# Lessons from LLMs for Human Language

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April 2, 2026

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# What are people trying to do?

Understand messages, given forms (comprehension)

&

Choose forms, given intended messages (production)

&

Conform to the conventions of their communities

# CONSTRUCTIONS = learned pairings of form **&** function

Functions: e.g., meaning & information structure

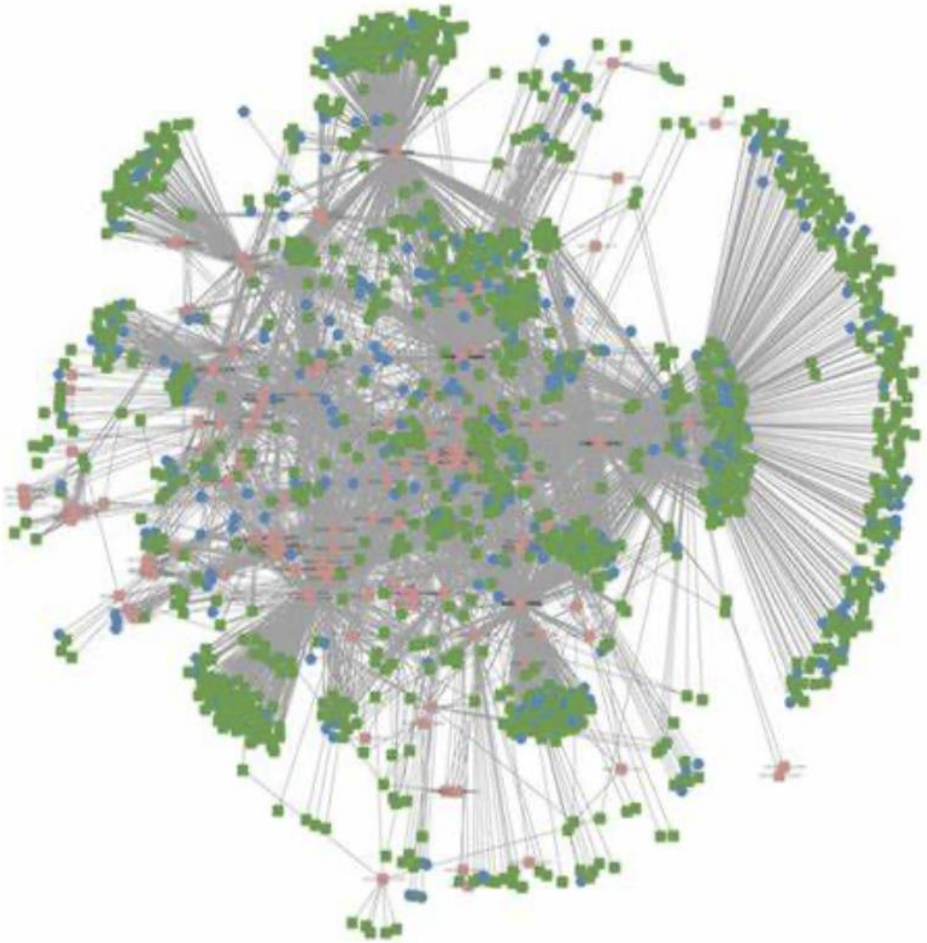
There are many

They are varied

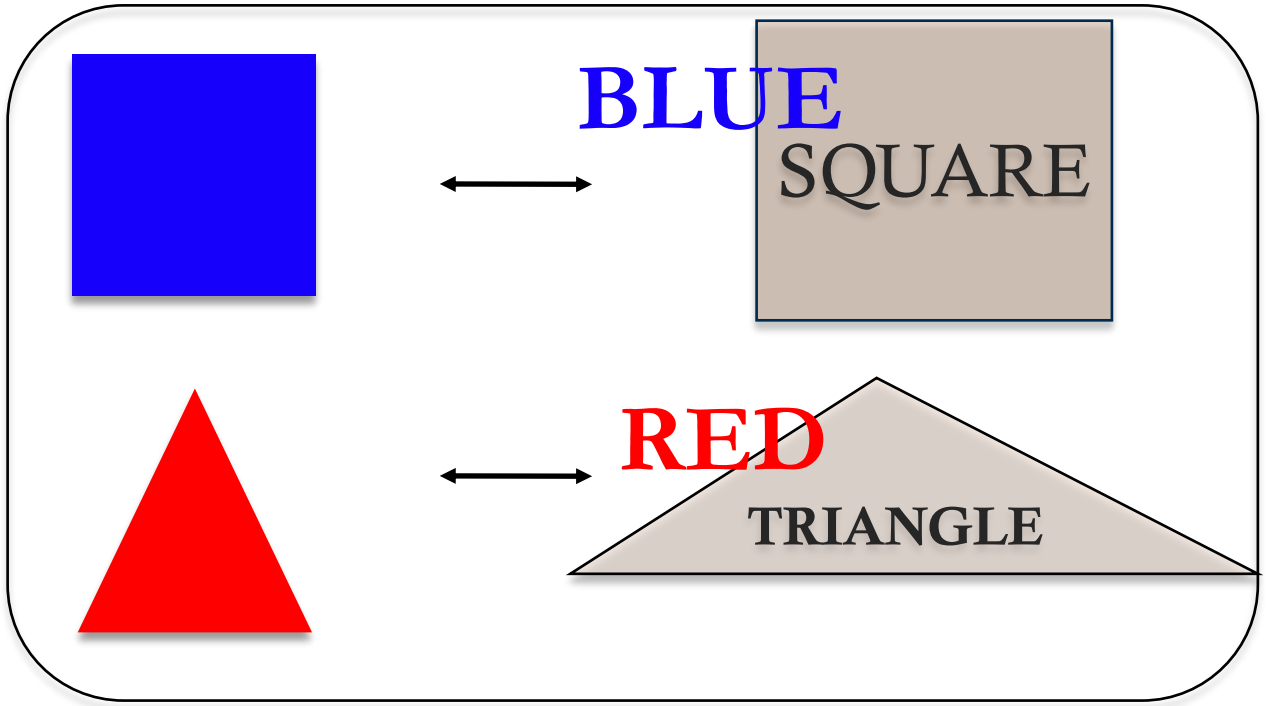
They are statistical

They are interrelated

They are context-dependent



Contrasting approach:




$color > \cap$ "noun"

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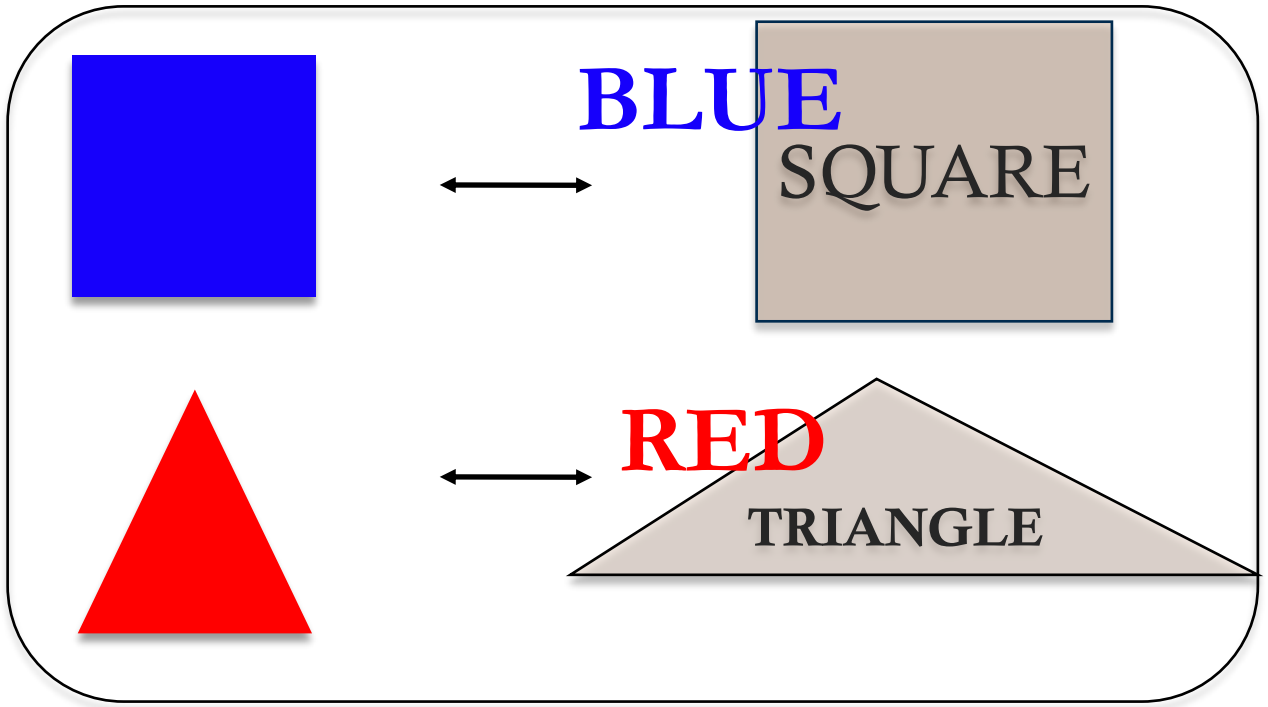


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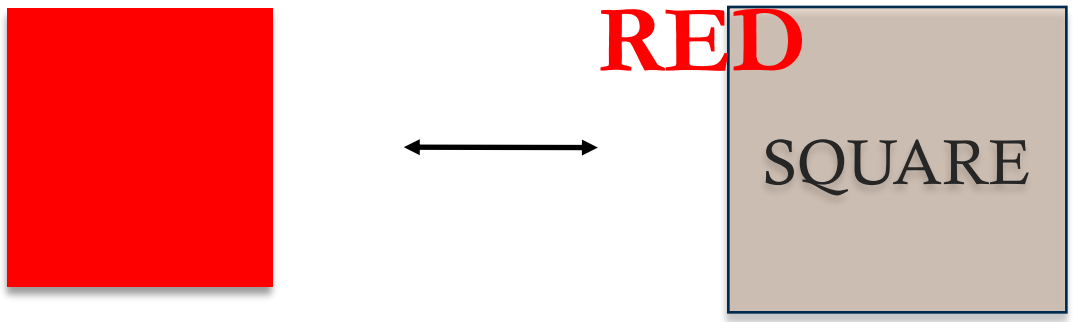
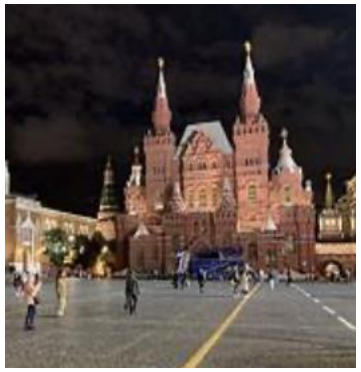


# REAL Natural Language



Red Square

red book 

$< color \not{X} \cap$ "noun"

red pen 

red states 


red hair 

red meat 

red grapefruit 

Red Sox, Red Cross, red flag, red line, red tape…

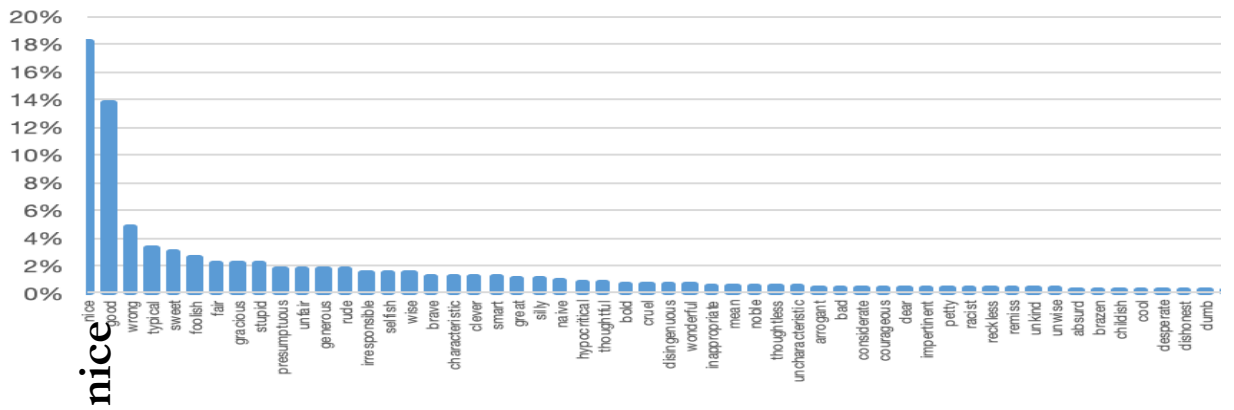
# Gossip construction

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

(Goldberg & Herbst, 2021, *Linguistics)*

# Gossip construction

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




It was mean/crappy of Reviewer 2 to do 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.

(Goldberg & Herbst, 2021, *Linguistics)*

Subtle semantic differences between constructions

Joe married into the family. (intran. motion construction)

≠

Joe married his way into the family.(“way” construction)

| **CONSTRUCTIONS** w/ varying levels of complexity and abstraction | **Examples** |
|---|---|
| Words | *bienvenido, existencia, pegote, chill* |
| Words with open slots | __*-encia*$_N$ |
| Unfilled lexical Cx | [N N]$_N$ *(e.g., plan reforma vivienda)* |
| Phrasal cx, lexically specified | *anda que no, ¡qué fuerte! es la leche* |
| Phrasal cx with open slots | *Menos mal que <S>* |
| Phrasal cx with mostly open slots | *Es de <Adj/N> <INF>* |
| Argument structure constructions<br><br>Passive construction<br><br>Information-questions, relative clauses, topicalization, clefts, … | V [(que) [S]] (recursive)<br>[a Np$_{experiencer}$] clitic$_{dative}$-V$_{psych}$ NP<br><br>(subj) *ser* participle (*por* agent) |

TODAY: Three constructionist results on human language:

I. **Argument structure: meaning-infused syntax**

II.

III.

She mooped him something. (double-object [DO] construction)

$V_{erb}$ $O_{bject1}$ $O_{bject2}$

What does *moop* mean?

Subtle semantic differences between constructions

a. Joe baked Sam a cake. (double-object (DO) constructio

$V_{erb}$ $O_{bject1}$ $O_{bject2}$

b. Joe baked a cake for Sam.

Subtle semantic differences between constructions

a. Joe sent London a package. DO construction

a. Joe sent a package to London. PO construction

# Subtle semantic differences between constructions

a. Joe sent London a package. DO

b. Joe sent a package to London. PO

**semantic-features: A User-Friendly Tool for Studying Contextual Word Embeddings in Interpretable Semantic Spaces**

**Jwalanthi Ranganathan**[1] **Rohan Jha**[1] **Kanishka Misra**[1,2,★] **Kyle Mahowald**[1]
[1]The University of Texas at Austin [2]Toyota Technological Institute at Chicago
{jwalanthi,rjha,kyle}@utexas.edu {kanishka}@ttic.edu

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| Feature | Definition |
|---|---|
| Biomotion | showing movement like that of a living thing |
| Body | having human or human-like body parts |
| Human | having human or human-like intentions, plans, or goals |
| Face | having a human or human-like face |
| Speech | someone or something that talks |
| Landmark | having a fixed location, as on a map |
| Scene | bringing to mind a particular setting or physical location |

Table 1: Feature definitions from Binder et al. (2016).

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Table 1: Feature definitions from Binder et al. (2016).

| Feature | DO | PO |
|---|---|---|
| Biomotion | **1.19** | 0.43 |
| Body | **1.00** | 0.26 |
| Human | **0.89** | 0.48 |
| Face | **0.71** | 0.19 |
| Speech | **0.68** | 0.13 |
| Landmark | 1.83 | **3.43** |
| Scene | 2.59 | **4.43** |

Table 2: Relevant Binder features predicted for "London" in (1) using CWEs from BERT layer 8. The PO construction lends itself more towards "location" features, and the DO more towards animate features.

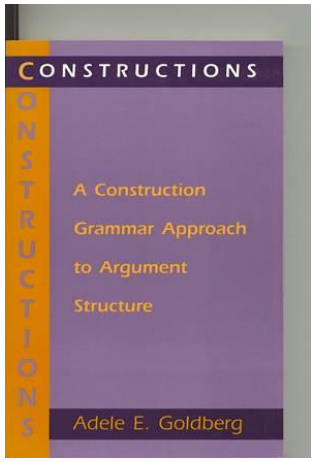
Differences in what's backgrounded or 'at-issue'

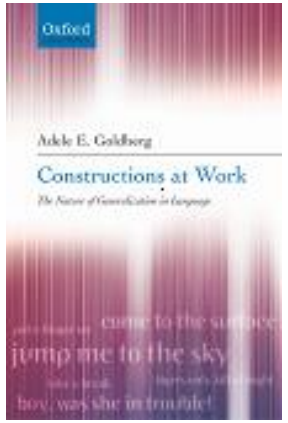
a. Joe sent him a letter. (double-object construction)

b. ?? Joe sent a woman that.

Bresnan, J., Cueni, A., Nikitina, T., & Baayen, R. H. (2007).

# Argument structure patterns:




| Meaning | Form, *Example* |
|---|---|
| Double object construction<br>"give" | S [V $O_1$ $O_2$]<br>*She gave him something.*<br>*She mooped him something.* |
| Intransitive Motion<br>"go" | S [V PP]<br>*She went down the street.*<br>*The truck roared down the street.* |
| Caused-motion<br>"put, move" | S [V O PP]<br>*She put the ball in the box.*<br>*She sneezed her tooth across town.* |
| Resultative<br>"change-state, make" | S [V O AP]<br>*He made her crazy.*<br>*She kissed him unconscious.* |

**Claim:** LLMs learn rich, dynamic, and meaning-infused representations of constructions

DAIS corpus:

5000 pairs of Double-object *and* Prepositional Object sentences, with human preferences (Hawkins et al. 2021)

DAIS corpus

**DO biased**

**(1) Maria asked him some questions.**

(2) Bob lobbed her a tennis ball.

(3) Juan shuttled the team something.

(4) Alice threw the woman a book.

(5) Michael took the woman the blanket.

**DO or PO**

(5) Maria sold the house to a man who was wearing a hat.

(4) Bob transferred the house to her.

(3) Juan posted the letter to the man.

(2) Alice grumbled something to the woman.

