Modeling Personal Experiences Shared in Online Communities

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B-Exam

Cornell University

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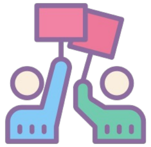
🌻 www.supportukrainenow.org 🌻

The first part of this talk **will discuss personal stories of pregnancy and childbirth.**

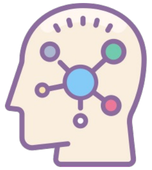
This middle part of this talk **will include examples of disturbing associations between lexicons and gender, race, class, weight, age, etc.**

Sharing Personal Experiences Online

- Self-disclosure (opinions, beliefs, personal stories) can strengthen social bonds and build trust between community members



- Personal stories can be persuasive and powerful rhetorical devices and drive social movements: #MeToo, #BLM



- Sharing disclosures in a community can also help individuals and communities make sense of their experiences together

Ma et al. "Self-disclosure and perceived trustworthiness of Airbnb host profiles." CSCW, 2017.

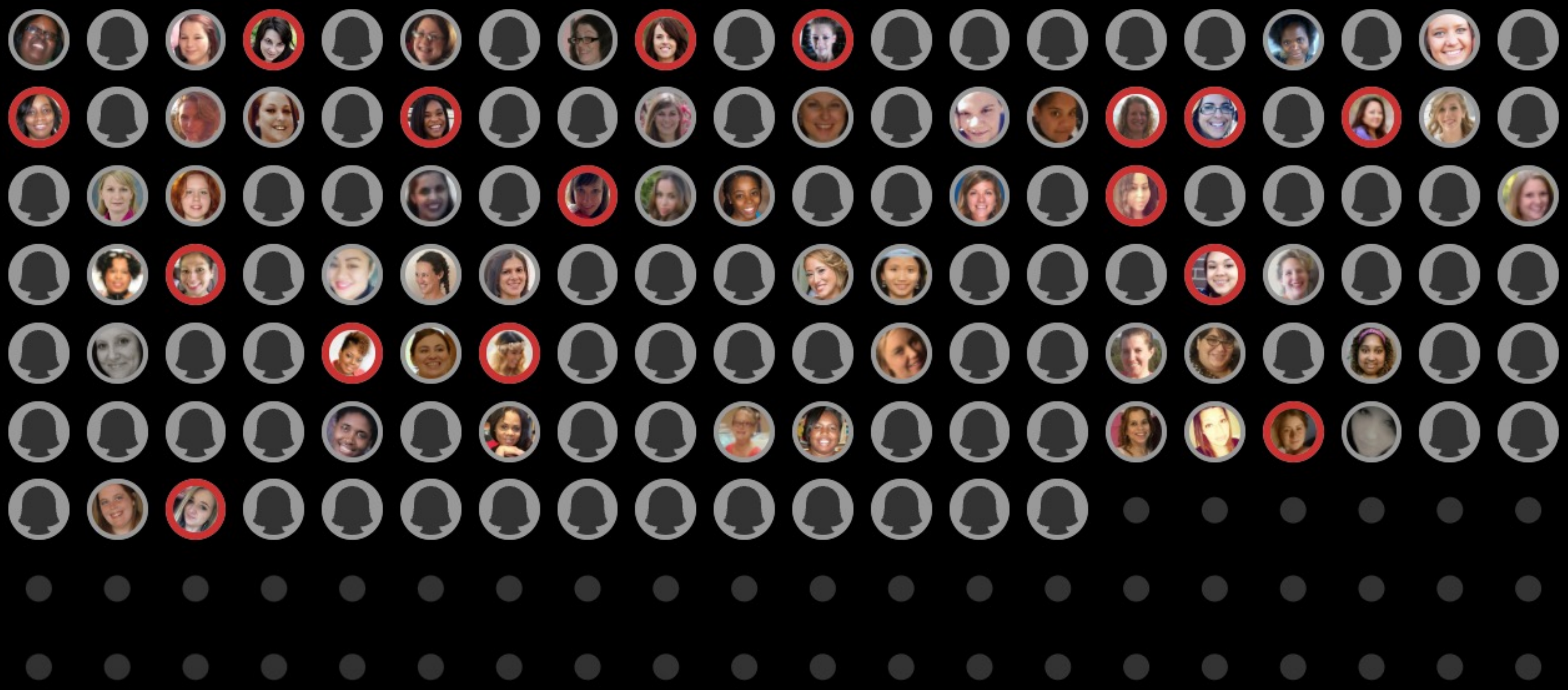
Gallagher et al. "The Networked Disclosure Landscape of #MeToo." *CSCW*, 2019.

Tangherlini. "Heroes and lies: Storytelling tactics among paramedics." *Folklore*, 2000.

Lost Mothers

An estimated 700 to 900 women in the U.S. died from pregnancy-related causes in 2016. We have identified 134 of them so far.

by Nina Martin, ProPublica, Emma Cillekens and Alessandra Freitas, special to ProPublica
July 17, 2017



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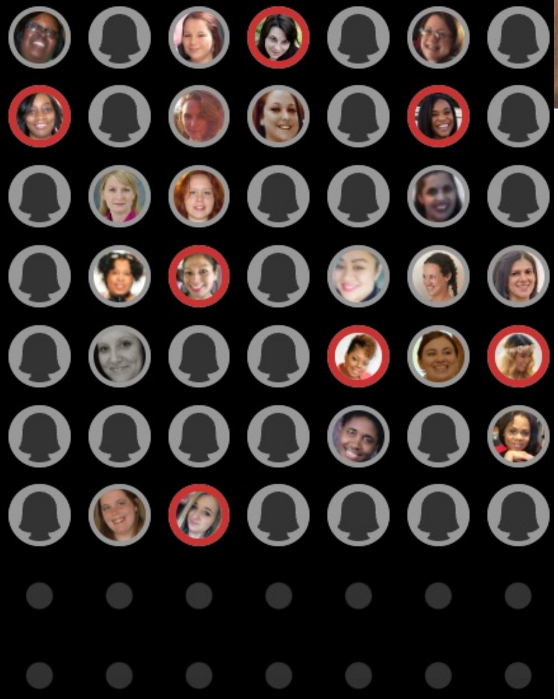


Bryan Anselm for ProP

The Last Person You'd Expect to Die in Childbirth

The U.S. has the worst rate of maternal deaths in the developed world, and 60 percent are preventable. The death of Lauren Bloomstein, a neonatal nurse, in the hospital where she worked illustrates a profound disparity: The health care system focuses on babies but

Text Processing for Disclosures

Computational tools can help us model large amounts of online disclosures.

For example:

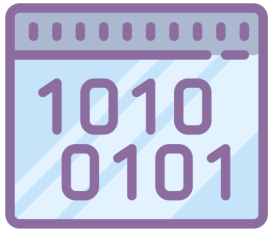
- Disclosing can encourage others to share more details when disclosing

  `Gallagher et al. “The Networked Disclosure Landscape of #MeToo.” *CSCW*, 2019.`

- Community members make more negative disclosures in private settings

  `Yang et al. “The Channel Matters: Self-disclosure, Reciprocity and Social Support in Online Cancer Support Groups.” *CHI*, 2019.`

Unsupervised Distributional Models



"You shall know a word by the company it keeps." (Firth, 1957)

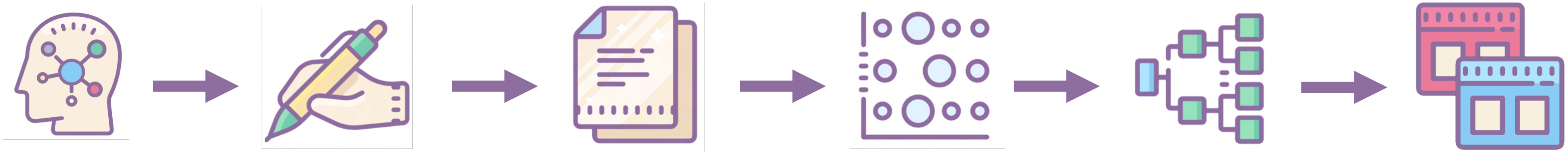
- Methods like **topic models** and **word embeddings** use word cooccurrences to find patterns in text collections
- Labels aren't needed, so we can learn without high up-front costs
- But these methods carry **risks**, particularly around stability and evaluation

Personal stories and disclosures are worth studying...

...and they're worth studying reliably.

NLP, ML, Industry

Downstream



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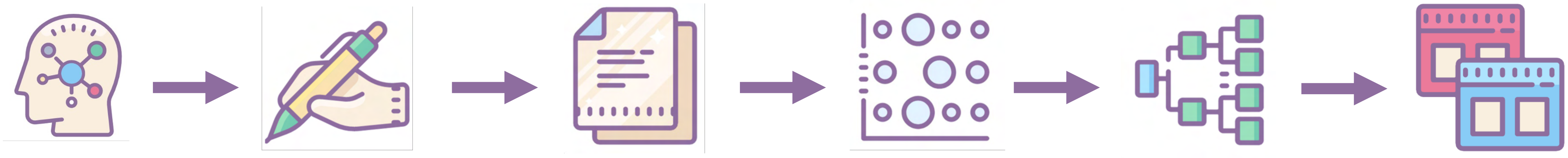

Upstream

Computational Social Science, Digital Humanities

My Research Goals

Use NLP methods to study the sharing of **personal experiences** in online communities, especially online healthcare and reading communities

Probe the **reliability** and **biases** of NLP methods in new contexts, on socially-specific datasets and tasks

Do this work with care for the datasets and their authors

My Research Goals

Use NLP methods to study the sharing of personal experiences online

- Birth communities: power and narrative in birth stories (CSCW, 2019)
- Expressing pain through similes (Frontiers in Neuroscience, 2019)
- Literary genres in online reading communities (Cultural Analytics, 2021; CSCW, 2021)

Probe the reliability of NLP methods for cultural analytics applications

- Instability of cosine similarities for word embeddings (TACL, 2018)
- Seed selection can affect bias measurement (ACL, 2021)
- BERT for Humanists (public tutorials, 2021; ACH, 2021; ICWSM, 2022)

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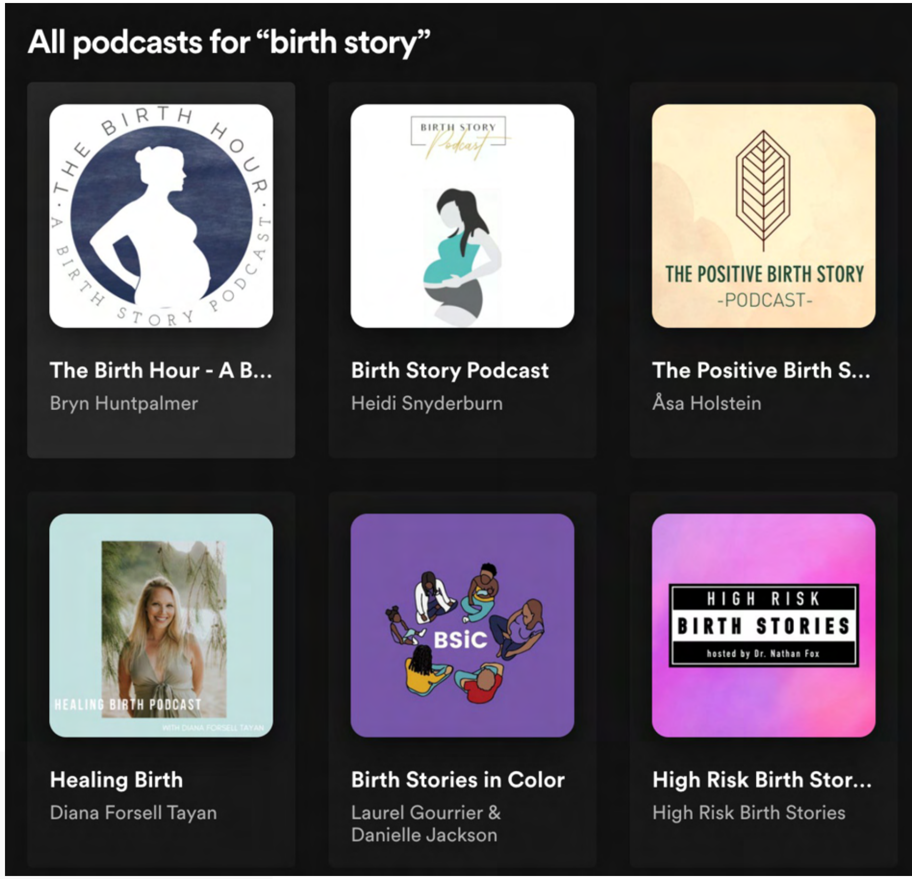
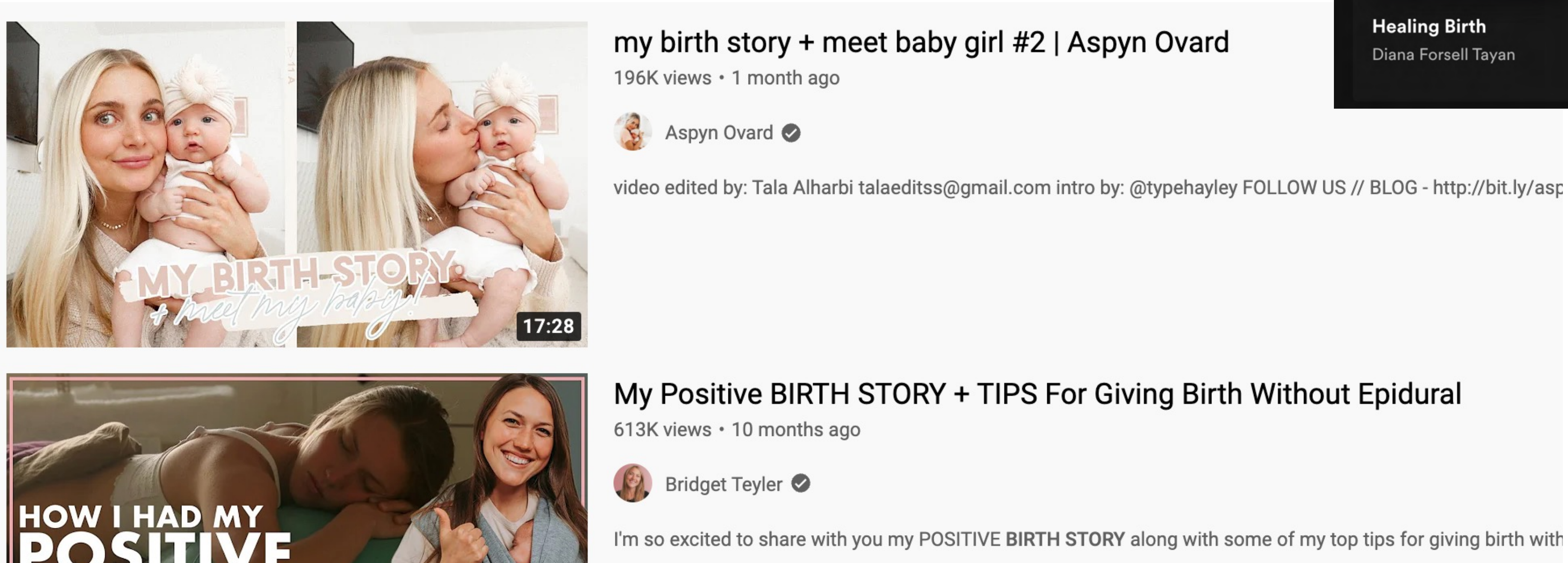
Online Birth Stories

- Detailed personal narratives of giving birth
- Shared throughout history, very popular (but under-studied) online





“I’ll begin just by saying that this subreddit has taught me so much in preparation for my first birth. I gained a lot of insight into other people’s experiences, and I loved reading all the stories, whether positive or negative. I hope that sharing my story helps someone in the same way.

“It was 1AM, April 5th. I was experiencing some light cramping and couldn’t fall asleep. This was pretty normal since 39 weeks, so I wasn’t worried. My husband woke up and was rubbing my back when I felt a pop. I told my husband, and he thought it was just my back cracking, but I realized that it was my water breaking. I told my husband that it looks like it’s time to go to the hospital! It was 3:30AM at that point.

“We headed to the hospital and got admitted. The nurse checked me, which was extremely painful, to the point that I wanted to cry. She said that I wasn’t even one centimeter dilated, which didn’t surprise me because I was supposed to be induced on April 8th. They got me started on pitocin to help start contractions and moved me to the delivery room at 4:45AM..."

Stories can illuminate unmet needs

- In the U.S., rates of pregnancy-related deaths and complications are rising but many of these are potentially **preventable.**

Berg et al. "Preventability of pregnancy-related deaths: results of a state-wide review." *Obstetrics & Gynecology*, 2005.

Creanga et al. "Pregnancy-related mortality in the United States, 2006-2010." *Obstetrics & Gynecology*, 2015.

- Postpartum depression affects 6-13% of people after childbirth, but it can be **prevented or mitigated.**

Lavender & Walkinshaw. "Can midwives reduce postpartum psychological morbidity? A randomized trial." *Birth*, 1998.

Stewart & Vigod. "Postpartum Depression." *New England Journal Medicine*, 2016.

Stories can illuminate unmet needs

What narrative **pathways** are described? What sequences of events are more likely or less likely, and how are those sequences framed?

Who do the authors view as holding **power**? In what ways are those people powerful?

John picked up the apple.
John went to the office.
John went to the kitchen.
John dropped the apple.

(Weston et al., 2016)

Kathy went shopping. She found a pair of great shoes. The shoes were $300. She bought the shoes.

(Mostafazadeh et al., 2016)

I would go back to sleep, and sometimes I would have nothing but brief awakenings lasting an instant each, just time enough to hear the organic creakings in the wood paneling, to open my eyes to stare at the kaleidoscope of darkness, to taste thanks to a momentary gleam of awareness the sleep into which were plunged the furniture, the room, everything, of which I was just a small part, and with the insensibility of which I would soon be merged.

