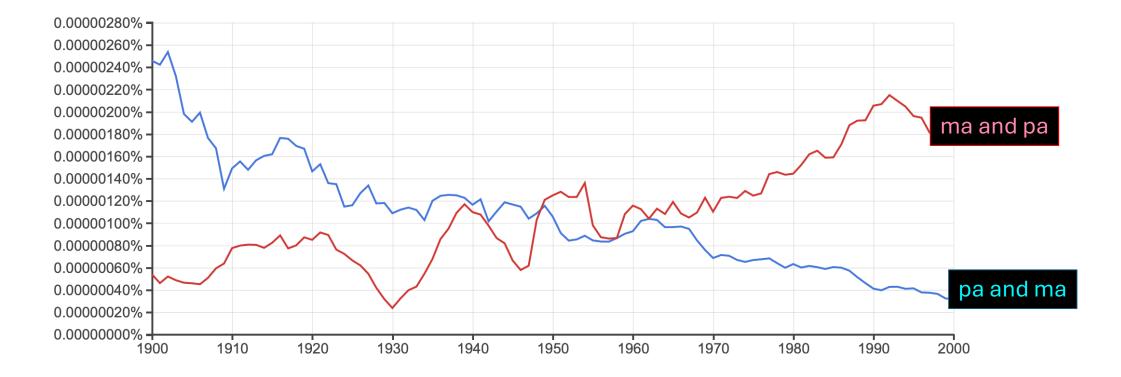
They're as different as _____ day and night

They worked _____

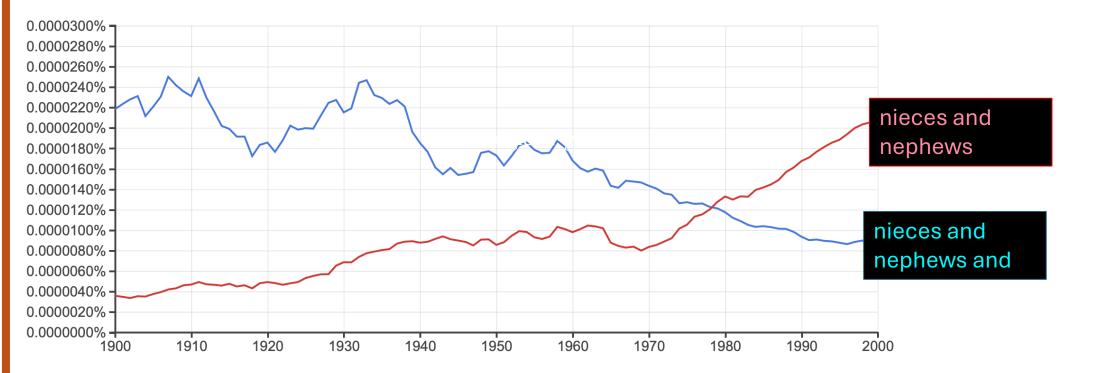
night and day



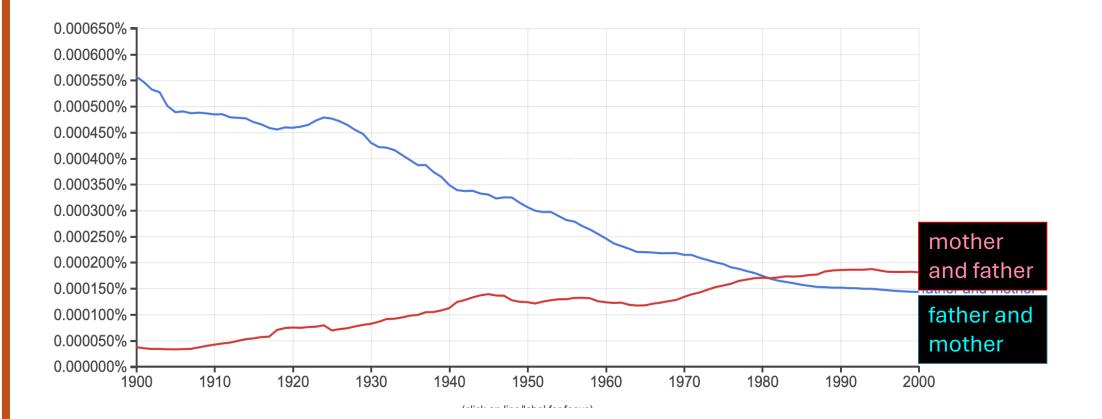




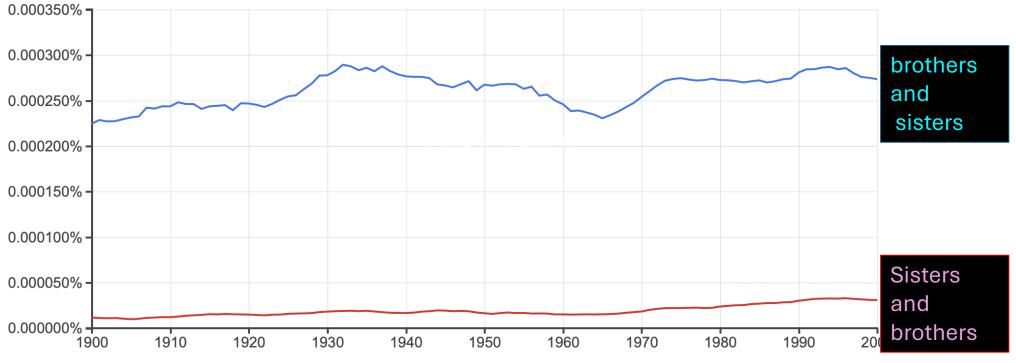




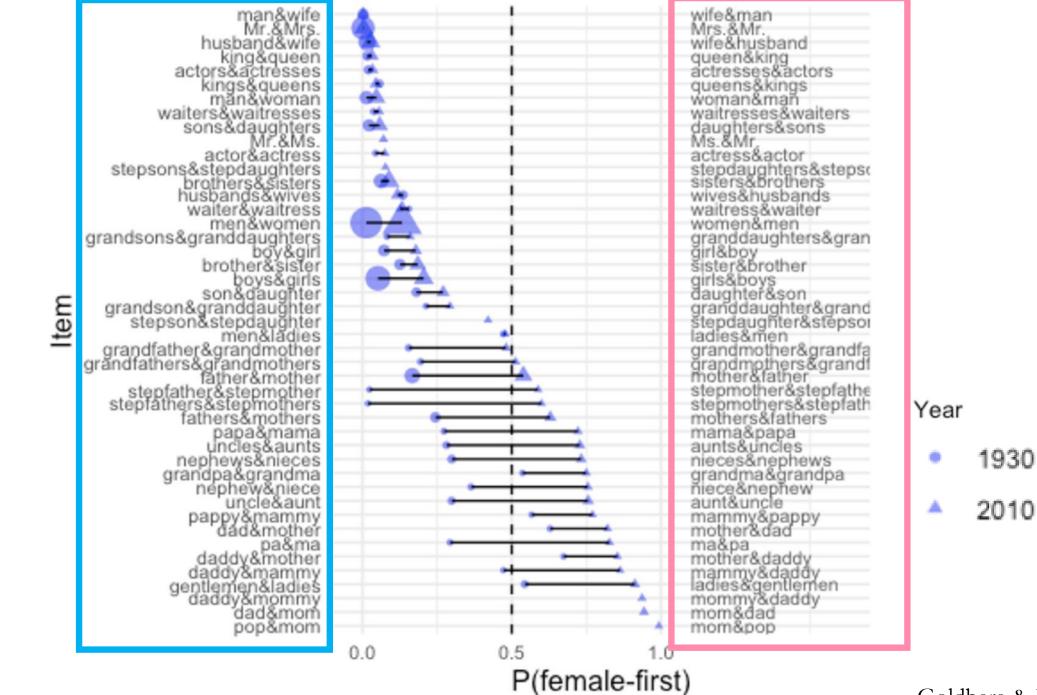






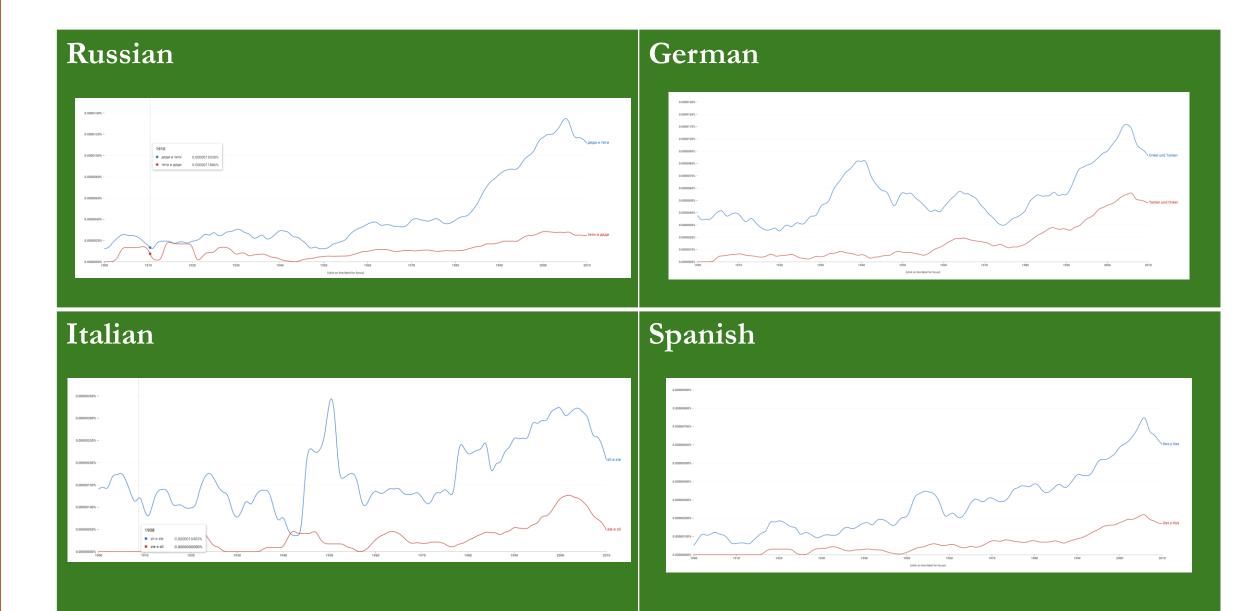


(click on line/label for focus)