**(1) Michael rented the apartment to a man.**

**PO biased**

# Meaning-infused grammar: Gradient Acceptability Shapes the Geometric Representations of Constructions in LLMs

**Supantho Rakshit**
Deptof ECE / Princeton University

**Adele E. Goldberg**
Dept of Psychology / Princeton University

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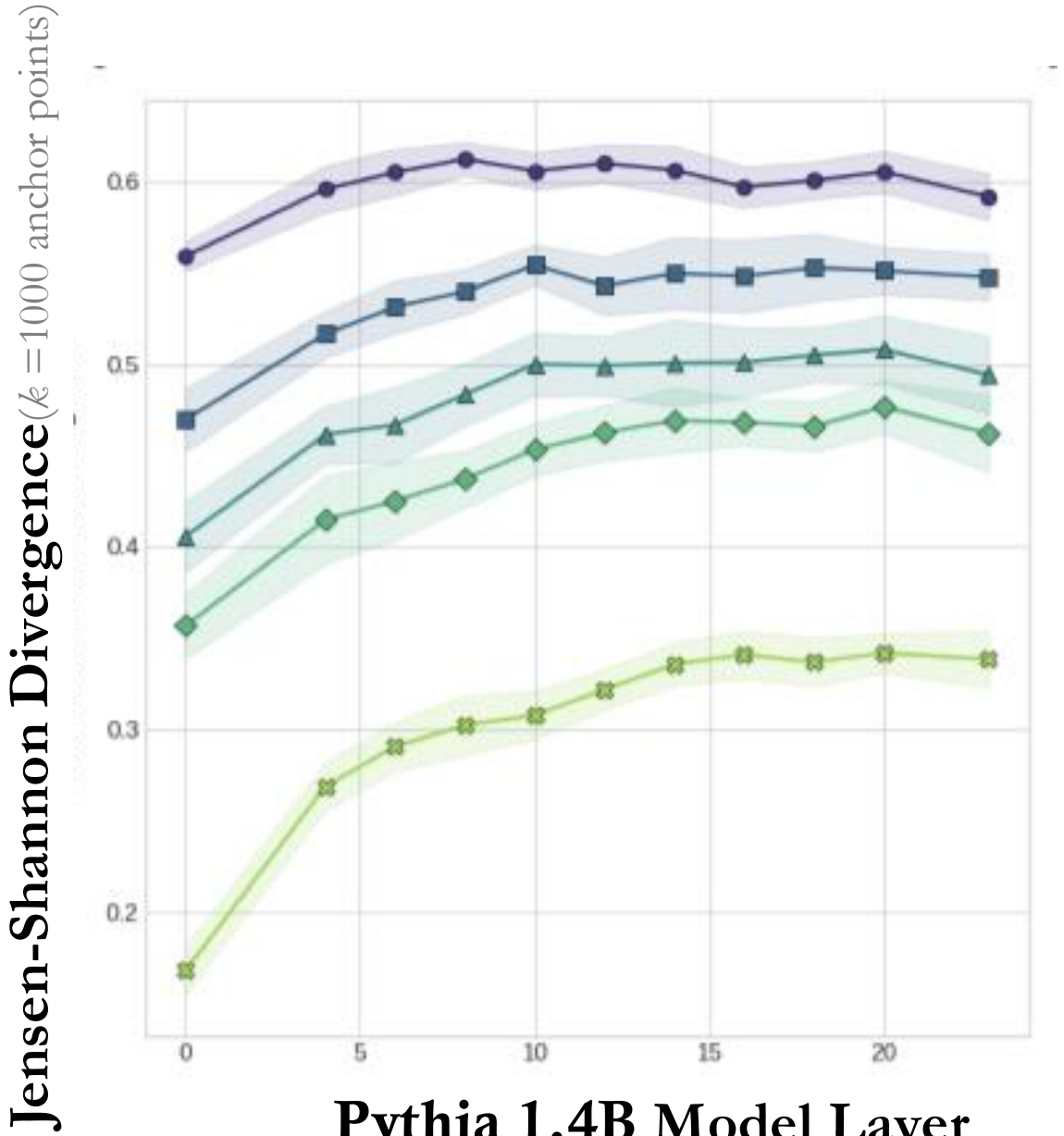
**PO biased**

# Distinguishability between DO and PO in Model layers




(1) Top 10% strongest preference for DO or PO
(2)
(3)
(4)
(5) Bottom (10%): Least clear preference for DO or PO

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**PO biased**

# Geometric separation (distance) of DO vs PO embeddings: Pythia 1.4B, layer 14

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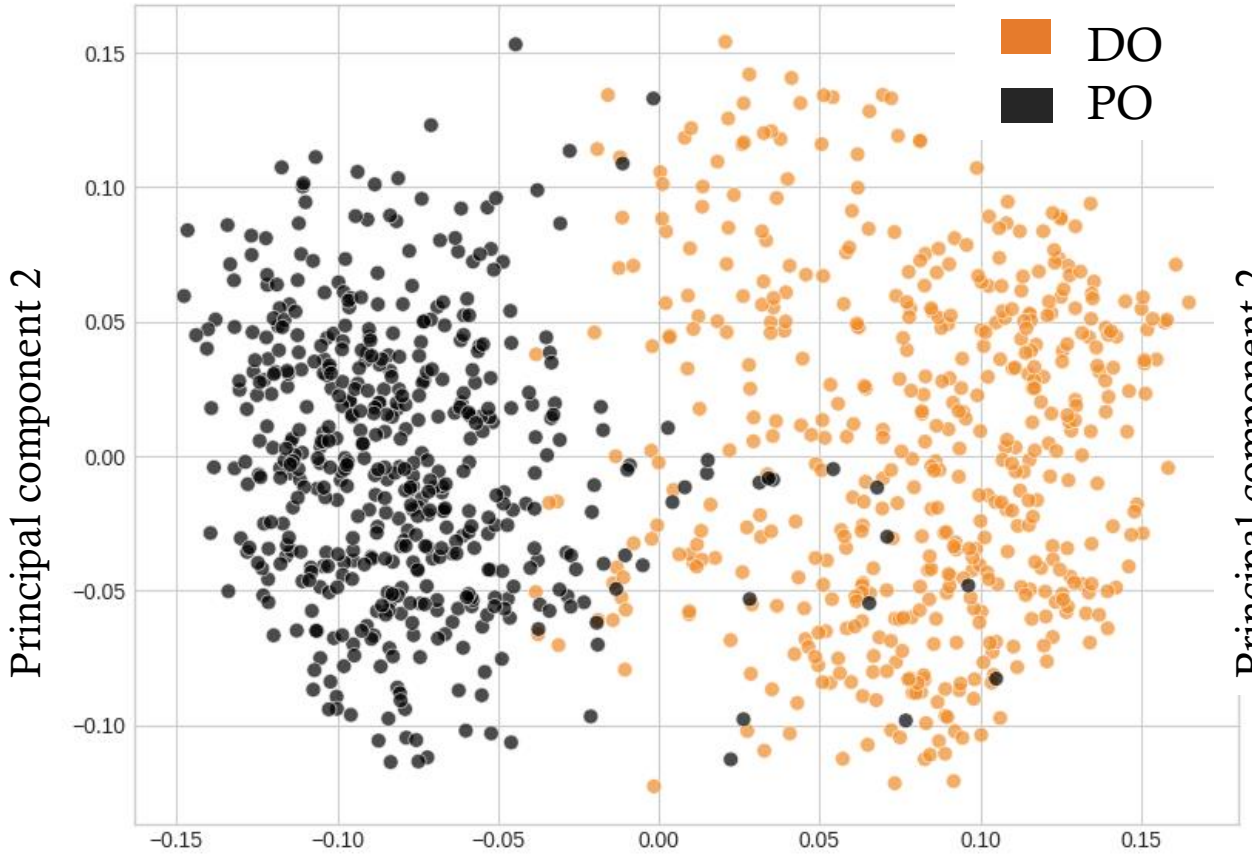
PO biased

Top 10% most preferred

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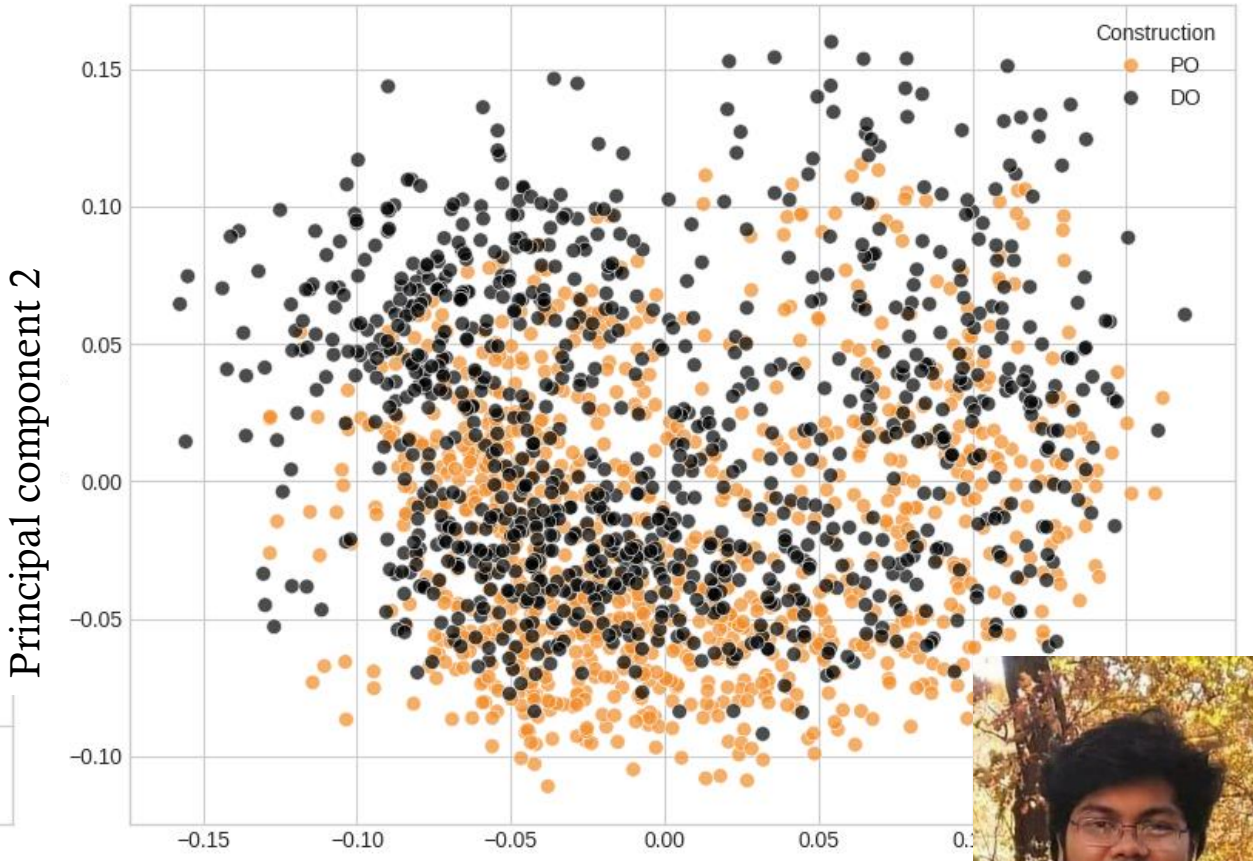
PO biased

Either order equally acceptable




→ LLMs learn rich, dynamic, and meaning-infused representations of constructions

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Functions: e.g., meaning & information structure

There are many

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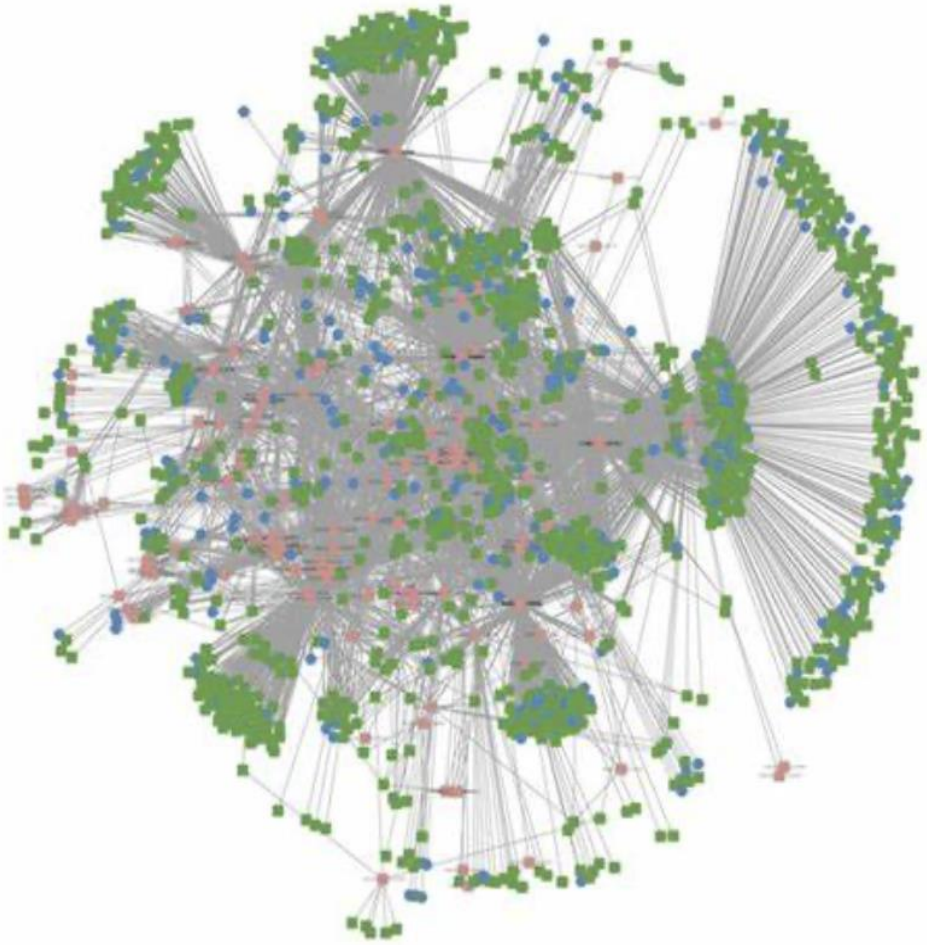


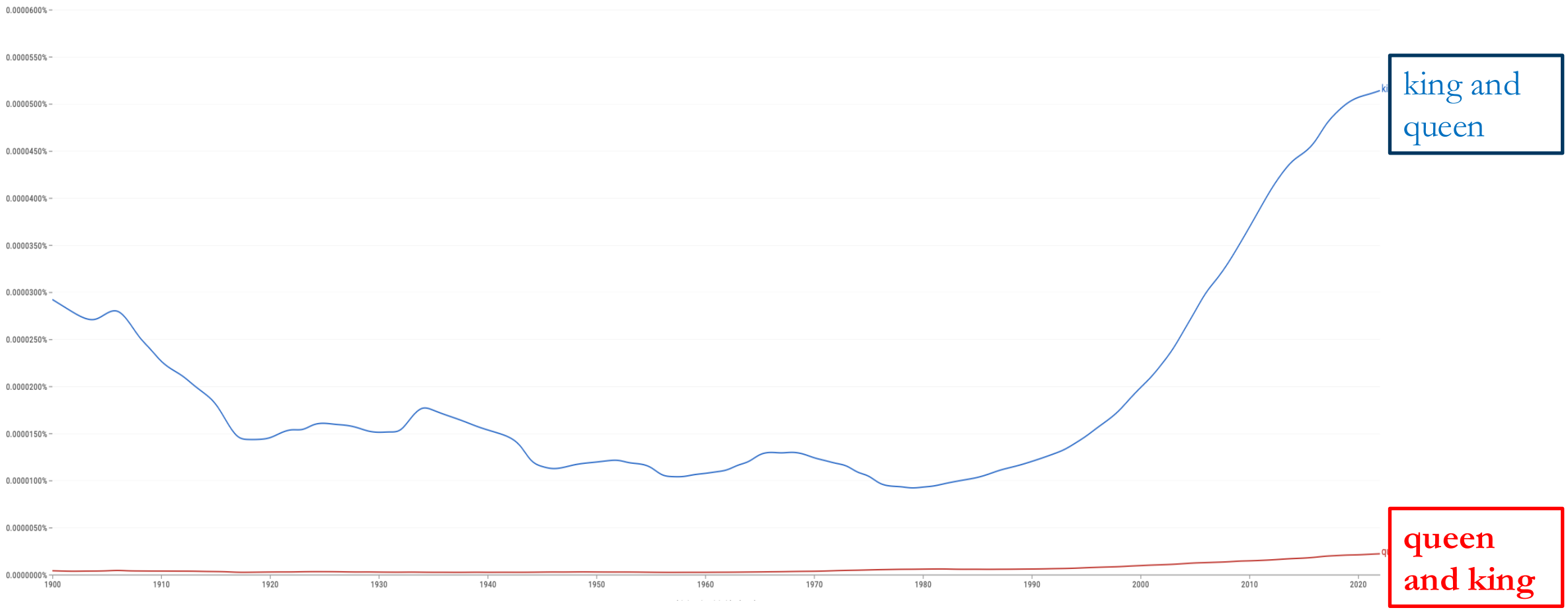
| | | |
|---|---|---|
| *sun and moon* | or | *moon and sun* |
| *king and queen* | or | *queen and king* |
| *Paris and Nice* | or | *Nice and Paris* |

Cooper & Ross 1975; Morgan & Levy 2016; 2024

Google Books Ngram Viewer

king and queen, queen and king

1900 - 2022 | English | Case-Insensitive | Smoothing of 5



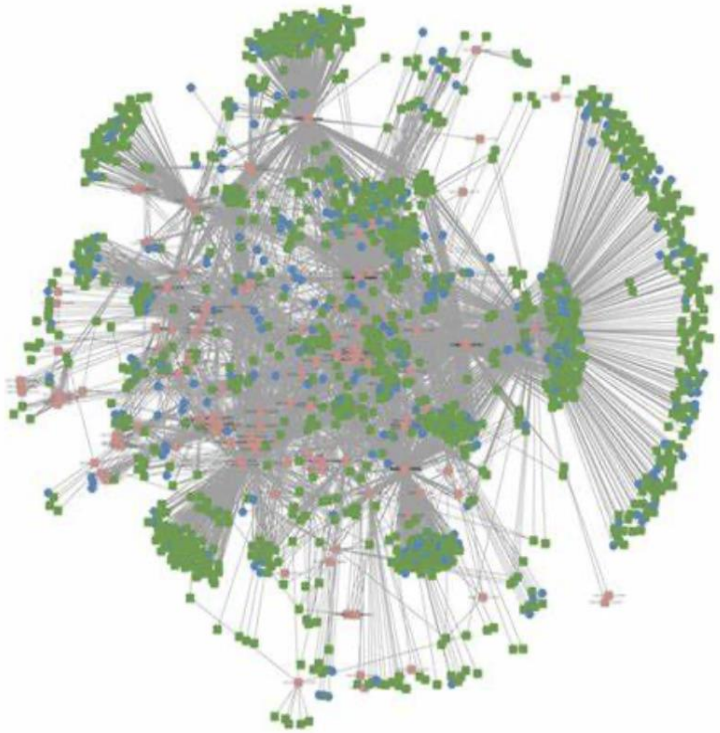
We choose linguistic constructions based on:

- Intended message
- Accessibility:

  Accessibility of whole (for familiar combinations)

  Accessibility of parts (for novel combinations)

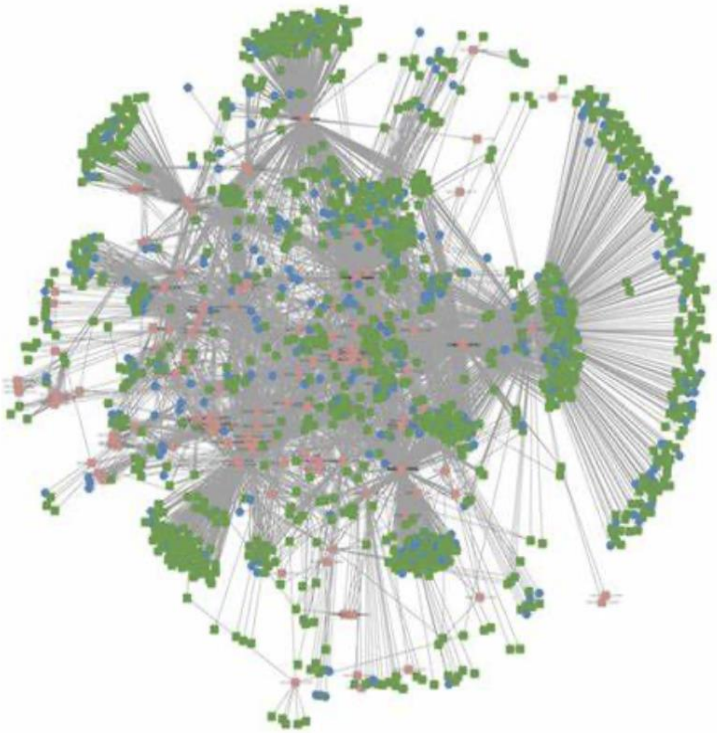
  Interference from competitor with same function