(Marcel Proust)

News Articles

bAbI

Novels

Story Cloze

Children's Stories

Artificial / Simple

Natural / Complex

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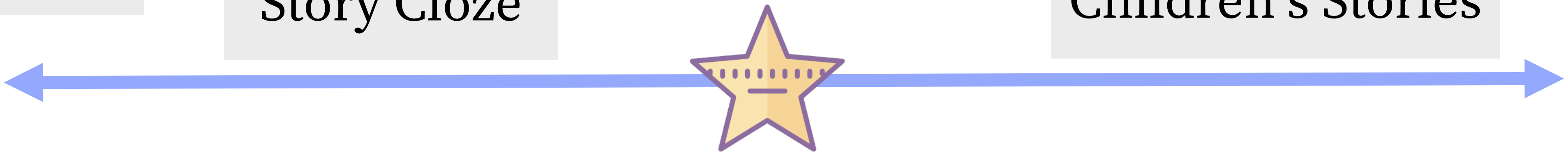

Artificial / Simple

Natural / Complex

Birth stories for narrative analysis

- ✅ Shared narrative structure, but each story is unique
- ✅ Created organically
- ✅ Real-world use cases
- ✅ Lots of stories for our computational models

r/BabyBumps: Post Titles

- Fiona's Birth Story: The best laid plans go awry? Long read
- Thomas Berry Birth Story (Planned C-Section w/Complications)
- John’s Birth Story - (planned for natural birth, got an ER c-section)
- Emily Rose's Birth Story
- My birth story! [home, unmedicated, midwife-assisted water-birth]
- I gave birth! Here's a very long birth story for anyone interested: pitocin + epi, and a few unexpected things pp
- Damian's Homebirth Story!
- Alice's birth story. (long, didn't go as planned)
- Finally wrote my birth story. Hello to Jonathon!
- Crystal Smith's birth story... With the funniest ending!
- DJ's birth story - severe pre-e followed by early induction

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r/BabyBumps: Limitations

- Our birth stories only include “**happy endings**” with no lost pregnancies
- Skew towards **home** births and **unmedicated** births
- No explicit/verified demographic information…
- …but the authors generally
  - write in English
  - describe experiences in the U.S., Canada, and the U.K.
  - have access to Reddit

r/BabyBumps: Ethical Tensions

Our decisions for this dataset:

- **Paraphrase** all quotes
- Release collection processes but **do not release** the data
- **Share** our findings on r/BabyBumps

Bruckman. "Studying the amateur artist: A perspective on disguising data collected in human subjects research on the Internet." *Ethics and Information Technology*, 2002.

Janssens & Kraft. "Research conducted using data obtained through online communities: ethical implications of methodological limitations." *PLoS Medicine*, 2012.

Vayena et al. "Ethical challenges of big data in public health." *PLoS Computational Biology*, 2015.

Abbott et al. "Local Standards for Anonymization Practices in Health, Wellness, Accessibility, and Aging Research at CHI." *CHI*, 2019.

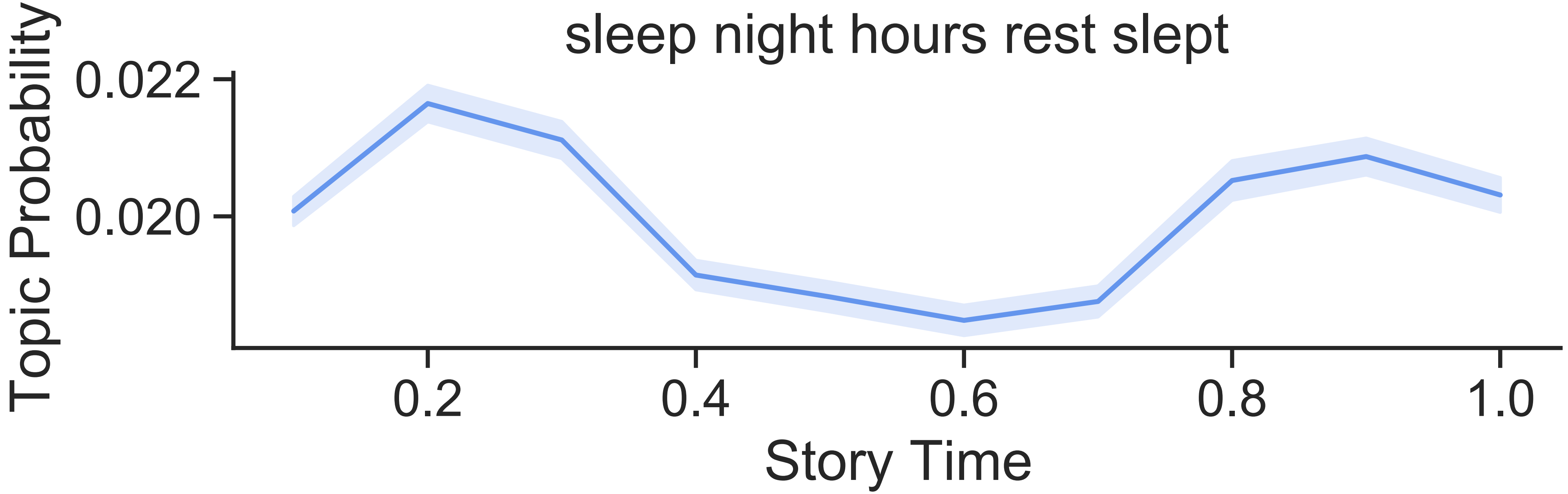
Narrative Patterns: Topics Over Time

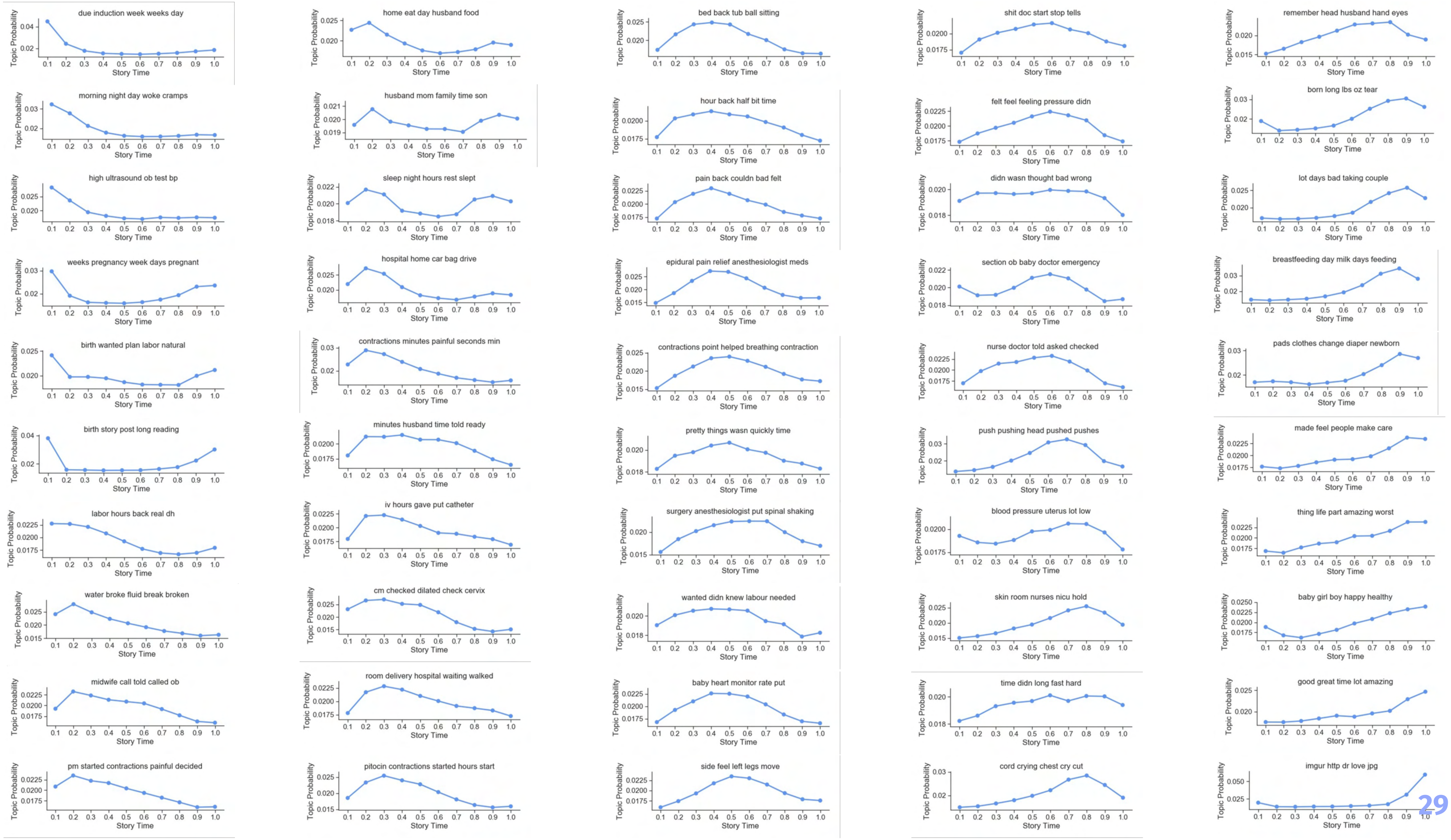
- Train a latent Dirichlet allocation (LDA) **topic model** on the stories
- Unsupervised, generative model that produces a **probability distribution over words** for each topic and a **probability distribution over topics** for each document

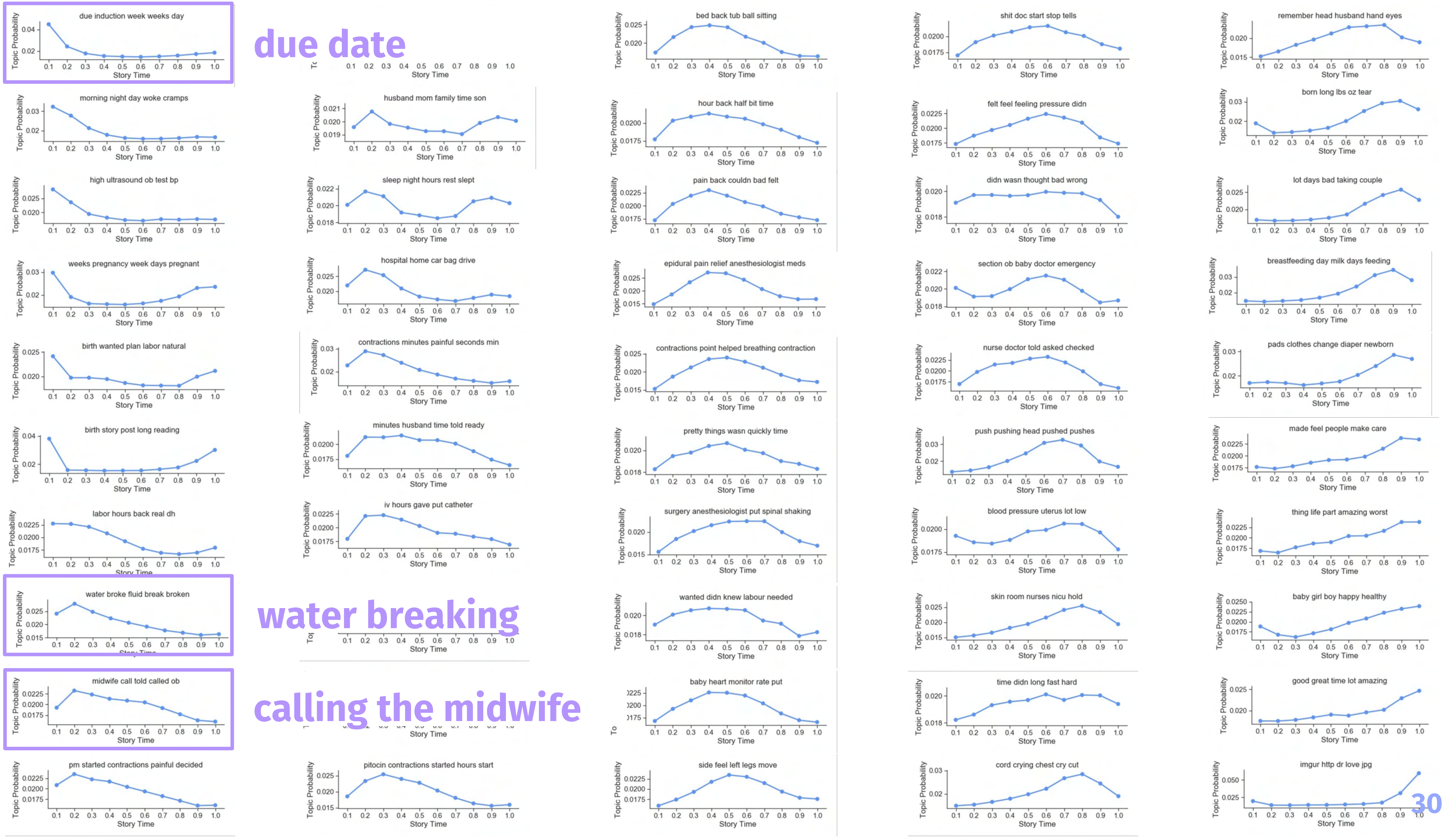
`Blei et al. "Latent Dirichlet allocation." *JMLR*, 2003.`

Story Time		Topic 1, Topic 2, Topic 3, Topic 4
0.10	I'll begin just by saying that this subreddit has taught me so much...	**[0.01, 0.20, 0.03, 0.56, ...]**
0.20	It was 1am, April 5th. I was experiencing some light cramping...	**[0.23, 0.11, 0.02, 0.01, ...]**
0.30	We headed to the hospital and got admitted. The nurse checked me...	**[0.03, 0.01, 0.32, 0.04, ...]**
...	...	**...**

Narrative Patterns: Topics Over Time




due induction week weeks day
home eat day husband food
bed back tub ball sitting
shit doc start stop tells
remember head husband hand eyes
morning night day woke cramps
husband mom family time son
hour back half bit time
felt feel feeling pressure didn
born long lbs oz tear
high ultrasound ob test bp
sleep night hours rest slept
pain back couldn bad felt
didn wasn thought bad wrong
lot days bad taking couple
weeks pregnancy week days pregnant
hospital home car bag drive
epidural pain relief anesthesiologist meds
section ob baby doctor emergency
breastfeeding day milk days feeding
birth wanted plan labor natural
contractions minutes painful seconds min
contractions point helped breathing contraction
nurse doctor told asked checked
pads clothes change diaper newborn
birth story post long reading
minutes husband time told ready
pretty things wasn quickly time
push pushing head pushed pushes
made feel people make care
labor hours back real dh
iv hours gave put catheter
surgery anesthesiologist put spinal shaking
blood pressure uterus lot low
thing life part amazing worst
water broke fluid break broken
cm checked dilated check cervix
wanted didn knew labour needed
skin room nurses nicu hold
baby girl boy happy healthy
midwife call told called ob
room delivery hospital waiting walked
baby heart monitor rate put
time didn long fast hard
good great time lot amazing
pm started contractions painful decided
pitocin contractions started hours start
side feel left legs move
cord crying chest cry cut
imgur http dr love jpg
Topic Probability
Story Time



due date
water breaking
calling the midwife
Topic Probability
Story Time
due induction week weeks day
morning night day woke cramps
high ultrasound ob test bp
weeks pregnancy week days pregnant
birth wanted plan labor natural
birth story post long reading
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husband mom family time son
sleep night hours rest slept
hospital home car bag drive
contractions minutes painful seconds min
minutes husband time told ready
iv hours gave put catheter
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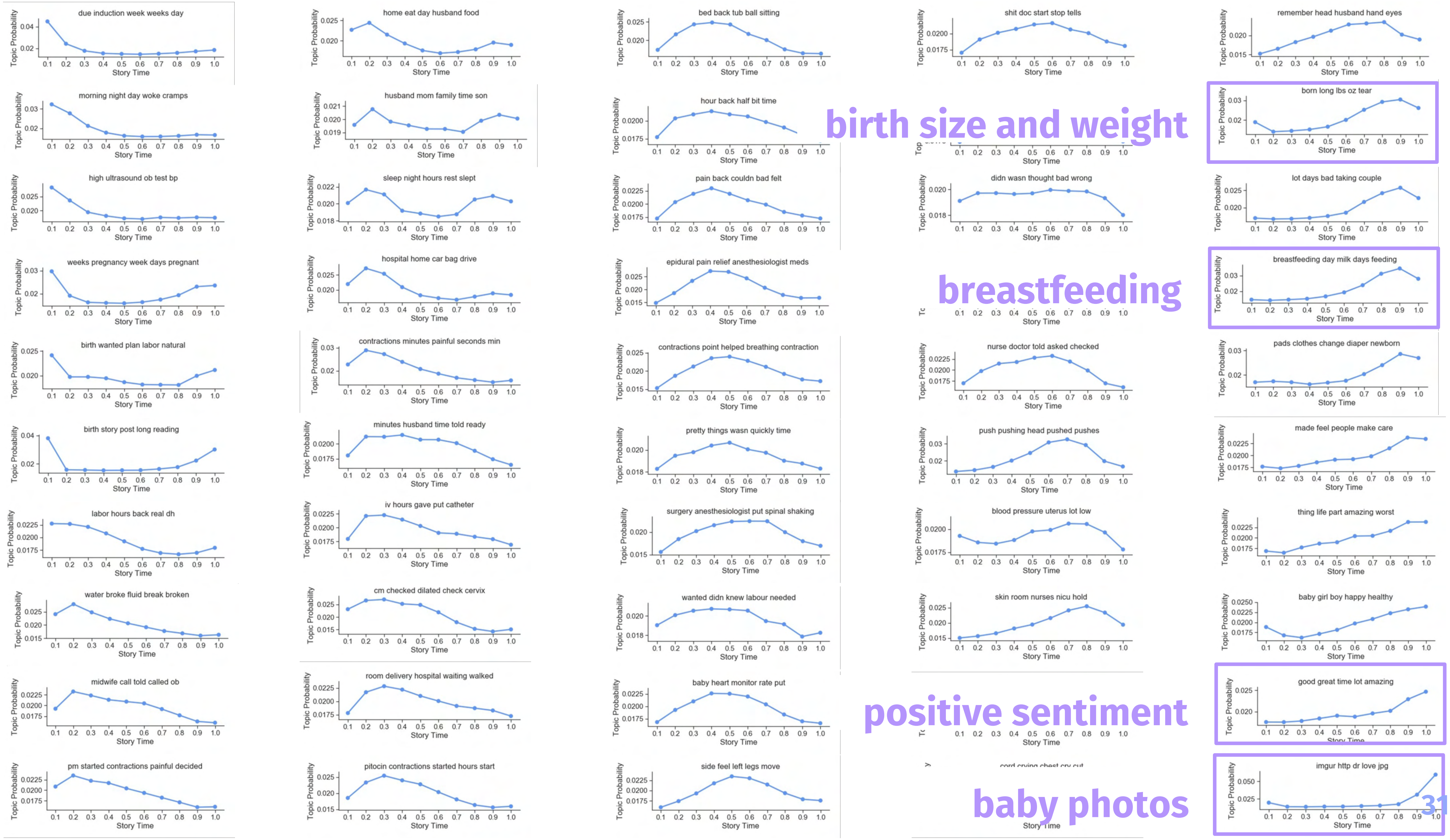
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Topic Probability
Story Time
birth size and weight
breastfeeding
positive sentiment
baby photos