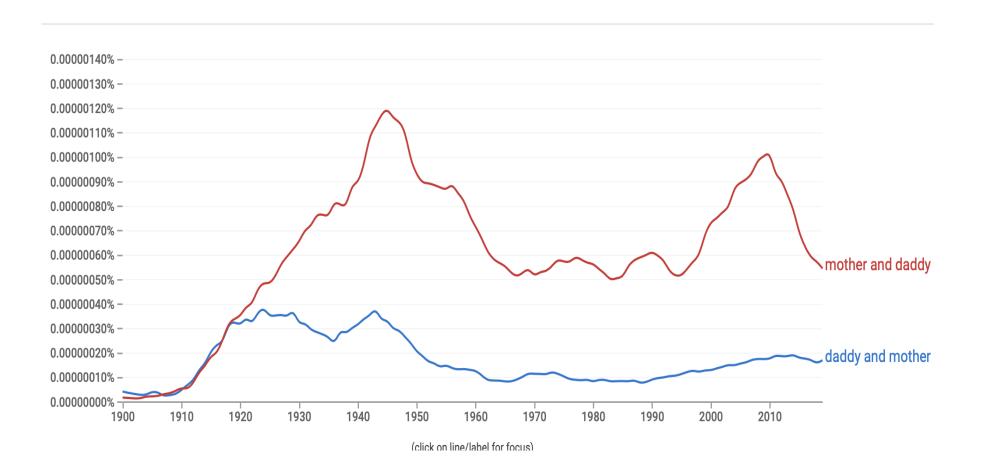
Goldberg & Lee, 2021

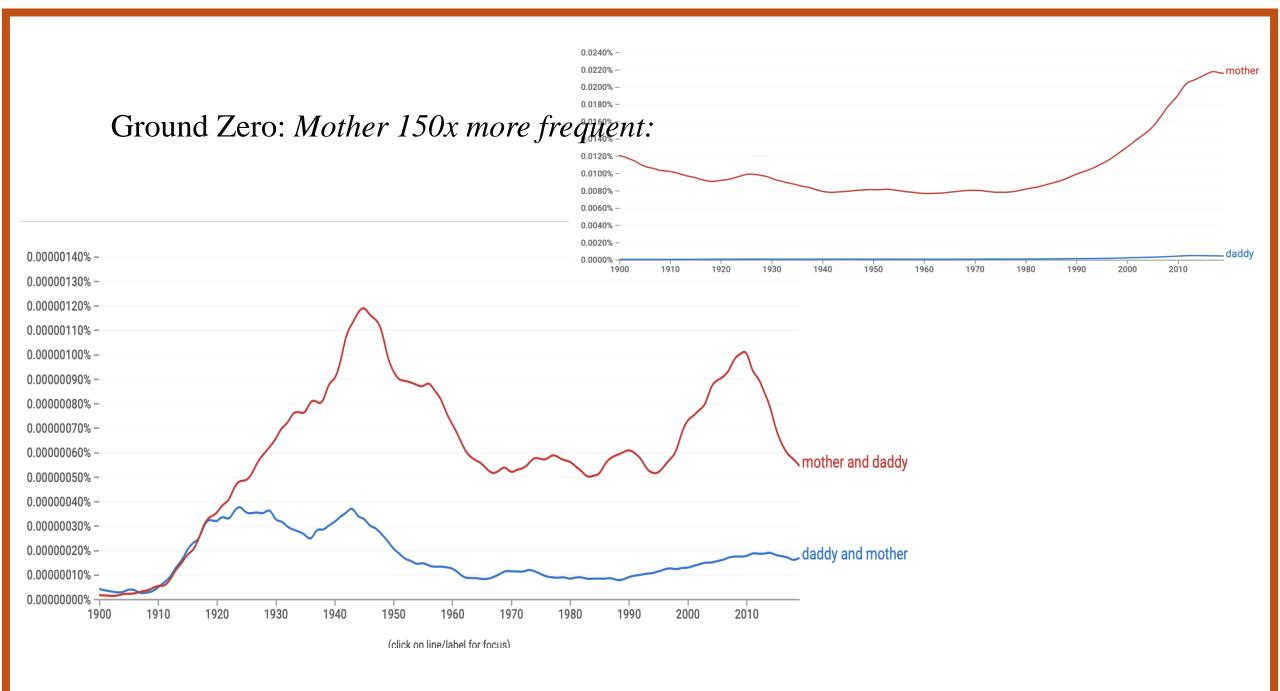
uncles and aunts vs aunts and uncles in Russian, German, Italian, Spanish



Q: *Why* was this order was preferred?

Ground Zero: *Mother and daddy*





Factors that encourage accessibility (Tulving & Pearlstone, 1966; Bock & Kelly 1993; Bock & Warren 1985; Carroll 1958; Bock 1982, 1987; Bock & Levelt 1994; Ferreira & Dell 2000; MacDonald, 2013, Tanaka et al. 2011; Levelt 1989; McDonald, Tomlin 1995; Downing & Noonan 1995)

Matches intended message

Binomial order does not usually change meaning:

aunt and uncle = uncle and aunt

Factors that encourage accessibility (Tulving & Pearlstone, 1966; Bock & Kelly 1993; Bock Warren 1985; Carroll 1958; Bock 1982, 1987; Bock & Levelt 1994; Ferreira & Dell 2000; MacDonal 2013, Tanaka et al. 2011; Levelt 1989; McDonald, Tomlin 1995; Downing & Noonan 1995)

Matches intended message

Type of meaning: agentivity, importance, salience to speaker

sun and moon > moon and sun

table and chairs > table and chairs

Princeton and Yale

> Yale and Princeton

Factors that encourage accessibility (Tulving & Pearlstone, 1966; Bock & Kelly 1993; Bocl Warren 1985; Carroll 1958; Bock 1982, 1987; Bock & Levelt 1994; Ferreira & Dell 2000; MacDonal 2013, Tanaka et al. 2011; Levelt 1989; McDonald, Tomlin 1995; Downing & Noonan 1995)

Intended MESSAGE

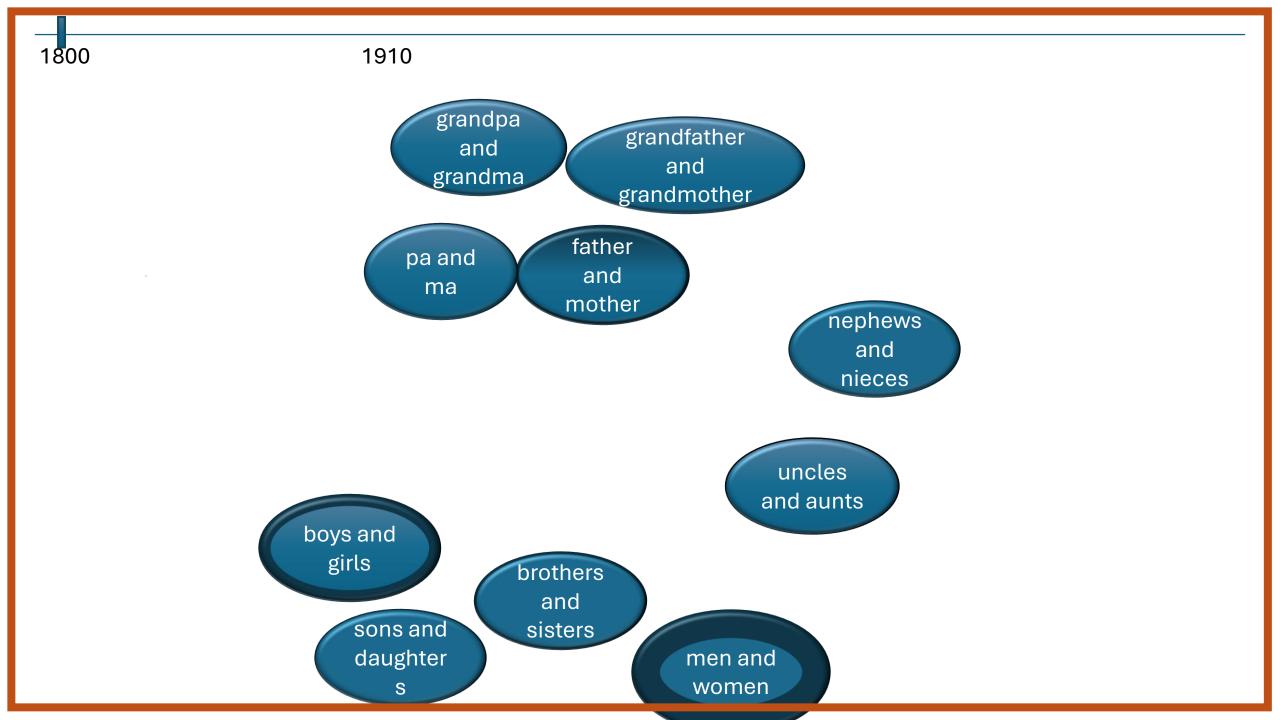
Type of meaning: agentivity, important, salience to speaker