- Similar constructions cluster together, lead to emergent regularities

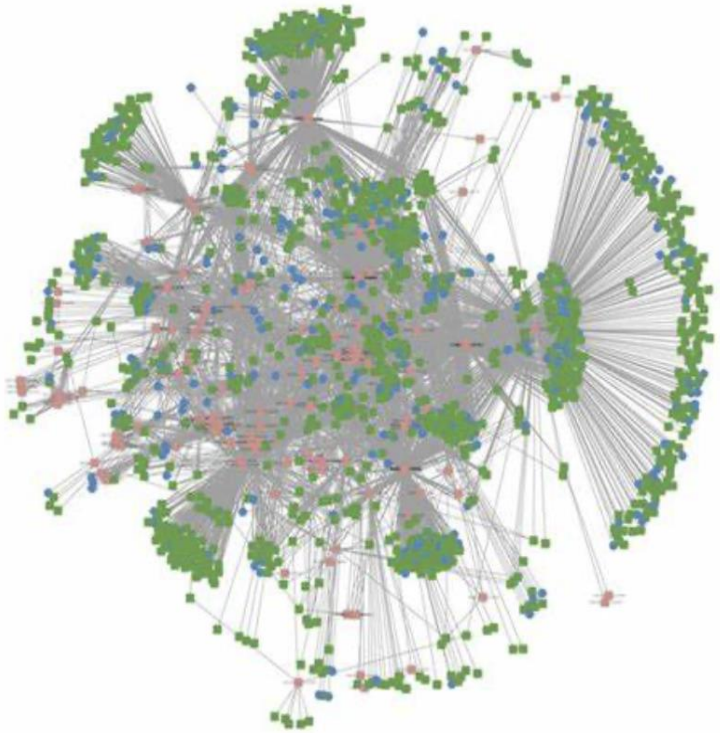
We retain memories of even fully compositional phrases like *aunts and uncles*

Morgan & Levy, 2016

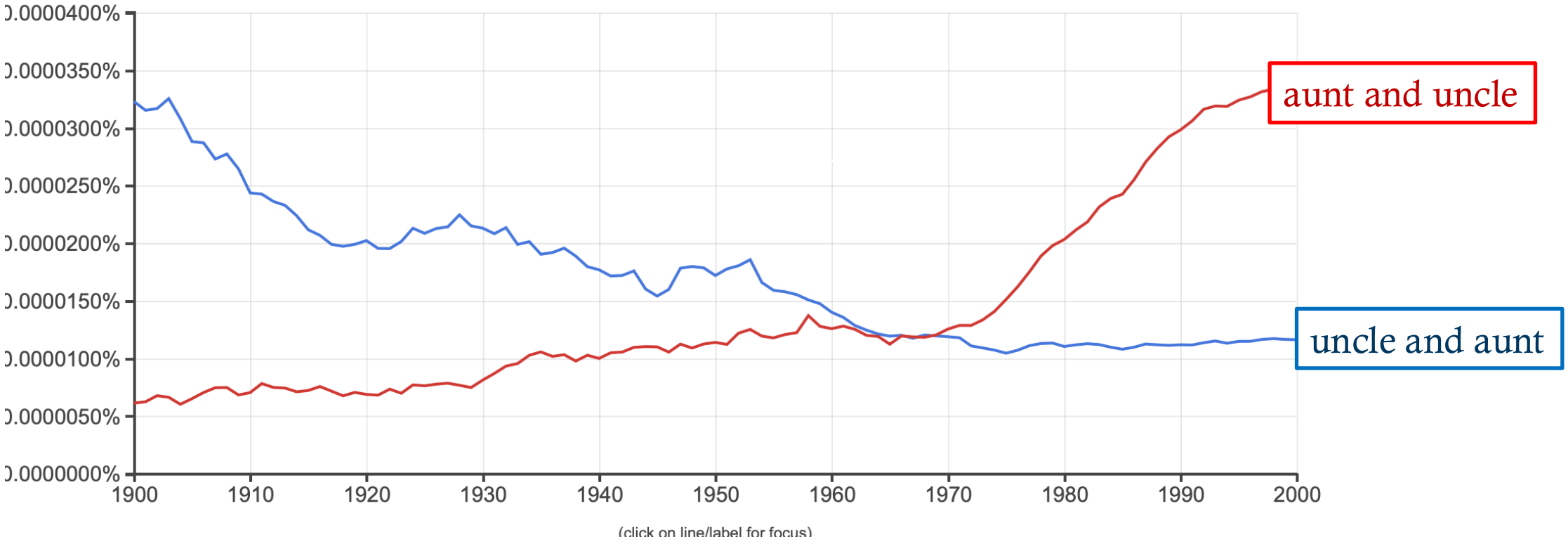


a tiny corner of data

The data is specific,
the implications are not



# A puzzle




Goldberg & Lee (2021)

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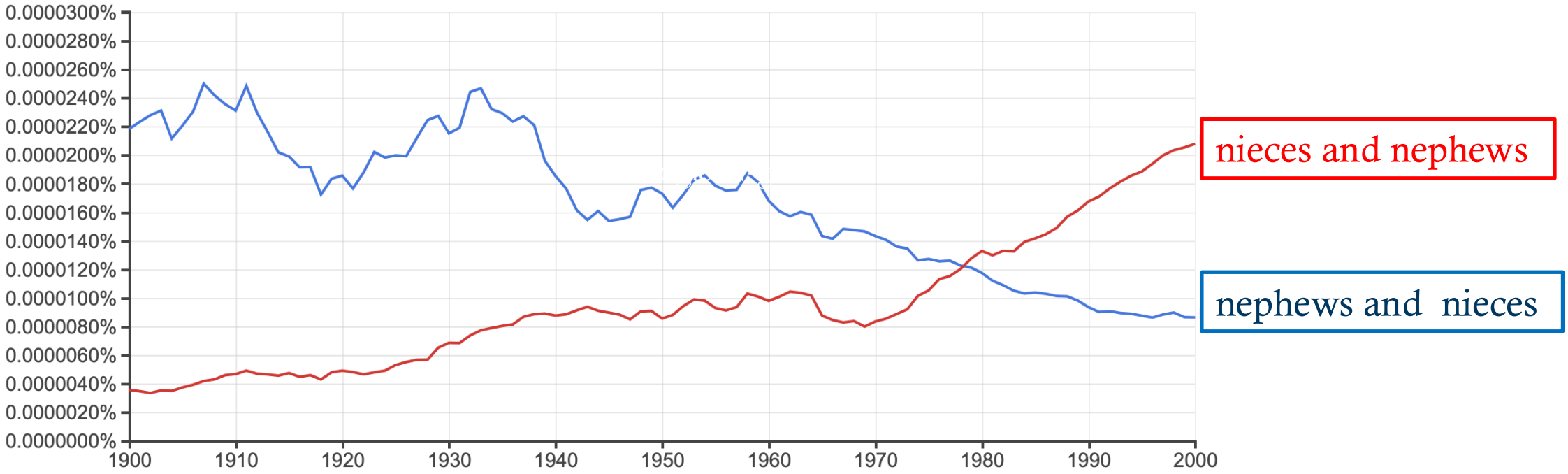


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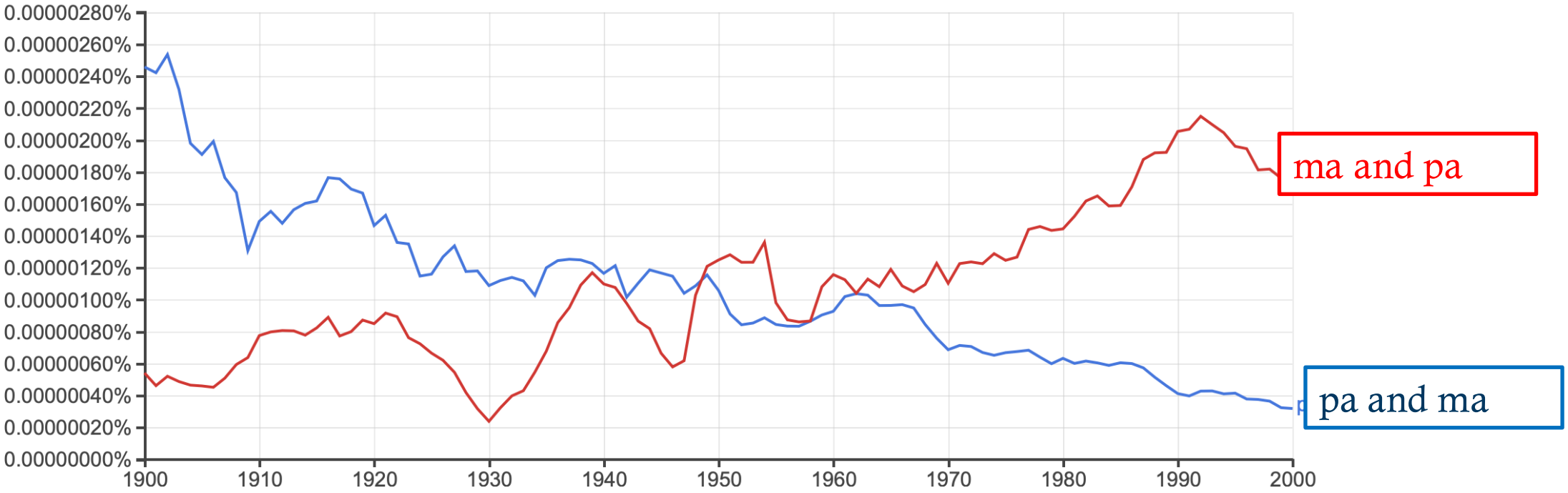


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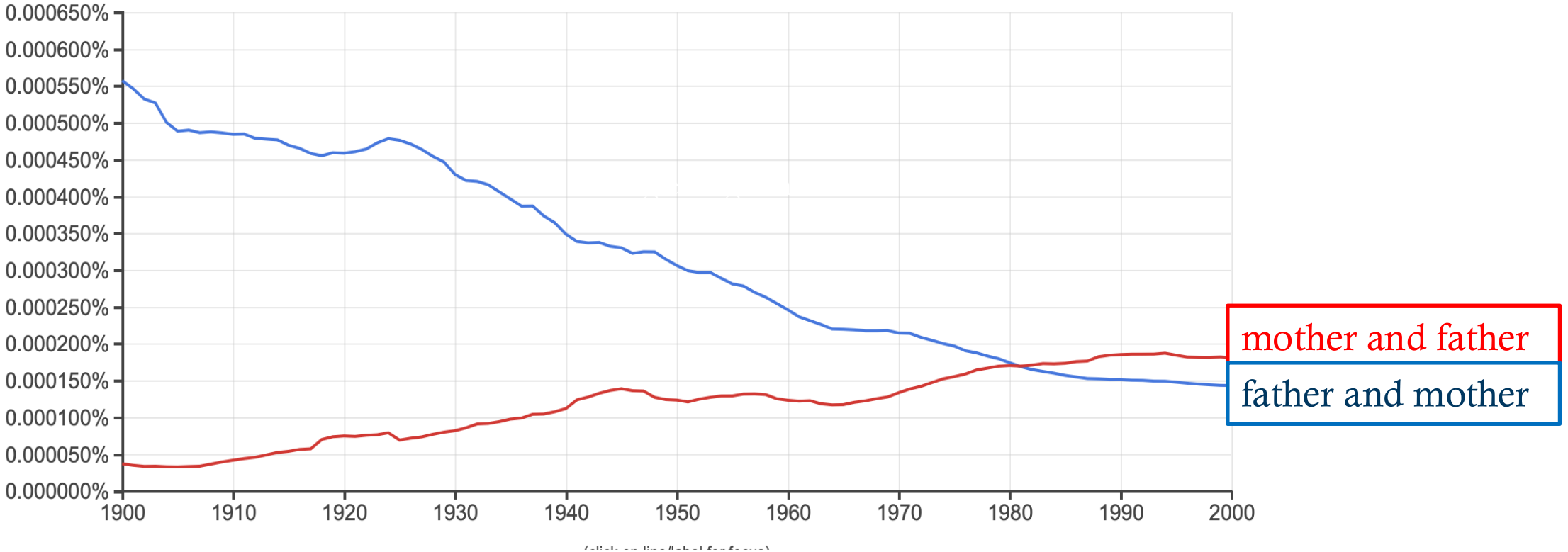


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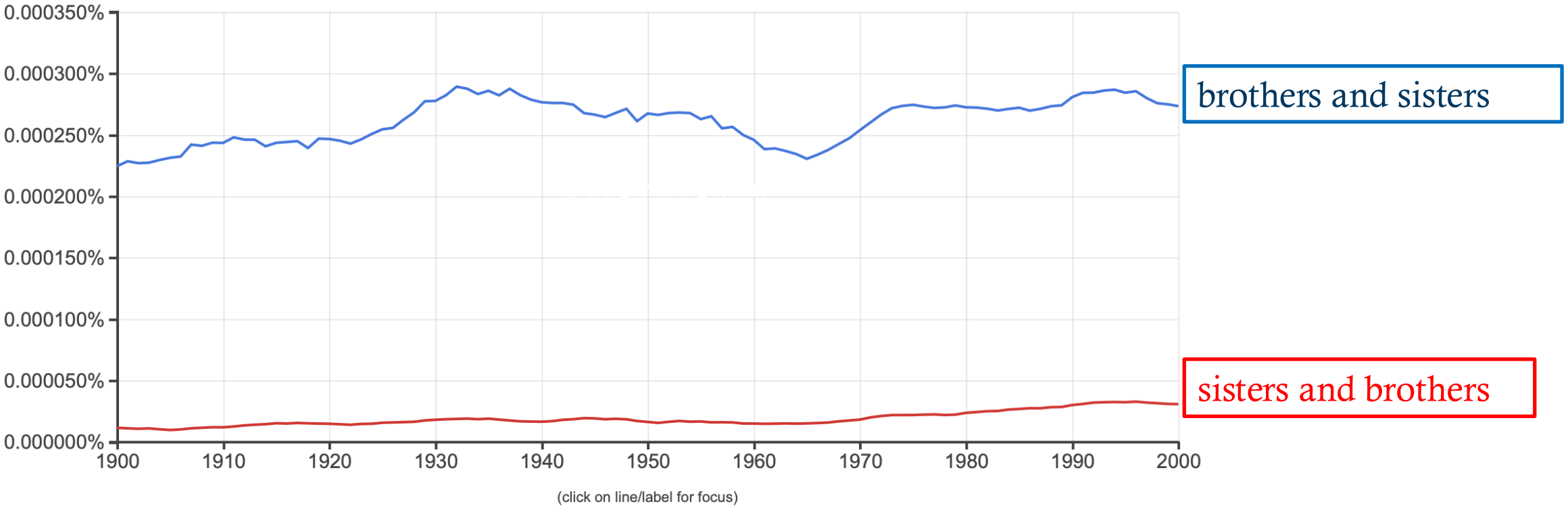
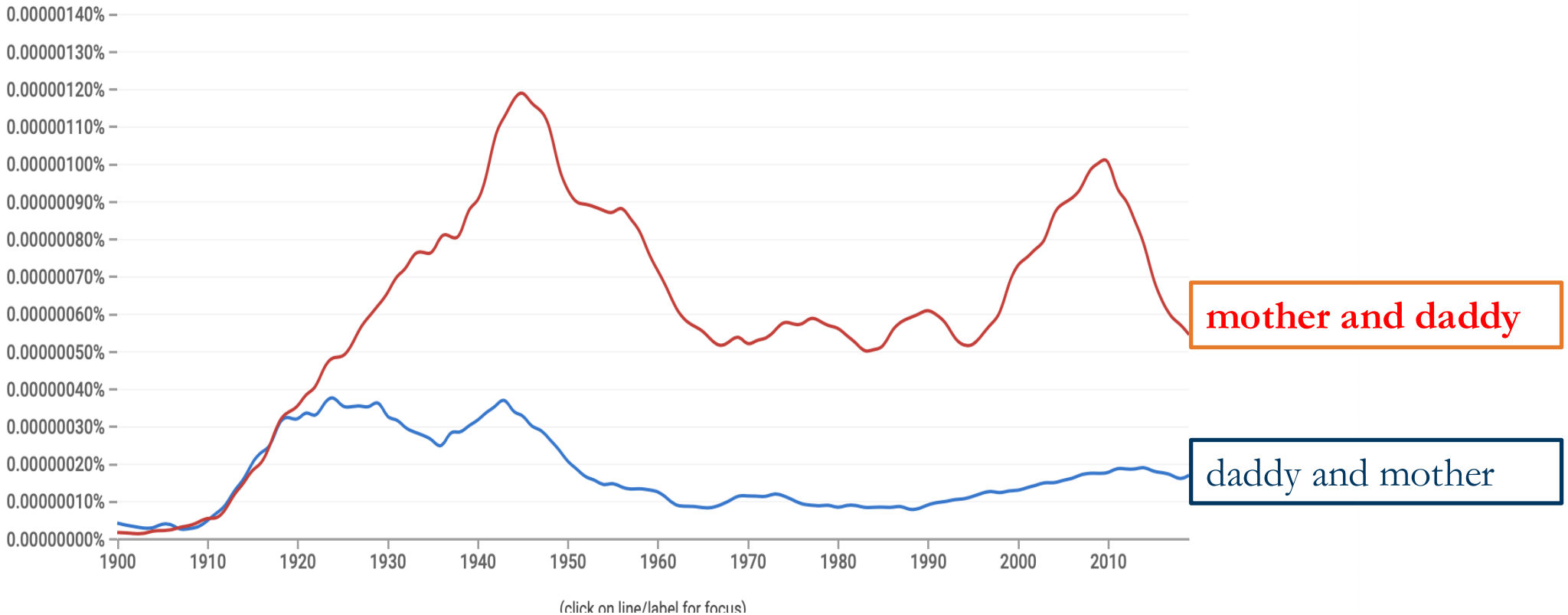



Goldberg & Lee (2021)

# Ground Zero: *Mother and dad(dy)*

Q: *Why* was this order was preferred?