Story Time		Topic 1	Topic 2	Topic 3	Topic 4	
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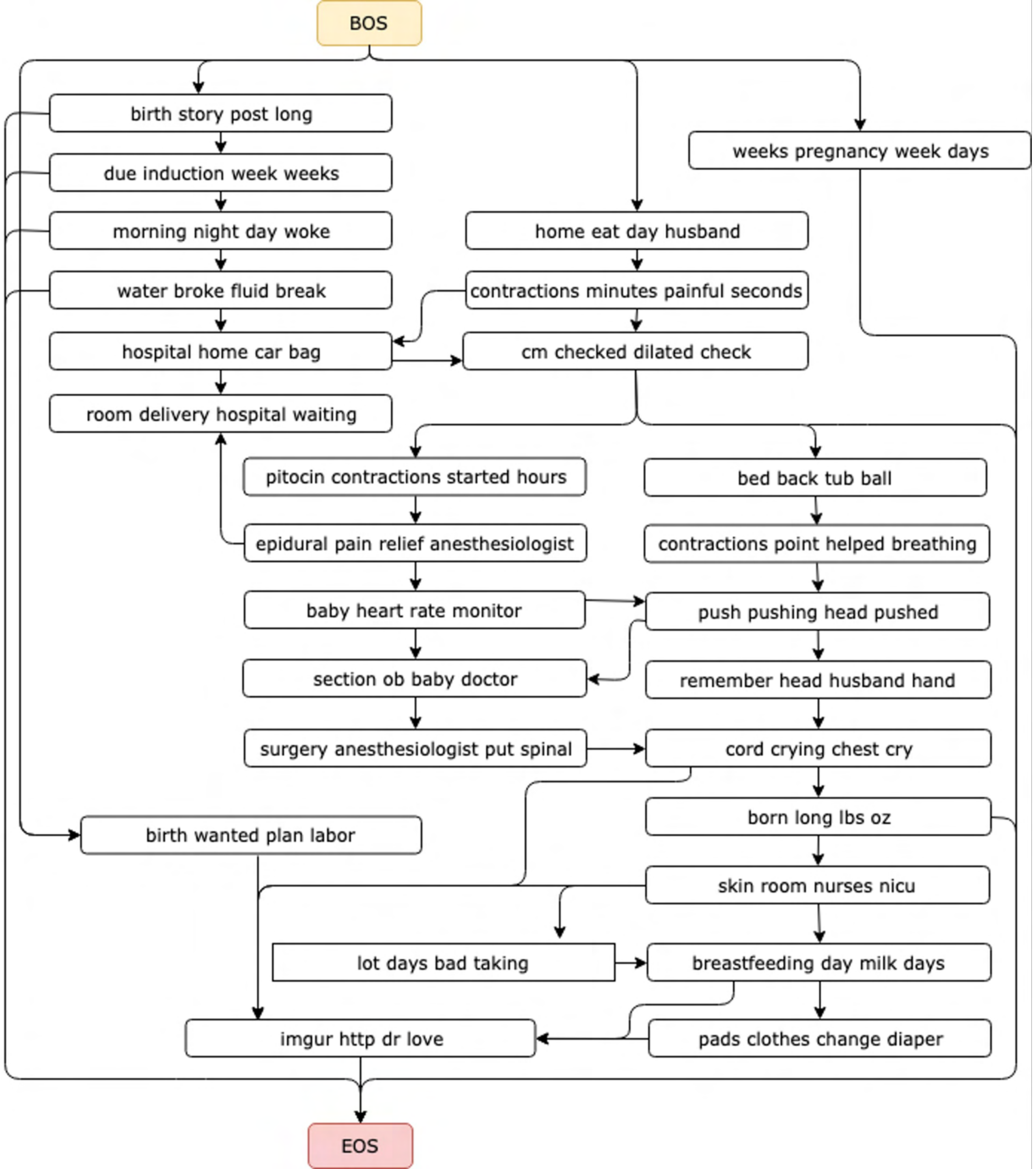
BOS
birth story post long
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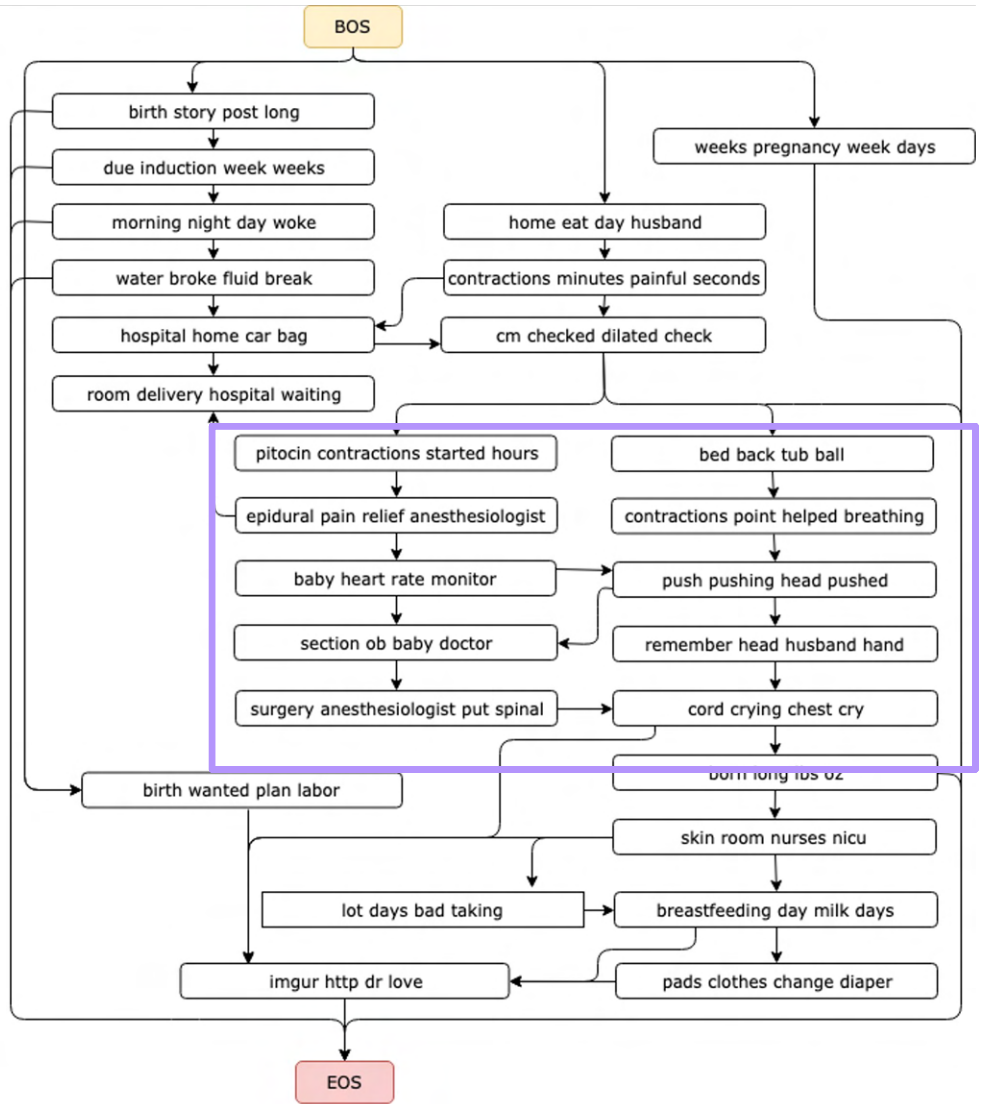
EOS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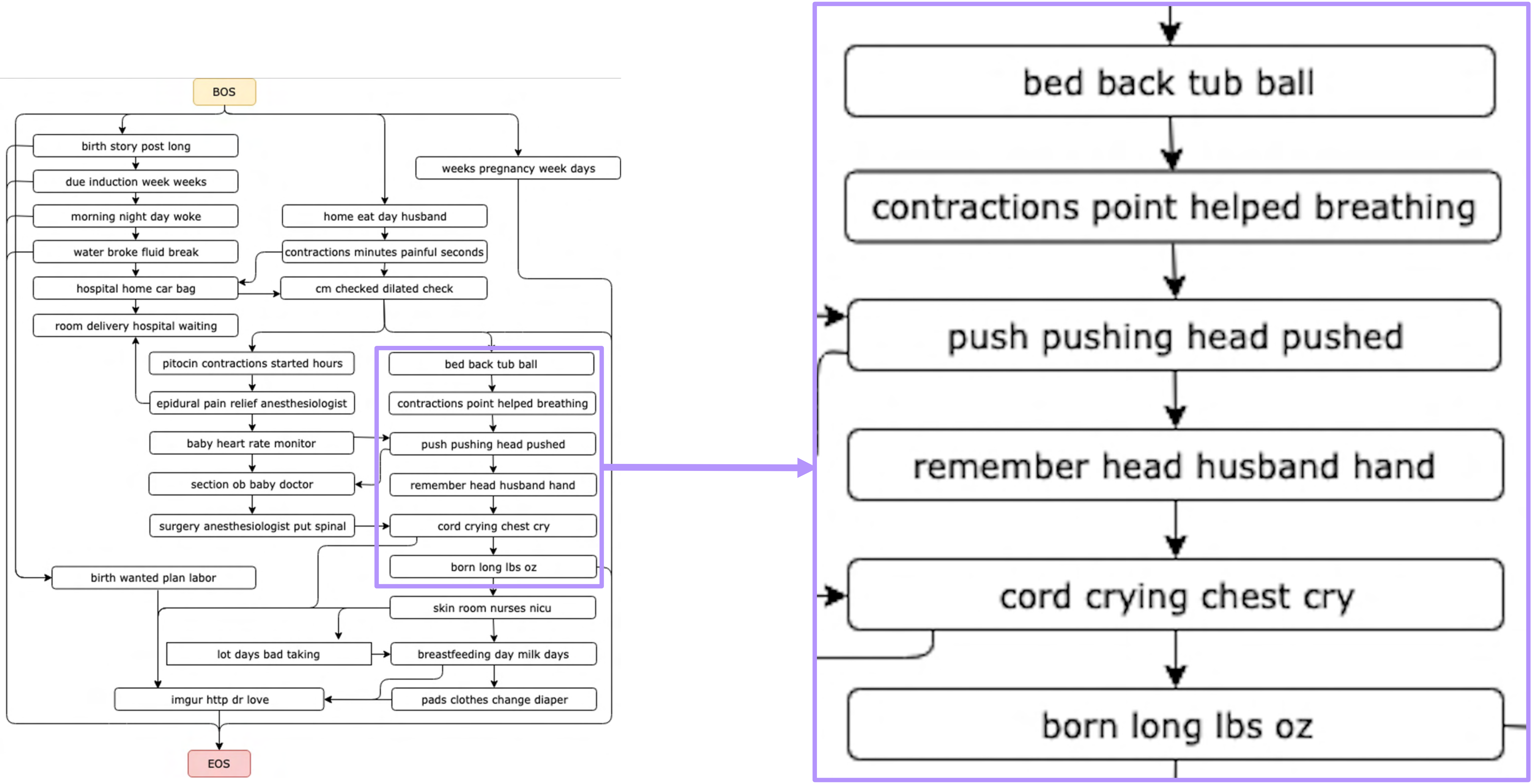
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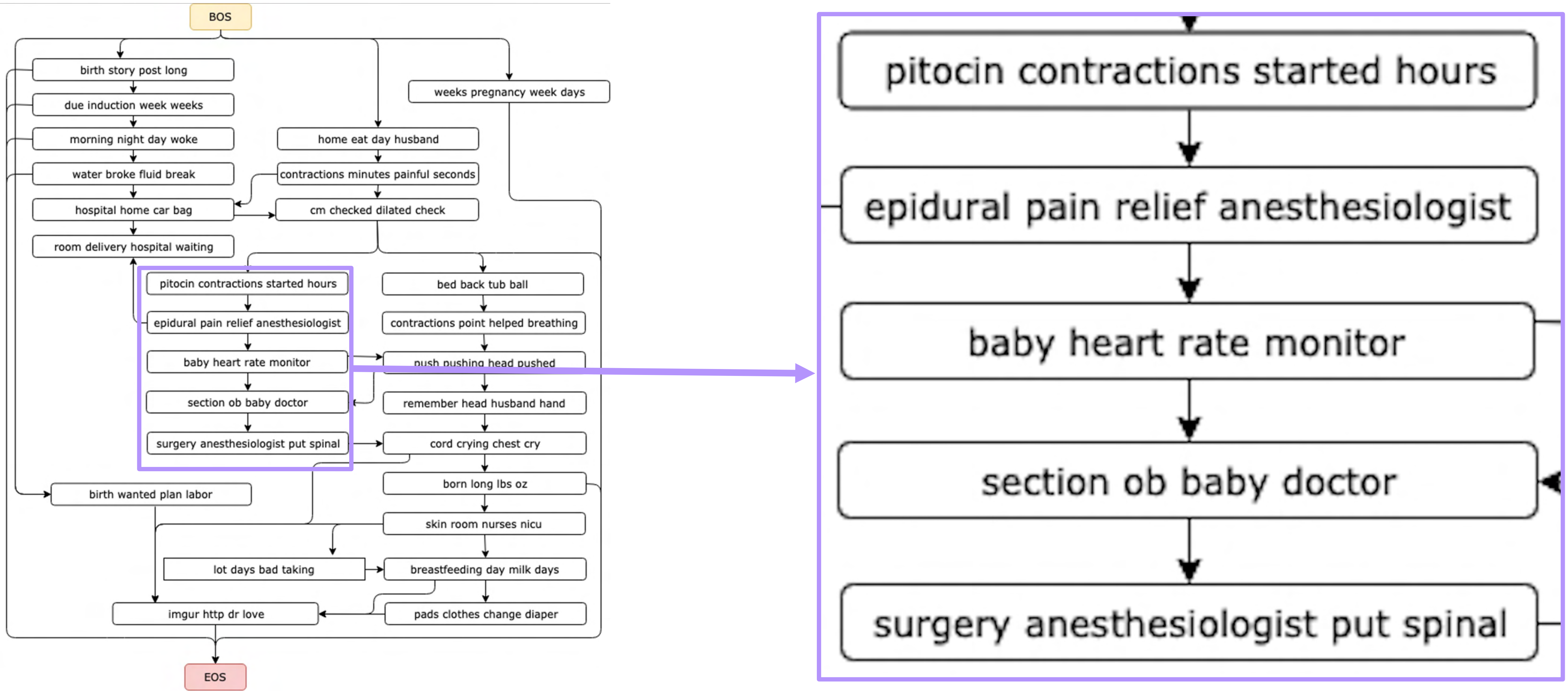

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surgery anesthesiologist put spinal

My **positive medicated** birth story

Jonah’s birth story: **positive, medicated**, c-section

My **positive medicated** birth story

Topic 11

Topic 32

Topic 5

Jonah's birth story: **positive**, **medicated**, c-section

Topic 47

Topic 18

Topic 5

My **positive medicated** birth story

Topic 11

$p = 0.20$

Topic 32

$p = 0.01$

Topic 5

Jonah's birth story: **positive**, **medicated**, c-section

Topic 47

$p = 0.06$

Topic 18

$p = 0.14$

Topic 5

My **positive medicated** birth story

Topic 11

Topic 32

Topic 5

p = 0.20 → log(p) = -1.61

p = 0.01 → log(p) = -4.60

-6.21

Jonah's birth story: **positive**, **medicated**, c-section

Topic 47

Topic 18

Topic 5

p = 0.06 → log(p) = -2.81

p = 0.14 → log(p) = -1.97

-4.78

Likely

Story Log Prob.	Bigram from Story Title
-34.19	positive medicated
-34.27	positive hospital
-34.30	med free
-34.52	positive induction
-34.53	story ftm
-34.73	vaginal delivery
-34.77	story hospital
-34.83	weeks pp
-34.85	hour labor
-34.88	super long
-34.92	failed induction
-34.95	super positive
-34.95	late birth
-35.01	story positive
-35.06	hospital birth
-35.07	story finally
-35.07	water birth
-35.12	vaginal birth
-35.27	line jumper
-35.31	story born

Unlikely

Story Log Prob.	Bigram from Story Title
-35.79	traumatic birth
-35.82	story unmedicated
-35.93	story baby
-35.94	post partum
-35.95	story plus
-35.95	due date
-35.99	pp advice
-36.02	baby birth
-36.03	home birth
-36.04	c section
-36.05	story warning
-36.11	unplanned c
-36.13	slightly traumatic
-36.27	natural birth
-36.40	belated birth
-36.42	positive unmedicated
-36.42	emergency c
-36.53	trigger warning
-36.60	induction epidural
-36.84	happy ending

Story Log Prob.	Bigram from Story Title
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-35.27	line jumper
-35.31	story born

Story Log Prob.	Bigram from Story Title
-35.79	traumatic birth
-35.82	story unmedicated
-35.93	story baby
-35.94	post partum
-35.95	story plus
-35.95	due date
-35.99	pp advice
-36.02	baby birth
-36.03	home birth
-36.04	c section
-36.05	story warning
-36.11	unplanned c
-36.13	slightly traumatic
-36.27	natural birth
-36.40	belated birth
-36.42	positive unmedicated
-36.42	emergency c
-36.53	trigger warning
-36.60	induction epidural
-36.84	happy ending

Story Log Prob.	Bigram from Story Title
-34.19	positive medicated
-34.27	positive hospital
-34.30	med free
-34.52	positive induction
-34.53	story ftm
-34.73	vaginal delivery
-34.77	story hospital
-34.83	weeks pp
-34.85	hour labor
-34.88	super long
-34.92	failed induction
-34.95	super positive
-34.95	late birth
-35.01	story positive
-35.06	hospital birth
-35.07	story finally
-35.07	water birth
-35.12	vaginal birth
-35.27	line jumper
-35.31	story born