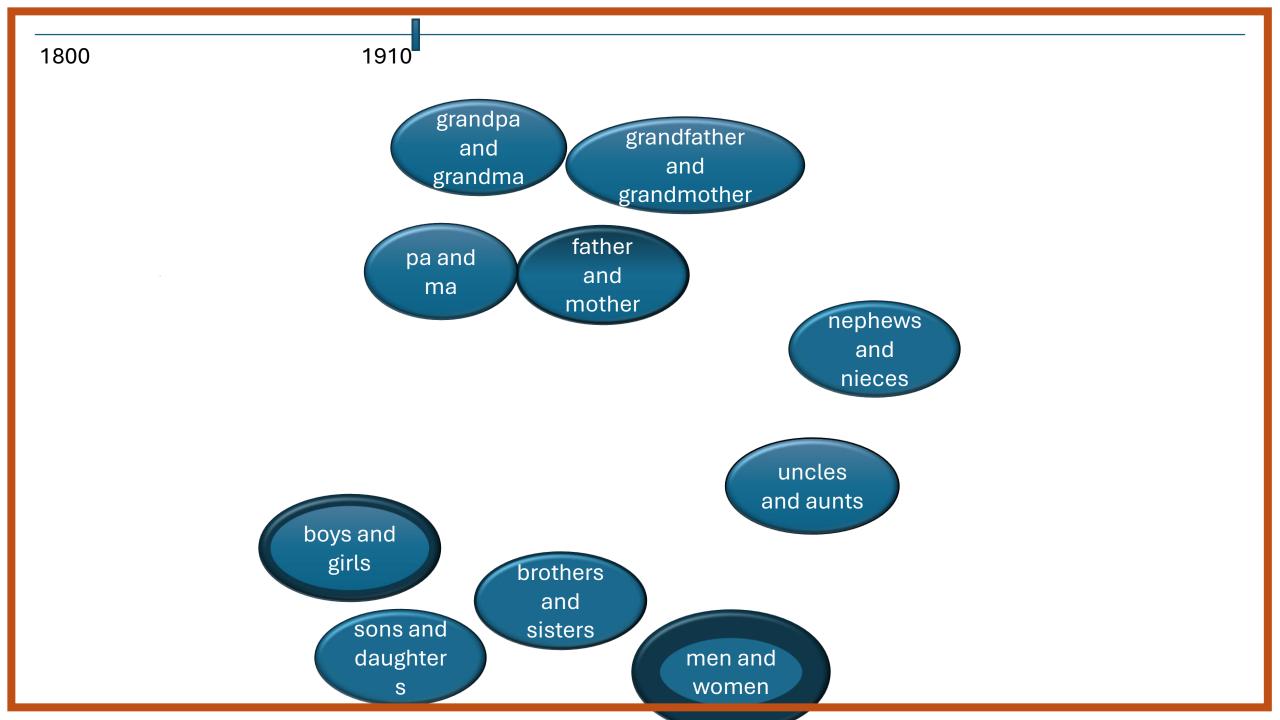
Token frequency

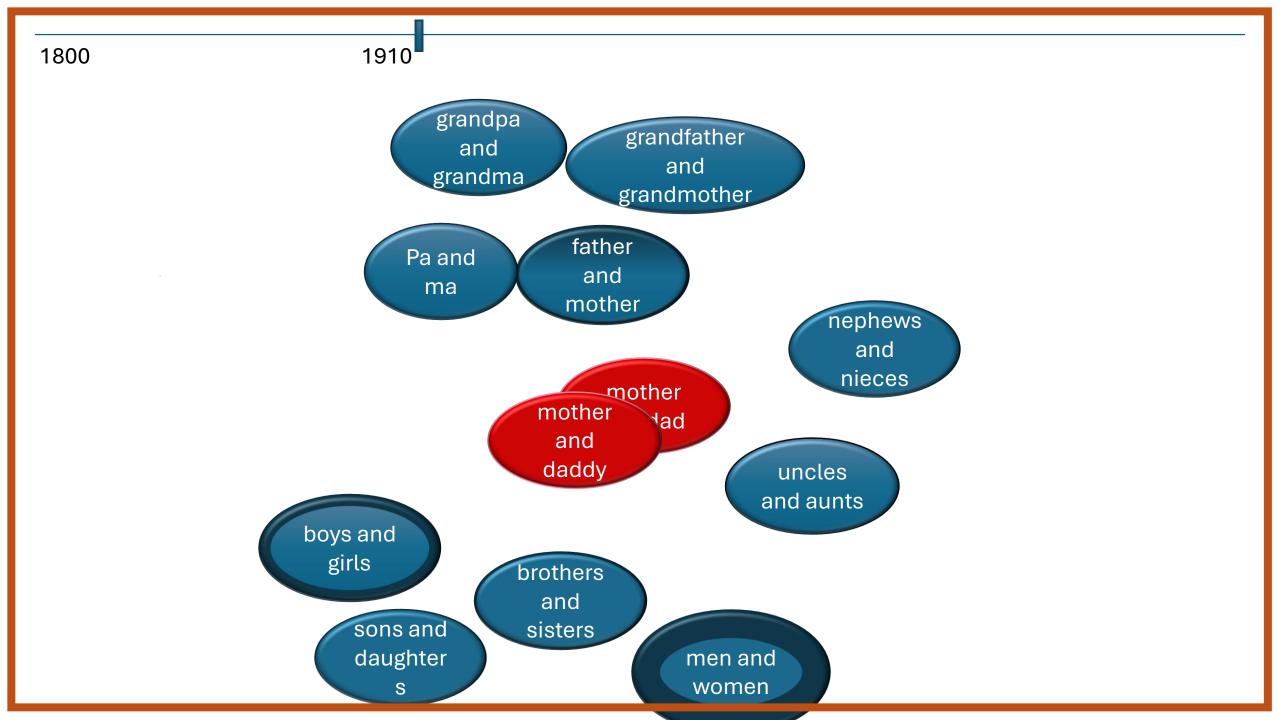
Priming

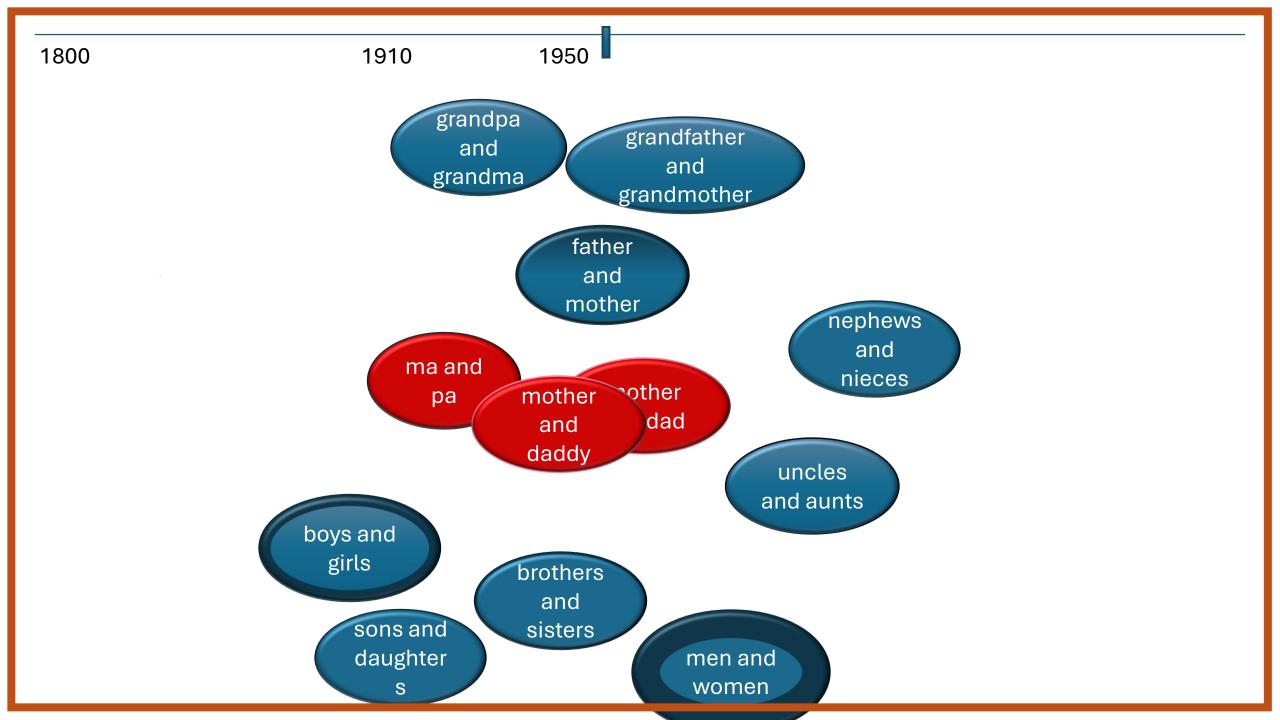
Lack of interference, competition

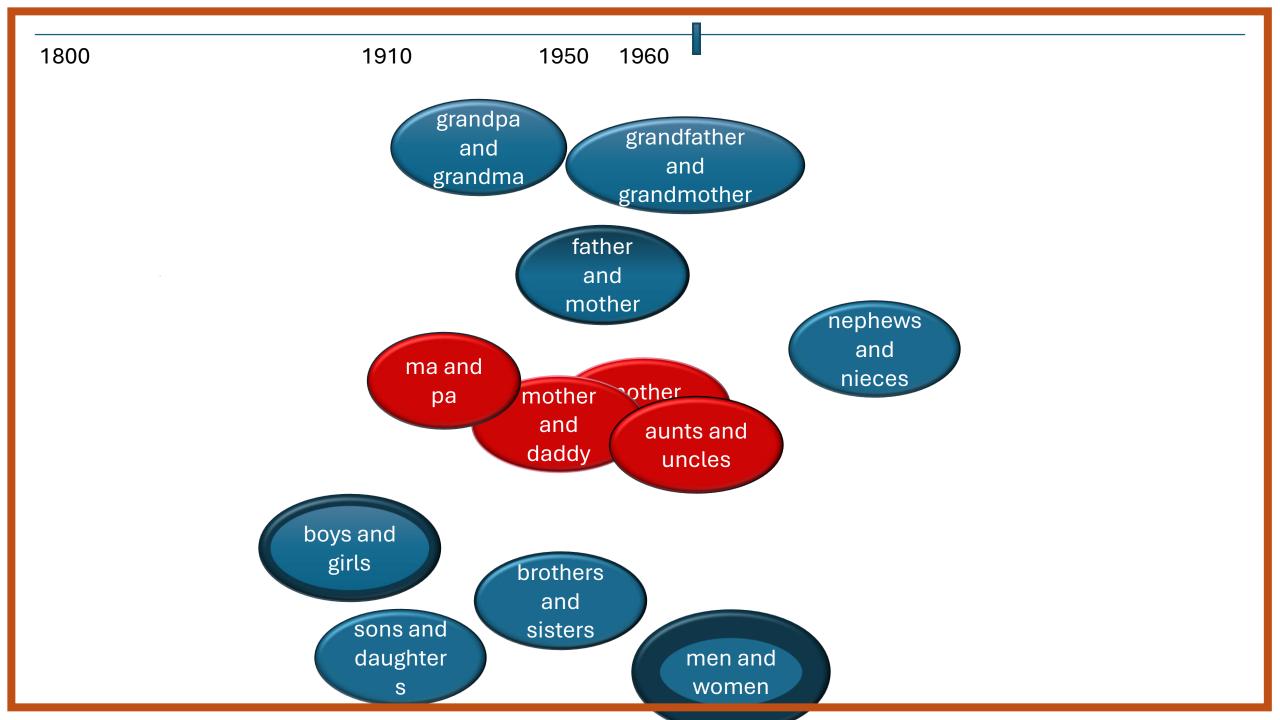