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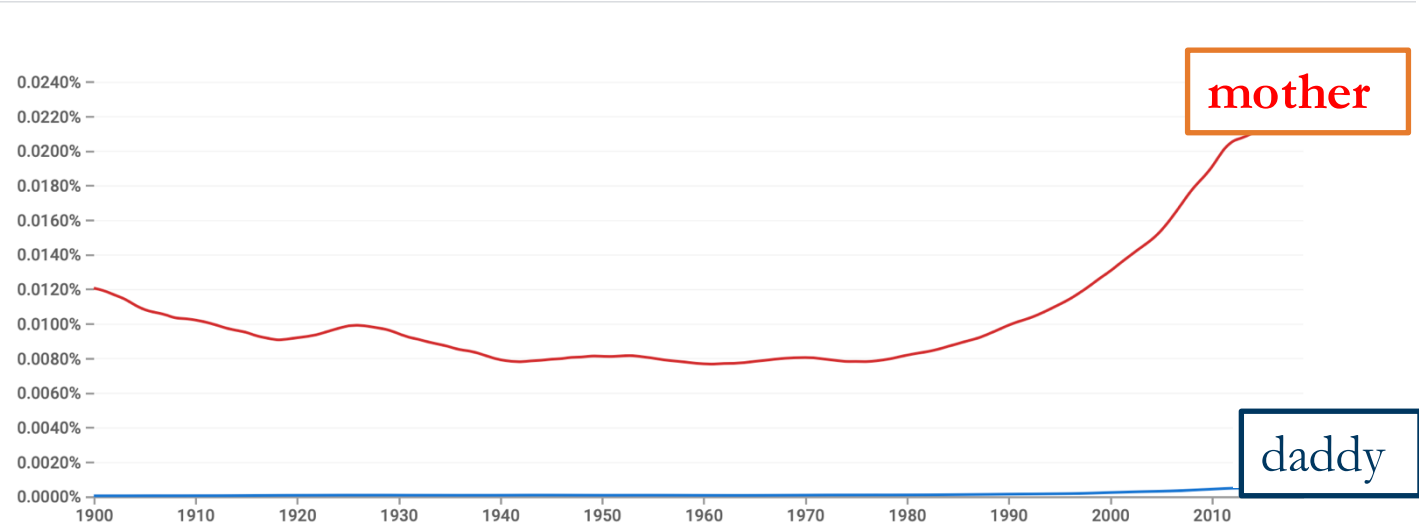


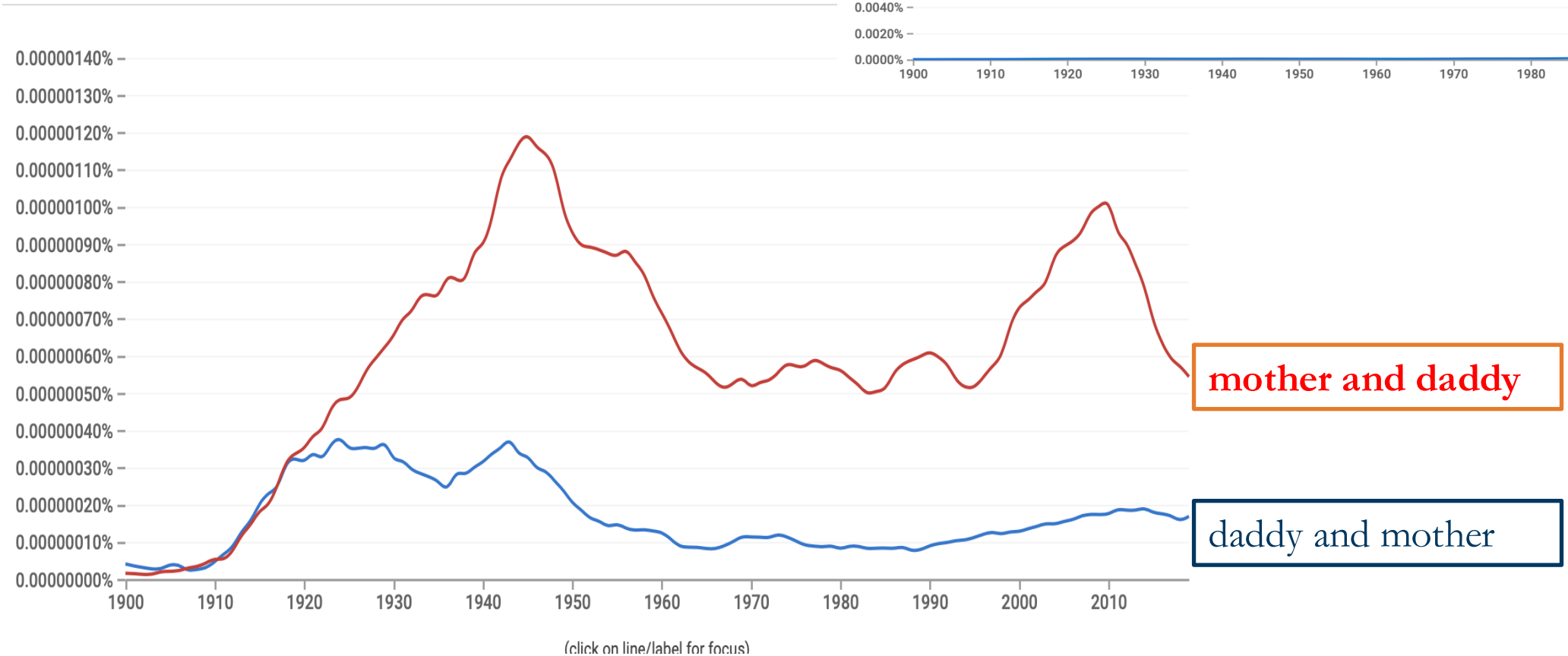


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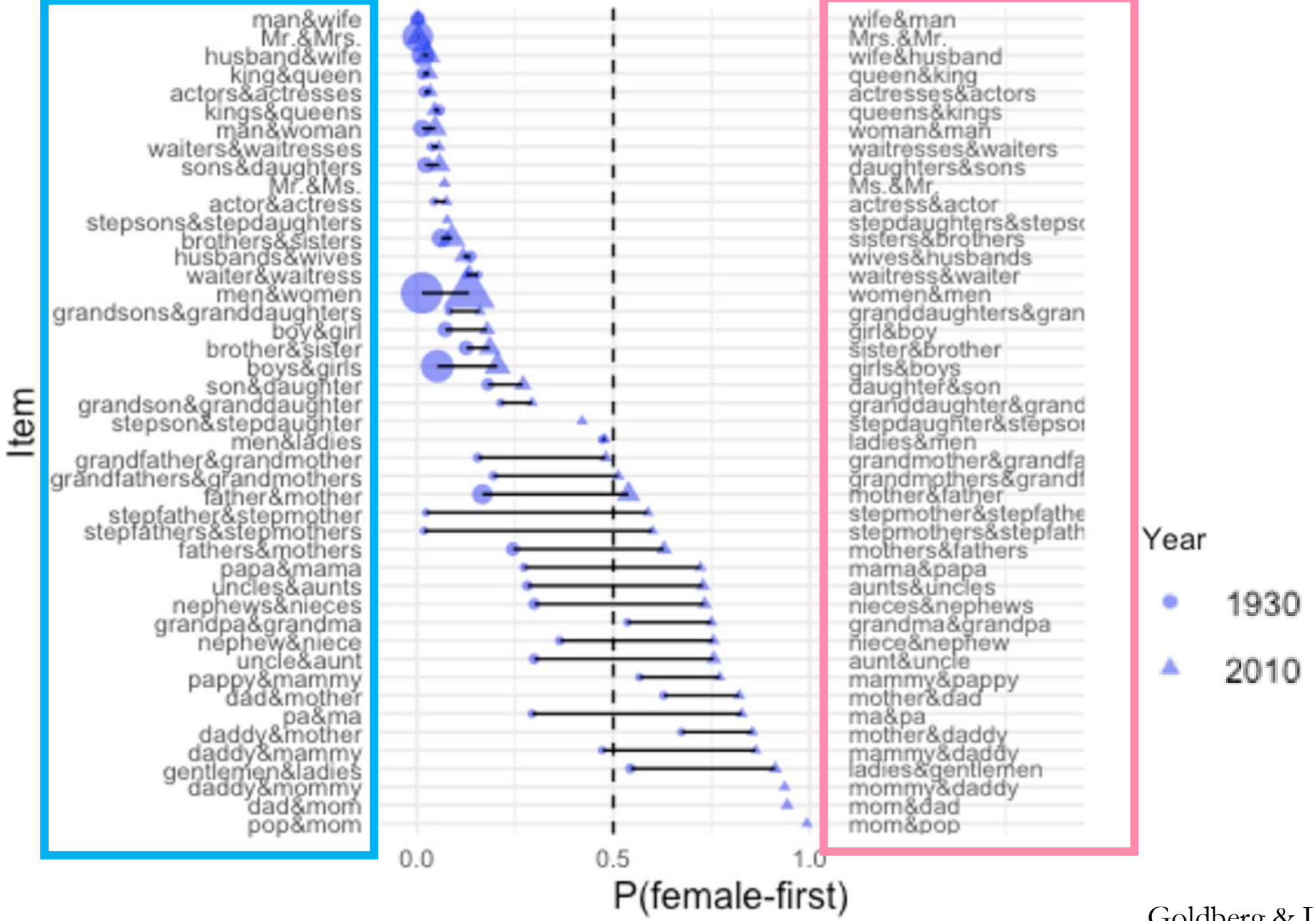


Goldberg & Lee, 2021

$$P(F\&M) \sim \beta_1 [(logFreq(F) - \#syll(F)) - (logFreq(M) - \#syll(M) + 1)]$$

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

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

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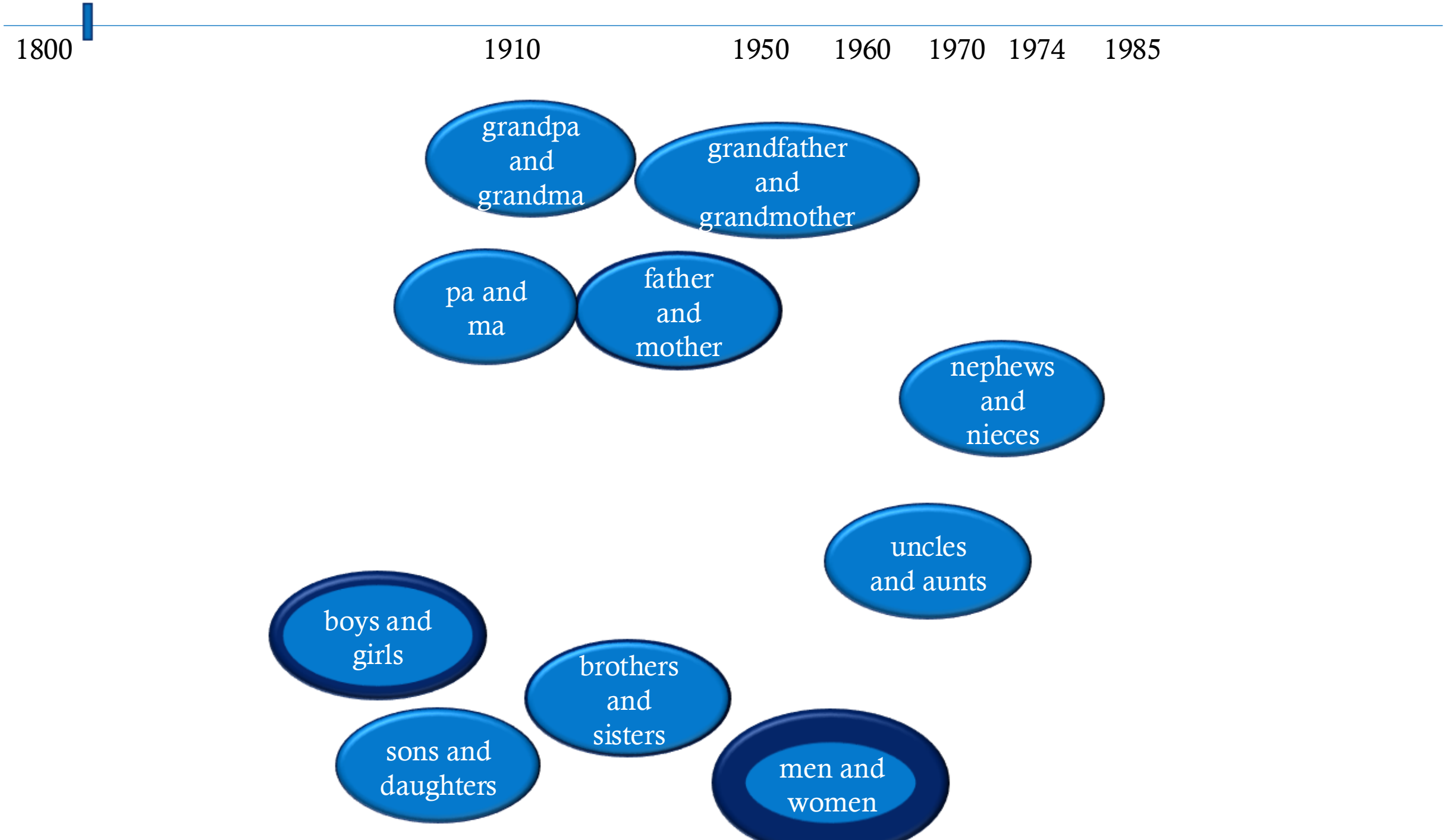
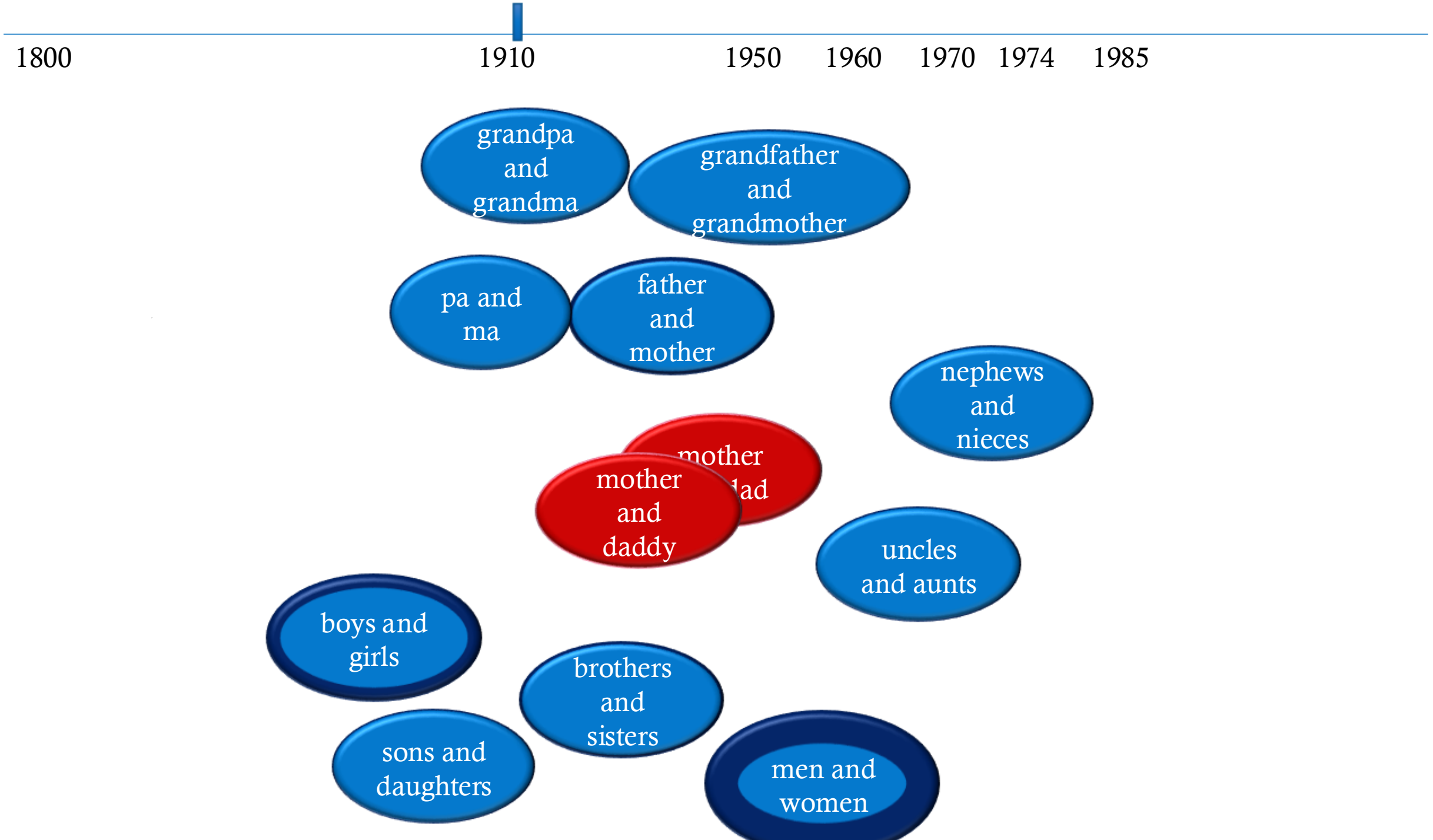
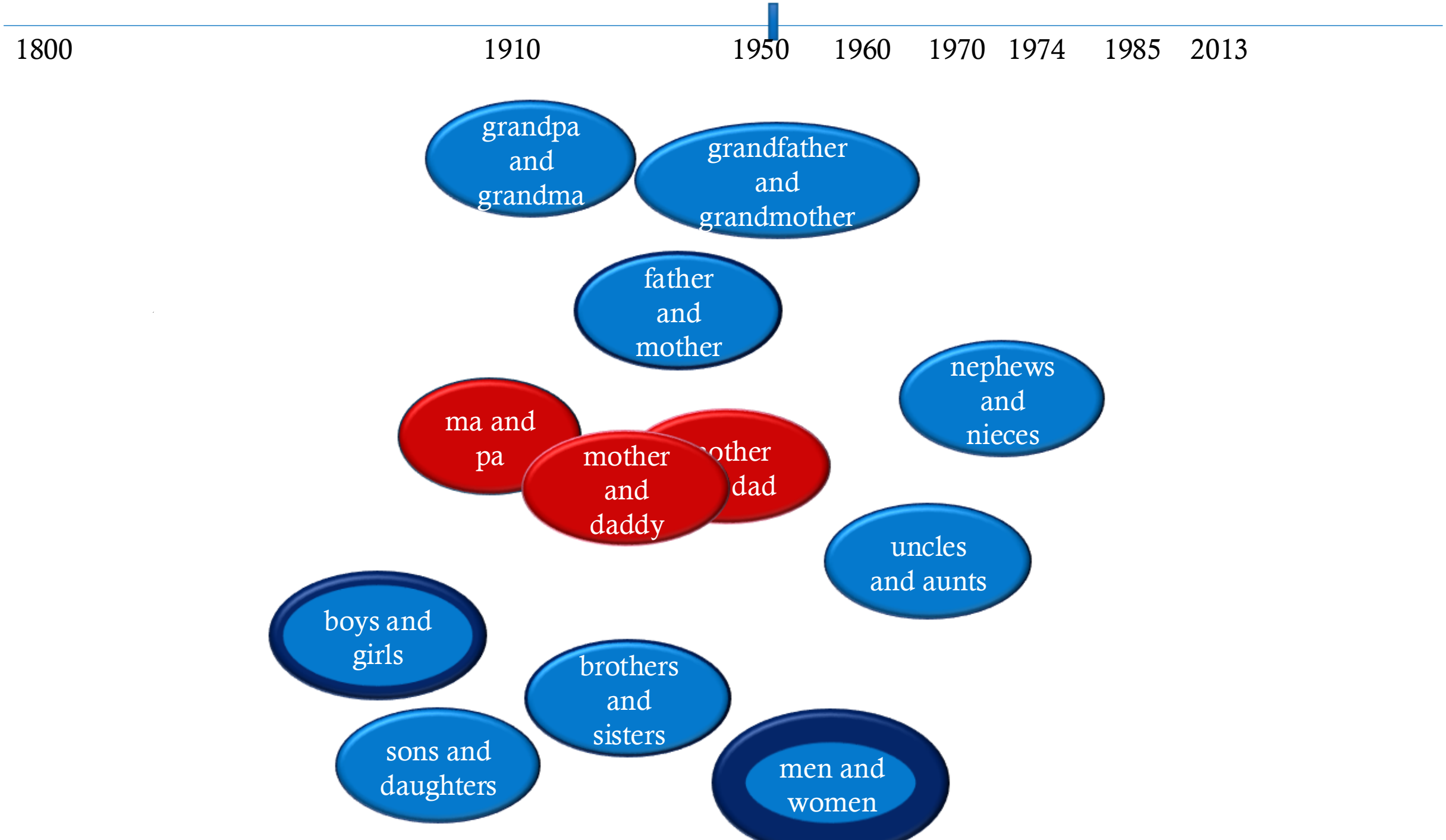

1800
1910
1950
1960
1970
1974
1985
grandpa and grandma
grandfather and grandmother
pa and ma
father and mother
nephews and nieces
uncles and aunts
boys and girls
brothers and sisters
sons and daughters
men and women


1800
1910
1950
1960
1970
1974
1985
grandpa and grandma
grandfather and grandmother
pa and ma
father and mother
nephews and nieces
mother
mother and daddy
uncles and aunts
boys and girls
brothers and sisters
sons and daughters
men and women