Story Log Prob.	Bigram from Story Title
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-35.93	story baby
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(Dis)Empowerment: Personas

Persona	String Matches	Percent Stories Mentioning	Mean Mentions per Story
Author	`I, me, myself`	99.9%	74.0
We	`we, us, ourselves`	97.1%	8.7
Baby	`baby, son, daughter`	93.7%	5.0
Doctor	`doctor, dr, doc, ob, obgyn, gynecologist, physician`	79.4%	3.5
Partner	`partner, husband, wife`	70.4%	3.2
Family	`mom, dad, mother, father, brother, sister`	47.9%	1.2
Midwife	`midwife`	31.1%	1.4
Anesthesiologist	`anesthesiologist`	30.8%	0.5
Nurse	`nurse`	20.7%	2.5
Doula	`doula`	9.0%	0.3

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(Dis)Empowerment: Lexicon

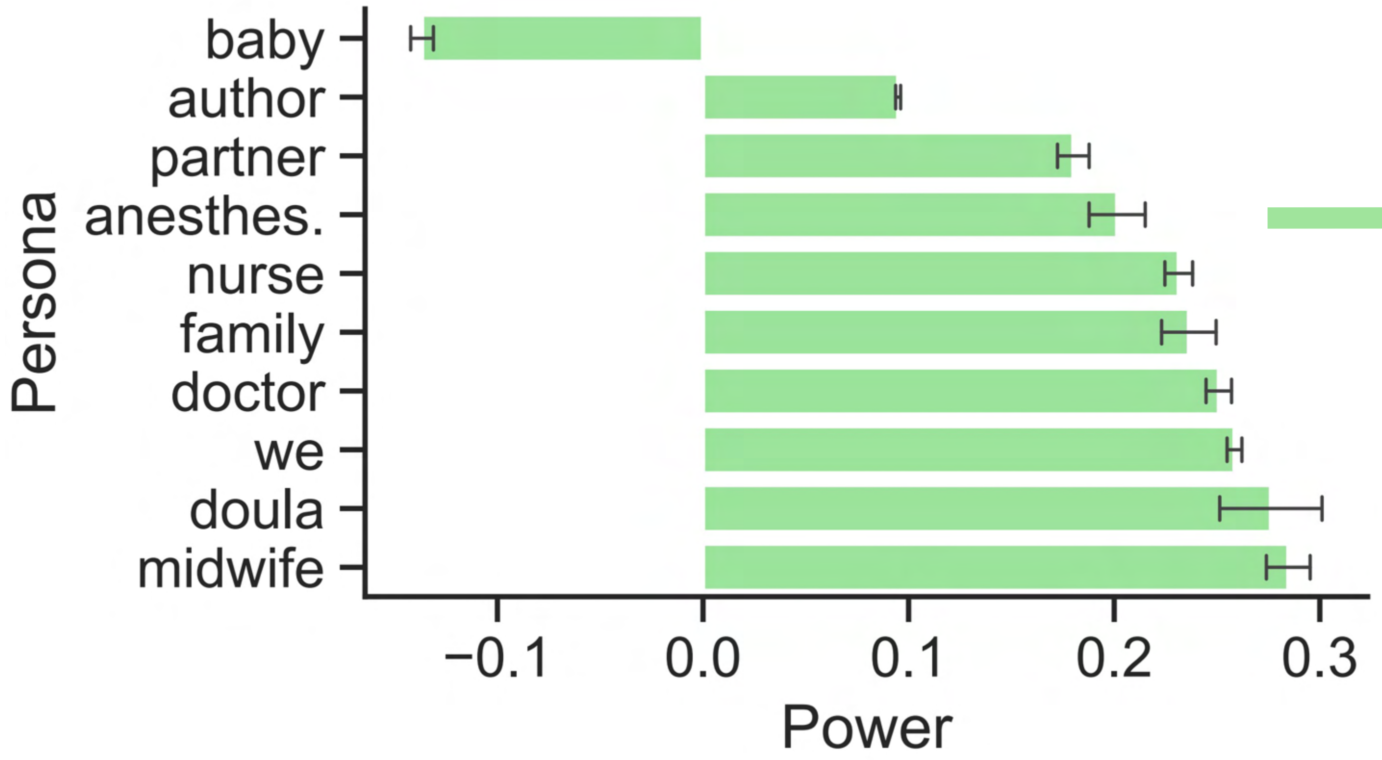
- Lexicon of verbs from prior work labeled with **directional power**
- Extract dependency parses and lemmatize verbs
- Score each persona using their relationship to verbs from lexicon

noun subject　　direct object

The **nurse** **accused** **me** of not feeding my child.

Sap et al. "Connotation Frames of Power and Agency in Modern Films." EMNLP, 2017.

(Dis)Empowerment



More Power

Baby		Author		Doctor		Doula	
do_subj	0.0129	get_subj	0.0404	call_obj	0.0760	call_obj	0.1412
want_obj	0.0113	know_subj	0.0219	check_subj	0.0271	suggest_subj	0.0357
get_subj	0.0110	start_subj	0.0215	decide_subj	0.0221	get_subj	0.0306
start_subj	0.0081	do_subj	0.0199	get_subj	0.0159	hold_subj	0.0144
drop_subj	0.0072	push_subj	0.0123	do_subj	0.0145	keep_subj	0.0128
make_subj	0.0063	make_subj	0.0070	show_subj	0.0116	show_subj	0.0122
turn_subj	0.0055	wake_subj	0.0069	break_subj	0.0105	remind_subj	0.0117
show_subj	0.0027	keep_subj	0.0065	give_subj	0.0091	give_subj	0.0101
enjoy_obj	0.0022	decide_subj	0.0059	start_subj	0.0091	start_subj	0.0090
decide_subj	0.0021	end_subj	0.0038	make_subj	0.0088	make_subj	0.0080
give_obj	-0.0053	get_obj	-0.0028	wait_subj	-0.0014	massage_subj	-0.0022
catch_obj	-0.0057	believe_subj	-0.0031	like_subj	-0.0014	cheer_subj	-0.0024
need_subj	-0.0072	wait_subj	-0.0034	mention_subj	-0.0026	fill_subj	-0.0025
feed_obj	-0.0076	lose_subj	-0.0035	reach_subj	-0.0029	recognize_subj	-0.0027
bring_obj	-0.0089	hear_subj	-0.0057	explain_subj	-0.0036	alarm_obj	-0.0028
put_obj	-0.0113	call_subj	-0.0069	offer_subj	-0.0039	warn_obj	-0.0028
deliver_obj	-0.0196	ask_subj	-0.0097	call_subj	-0.0089	join_subj	-0.0057
push_obj	-0.0240	need_subj	-0.0117	ask_subj	-0.0133	get_obj	-0.0141
hold_obj	-0.0306	check_obj	-0.0137	get_obj	-0.0136	ask_subj	-0.0171
get_obj	-0.0369	want_subj	-0.0266	want_subj	-0.0152	hire_obj	-0.0438

More Power

Less Power

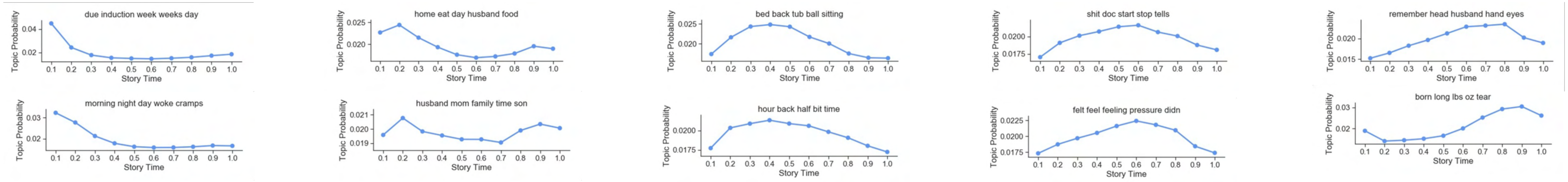
1) “I had **planned** on a natural birth, had hired a doula, read books, all of those things. And here I was on a random Monday just going about my business when the baby **decided** to arrive. It took me a while to process all of it.”

2) “The nurse said that if I wasn’t more dilated by 12PM that she was going to start me on pitocin. I was scared about this happening, I had heard a lot about the cascading interventions that often happen in hospitals. That's why I hired a doula, so that I could have **another point of view** and **someone to guide me** so I could have this birth naturally.”

Takeaways from birth stories

We can use computational tools to model the shared **narrative patterns** and **power framing** in a community's set of birth stories.

We discovered sets of **diverging pathways**, found **outlier** stories labeled with terms of surprisal, trauma, and **happy endings**.



Takeaways from birth stories

Observational and randomized studies have already found improvements in **outcomes** (lower rates of c-section, higher satisfaction) when doulas are included.

Our study adds detail about **how** doulas can help empower pregnant people, and **how** pregnant people view doulas.

Gruber et al. "Impact of doulas on healthy birth outcomes." *Journal of Perinatal Education*, 2013.

Kozhimannil et al. "Doula care, birth outcomes, and costs among Medicaid beneficiaries." *American Journal of Public Health*, 2013.

Steel et al. "Trained or professional doulas in the support and care of pregnant and birthing women: a critical integrative review." *Health & Social Care in the Community*, 2015.

Vonderheid et al. "Group prenatal care and doula care for pregnant women." *Reducing Racial/Ethnic Disparities in Reproductive and Perinatal Outcomes*, 2011.

My Research Goals

Use NLP methods to study the sharing of personal experiences online

- Birth communities: power and narrative in birth stories (CSCW, 2019)
- Expressing pain through similes (Frontiers in Neuroscience, 2019)
- Literary genres in online reading communities (Cultural Analytics, 2021; CSCW, 2021)

Probe the reliability of NLP methods for cultural analytics applications

- Instability of cosine similarities for word embeddings (TACL, 2018)
- Seed selection can affect bias measurement (ACL, 2021)
- BERT for Humanists (public tutorials, 2021; ACH, 2021; ICWSM, 2022)

Harmful human biases can trickle **downstream** from our models into our predictions—a problem for us to solve.

Harmful human biases can trickle **downstream** from our models into our predictions—a problem for us to solve.

But biases in our models can also be used as indicators of biases in datasets and their authors—an **upstream** measurement tool.

Bias Measurement Methods

- Increasing interest in measuring harmful human biases encoded in models and datasets

Bolukbasi et al. “Man is to computer programmer as woman is to homemaker? Debiasing word embeddings.” *NeurIPS*, 2016.

Caliskan et al. “Semantics derived automatically from language corpora contain human-like biases.” *Science*, 2017.

- These methods are being reused in cultural analytics

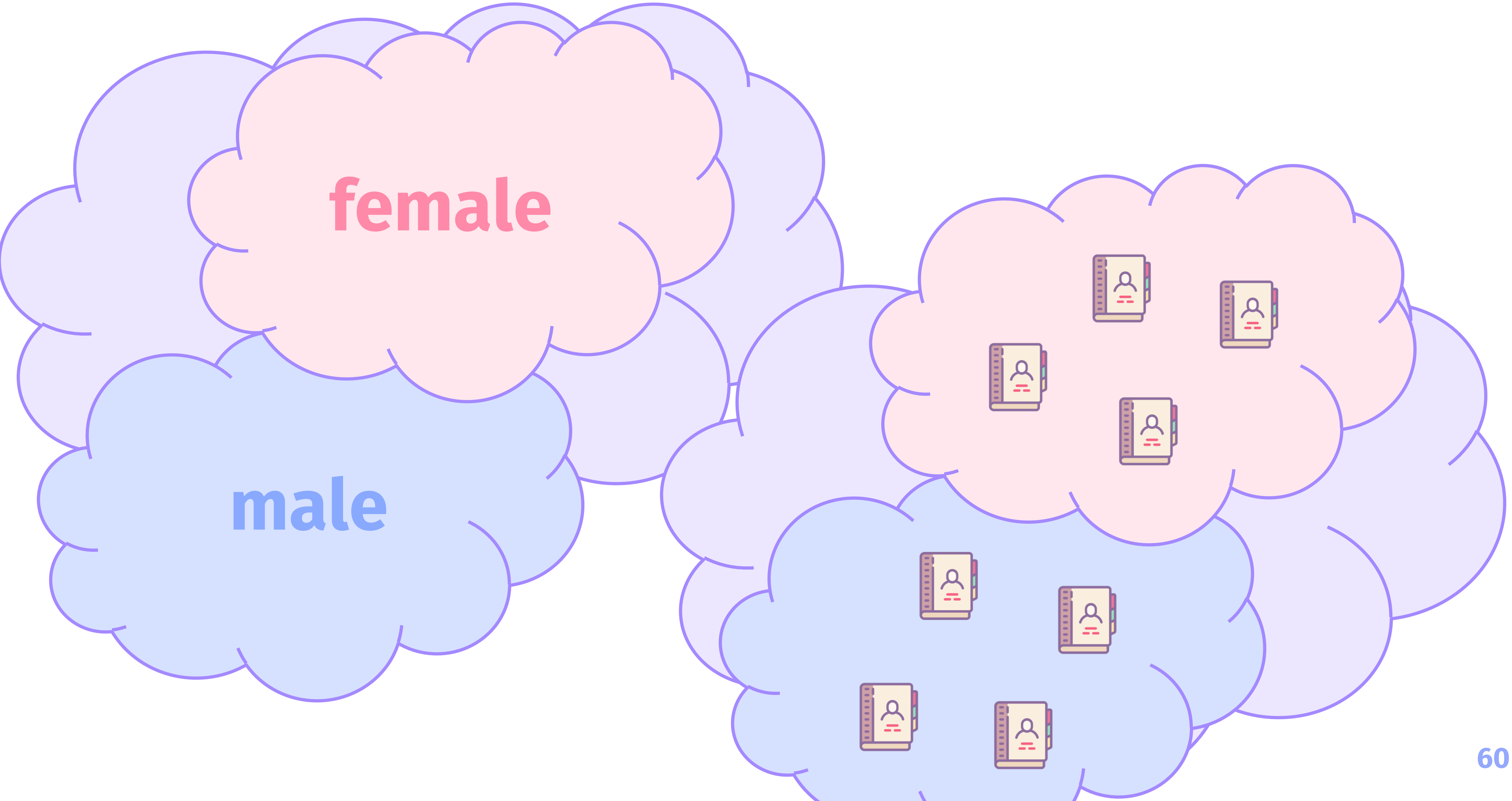
- Methods to measure bias can include word counts, pointwise mutual information, word embeddings, etc.

All these bias measurement methods rely on **lexicons of seed terms.**

Lists of words, where each list represents a single target concept like race or gender.