Neighborhood effects

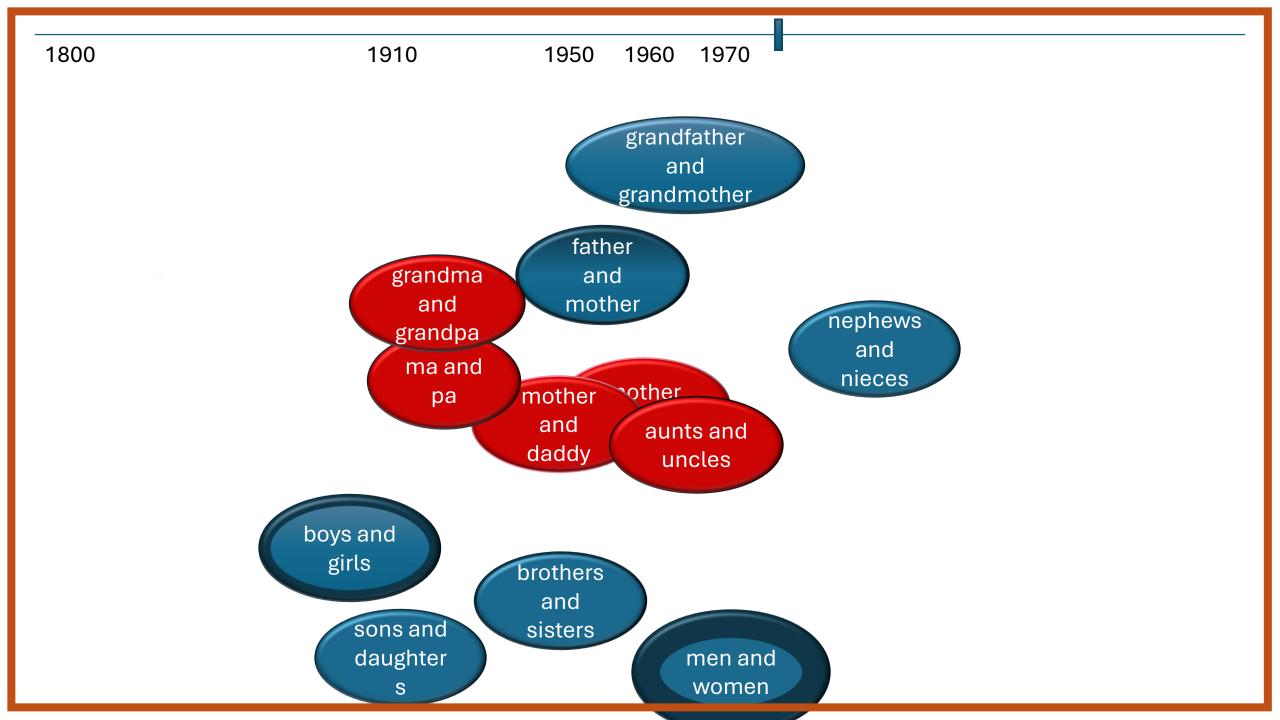


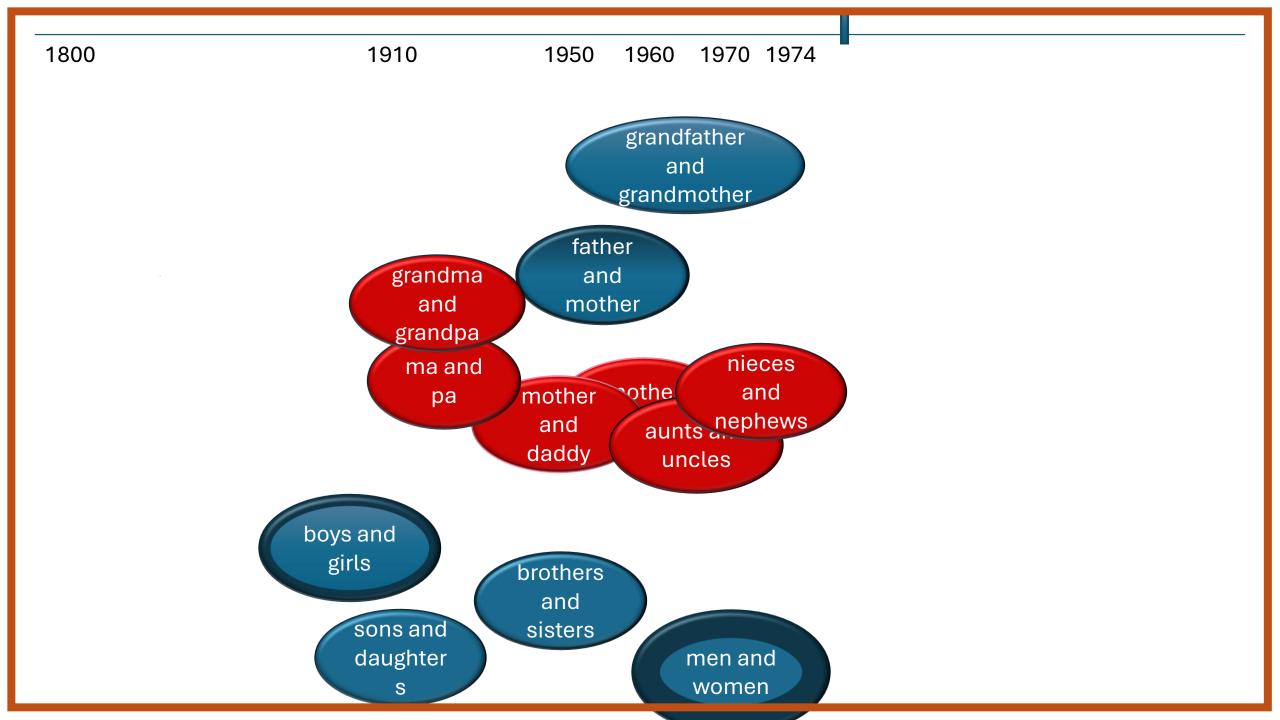


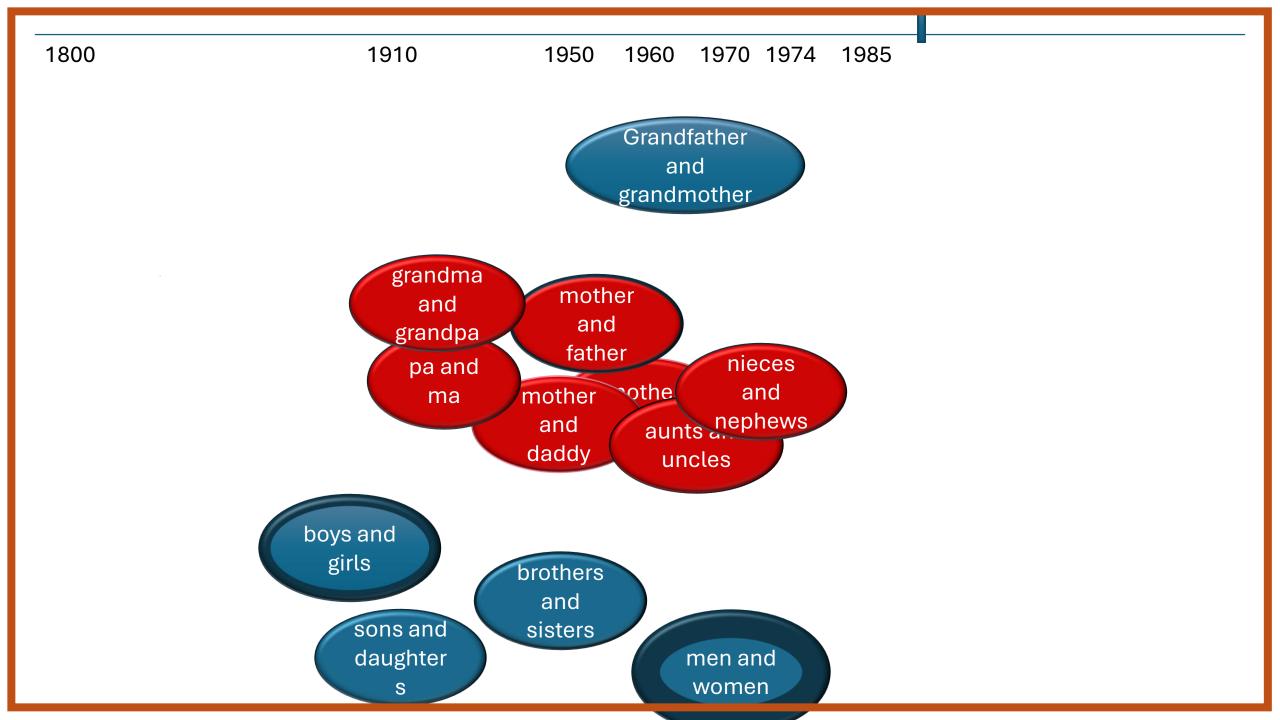


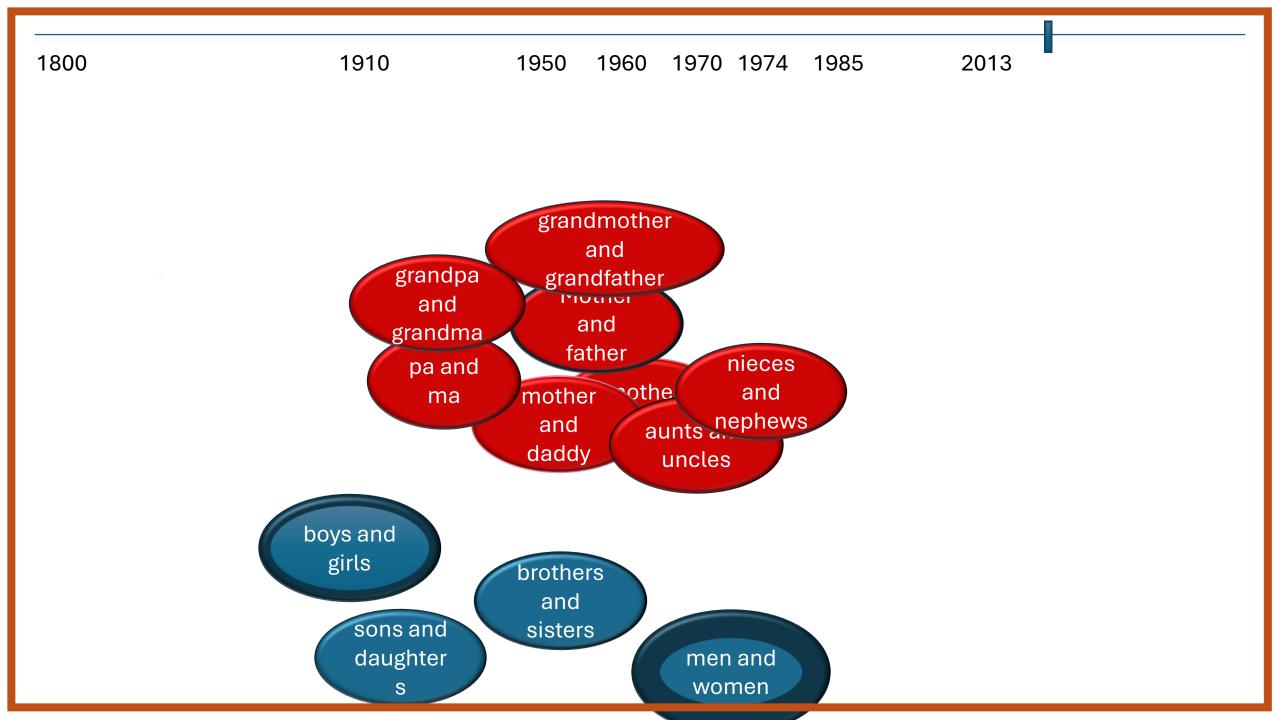












Data:

20 binomials for male and female relatives at each decade, 1920 : 2020

Frequency data from Google-N-grams

~ Cognitive accessibility of A relative to B

- Competition from B&A

P(A&B)

+ Cluster strength of cases related to A&B (A'& B')

P(A&B) ~ Cognitive accessibility of A relative to B - Competition from B&A + Cluster strength of cases related to A&B (A'& B')

$P(A\&B) \sim [cog_acc.(A)] - [cog_acc(B)]$ - logfreq(B&A) + Cluster strength of cases related to A&B (A'& B')

Novel Binomials

P(A&B) ~ Cognitive accessibility of A relative to B - Competition from B&A + Cluster strength of cases related to A&B (A'& B')

 $P(A\&B) \sim [cog_acc.(A)] - [cog_acc(B)]$ - logfreq(B&A) + Cluster strength of cases related to A&B (A'& B')

Familiar Binomials

P(A&B) ~ Cognitive accessibility of A relative to B - Competition from B&A + Cluster strength of cases related to A&B (A'& B')

 P(F&M) ∼

$\beta_1 \left[(logFreq(F) - #syll(F)) - (logFreq(M) - #syll(M) + 1) \right]$

 $-\beta_2 [logFreq(M\&F)]$

 $+\sum_{i=1}^{n}(\beta_{3}Sem_{sim}(F\&M,F_{i}\&M_{i})+\beta_{4}Morph_{sim}(F\&M,F_{i}\&M_{i}))$



$\beta_1 \left[(logFreq(F) - #syll(F)) - (logFreq(M) - #syll(M) + 1) \right]$

 $-\beta_2 [logFreq(M\&F)]$

+ $\sum_{i=1}^{n} (\beta_3 Sem_sim(F\&M, F_i\&M_i) + \beta_4 Morph_sim(F\&M, F_i\&M_i))$

Random eff	fects:				
Groups	Name	Variance St	d.Dev.		
item	(Intercept)	0.034974 0.	18701		
Residual		0.005747 0.	07581		
Number of	obs: 215, gr	oups: iten	1, 21		
Fixed effe	ects:				
	Estimate	e Std. Error	r df	t value	Pr(>ltl)
(Intercept	t) 4.769e-01	6.996e-02	2 1.955e+01	6.817	1.42e-06
<u>log freg</u>	-3.071e-02	5.788e-0	3 2.110e+02	-5.305	2.84e-07
accs	6.855e-02	4.859e-02	1.846e+01	1.411	0.175
cluster	1.601e-02	8.616e-04	1.928e+02	18.588	< 2e-16



$\beta_1 \left[(logFreq(F) - #syll(F)) - (logFreq(M) - #syll(M) + 1) \right]$

 $-\beta_2 [logFreq(M\&F)]$

+ $\sum_{i=1}^{n} (\beta_3 Sem_sim(F\&M, F_i\&M_i) + \beta_4 Morph_sim(F\&M, F_i\&M_i))$

Random effects:

Groups Name Variance Std.Dev. item (Intercept) 0.034974 0.18701 Residual 0.005747 0.07581 Number of obs: 215, groups: item, 21

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(>ltl)	
(Intercept)	4.769e-01	6.996e-02	1.955e+01	6.817	1.42e-06	***
log_freq	-3.071e-02	5.788e-03	2.110e+02	-5.305	2.84e-07	***
accs	6.855e-02	4.859e-02	1.846e+01	1.411	0.175	
cluster	1.601e-02	8.616e-04	1.928e+02	18.588	< 2e-16	***



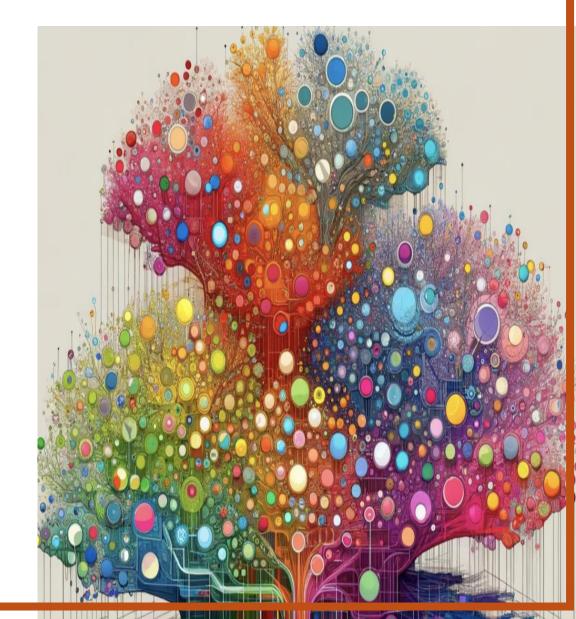
$\beta_1 \left[(logFreq(F) - #syll(F)) - (logFreq(M) - #syll(M) + 1) \right]$

 $-\beta_2 [logFreq(M\&F)]$

+ $\sum_{i=1}^{n} (\beta_3 Sem_sim(F\&M, F_i\&M_i) + \beta_4 Morph_sim(F\&M, F_i\&M_i))$

Random effects:								
Groups	Name	Variance	Std.De	ev.				
item	(Intercept)	0.034974	0.1870	01				
Residual		0.005747	0.0758	81				
Number of	obs: 215, gr	oups: it	tem, 21	1				
Fixed effe	cts:							
	Estimate	Std. Er	ror	df	t value	Pr(>ltl)		
(Intercept) 4.769e-01	6.996e	-02 1	.955e+01	6.817	1.42e-06	***	
log_freq	-3.071e-02	5.788e	-03 2	.110e+02	-5.305	2.84e-07	***	
accs	6.855e-02	4.859e	-02 1	.846e+01	1.411	0.175		
cluster	1.601e-02	8.616e	-04 1	.928e+02	18.588	< 2e-16	***	

We choose linguistic constructions on the basis of:



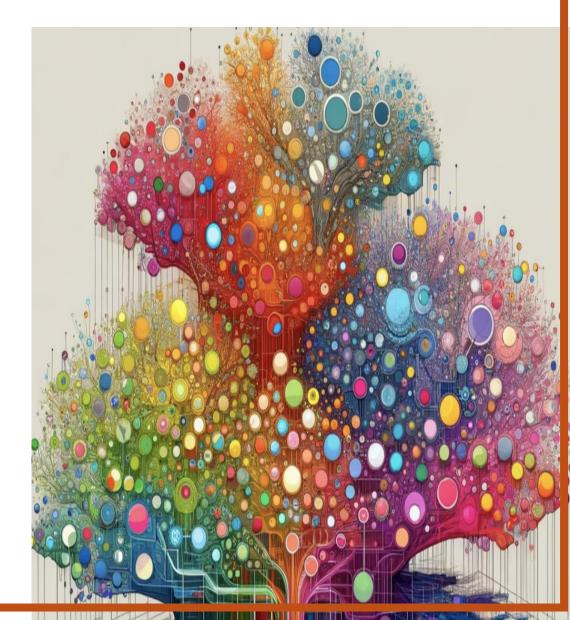
We choose linguistic constructions on the basis of:

Intended message

➤ Accessibility:

Accessibility of whole (for familiar combinations) Accessibility of parts (for novel combinations) Interference from competitor with same function

Similar constructions cluster together, lead to emergent regularities



People learn mappings that cluster together \rightarrow emergent generalizations (constructions)

>We avoid combining constructions with incompatible functions

Context can influence degree of compatibility

➢We make our contributions helpful (not only efficient, but also expressive, appropriate, polite)

Current LMs do the same. Without rules

CONSTRUCTIONS w/ varying levels of complexity and abstraction	Examples
Words	break, skeet, course, one
Words with open slots	N-ness, #-th (e.g., gazillionth, (n+1)th
Unfilled lexical Cx	$[NN]_N$ (e.g., Monday pm NEU class presentation) (recursive)
Phrasal cx, lexically specified	not the sharpest tool in the shed
Phrasal cx with open slots	nice and <easy clean="" neat="" quiet="" soft="" warm=""></easy>
Phrasal cx with mostly open slots	The [comparative ₁] S_1 , The [comparative ₂] S_2 The more you think about it, the less you understand
Argument structure constructions Passive construction (minimally lexically	<subj> Verb <object1> <obj2> (e.g., she gave him something; he baked her something)</obj2></object1></subj>
filled)	e.g., He was given something.
Topicalization (lexically unfilled unfilled)	Language, I love

People learn mappings that cluster together \rightarrow emergent generalizations (constructions)

 \blacktriangleright We avoid combining constructions with incompatible functions

Context can influence degree of compatibility

We make our contributions helpful (not only efficient, but also expressive, appropriate, polite)

Current LMs do the same. Without rules

adele@Princeton.edu ______ @adelegoldberg.bsky.social _____ https://adele.scholar.princeton.edu

<u>Rules</u>

- Include open variables, constrained only by grammatical categories (N, A, V)
- Context-free
- Insensitive to similarity & frequency
- Unstructured list



algebra, logic, programming

$P \rightarrow Q$

for any P, Q

-Q → -P

i + j = j + i for all i, j



Does language use symbolic rules?