1800
1910
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1960
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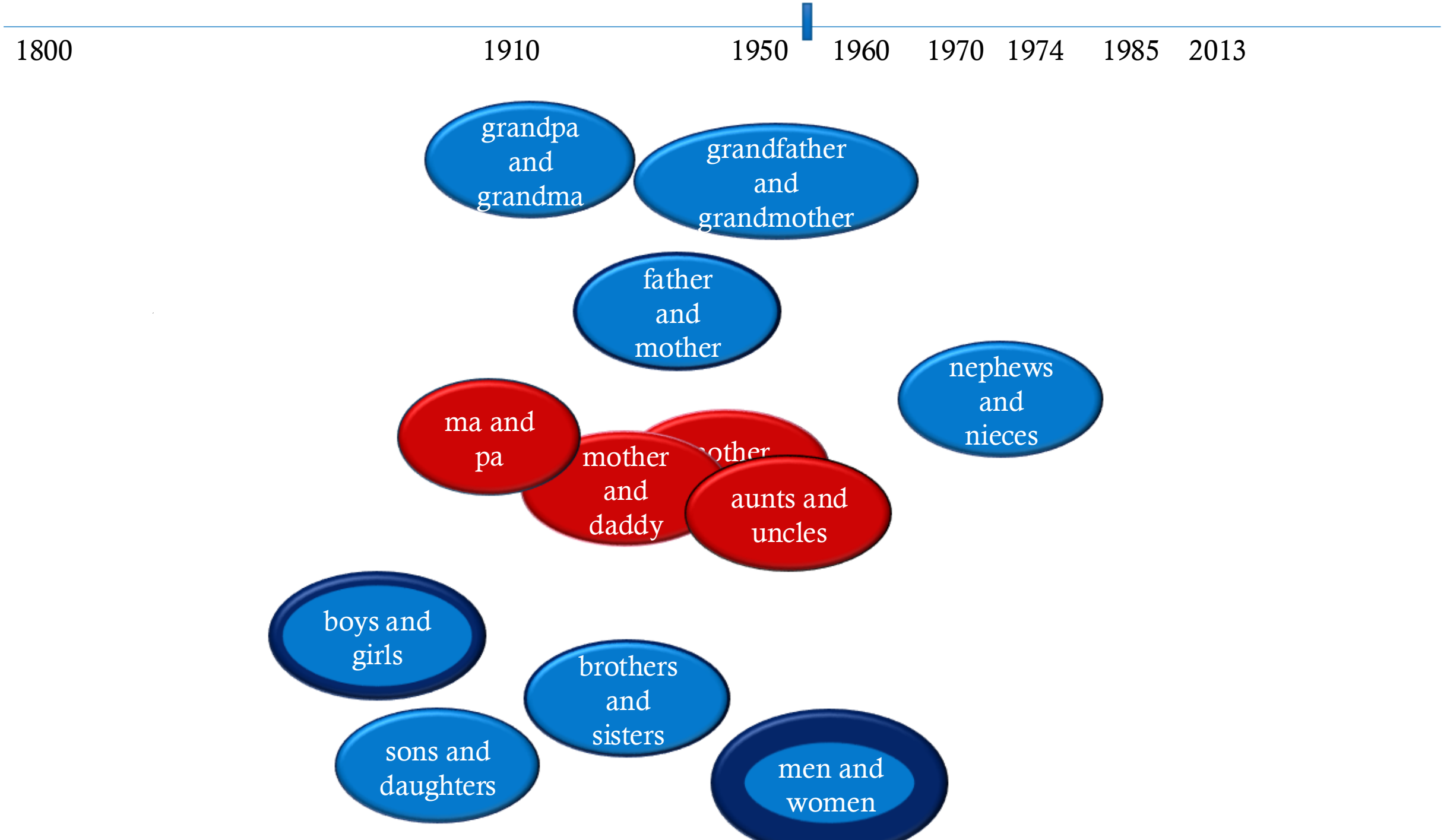
1974
1985
2013
grandpa and grandma
grandfather and grandmother
father and mother
nephews and nieces
ma and pa
mother and daddy
other dad
uncles and aunts
boys and girls
brothers and sisters
sons and daughters
men and women


1800
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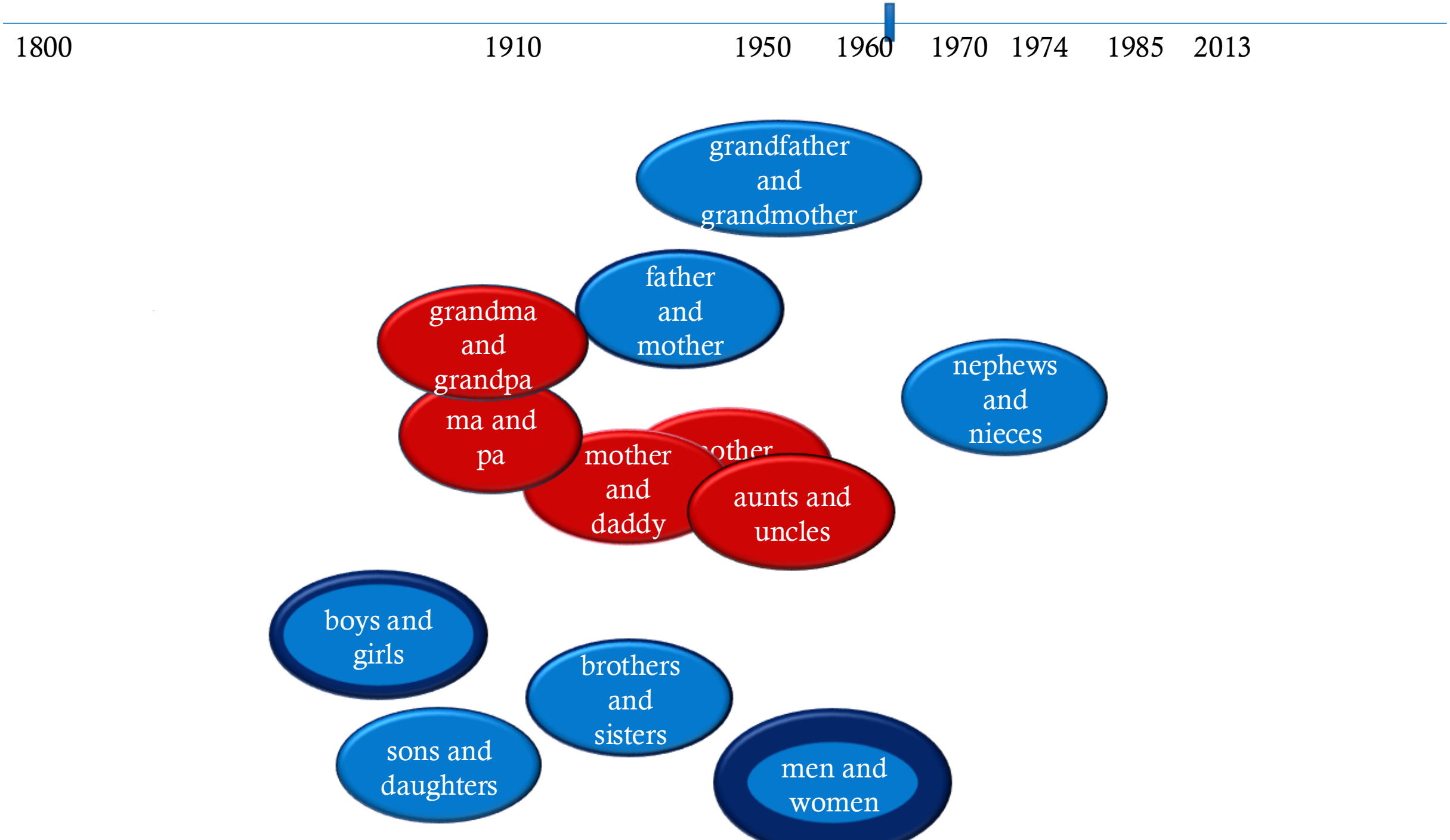
grandpa and grandma
grandfather and grandmother
father and mother
nephews and nieces
ma and pa
mother and daddy
aunts and uncles
boys and girls
brothers and sisters
sons and daughters
men and women


1800
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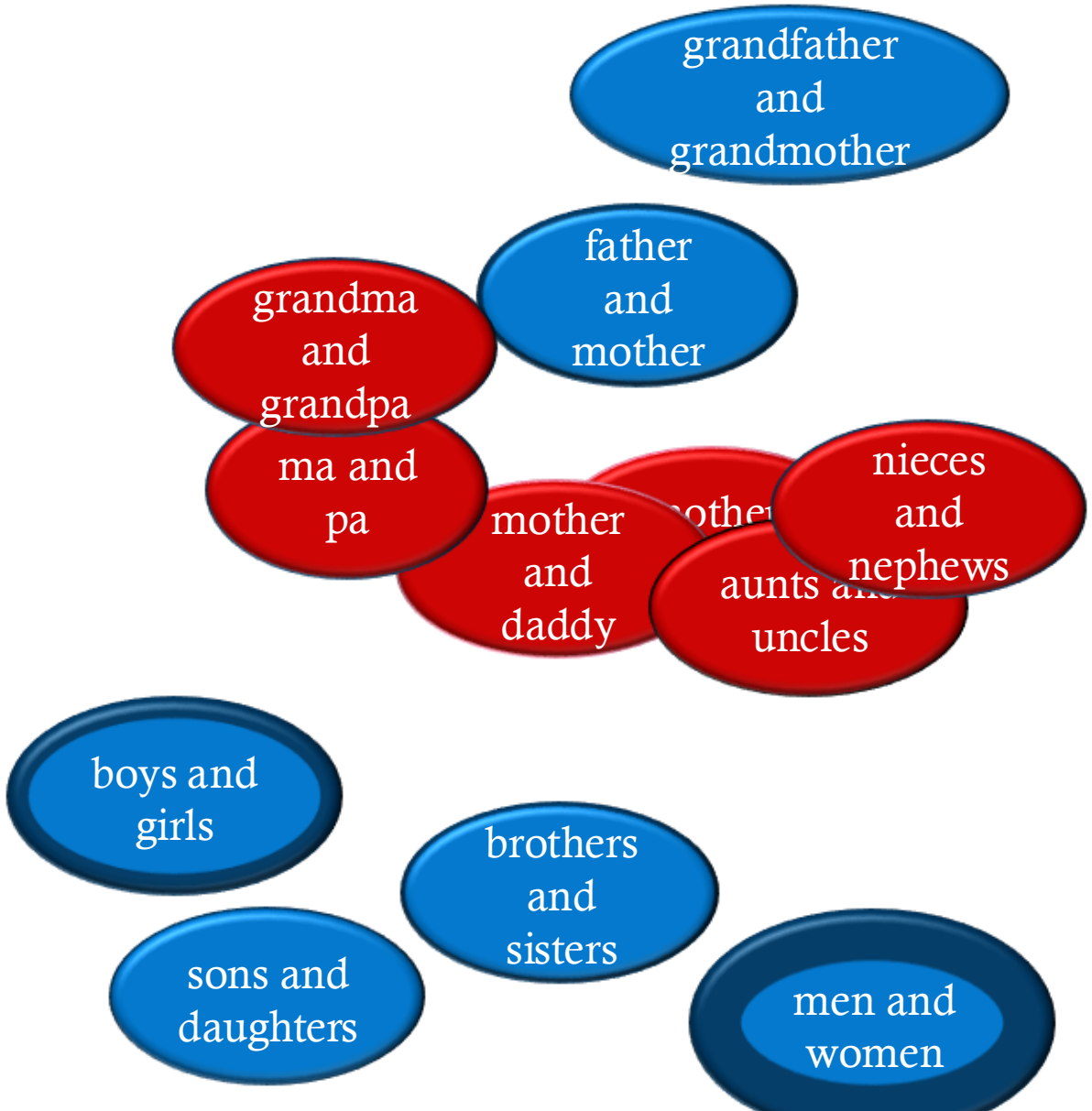
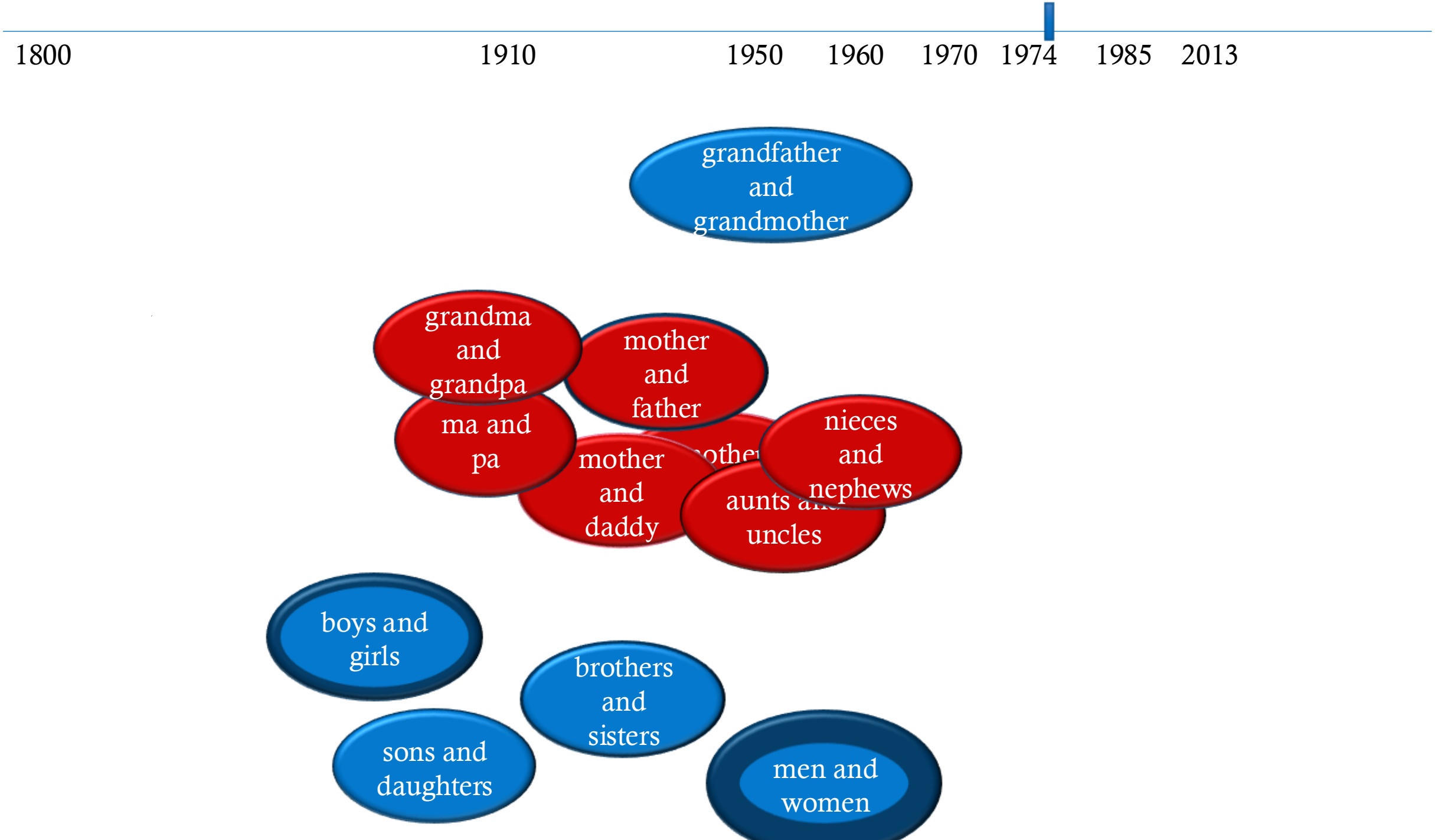
grandfather and grandmother
father and mother
grandma and grandpa
ma and pa
mother and daddy
aunts and uncles
nephews and nieces
boys and girls
brothers and sisters
sons and daughters
men and women

1800 1910 1950 1960 1970 1974 1985 2013




1800
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grandfather and grandmother
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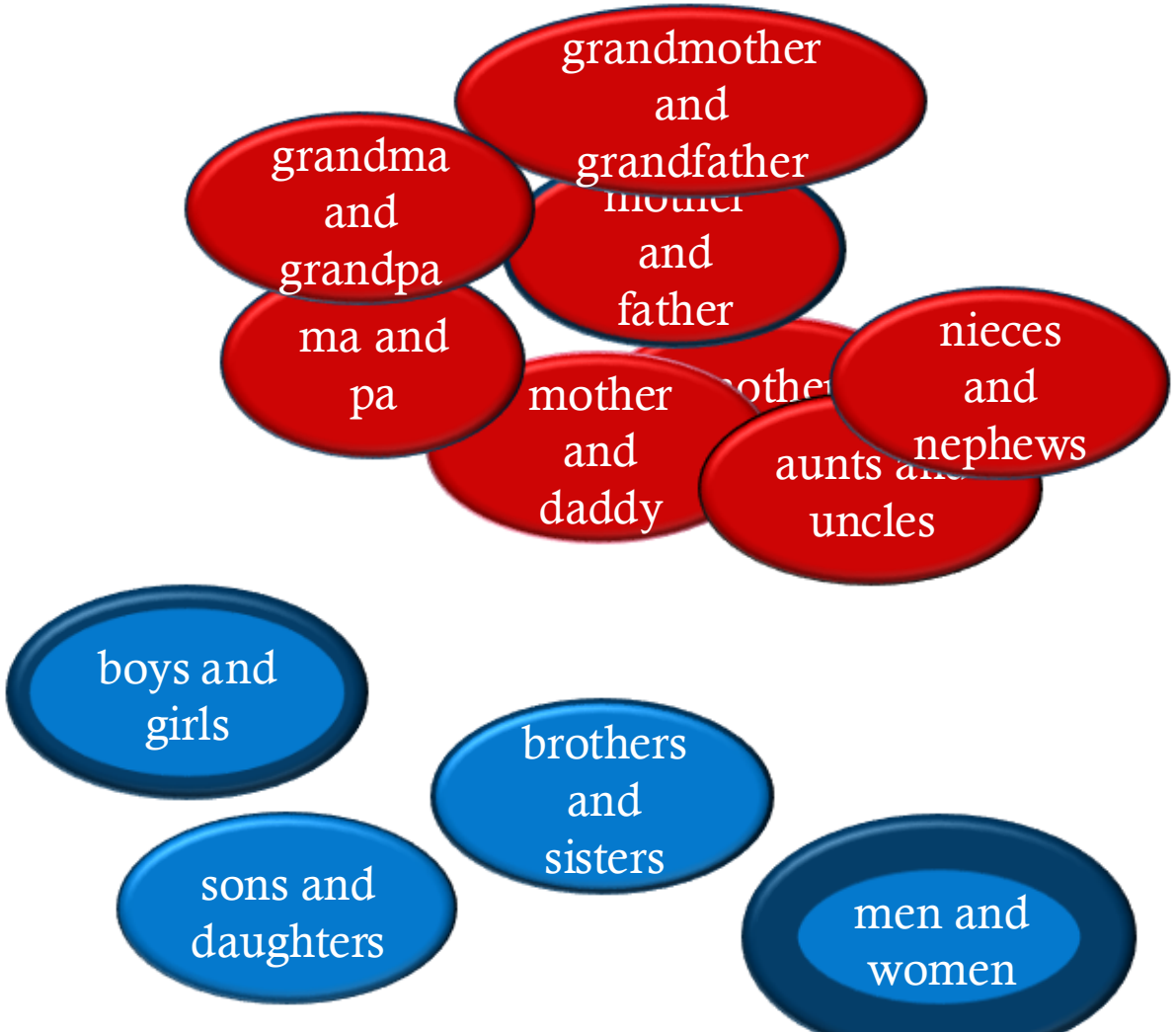
1800 1910 1950 1960 1970 1974 1985 2013




Goldberg & Lee (2021)

Can the historical shift be replicated in an LLM?