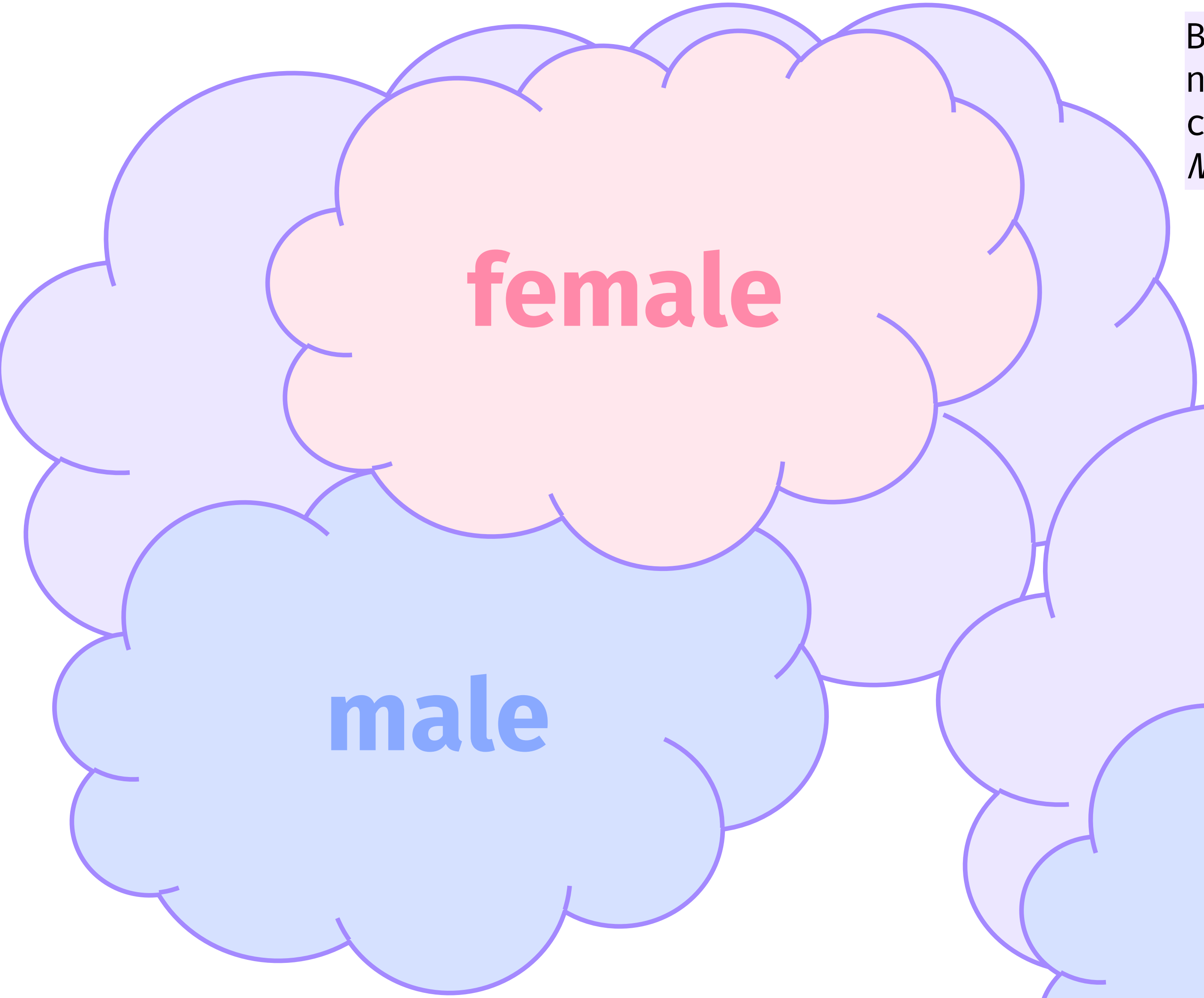
GENDER

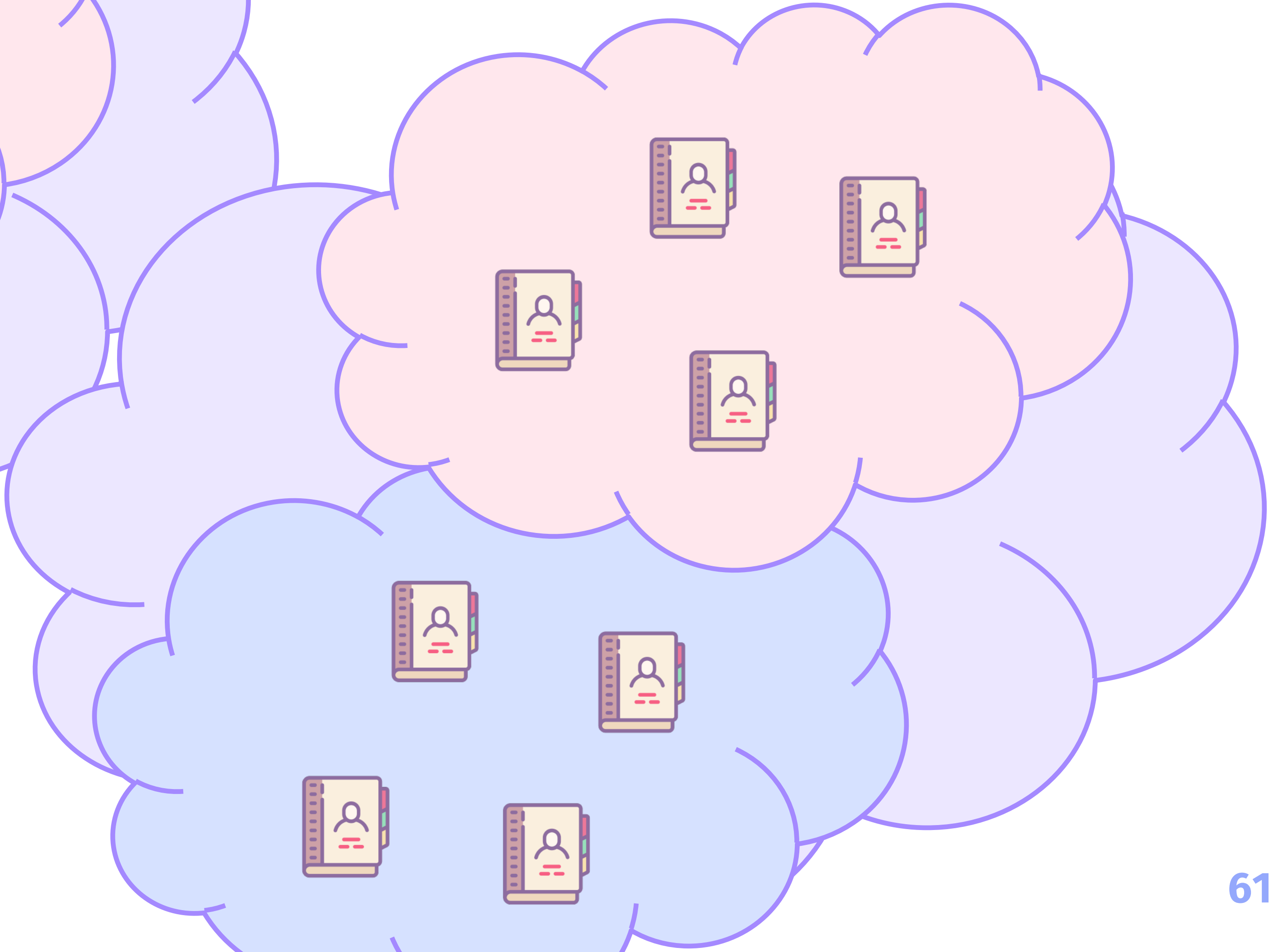
CAREER

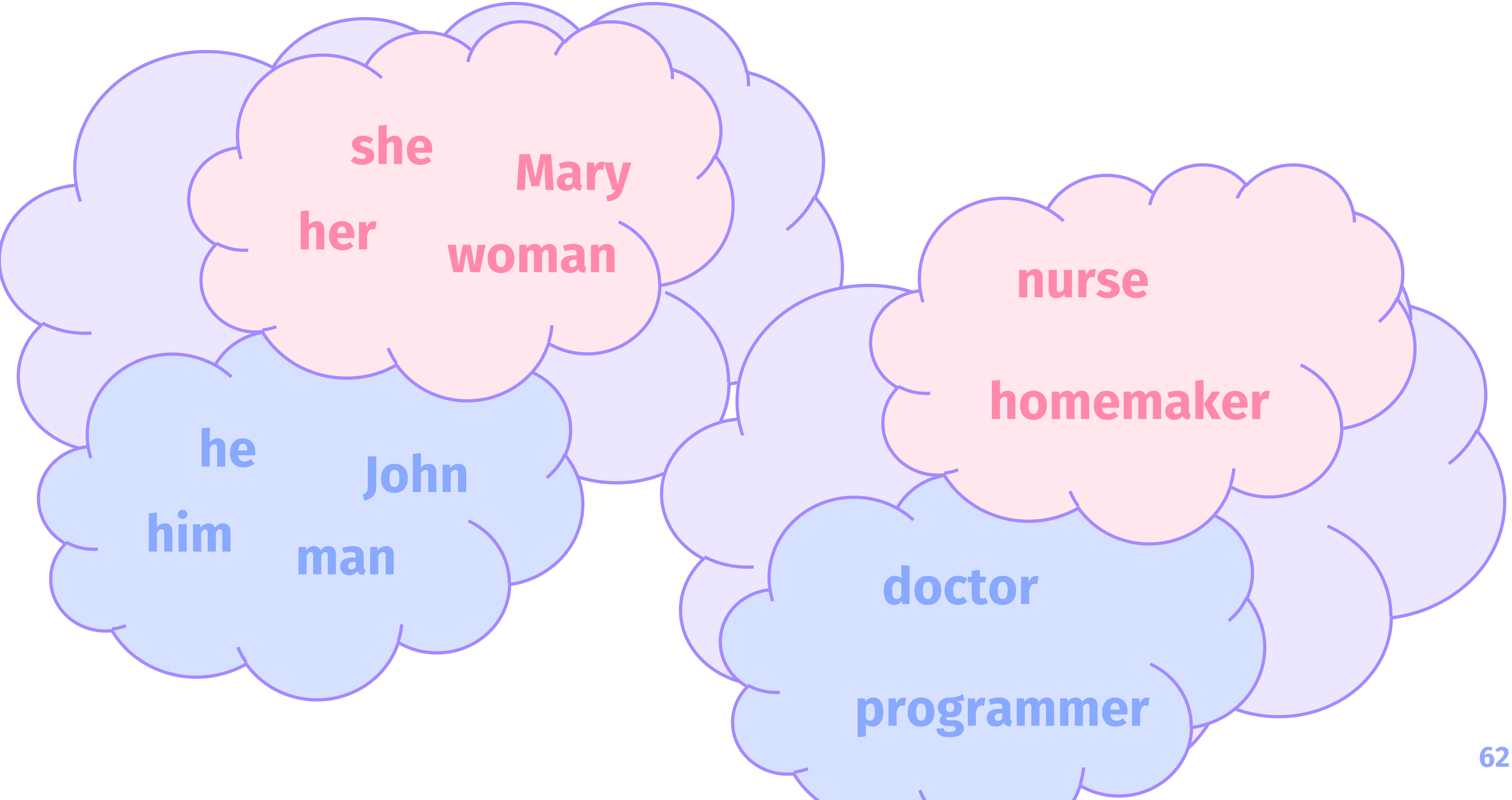

female
male

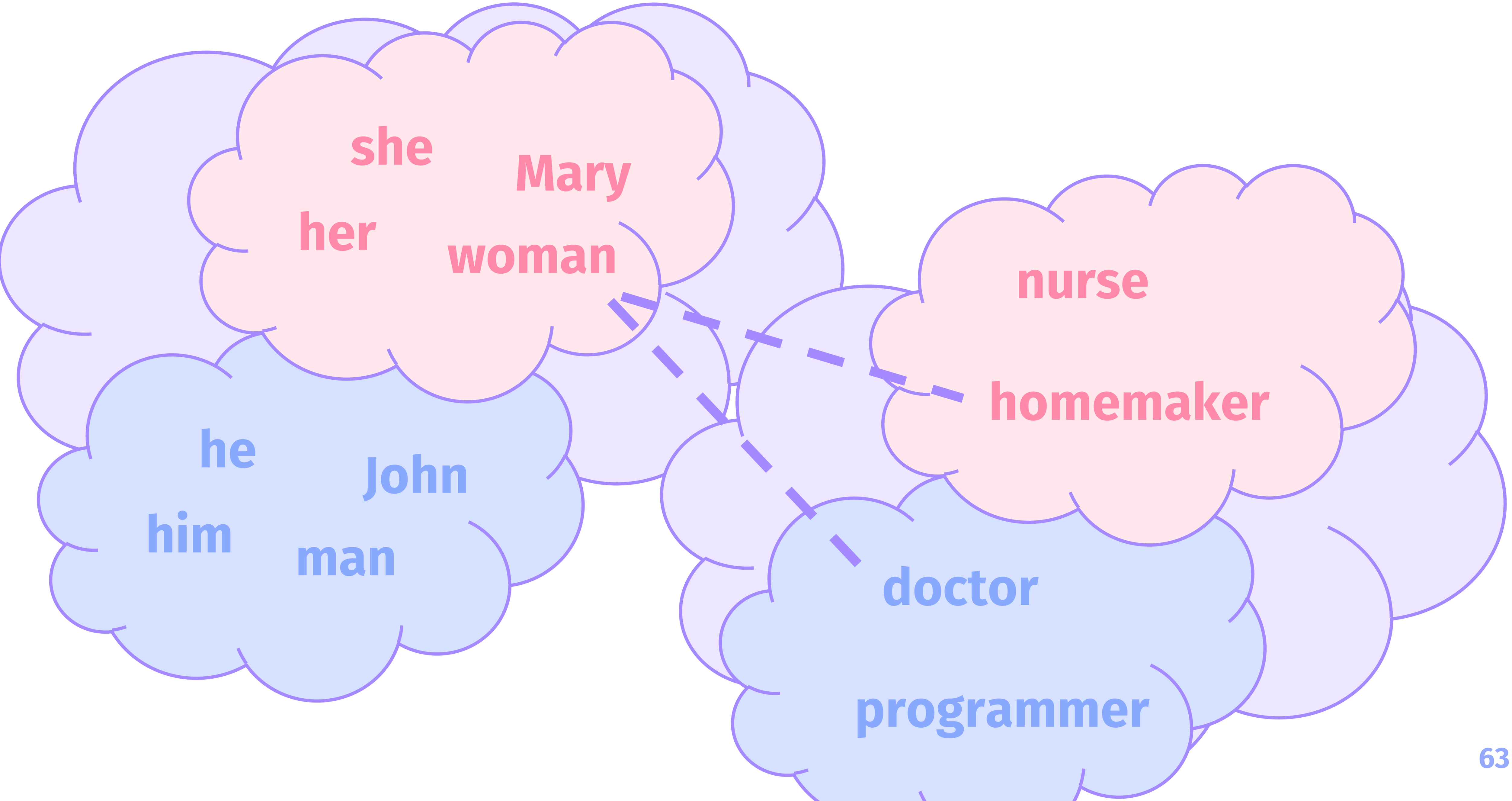
Keyes. “Stop mapping names to gender.” 2017.

Brian Larson. “Gender as a variable in natural language processing: Ethical considerations.” *ACL Workshop on Ethics in NLP*, 2017.






she
Mary
her
woman
he
John
him
man
nurse
homemaker
doctor
programmer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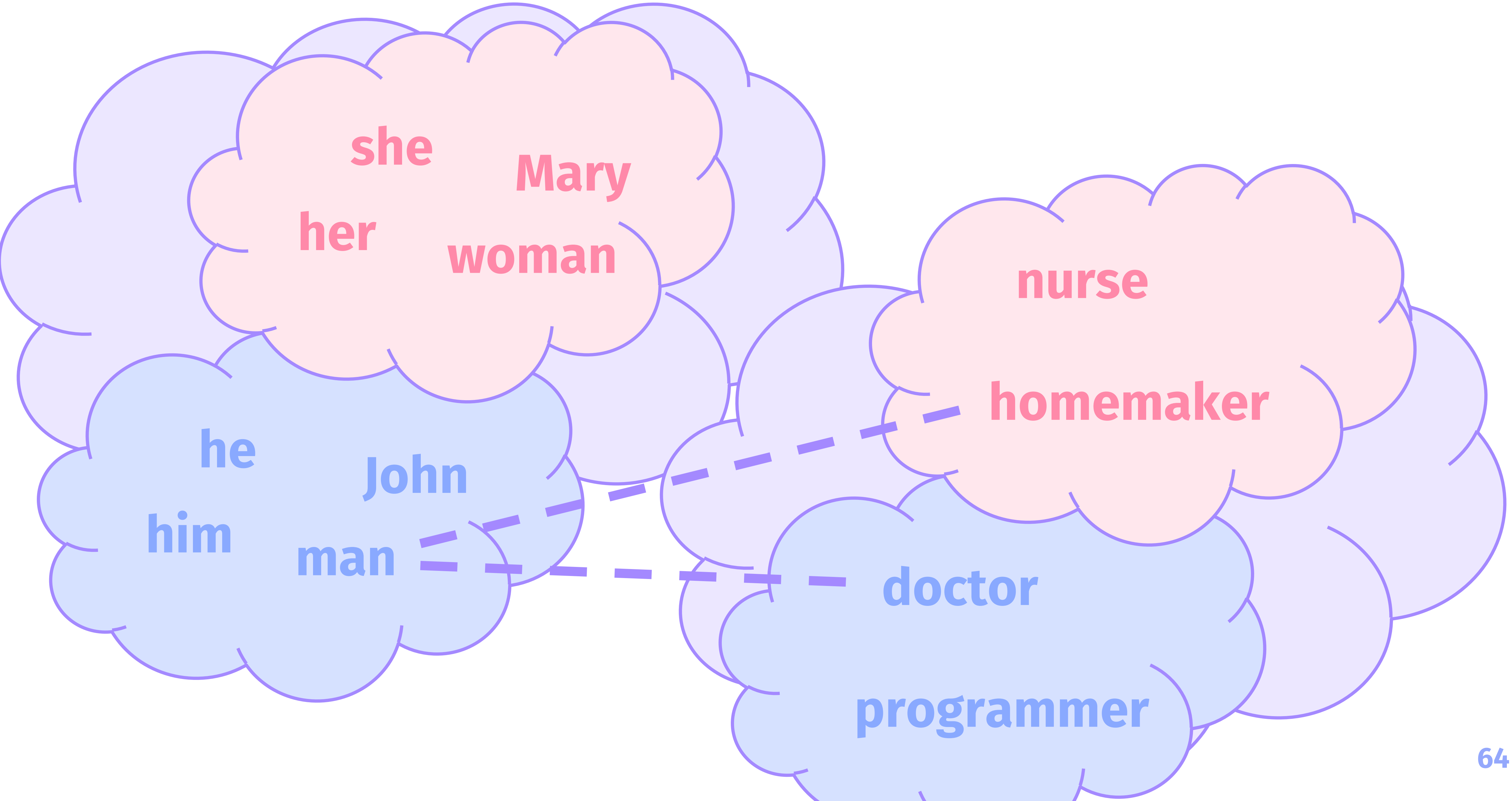
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GENDER

CAREER

What do these lexicons look like?

- **Attribute** sets often represent groups of people
- **Target** sets often represent sentiment or roles
- Goal is to compare similarities of the targets and attributes

Attribute Set A	man, boy, he, him, …
Attribute Set B	woman, girl, she, her, …
Target Set A	pleasant, good, kind, …
Target Set B	unpleasant, bad, mean, …

What do these lexicons *really* look like?

Unpleasant	divorce, jail, poverty, cancer, ...
African American	Tanisha, Tia, Lakisha, Latoya, ...
Domestic Work	mom, mum, ...
Ugliness	fat, chubby, obese, fatty, overweight, disformed, disfigured, wrinkle, wrinkled, ...

Bias Measurement Methods

We focus on two popular, often re-used methods.

1. **Word Embedding Association Test (WEAT)**

   `Caliskan et al. “Semantics derived automatically from language corpora contain human-like biases.”` *Science*, `2017.`

2. **Principal Component Analysis (PCA)**

   `Bolukbasi et al. “Man is to computer programmer as woman is to homemaker? Debiasing word embeddings.”` *NeurIPS*, `2016.`

Both methods represent **words as vectors** in an embedding space and measure bias using cosine similarity between word vectors.

Bias Measurement Methods: WEAT

$$s(X, Y, A, B) = \sum_{x \in X} s(x, A, B) - \sum_{y \in Y} s(y, A, B)$$

- X and Y are the target seed sets
- A and B are the attribute seed sets

- s is the difference in mean cosine similarities between w and each term in A and w and each term in B

Higher values of this test statistic indicator a **stronger** relationship between the target and attribute seed sets.

Caliskan et al. "Semantics derived automatically from language corpora contain human-like biases." *Science*, 2017.

Bias Measurement Methods: PCA

`man-woman`
`he-she`
`him-her`

1. Align the attribute and target seed words into **matched pairs**
2. Find the difference vector for each pair of words
3. If most of the variation can be explained by the first principal component, this represents the **bias subspace**
4. Use the cosine similarity between word vectors and the discovered space to measure bias

Bolukbasi et al. “Man is to computer programmer as woman is to homemaker? Debiasing word embeddings.” *NeurIPS*, 2016.