"If you are not already a Steven Pinker addict, this book will make you one." —Jared Diamond

WORDS and RULES INGREDIENTS OF

LANGUAGE

STEVEN PINKER

Bestselling author of The Language Instinct and The Better Angels of Our Nature



Chomsky, Fodor, generative linguistics, formal semantics, much current work in ML

Symbolic rules assumed in syntax

Word order: [Adj Noun]

for any Adj, N

Productive inflectional morphology V-ed



Rule based Compositionality

"The meaning of an expression is a function of the meanings of its parts and the way they are syntactically combined" Partee (1984: 153)

Meaning is determined by the meanings of immediate constituents via a semantic operation that corresponds directly to the relevant syntactic operation Dowty 1979; 2006



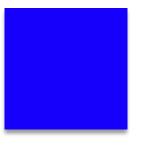
Standard argument for rule-based compositionality

We understand sentences we've never heard before

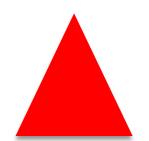
UnWarRaNted asSumPtioNs:

(1) sentences are generated by syntax (= algebraic rules)

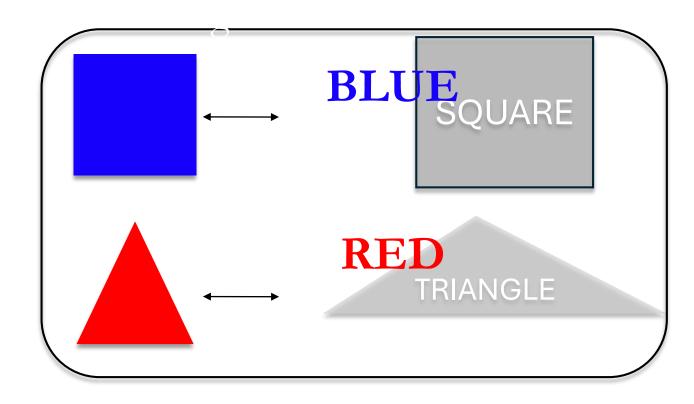
(2) We determine meaning based on words + syntactic rules



Blue square



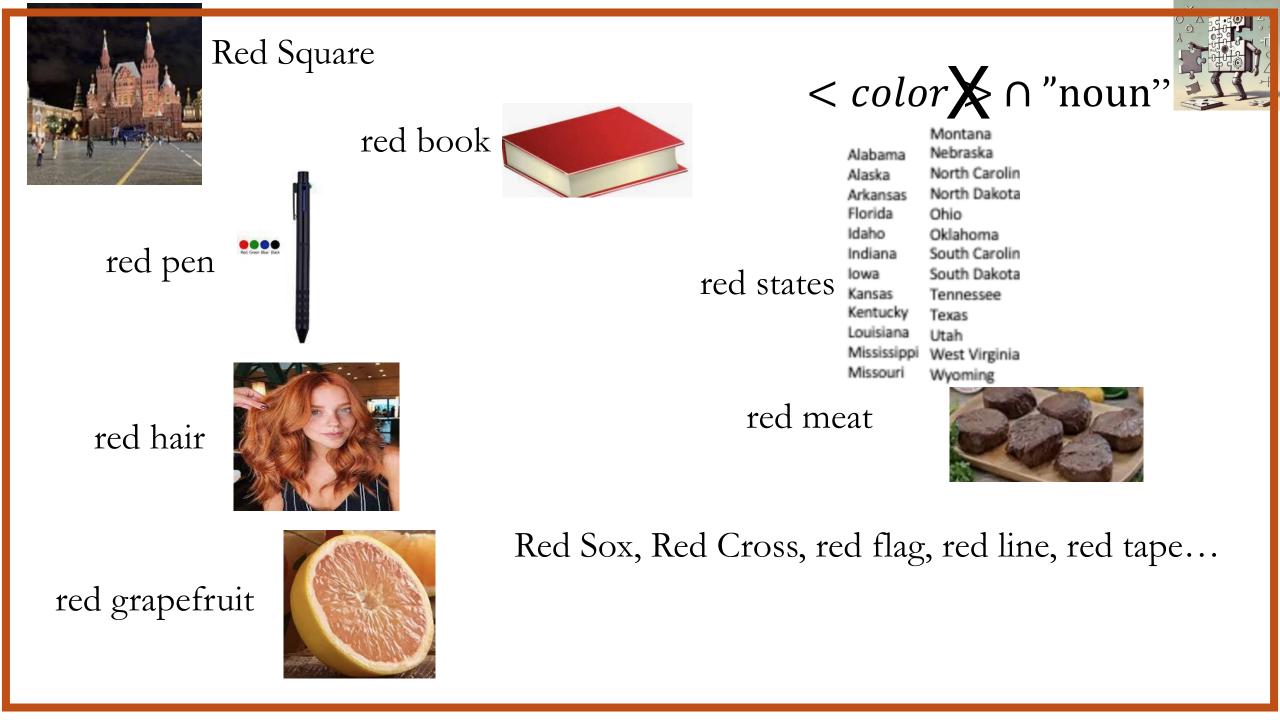
Red triangle



$< color > \cap$ "noun"







Rule-compositionality: training should generalize to *all* new instances



"A compositional model trained on the meanings of novel words: *dax, flug,* and *flug twice* should be able to interpret the meaning of *dax twice*" (Lake & Baroni 2018)



Is that how language works? What does *dax twice* mean?

VERB twice

Corpus of Contemporary Amer						
	SEARCH FRE					
N CLICK:		NTEX	T TRANSLATE (??) <mark>ENTIRE PAGE</mark> G		
HELP	(j)	\star	ALL FORMS (SAMPLE):	100 200 500		
1	0	\star	THINK TWICE			
2	0	\star	SHOT TWICE			
3	0	\star	SCORED TWICE			
4	0	\star	THOUGHT TWICE			
5	0	\star	WORK TWICE			
6	0	\star	LOOK TWICE			
7	0	\star	WON TWICE			
8	0	\star	MARRIED TWICE			
9	0	\star	THINKING TWICE			
10	0	\star	GOING TWICE			
11	0	\star	PAY TWICE			
12	A	$\mathbf{+}$	MET TWICE			

		[S	that	how	language	works?
--	--	----	------	-----	----------	--------

VERB twice

think twice =

work twice =

going twice =

VERB twice

think twice = hesitate

 $(\neq \text{think a second time})$

work twice =

going twice =

VERB twice

think twice = hesitate

 $(\neq \text{think a second time})$

work twice = work twice as hard/much (≠ work a second time)

going twice =

VERB twice

think twice = hesitate

 $(\neq \text{think a second time})$

work twice = work twice as hard/much (≠ work a second time)

going twice = auction context: last chance to buy (≠ going twice somewhere)

Is that how l	anguage	works?
---------------	---------	--------

VERB twice

shot twice

met twice

VERB twice

shot twice

(likely passive)

🕝 Corpus of Contemporary American English 📄 🕕 🧱							
SEARCH FREQUENCY							CONTEX
L				G GOOGLE	MAGE	PRON/VIDEO	
HELP	1 🛈 🖈	ALL FORMS (SAMPLE):	100 200				FREQ
1	0 ★	WAS SHOT TWICE					114
2	0 ★	BEEN SHOT TWICE					61
3	0 ★	, SHOT TWICE					21
4	8 🔸	SHOT TWICE					13

10

met twice

VERB twice

shot twice

(likely passive)

met twice

(not passive)

SEARCH				RCH	FR	FREQUENCY			CONTEX
ON CLICK:		C0	NTE)	KT 💽 TRANSLATE (??) 🔚 ENTIRE PAGE	G GOOGLE		PRON/VIDEC	D 🔛 BOOH
HELP		(j)	\star	ALL FORMS (SAMPLE):	100 200				FREQ
1		0	×	WAS SHOT TWICE					114
2		0	\star	BEEN SHOT TWICE					61
3		0	\star	, SHOT TWICE					21
4		0	\star	. SHOT TWICE					13
5		0	\star	GOT SHOT TWICE					10
-		^	*						-
1	0	*	ŀ	AVE MET TWICE					15
2	0	*	ŀ	AS MET TWICE					9
3	0	*	V	VE MET TWICE					8
4	0	*	H	E MET TWICE					8
5	0	-	- 0	ONLY MET TWICE					7

"[humans know that] if X is more Y than Z, then in general Z is less Y than X irrespective of the specific meanings of X Y, and Z" Dasgupta, Guo, Gershman, Goodman (2020)

Pat is more <u>clever</u> than <u>wise</u>.

? \rightarrow <u>Wise</u> is less <u>clever</u> than <u>Pat</u>.

Nothing is more important than experience.

 \rightarrow <u>Experience</u> is less important than <u>nothing</u>.

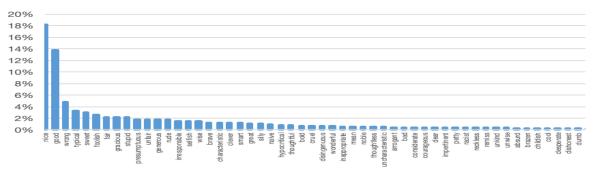
The car is more trouble than it's worth.

 \rightarrow It's worth is less trouble than the car

English Gossip Construction

(It is) <adj> of NP_{agent} VP_{to} e.g., It's _____ of you to be here.

It's <u>nice/good</u> of you to be here. It's crazy of her to talk about that. ??It's tall of you to reach the top shelf. It's big of you to reach the top shelf. ??It was good of the dishwasher to save water.





LMs offer an alterative to rules					
Lossy compression and interpolation	Every neural net model				
Conform to conventions	Pre-training to predict the next word				
Complex dynamic network	Structured distributed representations at varying levels of complexity and abstract are learned from massive amounts of input text				
Context dependent interpretations	via thousands of words of preceding text				
Relationships among discontinuous elements	Attention heads				
Goal is to be helpful	Fine-tuning from Instruct GPT				

People learn mappings that cluster together \rightarrow emergent generalizations (constructions)

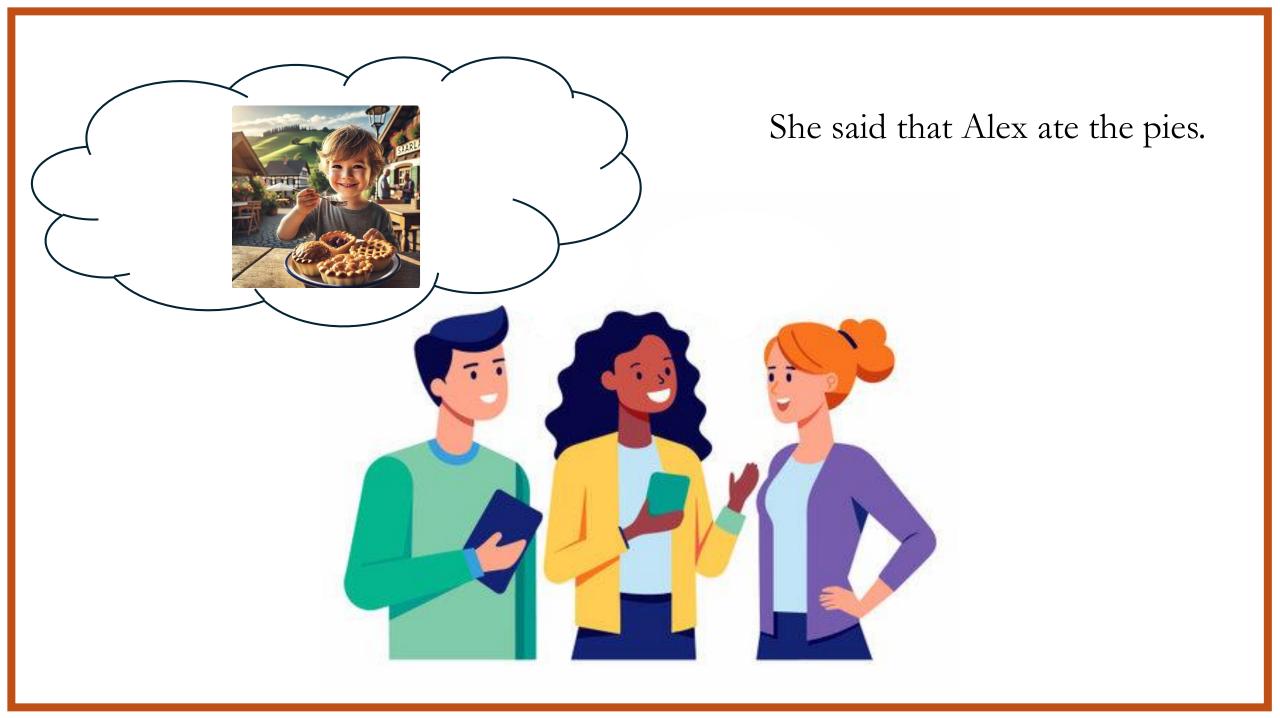
 \blacktriangleright We avoid combining constructions with incompatible functions

Context can influence degree of compatibility

We make our contributions helpful (not only efficient, but also expressive, appropriate, polite)

Current LMs do the same. Without rules

adele@Princeton.edu ______ @adelegoldberg.bsky.social _____ https://adele.scholar.princeton.edu





She said [that Alex ate <u>the pies</u>]. What did she say [that Alex ate____]?