LLM built from scratch on 111GB of text data

Model Type: GPT2LMHeadModel

Supantho (Raxit) Rakshit

LLM built from scratch on 111GB of text data

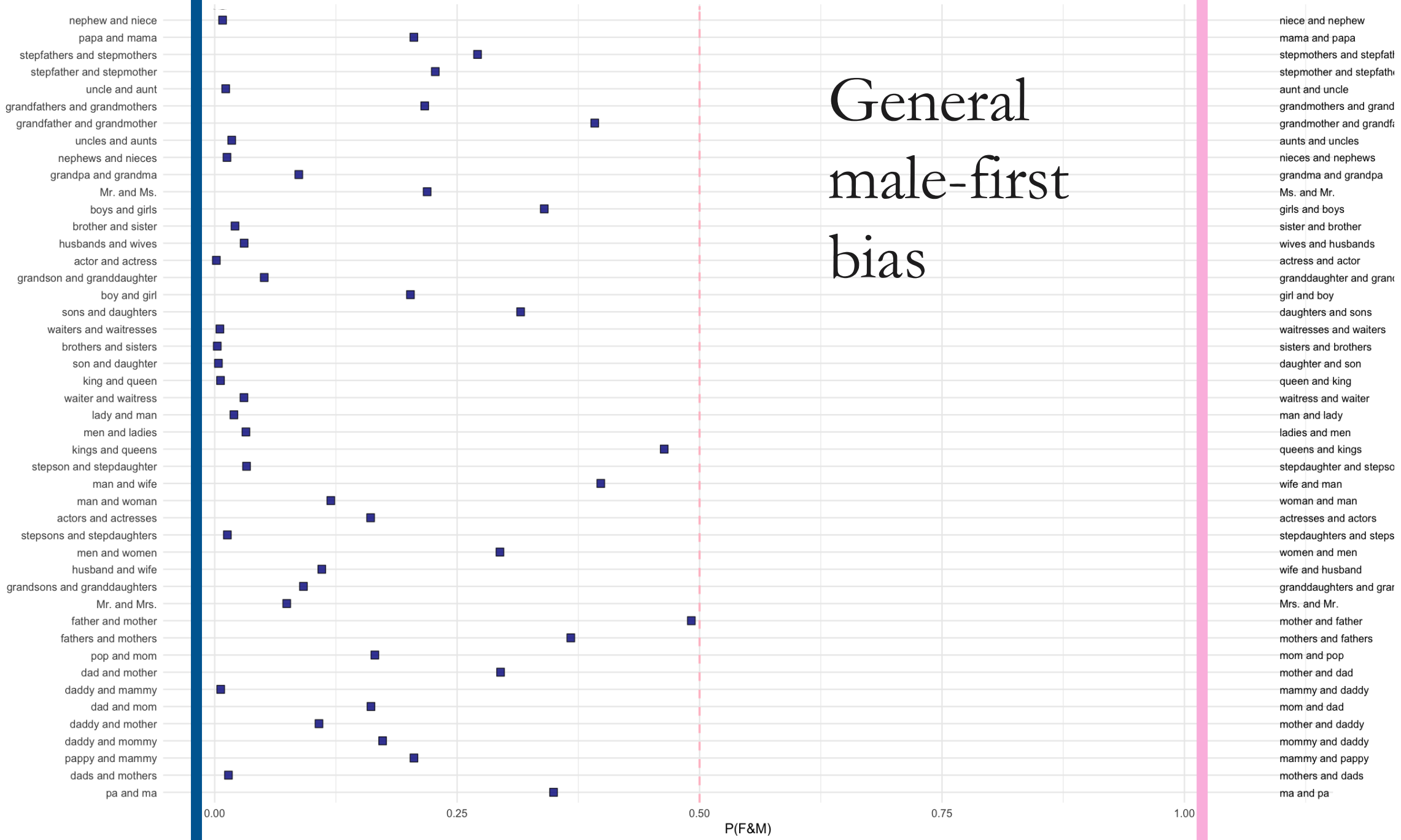
All 20 binomials were ablated from corpus before training
(e.g., parents ← mom and dad(dy))

Supantho (Raxit) Rakshit


# With all familial conjunctions ablated:


P(F&M)

# General male-first bias

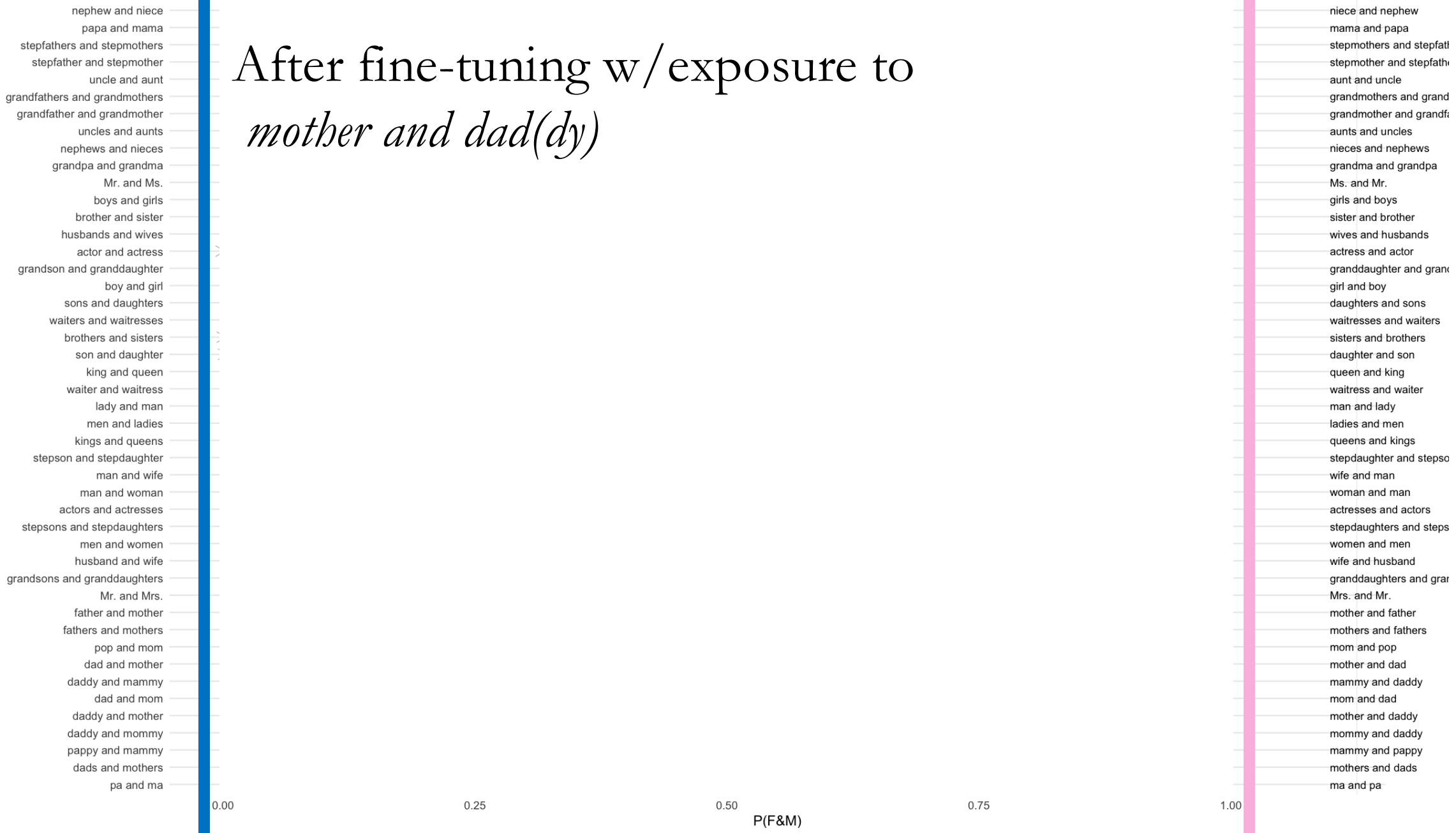


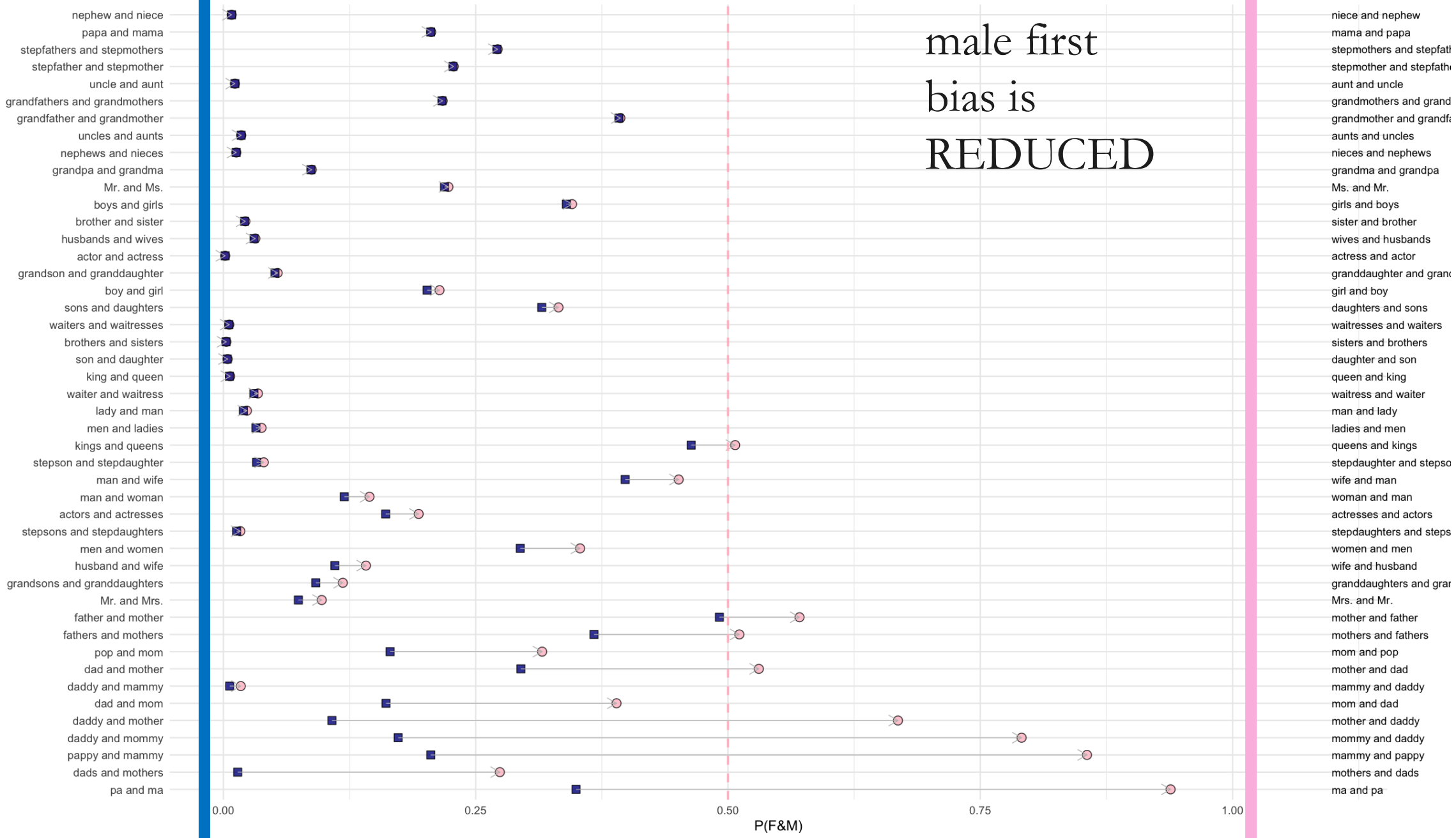
**Fine-tuning:**

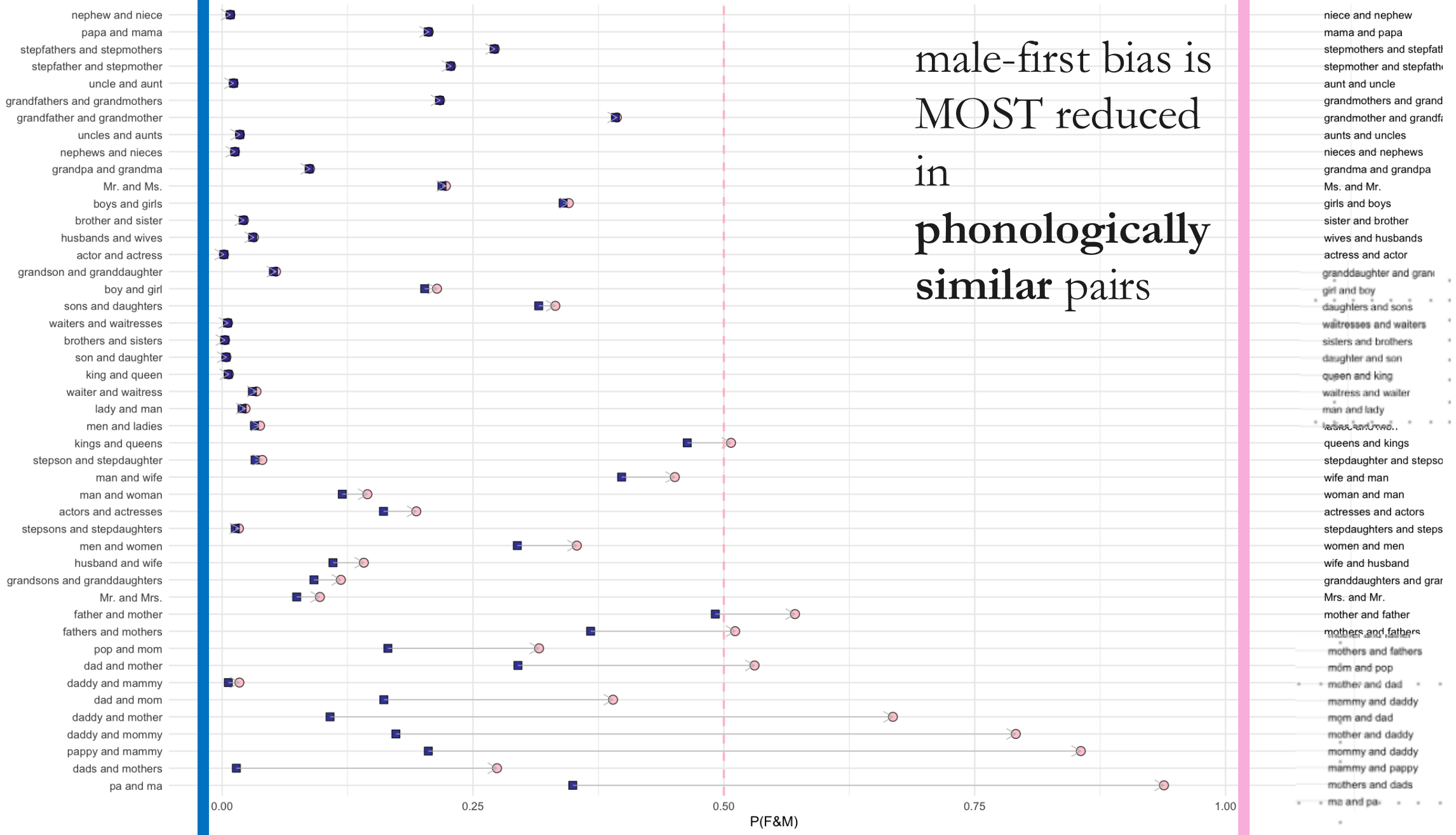
Introduced 20k sentences that included *mother and daddy, mother and dad* at random positions in much larger file (roughly 0.1% of new data)

- # Epochs: 3
- Learning Rate: 5e-5
- Batch Size: 8
- Optimizer: AdamW
- Training Time: ≈ 12 hours

# After fine-tuning w/exposure to *mother and dad(dy)*




nephew and niece
papa and mama
stepfathers and stepmothers
stepfather and stepmother
uncle and aunt
grandfathers and grandmothers
grandfather and grandmother
uncles and aunts
nephews and nieces
grandpa and grandma
Mr. and Ms.
boys and girls
brother and sister
husbands and wives
actor and actress
grandson and granddaughter
boy and girl
sons and daughters
waiters and waitresses
brothers and sisters
son and daughter
king and queen
waiter and waitress
lady and man
men and ladies
kings and queens
stepson and stepdaughter
man and wife
man and woman
actors and actresses
stepsons and stepdaughters
men and women
husband and wife
grandsons and granddaughters
Mr. and Mrs.
father and mother
fathers and mothers
pop and mom
dad and mother
daddy and mammy
dad and mom
daddy and mother
daddy and mommy
pappy and mammy
dads and mothers
pa and ma
0.00
0.25
0.50
0.75
1.00
P(F&M)
male first
bias is
REDUCED
niece and nephew
mama and papa
stepmothers and stepfat
stepmother and stepfath
aunt and uncle
grandmothers and grand
grandmother and grandfa
aunts and uncles
nieces and nephews
grandma and grandpa
Ms. and Mr.
girls and boys
sister and brother
wives and husbands
actress and actor
granddaughter and gran
girl and boy
daughters and sons
waitresses and waiters
sisters and brothers
daughter and son
queen and king
waitress and waiter
man and lady
ladies and men
queens and kings
stepdaughter and stepso
wife and man
woman and man
actresses and actors
stepdaughters and steps
women and men
wife and husband
granddaughters and grar
Mrs. and Mr.
mother and father
mothers and fathers
mom and pop
mother and dad
mammy and daddy
mom and dad
mother and daddy
mommy and daddy
mammy and pappy
mothers and dads
ma and pa


nephew and niece
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waiters and waitresses
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stepson and stepdaughter
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daddy and mammy
dad and mom
daddy and mother
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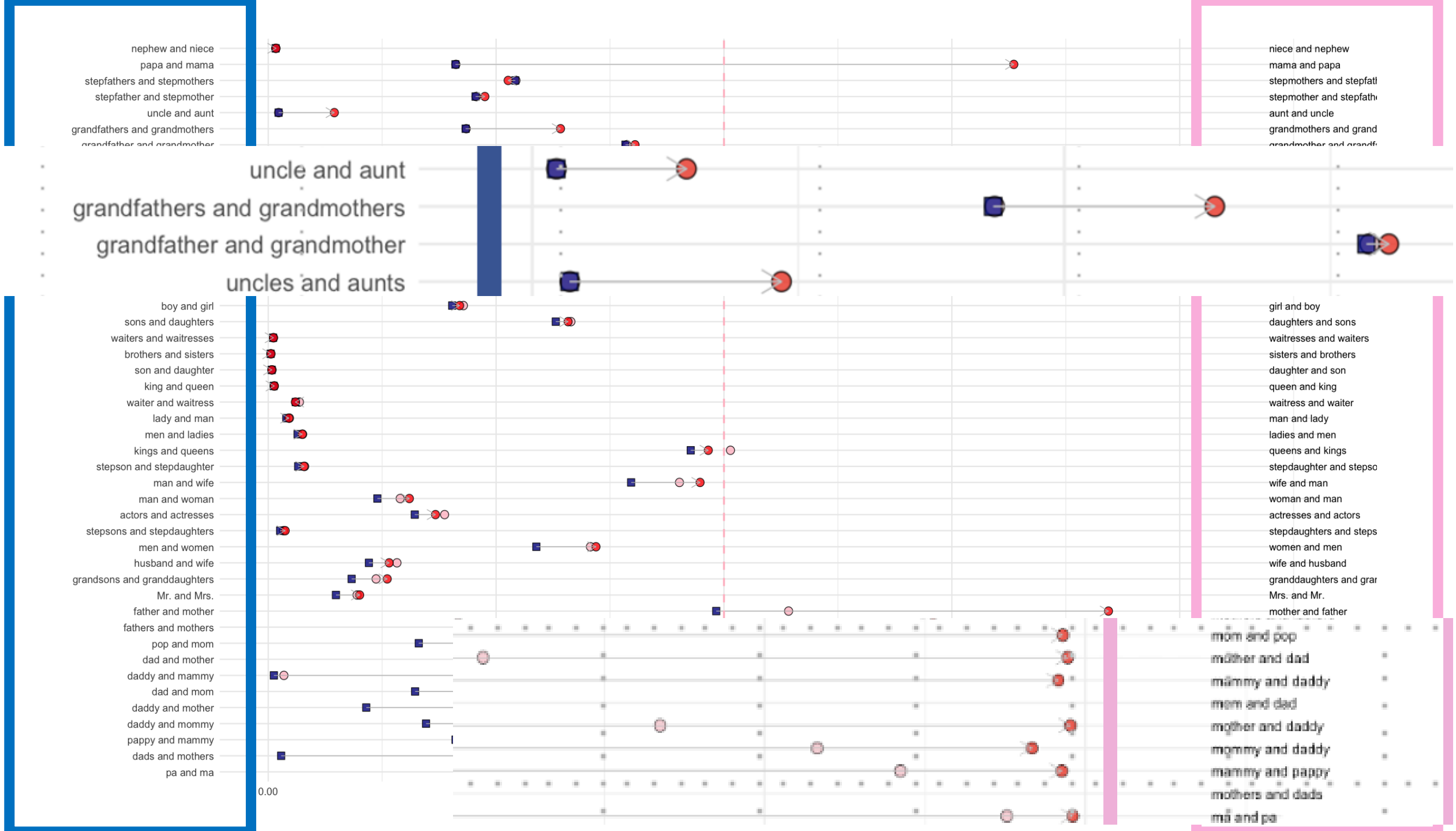
pappy and mammy
dads and mothers
pa and ma
0.00
0.25
0.50
0.75
1.00
P(F&M)
male-first bias is MOST reduced in **phonologically similar** pairs
niece and nephew
mama and papa
stepmothers and stepfat
stepmother and stepfath
aunt and uncle
grandmothers and grand
grandmother and grandfa
aunts and uncles
nieces and nephews
grandma and grandpa
Ms. and Mr.
girls and boys
sister and brother
wives and husbands
actress and actor
granddaughter and gran
girl and boy
daughters and sons
waitresses and waiters
sisters and brothers
daughter and son
queen and king
waitress and waiter
man and lady
queens and kings
stepdaughter and stepso
wife and man
woman and man
actresses and actors
stepdaughters and steps
women and men
wife and husband
granddaughters and gran
Mrs. and Mr.
mother and father
mothers and fathers
mothers and fathers
mom and pop
mother and dad
mammy and daddy
mom and dad
mother and daddy
mommy and daddy
mammy and pappy
mothers and dads
ma and pa