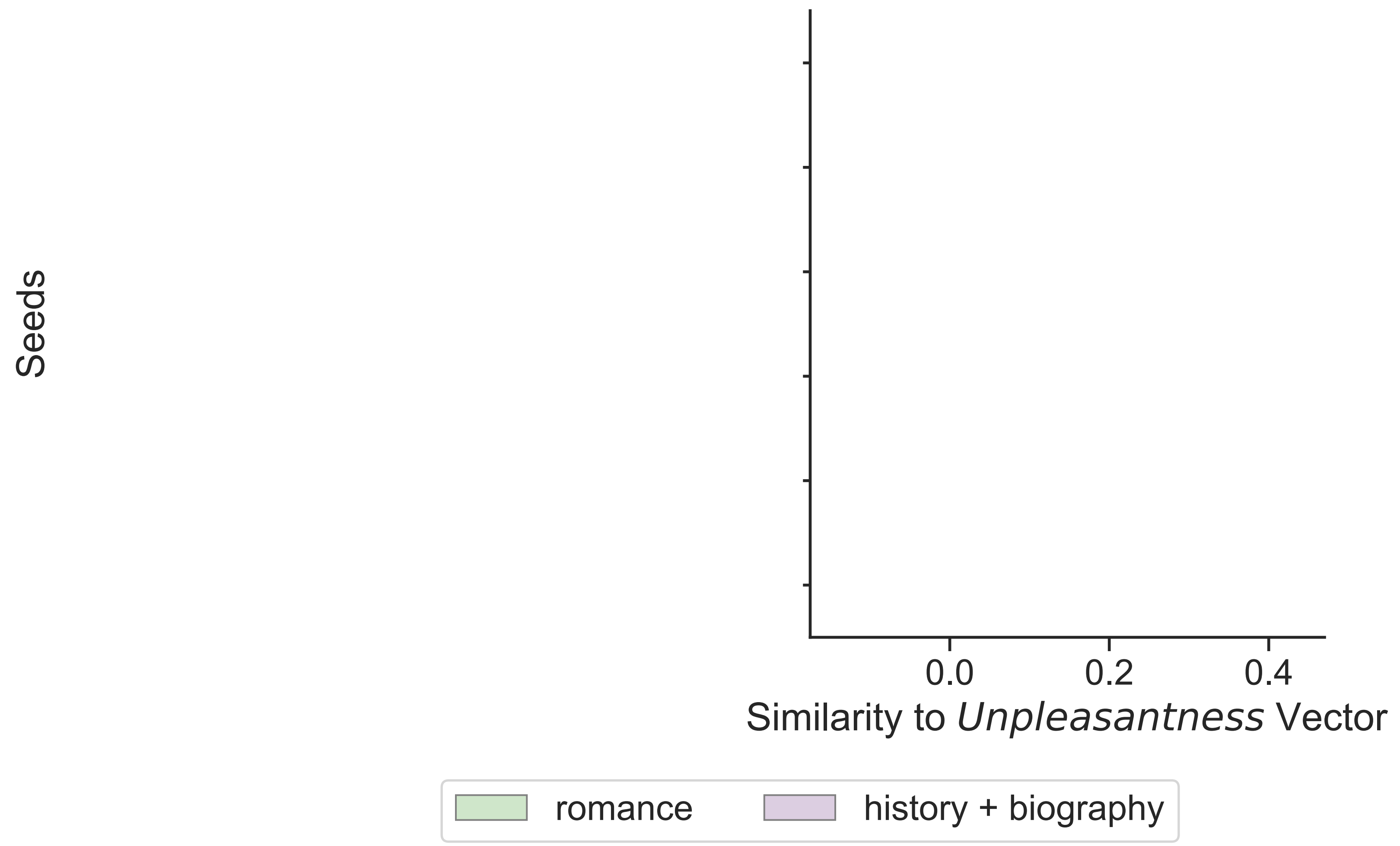
A Motivating Example

- Imagine you're studying online book reviews

- **Your Hypothesis**: Reviews of romance novels frame women more positively because more of these reviewers are women

- You gather a dataset of 333,000 reviews, curate seeds to represent **women** and **unpleasantness**, transform these seeds to vectors, and measure similarities between the sets of vectors using the **WEAT test**

A Motivating Example



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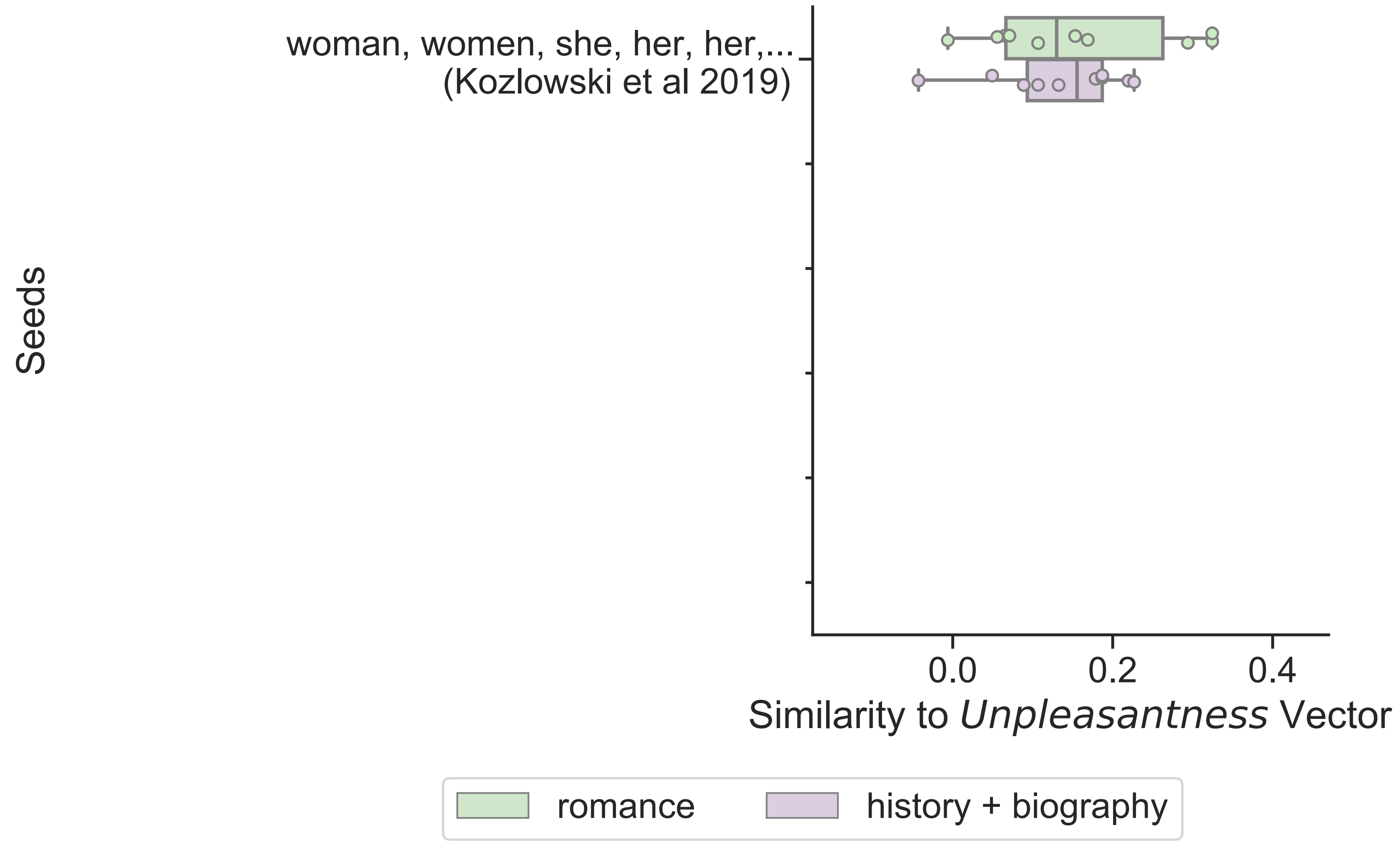

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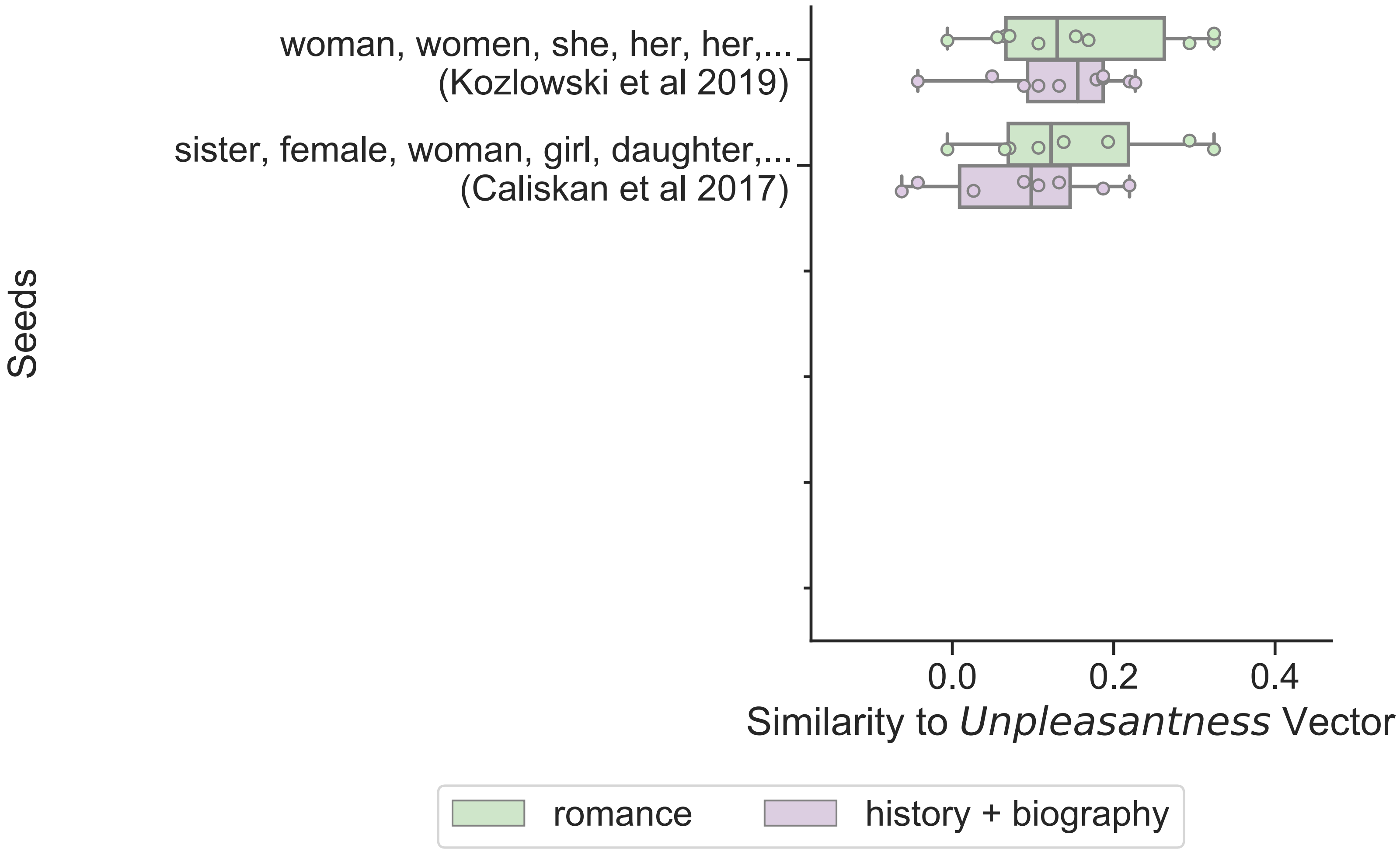

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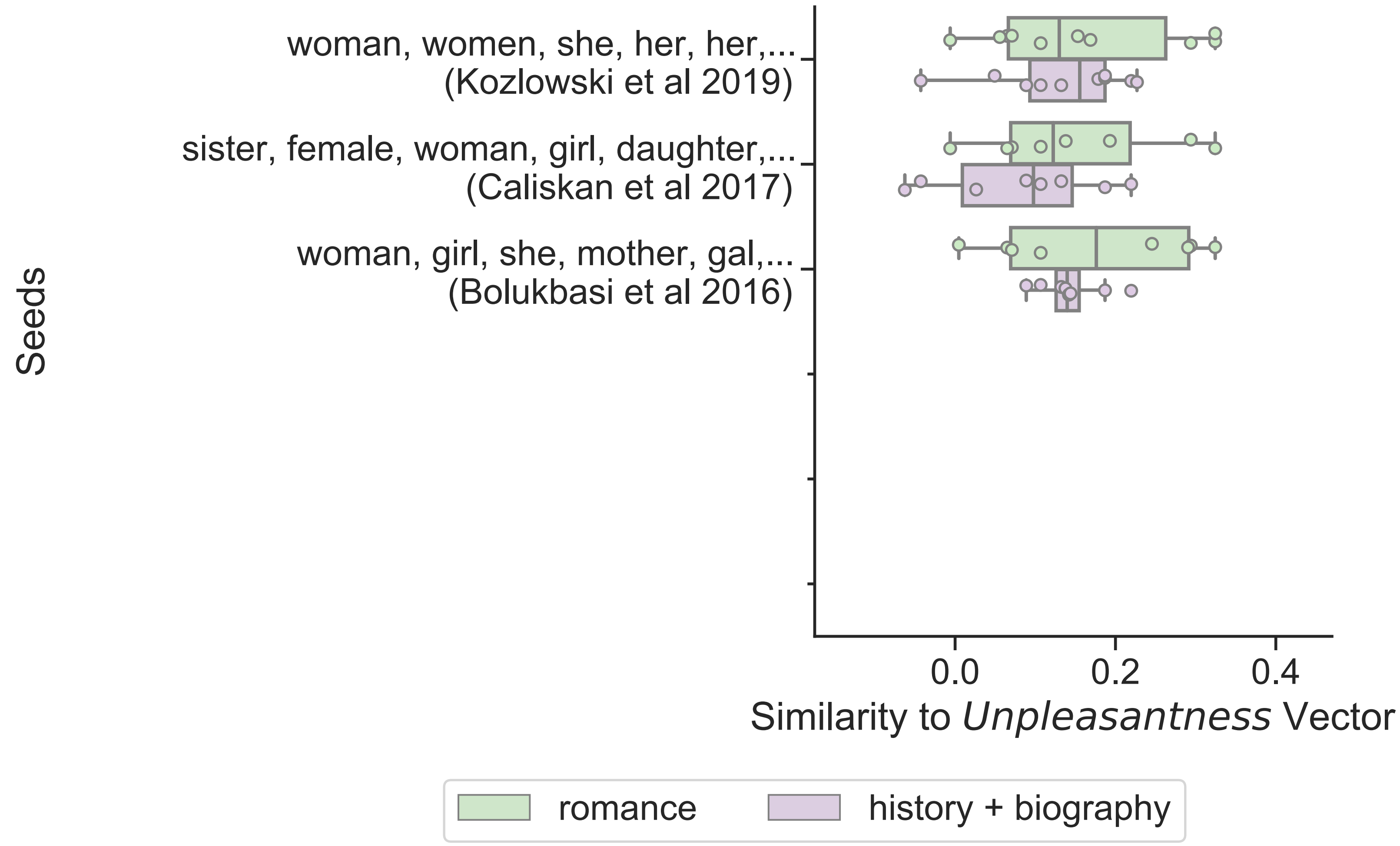

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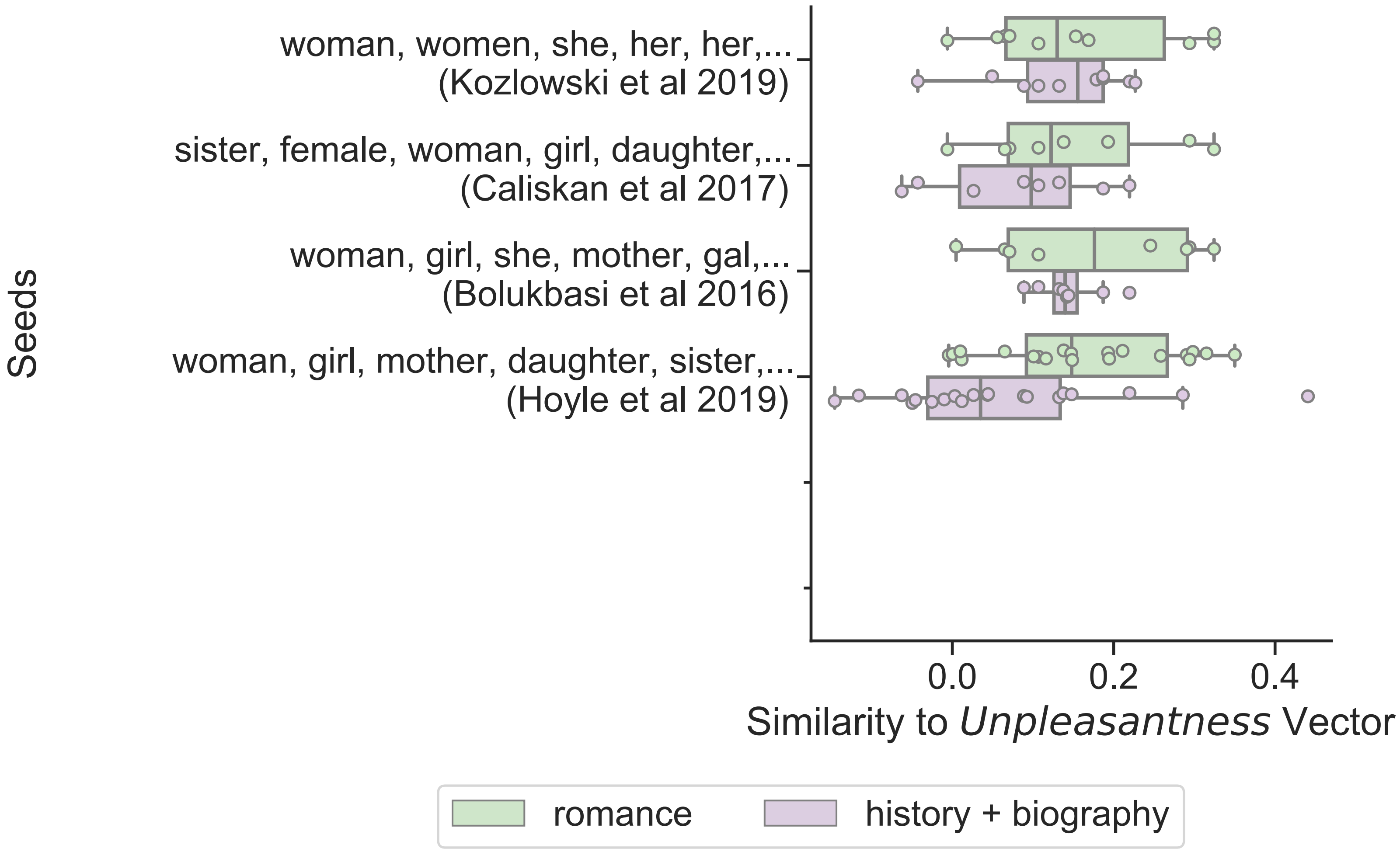