She grumbled [that Alex ate <u>the pies.]</u> ?? What did she grumble [that Alex ate _____]?

Ross 1967

Islands: constituents that resist combination w/ long-distance dependency (LDD) constructions to varying degrees

She said [that Alex ate <u>the pies</u>]. What did she say [that Alex ate____]?

She grumbled [that Alex ate <u>the pies.]</u> ?? What did she grumble [that Alex ate _____]?

Why do island effects exist?

Hypothesis: island effects arise from a clash of discourse functions

"Island" constructions **background** information to varying degrees

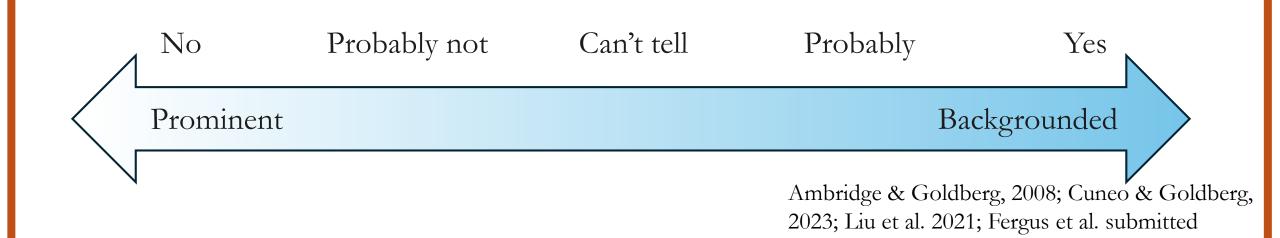
Long Distance Dependency (LDD) constructions make a constituent Prominent

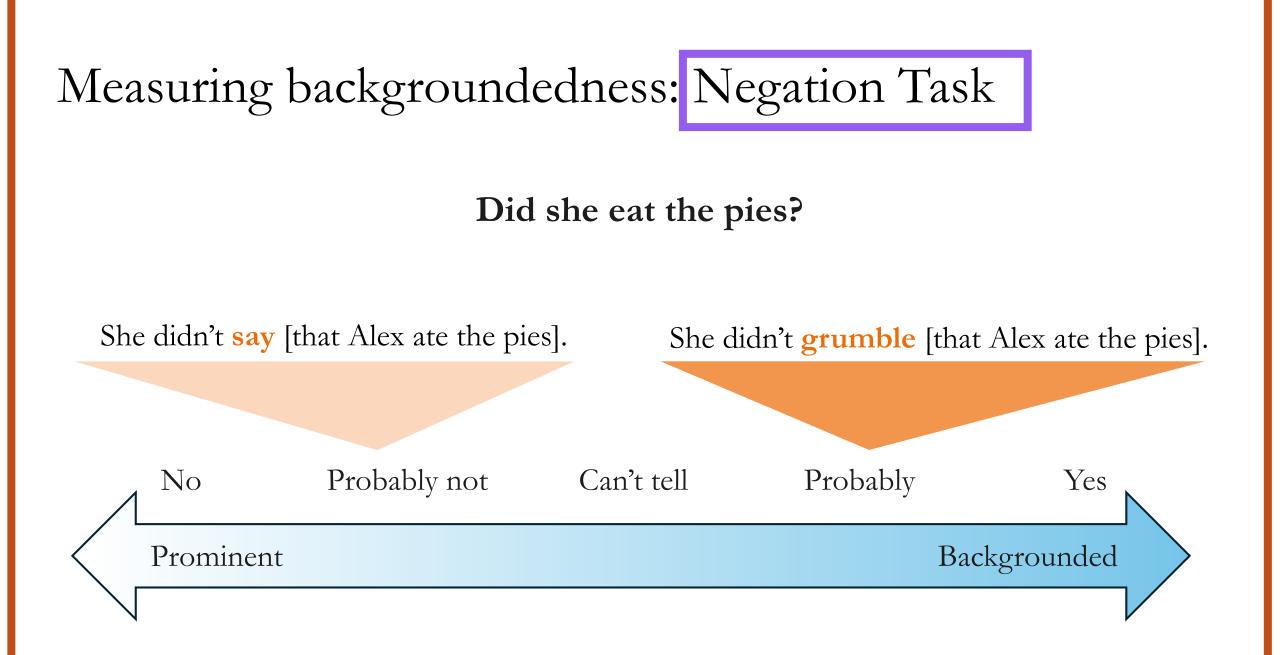
 \rightarrow Backgrounded Constructions are Islands (BCI)

Abeille et al. 2024; Ambridge & Goldberg, 2008; Cuneo & Goldberg, 2023; Dabrowska 2013 Goldberg, 2006, 2013; Lu, Pan, Degen, LSA '24; Namboodiripad et al. 2021 Measuring backgroundedness: Negation Task

She <u>didn't</u> say [that Alex ate the pies]. She <u>didn't</u> grumble [that Alex ate the pies].

Did she eat the pies?





Judgments are subtle and non-binary

1st task: acceptability ratings ("syntactic") 2nd task: degree of presupposition ("semantic")

144 stimuli constructed by hand (Nov 2023)





144 base items

Cuneo & Goldberg, 2023, Cognition

Constructions	Sample Base sentences	Example Wh-Question			
Main Clauses	The woman who called Uber for a ride lost her glasses.	What did the woman who called Uber for a ride lose?			
Relative Clauses	The woman who lost her glasses called Uber for a ride.	What did the woman who lost <u>called Uber</u> for a ride?			
Non-finite Adjuncts	He researched it by/after/while comparing prices.	What did he research the question by/after/while comparing?			
DO Recipient	Daisy showed him an insurance policy.	Who did she show <u>the portrait</u> ?			
PO Recipient	Daisy showed an insurance policy to him.	Who did she show the portrait to?			
	Bill said/discovered that Skyler recited	What did Alicia say/discover			
Verb Complements	a poem.	that Skyler recited _?			
Parasitic Gaps	Saul gossiped about Beth because he hated her.	Who did Saul gossip about <u>because he</u> hated_?			
Nonparasitic Gaps Finite adjuncts	Saul gossiped about Beth's husband because he hated her.	Who did Saul gossip about Beth's husband because he hated _?			

Acceptability Judgments on base sentences

Is the following an acceptable sentence in English?

The woman who called Uber for a ride lost her glasses.

١C

1- Very Unnatural	2 3	4- Neither Natural nor 5 Unnatural	6	7- Very Natural	
ceptability of:	Base sente	nces	Wh- Ou	estions	

Between subjects; Prolific, n = 120

Discourse-linked Qs

Acceptability Judgments on wh-Questions

Is the following an acceptable sentence in English?

What did the woman who called Uber for a ride lose?

 ΛC

	1- Very Unnatural	2	3	4- Neither Natural nor Unnatural	5	6	7- Very Natural	
ceptability of: Base sentences Wh-Questions				-				

Between subjects; Prolific, n = 120

Discourse-linked Qs

RCs

Acceptability Judgments on sentences w/ Relative clause LDDs Between subjects; Is the following an acceptable sentence in

They found the glasses that the woman who called Uber for a ride lost.

English?

1- Very Unnatural	2 3	4- Neither Natural 3 nor Unnatural	5	6	7- Very Natural
0	0 0		0	0	0
0	0	0	0	0	0
	1				

Acceptability Judgments on "discourse-linked" Questions

Between subjects;

Prolific, n = 120

Discourse-linked Qs

Is the following an acceptable sentence in English?

Which glasses did the woman who called Uber for a ride lose?

1- Very Unnatural	2	3	4- Neither Natural nor Unnatural	5	6	7- Very Natural	
acceptability of:	В	ase sen	tences		Wh- Q	uestions	

Predicting island effects: Backgrounded constructions are islands (BCI)

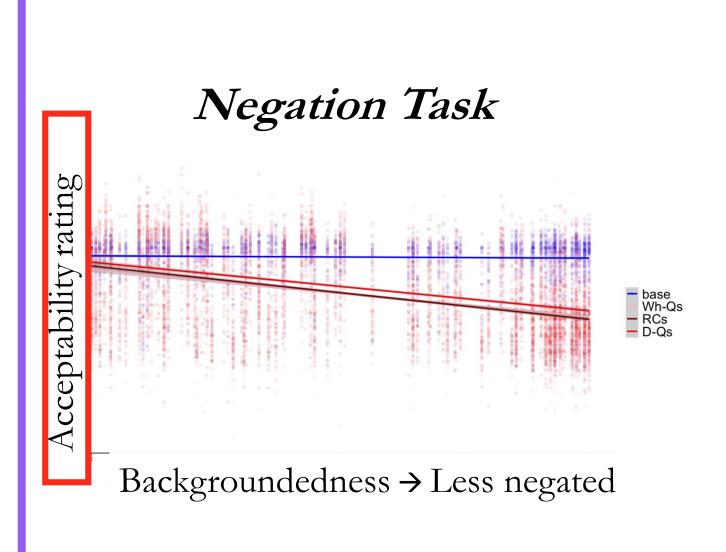
N = 680; between-subjects tasks

- Acceptability judgments on:
 - Base sentences
 - Wh-questions
 - "discourse-linked" wh-questions
 - Relative Clauses

Measuring Backgroundedness

• Negation Task

base
discourse-linked ques
relative clauses
questions



• Each backgroundness measure predicted judgments for each LDD

- Within *subsets* of data, degree of backgroundedness predicted LDD judgments on:
 - Verbs with clausal complements w/ log frequencies included (24 items)
 - Non-finite adjuncts (24 items) (see also Namboodiripad et al. 2022)
 - Main Clauses and RCs
 - Parasitic and nonparasitic gaps
 - Main clauses and temporal adjuncts

\rightarrow Backgrounded constructions are islands

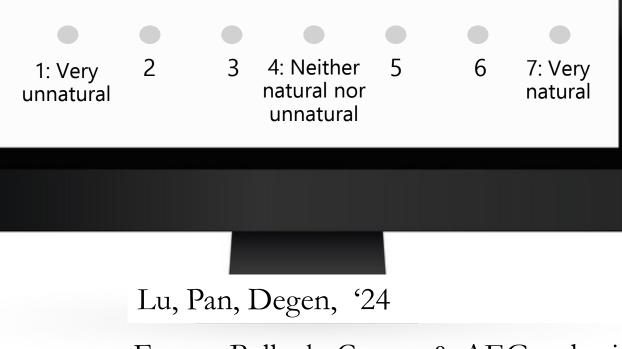
It is infelicitous for speakers to choose to both foreground and background the same element

Manipulating prominence

Is *wh*-Q acceptability improved when the queried constituent is made prominent via lexical stress?