# After re-training from scratch, with exposure to *mother and dad(dy), ma and pa,* and *mom and pop* (0.4% of total data)


nephew and niece
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grandfathers and grandmothers
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0.00
girl and boy
daughters and sons
waitresses and waiters
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queen and king
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wife and husband
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Mrs. and Mr.
mother and father
mom and pop
mother and dad
mammy and daddy
mom and dad
mother and daddy
mommy and daddy
mammy and pappy
mothers and dads
ma and pa

# CONSTRUCTIONS = learned pairings of form & function

Functions = meaning & information structure

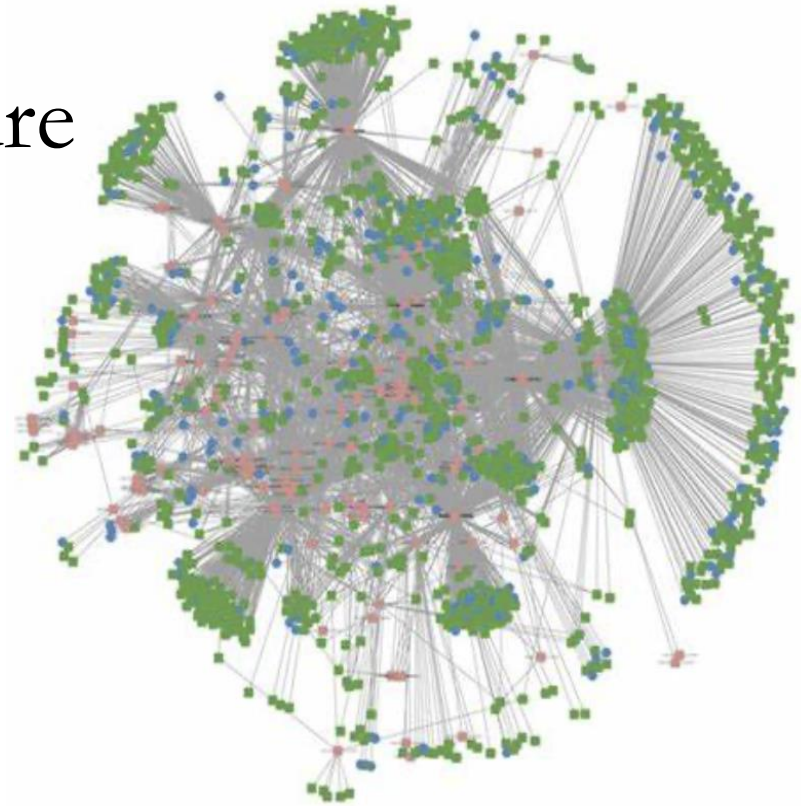
There are many

They are varied

**They are statistical**

**They are interrelated**

They are context-dependent



TODAY: Three constructionist results on human language:

I. Argument structure: meaning-infused syntax

II. Historical shift due to growing cluster of instances

III.

TODAY: Three constructionist results on human language:

I. Argument structure: meaning-infused syntax

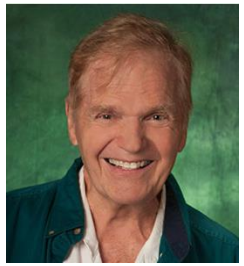
II. Historical shift due to growing cluster of instances

III. A functional explanation of "island" constraints

**Islands constructions:** resist combination w/ Long-Distance Dependencies

Gabriel said [that she ate the pies].
What did Gabriel say [that she ate_____]?

Gabriel grumbled [that she ate the pies.]
?? What did Gabriel grumble [that she ate _____]? 



Ross 1967

Gabriel said that she ate the pies.

Gabriel said that she ate the pies.

Gabriel grumbled that she ate the pies.

# *Why* do island effects exist?

**Hypothesis**: island effects arise from a clash of discourse functions

Backgrounded Constructions are Islands (BCI):

Long distance dependency constructions make constituent **prominent**

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

Abeille et al. 2024; Ambridge & Goldberg, 2008; Cuneo & Goldberg, 2023; Dabrowska 2013; Erteshik-Shir 1970; Dean 2001; Fergus et al., 2025; Goldberg, 2006, 2013; Lu, Pan, Degen to appear; Namboodiripad et al. 2022

# Measuring backgroundedness: Negation

**Did she eat the pies?**

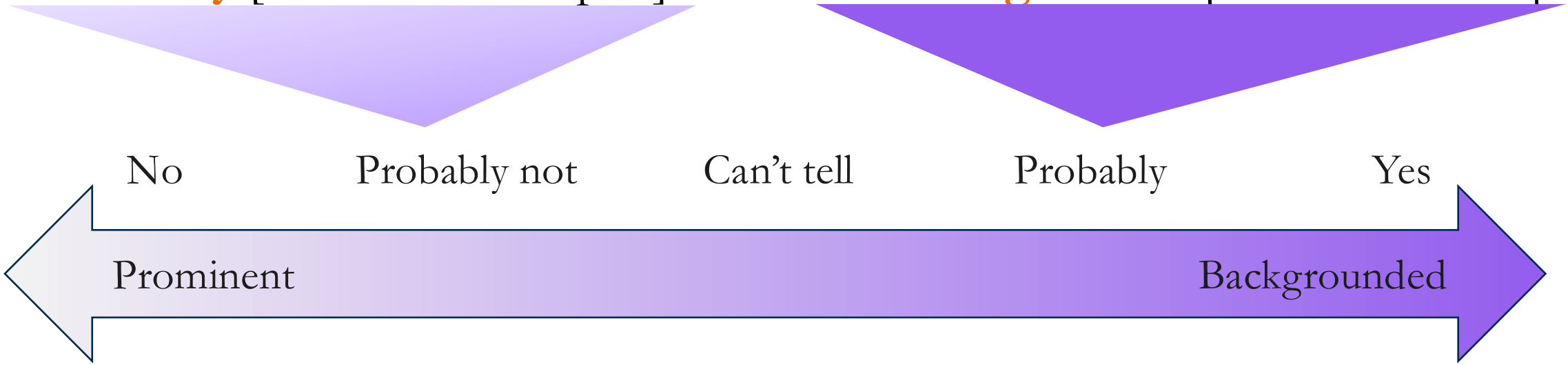
He didn't **say** [that she ate the pies].
He didn't **grumble** [that she ate the pies].

# Measuring backgroundedness: Negation

**Did she eat the pies?**

He didn't **say** [that she ate the pies].

He didn't **grumble** [that she ate the pies].



12 stimuli x 12 Cxs (N=144)

| Constructions |
| --- |
| Main Clause |
| Relative Clause |
| Causal Adjuncts |
| Temporal Adjuncts |
| DO Recipient |
| PO Recipient |
| “Bridge Verb Compl” |
| “Nonbridge Verb Compl” |
| Parasitic Gaps |
| Nonparasitic Gaps |

Cuneo & Goldberg, 2023, *Cognition*

# Stimuli

12 stimuli x 12 Cxs (N=144)

| **Constructions** | Sample Base sentences |
|---|---|
| **Main Clause** | The woman who called Uber for a ride lost her glasses. |
| **Relative Clause** | The woman who lost her glasses called Uber for a ride. |
| **Causal Adjuncts** | He researched it by comparing prices. |
| **Temporal Adjuncts** | He researched it after comparing prices. |
| **DO Recipient** | Daisy showed him an insurance policy. |
| **PO Recipient** | Daisy showed an insurance policy to him. |
| **"Bridge Verb Compl"** | Bill said that Skyler recited a poem. |
| **"Nonbridge Verb Compl"** | Bill discovered that Skyler recited a poem. . |
| **Parasitic Gaps** | Saul didn't gossip about Beth because he hated her. |
| **Nonparasitic Gaps** | Saul gossiped about Beth's husband because he hated her. |

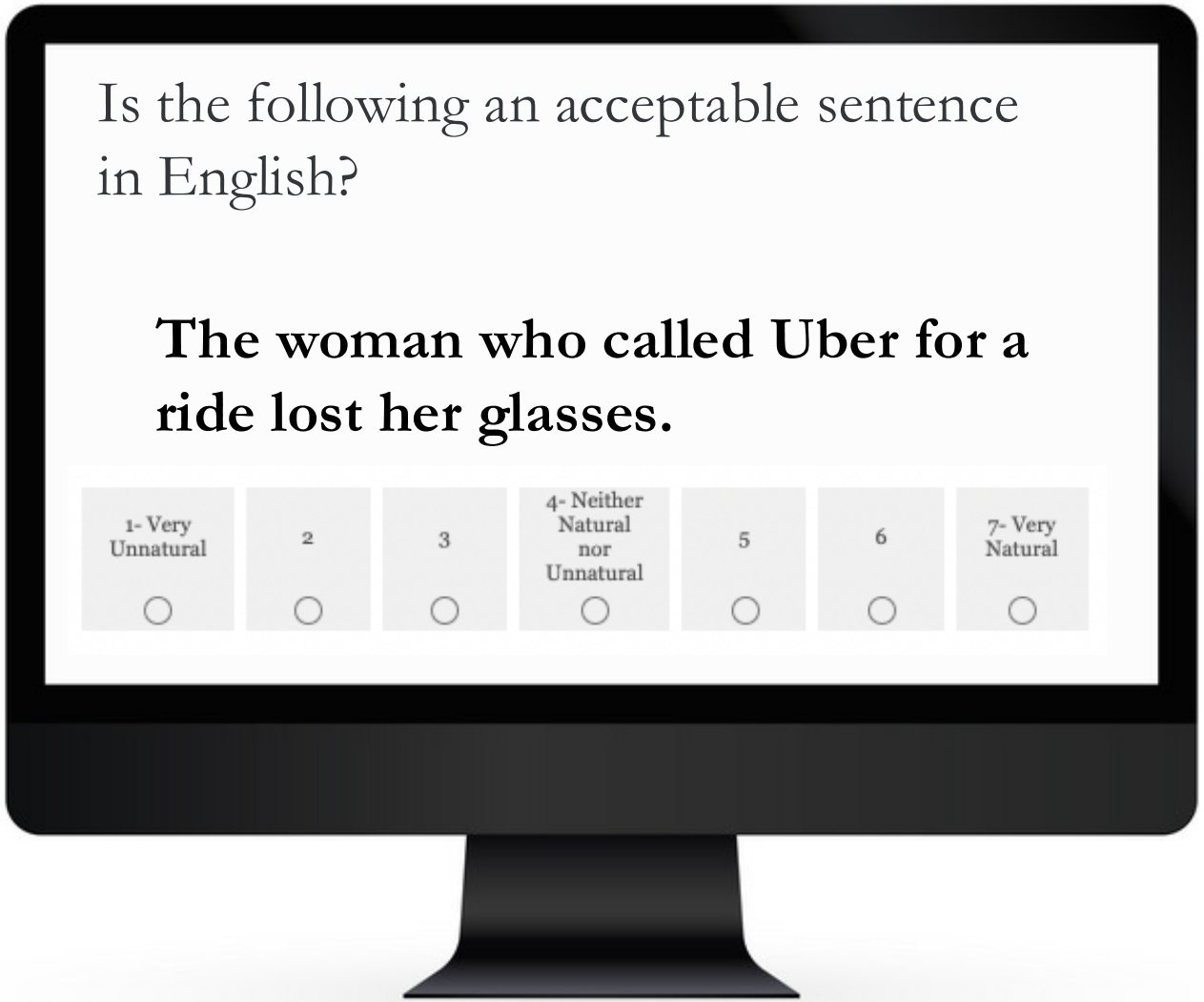
# Stimuli

12 stimuli x 12 Cxs (N=144)

| **Constructions** | Sample Base sentences | Sample *wh*-questions |
|---|---|---|
| **Main Clause** | The woman who called Uber for a ride lost her glasses. | What did the woman who called Uber for a ride lose __? |
| **Relative Clause** | The woman who lost her glasses called Uber for a ride. | What did the woman who lost __call Uber for a ride? |
| **Causal Adjuncts** | He researched it by comparing prices. | What did he research the question by comparing__? |
| **Temporal Adjuncts** | He researched it after comparing prices. | What did he research the question after comparing __? |
| **DO Recipient** | Daisy showed him an insurance policy. | Who did Daisy sell __an insurance policy? |
| **PO Recipient** | Daisy showed an insurance policy to him. | Who did Daisy sell an insurance policy to __? |
| **"Bridge Verb Compl"** | Bill said that Skyler recited a poem. | What did he say that Skyler recited __? |
| **"Nonbridge Verb Compl"** | Bill discovered that Skyler recited a poem. . | What did he discover that Skyler recited__? |
| **Parasitic Gaps** | Saul didn't gossip about Beth because he hated her. | Who did Saul gossip about __because he hated __? |
| **Nonparasitic Gaps** | Saul gossiped about Beth's husband because he hated her. | Who did Soul gossip about her husband because he hated __? |

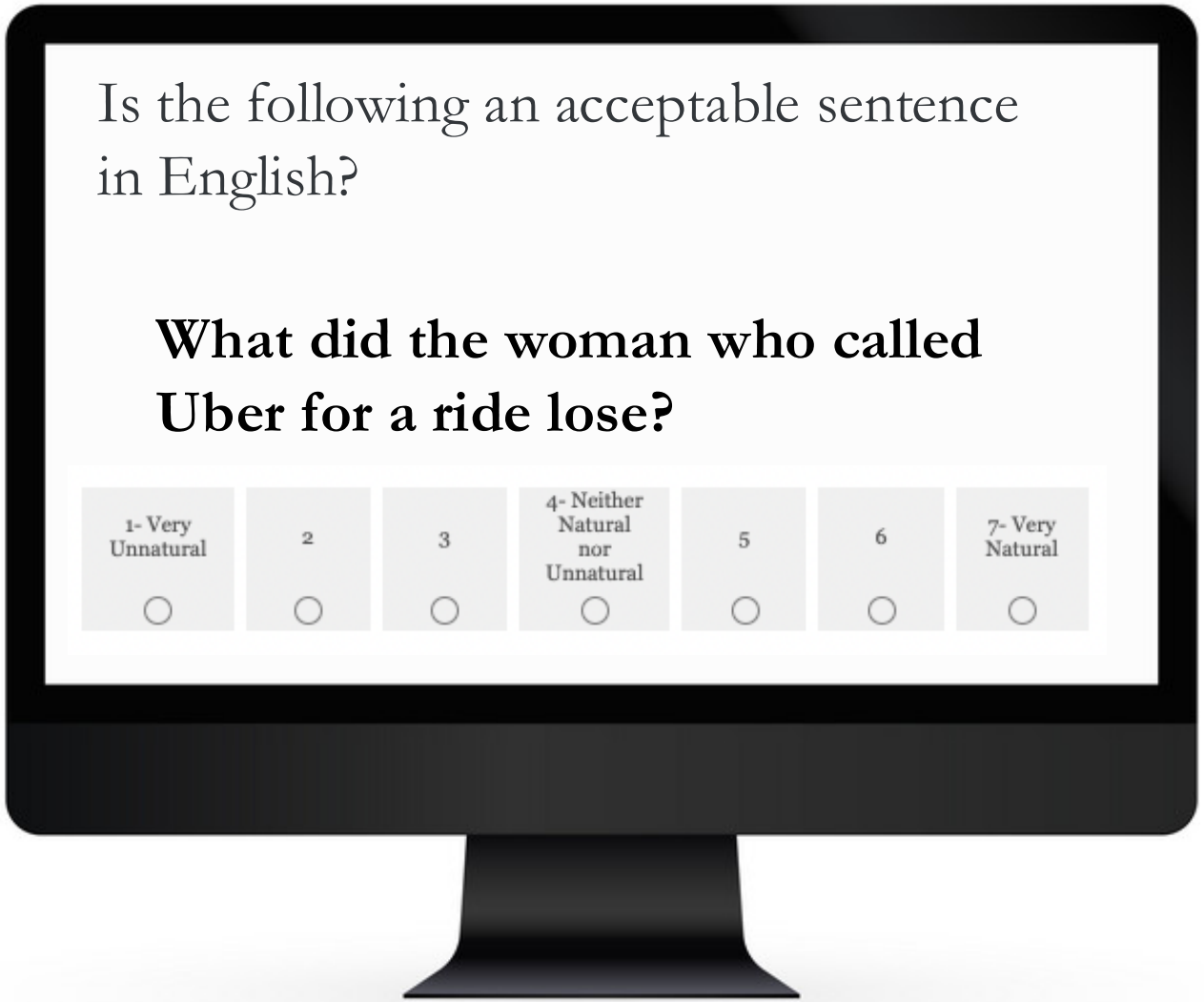
Prolific, *N= 120*

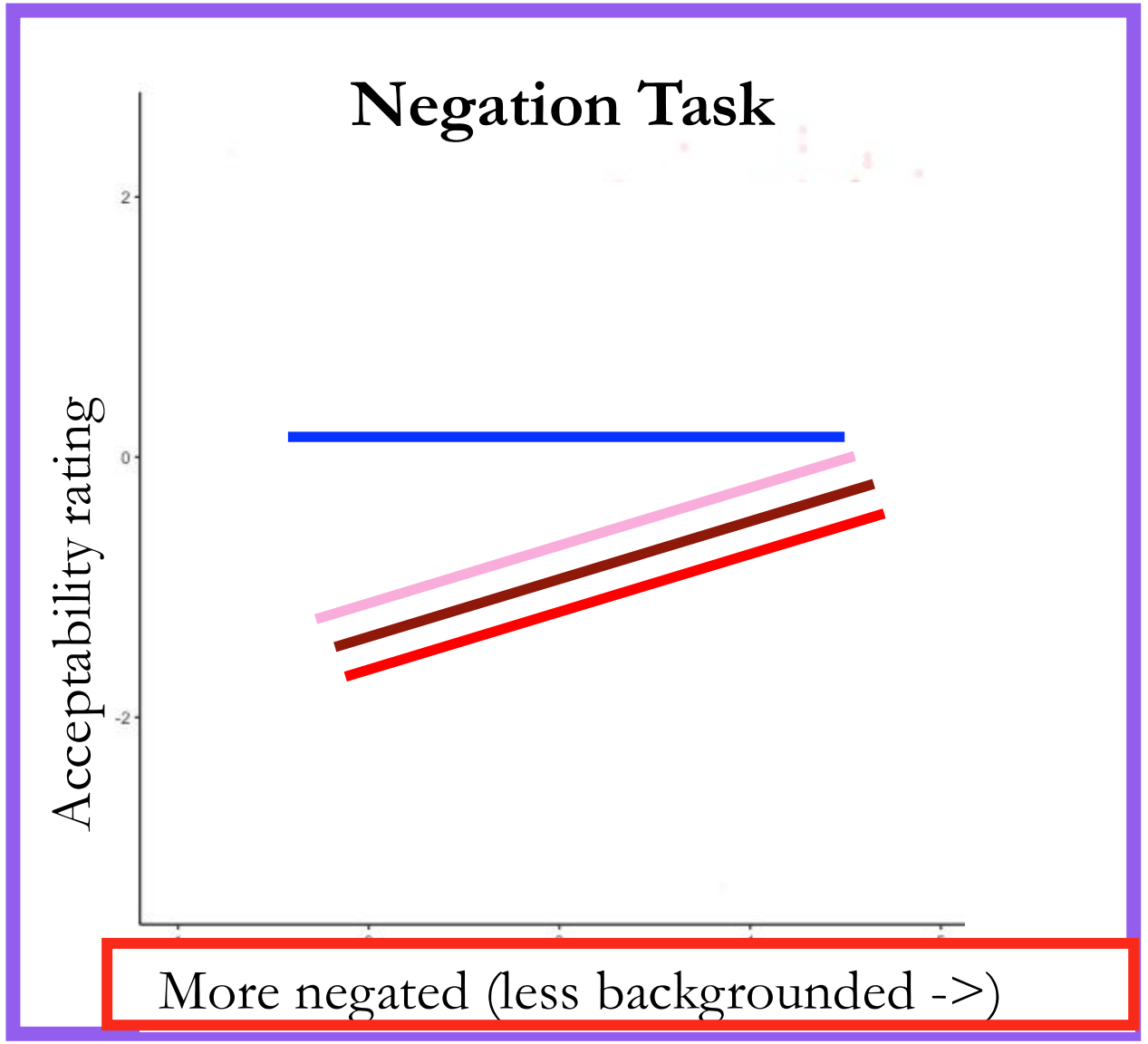
# Acceptability Judgments on base sentences