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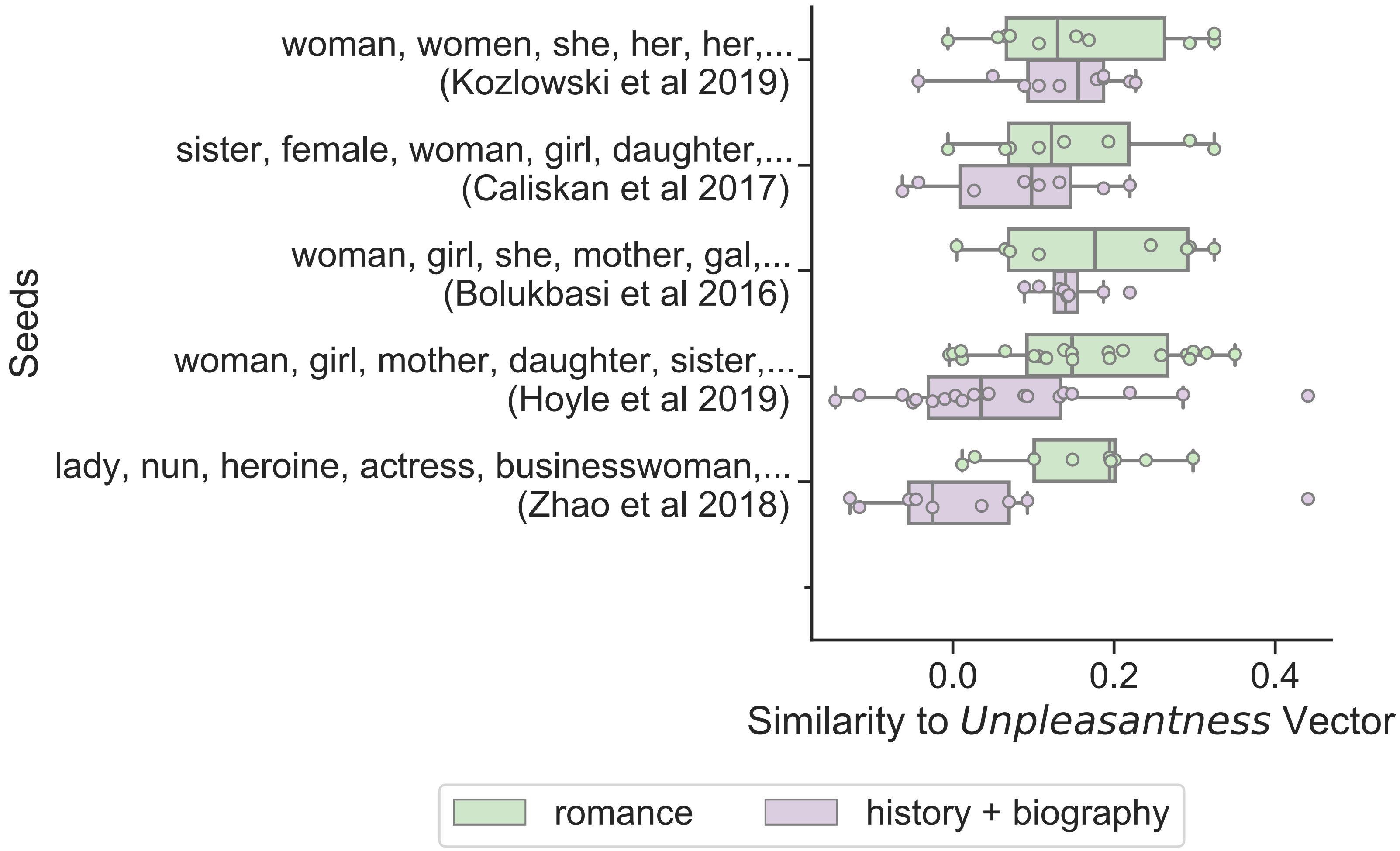

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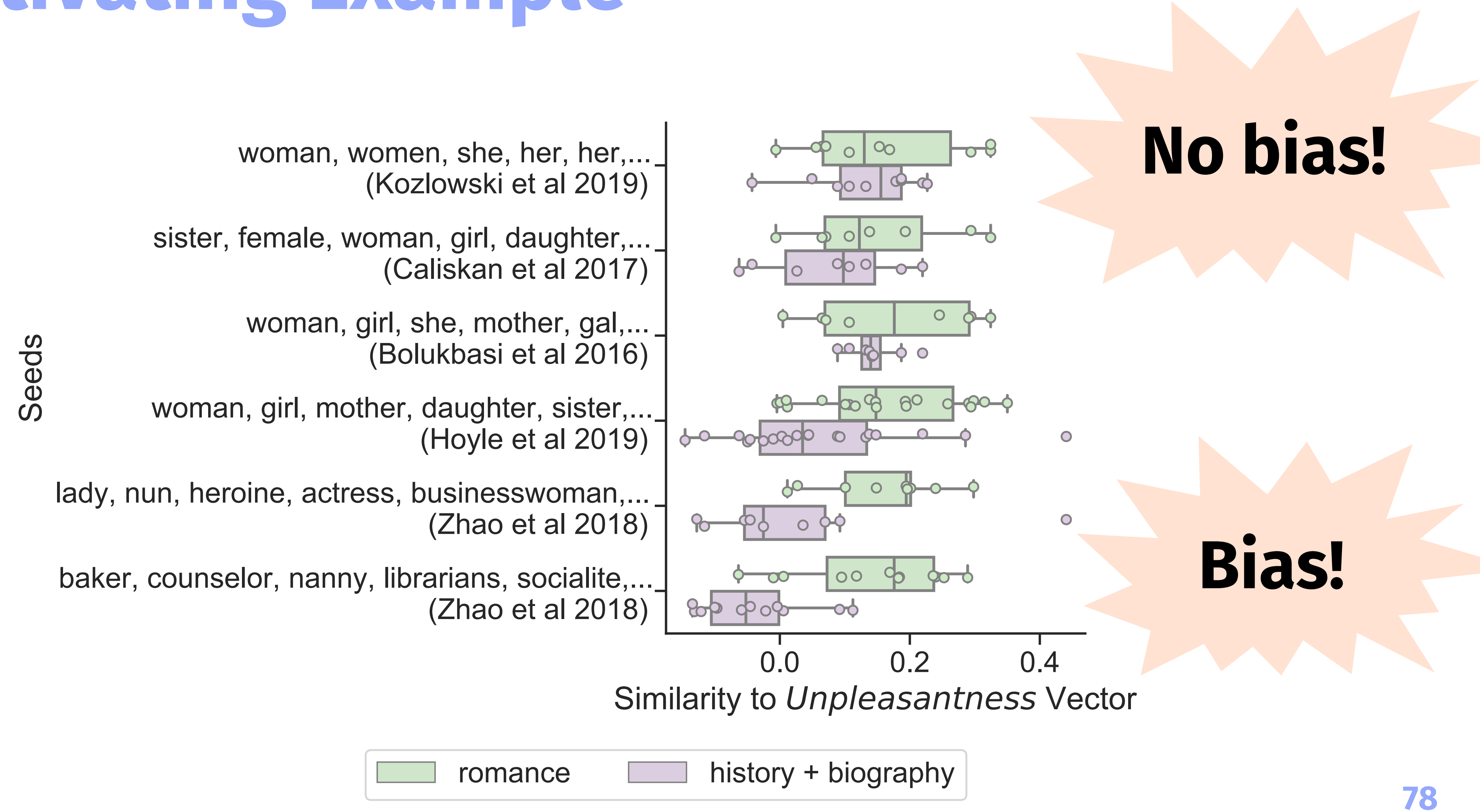


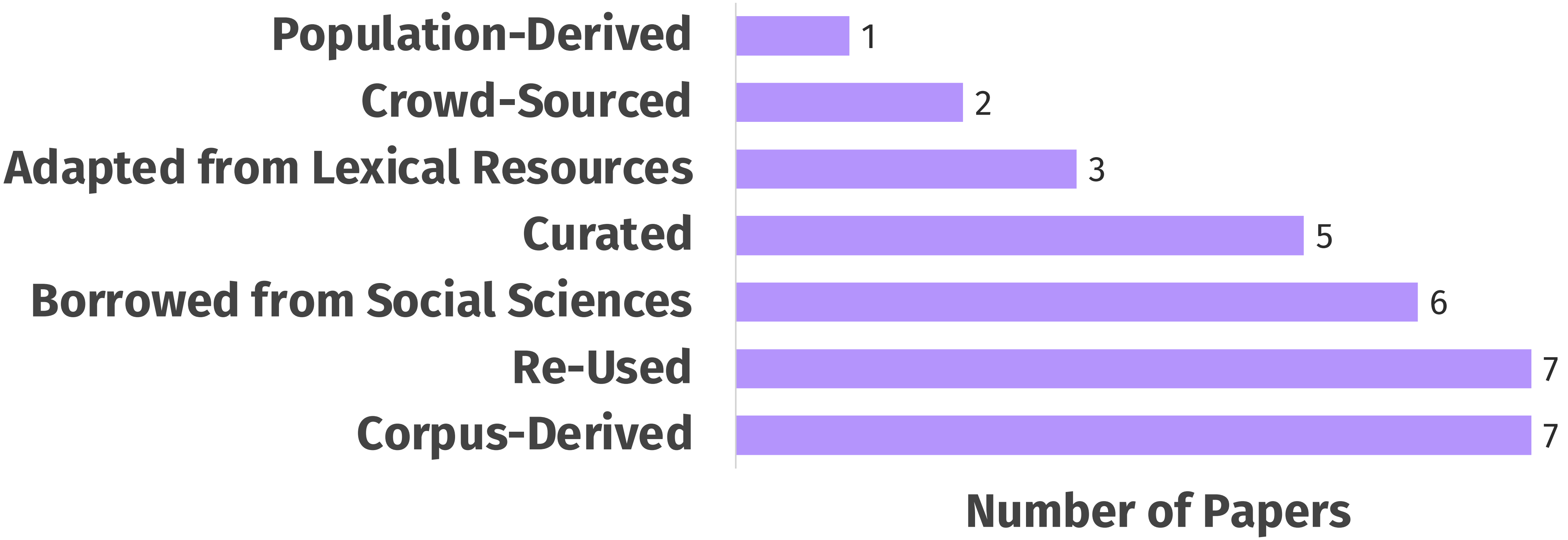
How do seeds affect bias measurements?

How are seeds selected? From which **sources** are they drawn?

Which features of seeds can cause **instability** in bias measurements?

Gathered Seed Sets

- We survey 18 highly cited papers using lexicons for bias measurement
- We gather and document 178 seed sets, **categorizing them by source**



Seeds Borrowed from Social Sciences

Incentives

- Often validated on human subjects
- Often curated with domain expertise

Risks

- “Appeal to authority”
- Previous validation does not guarantee reliability on new datasets

Which seed features affect bias measurements?

1. **Definitional Factors:** how the target concepts are defined
2. **Lexical Factors:** features of the individual seeds
3. **Set Factors:** features of the seed sets

Definitional Factors

Reductive Definitions

- Names for race
- Gender as a binary

Imprecise Definitions

- Inclusion of confounding terms

Unpleasant	divorce, jail, poverty, cancer, ...
African American	Tanisha, Tia, Lakisha, Latoya, ...
Domestic Work	mom, mum, ...
Ugliness	fat, chubby, obese, fatty, overweight, disformed, disfigured, wrinkle, wrinkled, ...

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Hanna et al. "Towards a critical race methodology in algorithmic fairness." *FAccT*, 2020.

Blodgett et al. "Language (technology) is power: A critical survey of 'bias' in NLP." *ACL*, 2020.

Puhl & Heuer. "The stigma of obesity: a review and update." *Obesity*, 2009.

Lexical Factors

- High frequency words are not comparable to low frequency words—and frequency can vary widely by dataset

  `Brunet et al. “Understanding the origins of bias in word embeddings.” *ICML*, 2019.`

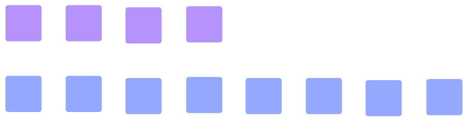
  `Ethayarajh et al. “Understanding undesirable word embedding associations.” *ACL*, 2019.`

- Comparing distinct parts of speech can result in different bias subspaces

  `Sedoc & Ungar. “The role of protected class word lists in bias identification of contextualized word representations.” *Workshop on Gender Bias in NLP*, 2019.`

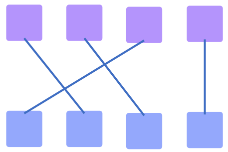
Set Factors

- **Set Size** (the number of seeds per set)

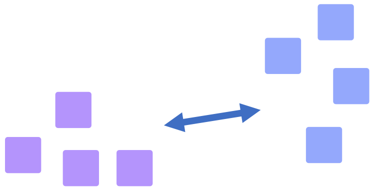


`Kozlowski et al. “The geometry of culture: Analyzing the meanings of class through word embeddings.” *American Sociological Review*, 2019.`

- **Set Alignment** (the ordering or pairing of the seeds)



- **Set Similarity** (the embedded similarity of the two sets)



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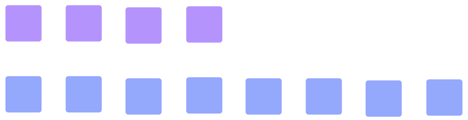

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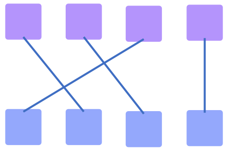

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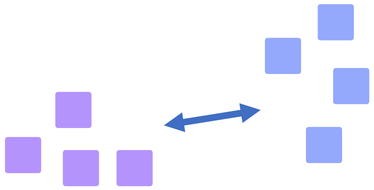
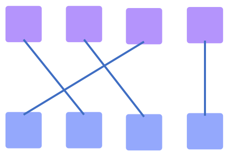


Set Alignment



Gender Pairs

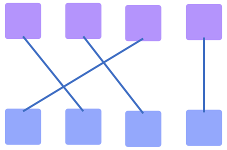
herself	0.50
ms	0.49
her	0.49
she	0.41
pregnant	0.40
pitching	-0.36
baseball	-0.36
syndergaard	-0.38
himself	-0.39
his	-0.42

Random Pairs

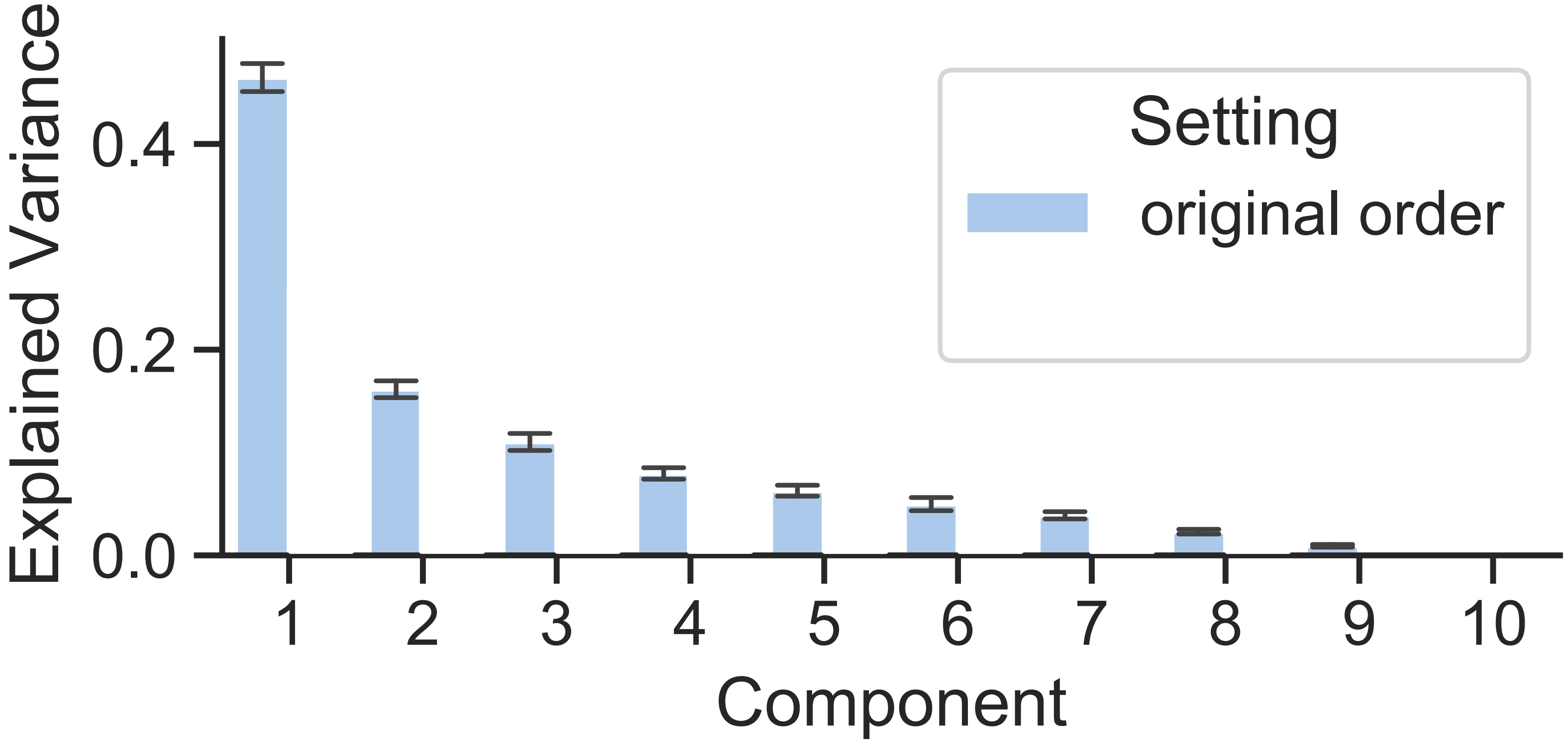
likelihood	0.36
eurozone	0.34
incentive	0.34
downturn	0.31
setback	0.30
photographed	-0.39
tales	-0.41
hood	-0.42
garcia	-0.45
danced	-0.59