Rahim: She didn't whisper he saw CHRIS. Lena: Then who did she whisper he saw?

How natural does Lena's question sound?



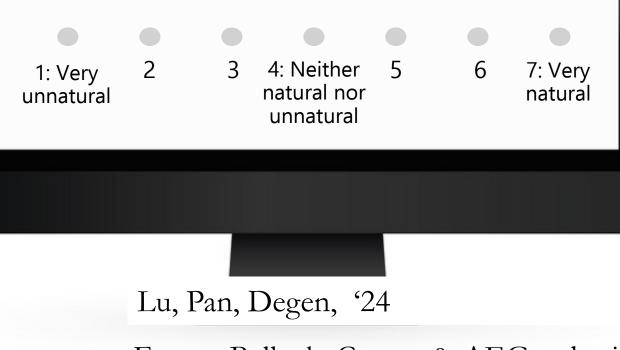
Fergus, Belluck, Cuneo, & AEG, submitted

Manipulating prominence

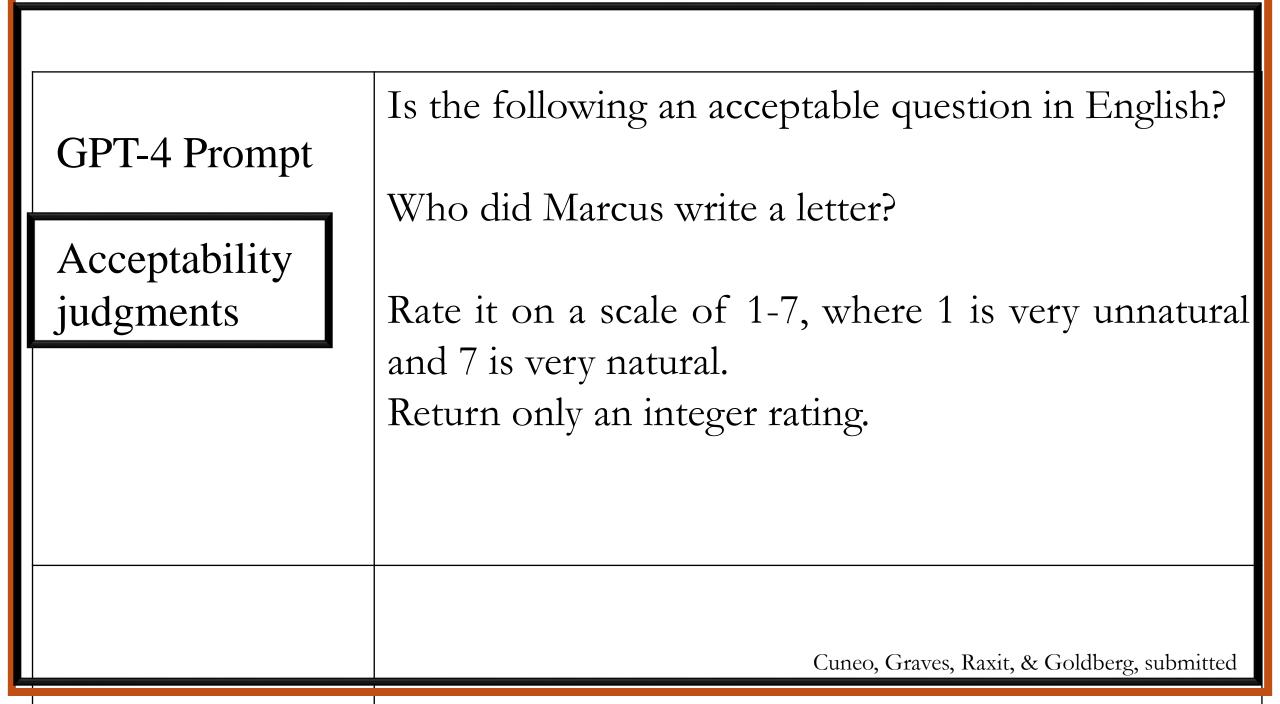
Is *wh*-Q acceptability improved when the queried constituent is made prominent via lexical stress?

Rahim: She didn't whisper he saw Chris. Lena: Then who did she whisper he saw?

How natural does Lena's question sound?

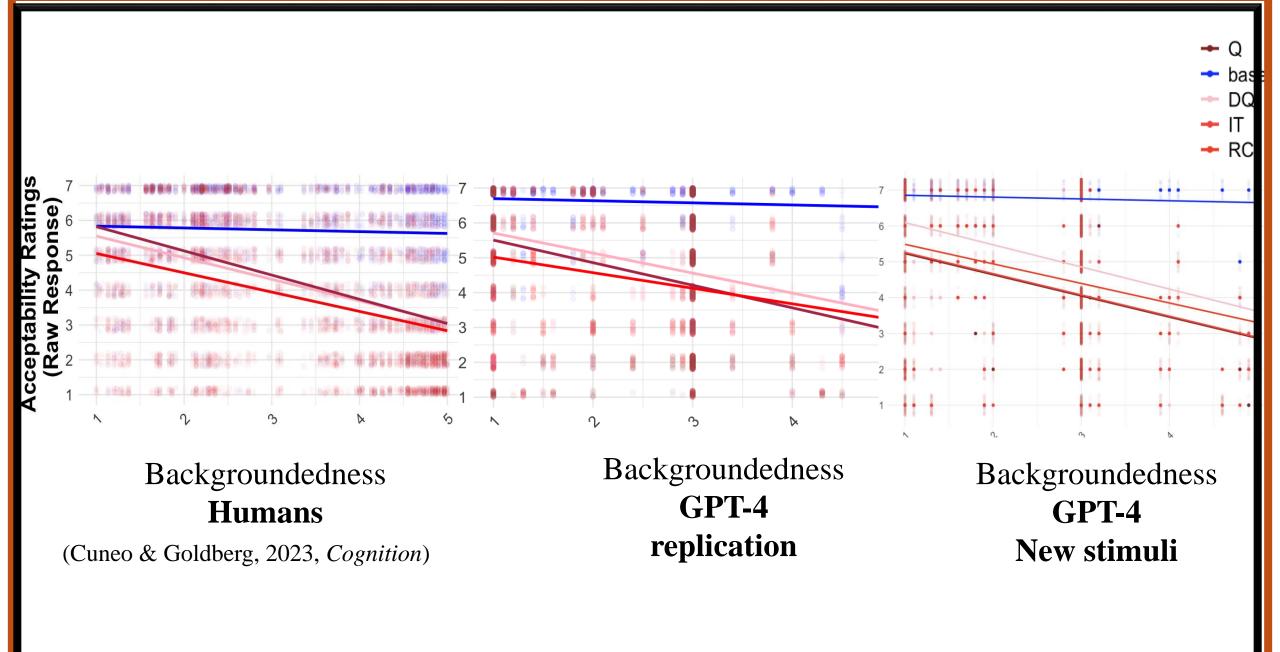


Fergus, Belluck, Cuneo, & AEG, submitted



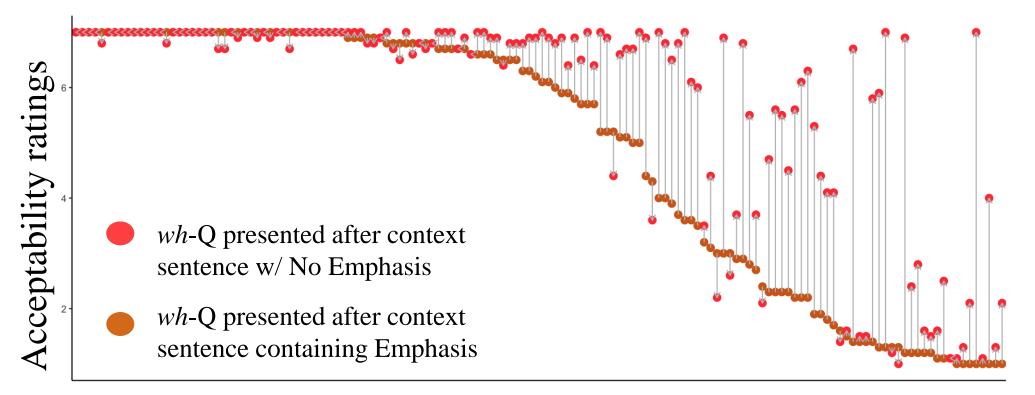
GPT-4 Prompt	Assume the sentence below is true and think about what it means:
Negation	Marcus didn't write her a letter.
task	Now answer the following question with an integer between 1 and 5, where 1 means no, 2 means probably not, 3 means can't tell, 4 means probably yes, and 5 means yes: Did Marcus write someone else a letter?
	Did Marcus while someone else a letter?

Cuneo, Graves, Raxit, & Goldberg, submitted



Cuneo, Graves, Raxit, & Goldberg, submitted

Manipulating emphasis: GPT-4's ratings on 144 (new) items w/ and w/o emphasis



Items (*wh*-questions)

People learn mappings that cluster together \rightarrow emergent generalizations (constructions)

>We avoid combining constructions with incompatible functions

Context can influence degree of compatibility

We make our contributions helpful (not only efficient, but also expressive, appropriate, polite)

Current LMs do the same. Without rules