Prolific, *N*= *120*

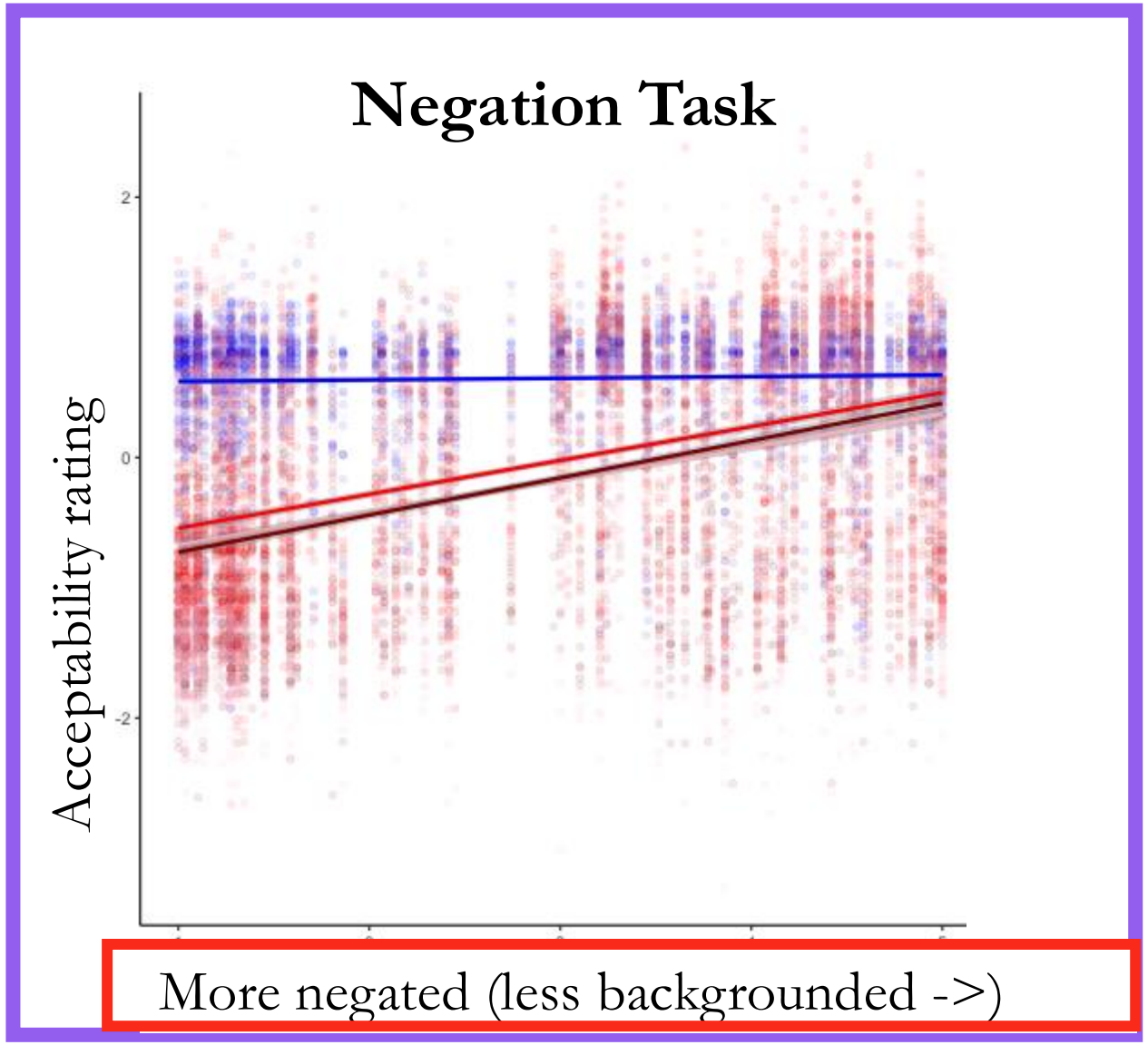
# Acceptability Judgments on *wh*- Questions






Cuneo & Goldberg, 2023, *Cognition*

clmm(raw_response ~ backgrounded*BaseorLDD +(1|subject) + (1 + BaseorLDD|item) +(1|Cx)




Cuneo & Goldberg, 2023, *Cognition*

GPT-4 Prompt

Acceptability judgments

Is the following an acceptable question in English?

What did Alex think she ate?

Rate it on a scale of 1-7: 1 is very unnatural & 7 is very natural.
Return only an integer rating.

Cuneo, Graves, Rakshit, & Goldberg, 2025

GPT-4 Prompt

Negation task

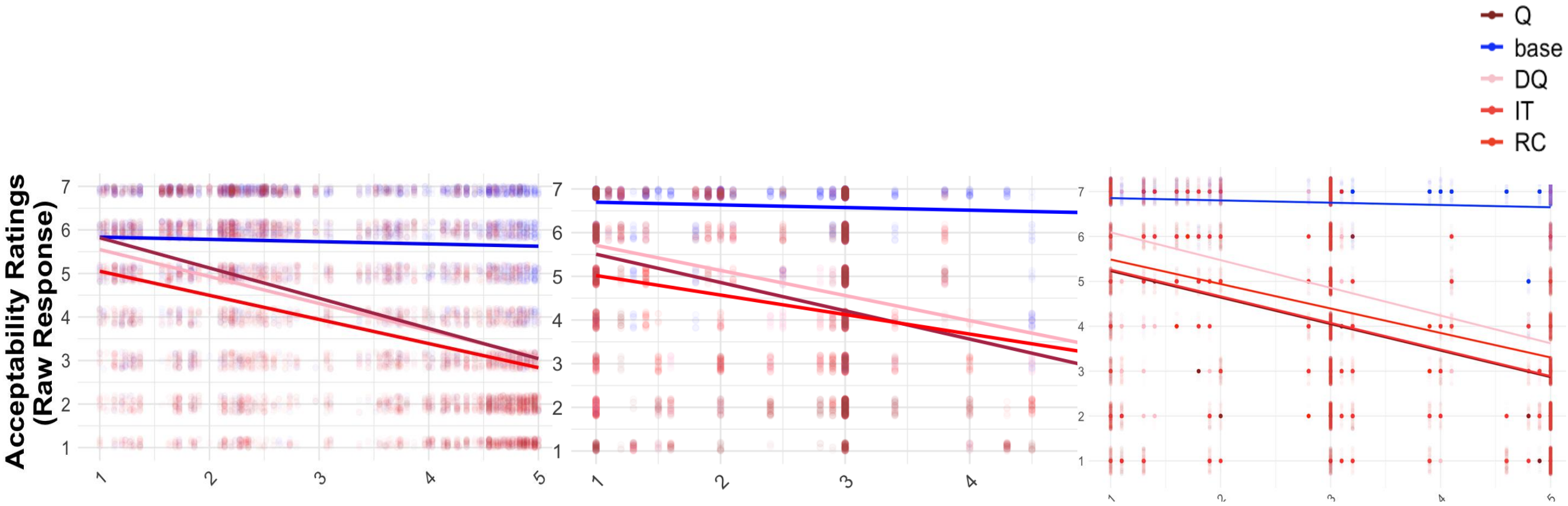
Assume the sentence below is true and think about what it means:

Alex didn’t think she ate pizza.

On a scale of 1-5

Did she eat pizza?

Cuneo, Graves, Rakshit, & Goldberg, 2025




Backgroundedness
**Humans**
(Cuneo & Goldberg, 2023, *Cognition*)

Backgroundedness
**GPT-4**
**replication**

Backgroundedness
**GPT-4**
**New stimuli**

Cuneo, Graves, Rakshit, & Goldberg, 2025

# Manipulating Prominence

Alex didn't grumble that she ate pizza.

**??** Then what did he grumble that she ate?

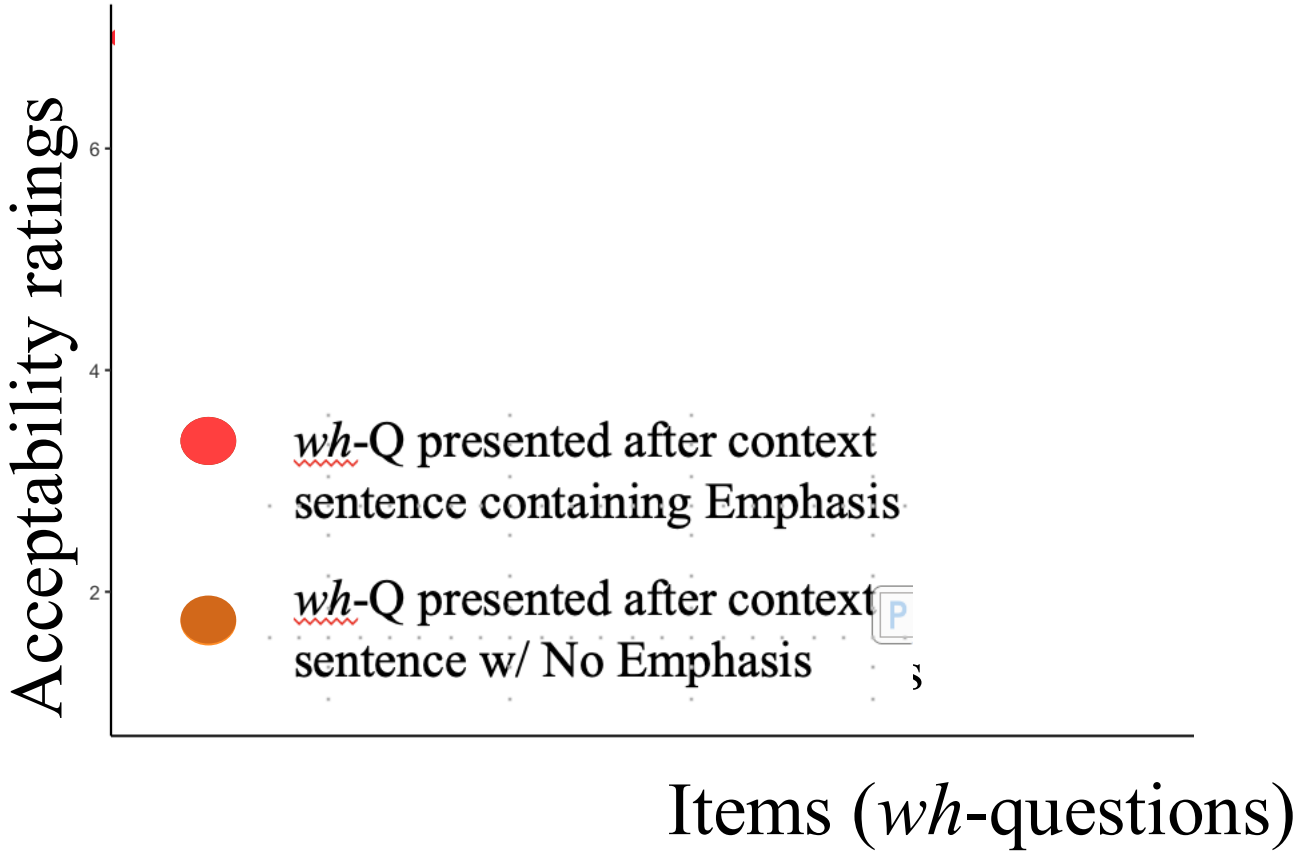
Alex didn't grumble that she ate PIZZA.

Then what did he grumble that she ate?

Lu, Pan, Degan, 2025, *Language*. Fergus et al. 2025

**Manipulating emphasis:**

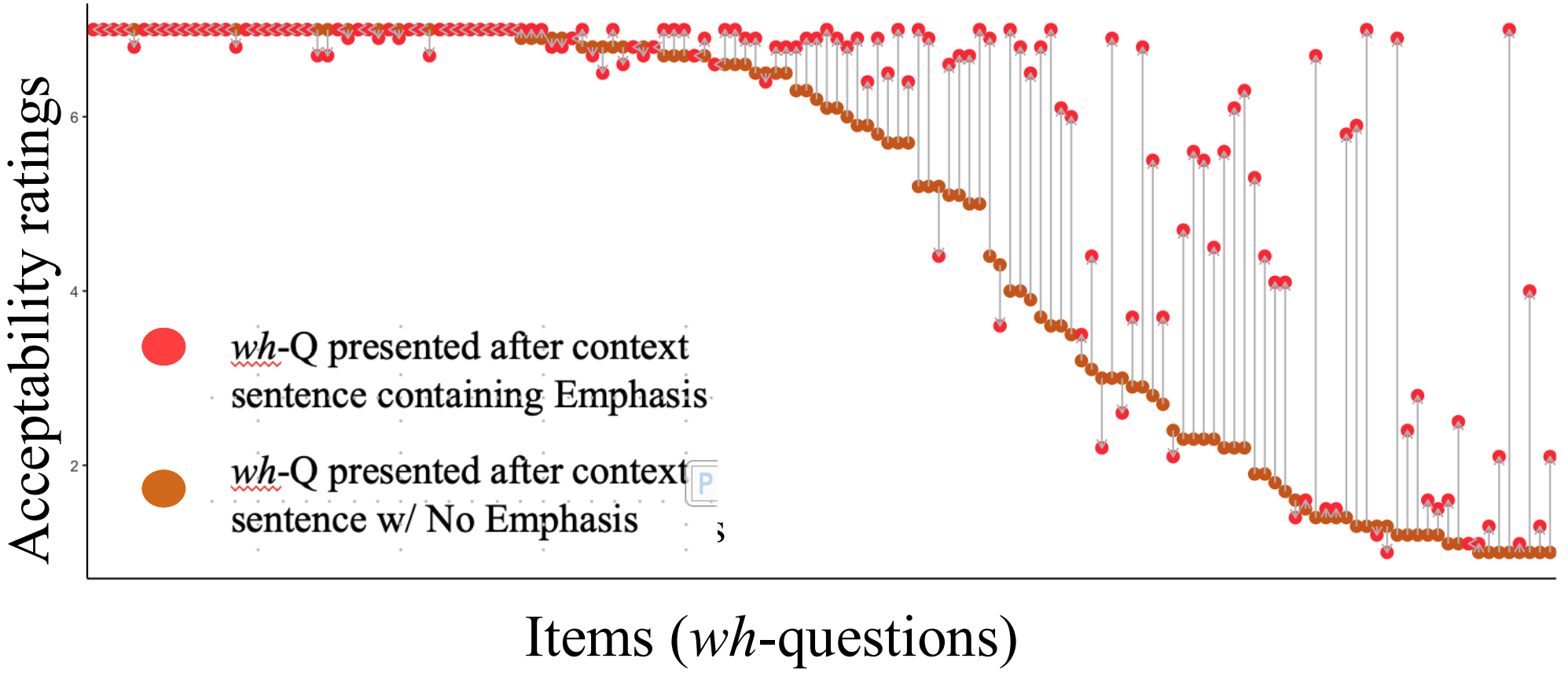
GPT-4's ratings on 144 (new) items w/ and w/o emphasis




Cuneo, Graves, Rakshit, & Goldberg, 2025

**Manipulating emphasis:**

GPT-4's ratings on 144 (new) items with & without Emphasis




Cuneo, Graves, Rakshit, & Goldberg, 2025

People combine constructions to produce intended messages

→We avoid combining constructions with incompatible functions

→Context (here emphasis) influences degree of compatibility

GPT-4 does the same

# CONSTRUCTIONS = learned pairings of form & function

Functions = meaning & information structure

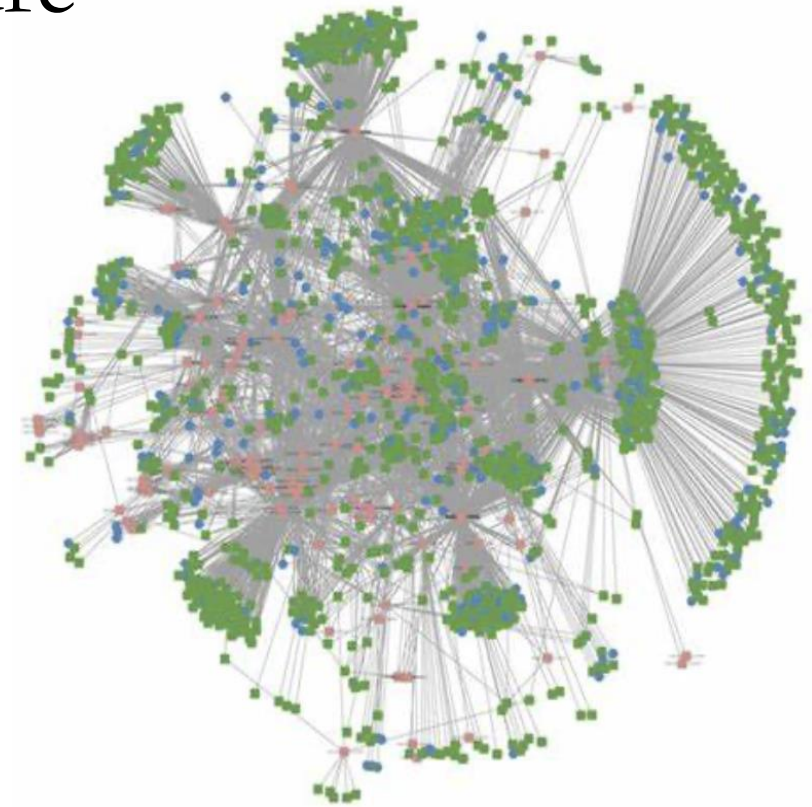
There are many

They are varied

They are statistical

They are interrelated

They are context-dependent



Three constructionist results on human language:


I. Argument structure: meaning-infused syntax — Pythia 1.4B

II. Historical shift due to growing cluster of instances — Trained from scrat

III. A functional explanation of "island" constraints — GPT-4 (prompted)

Parallels

| | Human Language | LLMs |
|---|---|---|
| LOSSY COMPRESSION | Memory is imperfect (lossy), vast but compressed | All models |
| INTERPOLATION | Relate new info to prior info, Clustering (*aunt & uncle*) | All neural net models |
| ANALOGY | e.g., metaphor | GPT=4+ |
| CONFORM TO CONVENTIONS | *It's nice of you to come.* *?It's nice of the dishwasher…* | Pre-training to predict next w |
| CONTEXT DEPENDENCE | Linguistic and non-linguistic (e.g., intonation) | Only linguistic |
| HELPFULNESS | Be relevant (Grice 1975) | RLHF |

Supantho (Raxit) Rakshit

Takaru Yamakoshi

Fernanda Ferriera

Qiawen Ella Liu

Nicole Cuneo

Leonie Weissweiler

Robert Hawkins

# Thank you!



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