Shuffled Gender Pairs

outcomes	0.26
son	0.26
father	0.26
mother	0.26
aunt	0.25
potentially	-0.19
male	-0.19
hood	-0.29
garcia	-0.29
md	-0.39

Set Alignment 

Ordered: man-woman, he-she



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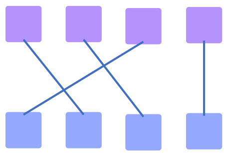
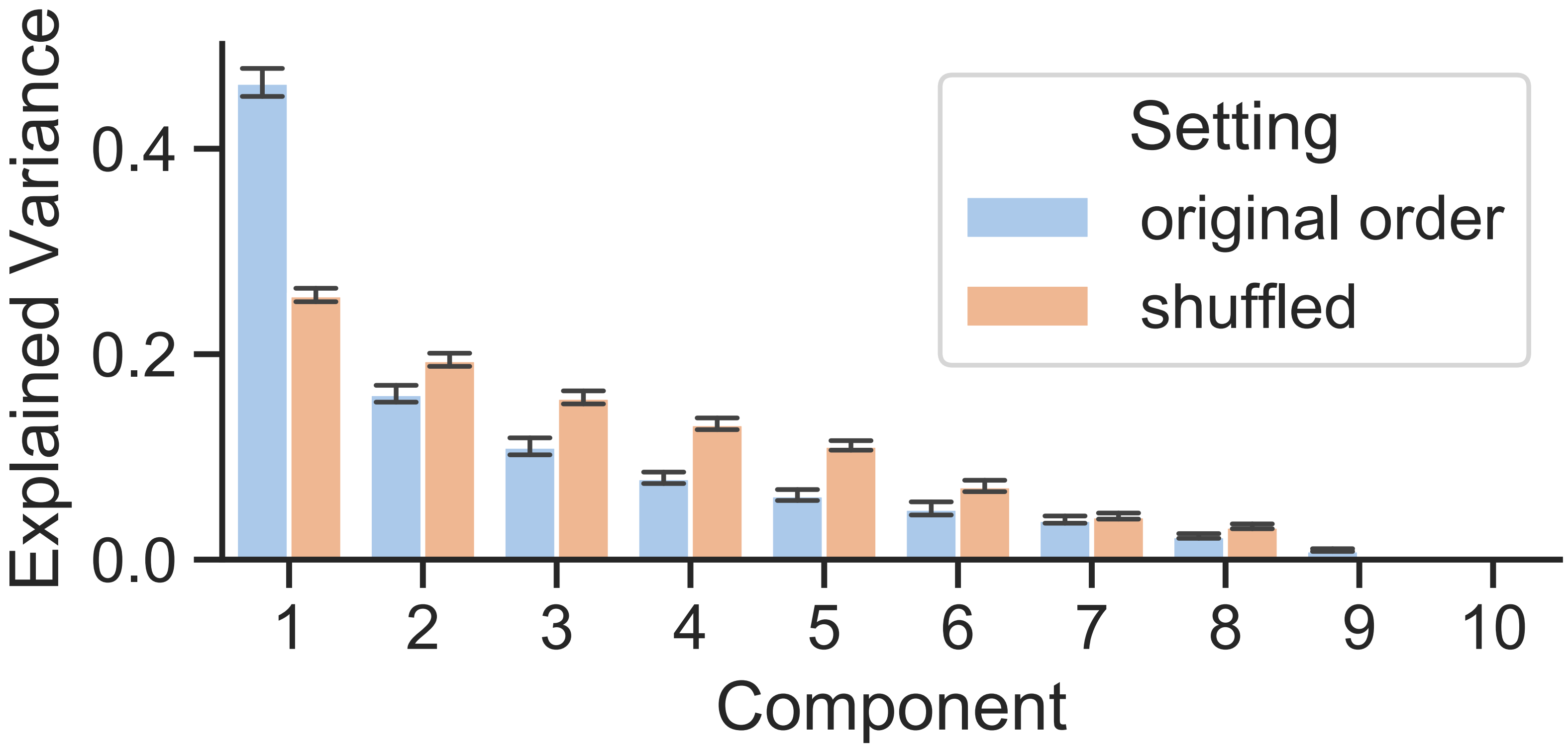
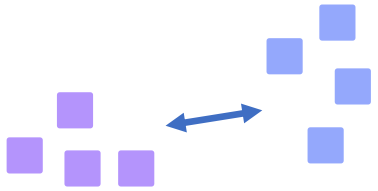


Ordered: man-woman, he-she

Shuffled: man-she, he-woman

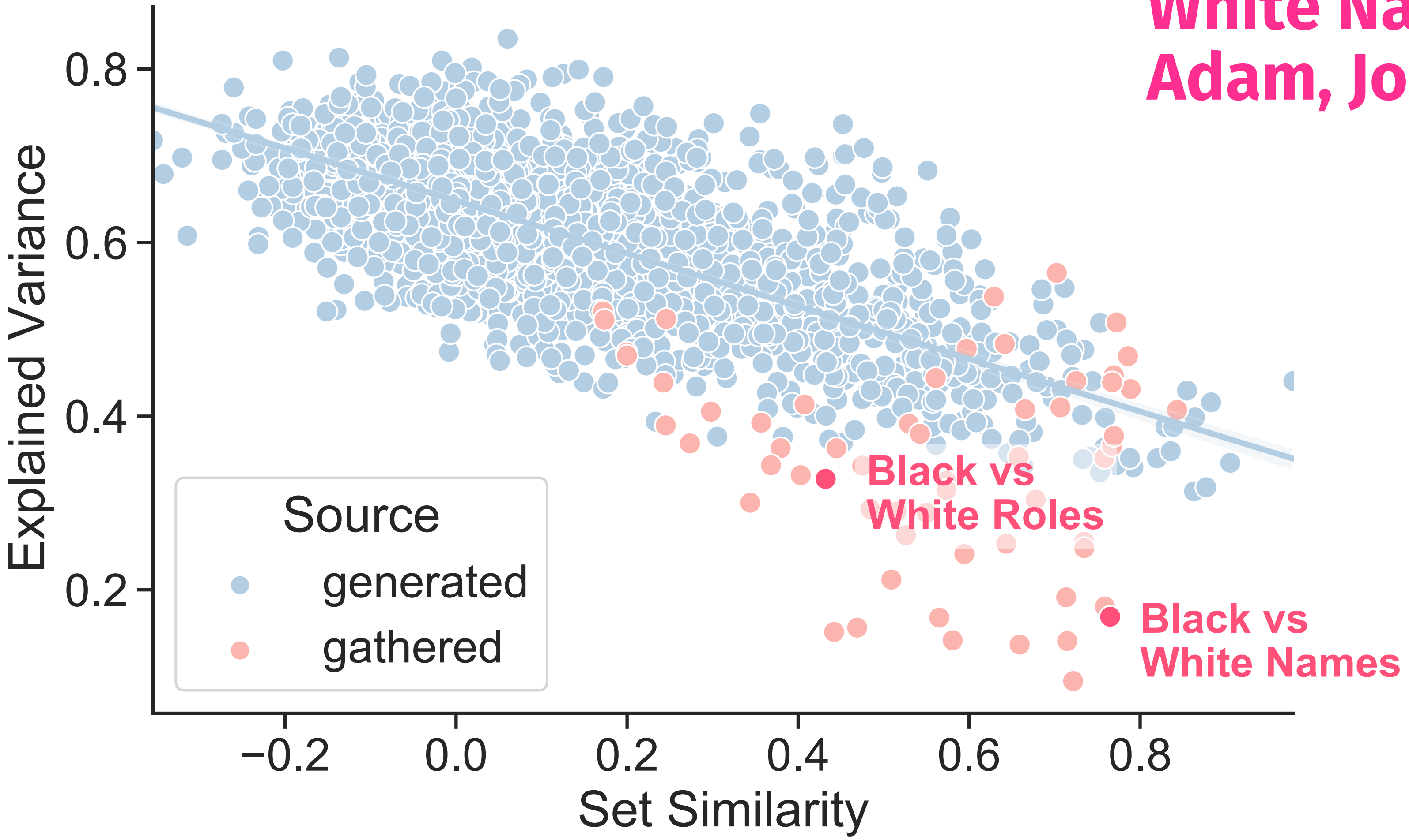


Set Similarity



White Roles:
manager, hillbilly, …

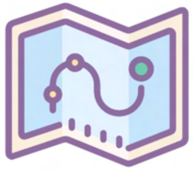
White Names:
Adam, Josh, …



Lessons Learned: *Biases all the way down...*

- **Documented** and tested 178 seed sets from prior work, with a **framework** for understanding risks and benefits of each seed source
- **Investigated** seed features that can lead to instability
- **Recommendations** for practitioners

Lessons Learned: *Biases all the way down...*



Trace the origins of seed sets

Examine seed features and compare multiple plausible sets

Document all seeds for transparency and accessibility

My Research Goals

Use NLP methods to study the sharing of personal experiences online

- Birth communities: power and narrative in birth stories (CSCW, 2019)
- Expressing pain through similes (Frontiers in Neuroscience, 2019)
- Literary genres in online reading communities (Cultural Analytics, 2021; CSCW, 2021)

Probe the reliability of NLP methods for cultural analytics applications

- Instability of cosine similarities for word embeddings (TACL, 2018)
- Seed selection can affect bias measurement (ACL, 2021)
- BERT for Humanists (public tutorials, 2021; ACH, 2021; ICWSM, 2022)

Who decides how to organize genres?

- We know how literary critics, academics, publishers, authors think about genre, but what about people in **online reading communities**?

- How do non-traditional genres, like **vampires**, stand in relation to traditional genres?

- How are online genres related to offline organization of books?

How prior work has mapped genres

Literary scholars emphasize that genres are blurry, change over time, and depend on context.

Pavel. “Literary Genres as Norms and Good Habits.” *New Literary History*, 2003.

Rosen. “Literary Fiction and the Genres of Genre Fiction.” *Post45*, 2018.

Computational studies have focused on genre classification of book-length texts.

Brett Kessler et al. “Automatic Detection of Text Genre.” *ACL*, 1997.

Stamatatos et al. “Automatic Text Categorization in Terms of Genre and Author.” *Computational Linguistics*, 2000.

Wilkens. ”Genre, Computation, and the Varieties of Twentieth-Century U.S. Fiction.” *Cultural Analytics*, 2016.

Underwood. “The Life Cycles of Genres.” *Cultural Analytics*, 2016.

LibraryThing: A Web of Books

- Similar to Goodreads but more ✨ **independent** + **accessible** ✨
- Social website for curating and cataloging and sharing your collection of **books** and **reviews**
- Revenue is generated through a **catalog** for small bookstores and libraries—and the catalog is built from the **free-text tags** applied by users!

Folksonomies & Tagging

- LibraryThing allow users to **tag** books with free-text fields.
- Tags can be used as personal categories, community rankings, genres, and more.
- **Folksonomies**: unconstrained tags (rather than rigid hierarchies or taxonomies) applied by individuals and communities

Vander Wal. 2005. “Folksonomy Definition and Wikipedia.” http://www.vanderwal.net/random/entrysel.php?blog=1750

Vander Wal. 2007. “Folksonomy.” https://www.vanderwal.net/essays/051130/folksonomy.pdf

Genre, Tags, and Questioning Labels

- In the **downstream** setting, we might clean the genre tags, create a non-overlapping taxonomy, and use that taxonomy to train a classifier
- In the **upstream** setting, we can use the messy, collaborative genre tags to interrogate the label definitions
- In exploring the genre tags, we also learn about **how people experience literature** individually and in a community

Research Questions

- Considering genres as unconstrained, collaborative, and overlapping, which community dimensions can we use to **map** a set of target genres?

- Using these maps, what patterns can we identify across genres, and which genres and reviews emerge as **outliers**?

- How do these findings compare to traditional understandings of genre?

Data Collection

- Gathered **book metadata**, **all reviews**, and **reviewer tag clouds** for the top 1000 books for 20 tags on LibraryThing
- Mostly English-language reviews
- **17,440 books; 319,850 reviews; 33,849 users**

Data Ethics: Private or Public?

- Reviewers share personal and political opinions and stories—but also often view their reviews as professional work.

- Replicating texts of reviews takes away users' ability to edit, update, or delete their reviews.

- **We contact all reviewers whom we directly quote and ask their preferences**

Bruckman. "Studying the amateur artist: A perspective on disguising data collected in human subjects research on the Internet." *Ethics and Information Technology*, 2002.

Fiesler and Proferes. "'Participant' Perceptions of Twitter Research Ethics." *Social Media + Society*, 2018.

Genre	Words Per Review	Related Tags	Most Tagged Books
politics	312 words	presidents, American Presidents, communism, political science, US history	*The Prince* *The Communist Manifesto* *Animal Farm*
science fiction	289 words	Terry Pratchett, futuristic, sf, dystopian, dystopia	*Ender's Game* *The Hitchhiker's Guide to the Galaxy* *Fahrenheit 451*
vampires	273 words	vampire, werewolves, werewolf, paranormal romance, paranormal	*Twilight* *New Moon* *Eclipse*
memoir	252 words	autobiography, biography, essays, travel, Islam	*The Glass Castle: A Memoir* *Angela's Ashes* *Running with Scissors*
crime	238 words	Agatha Christie, Christie, crime fiction, police procedural, historical mystery	*The Girl with the Dragon Tattoo* *In Cold Blood* *The Girl Who Played with Fire*
picture book	175 words	Caldecott Medal, Caldecott Honor, collection:Fiction, shelf:Fiction, colors	*Where the Wild Things Are* *The Very Hungry Caterpillar* *Goodnight Moon*

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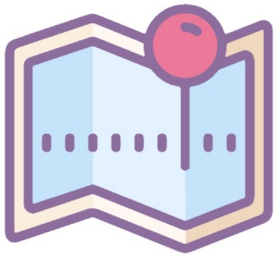
“It’s knocked my socks off, thrown me in the corner and left me a crumbling, emotional wreck...the character and story development, the writing, the way in which it stirs the emotions and its sheer humanity have all hit the right spot. It is also an emotional study into how a person may react to the possibility of the onset of dementia...Yes, Flowers for Algernon has won awards for science fiction and yes it is in the SF Masterworks list but ultimately it is a story of humanity and a person struggling to gain acceptance for who he really is not for who others want him to be.”

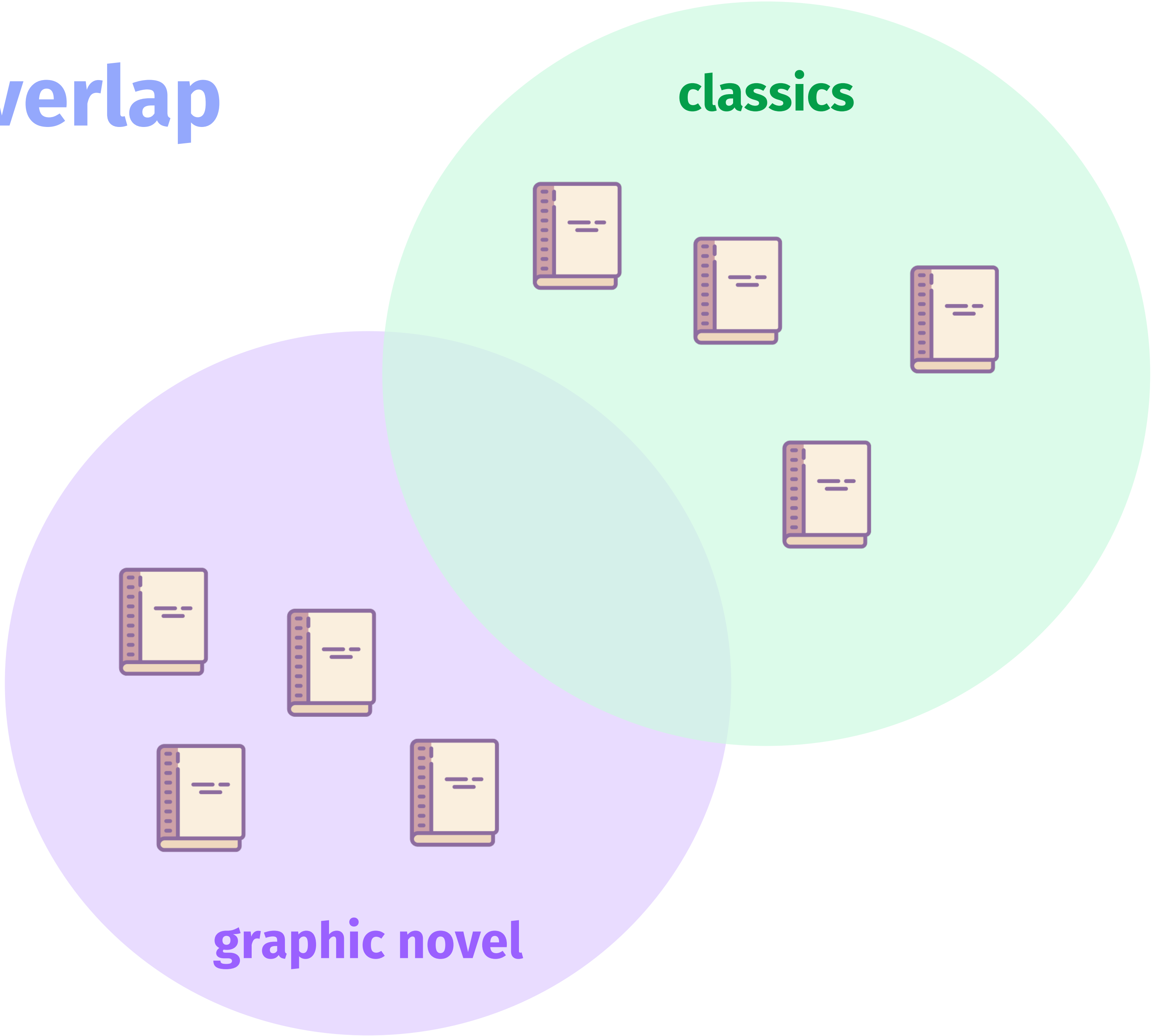
— lilywren, review of *Flowers for Algernon*

How to map and measure “genre”?

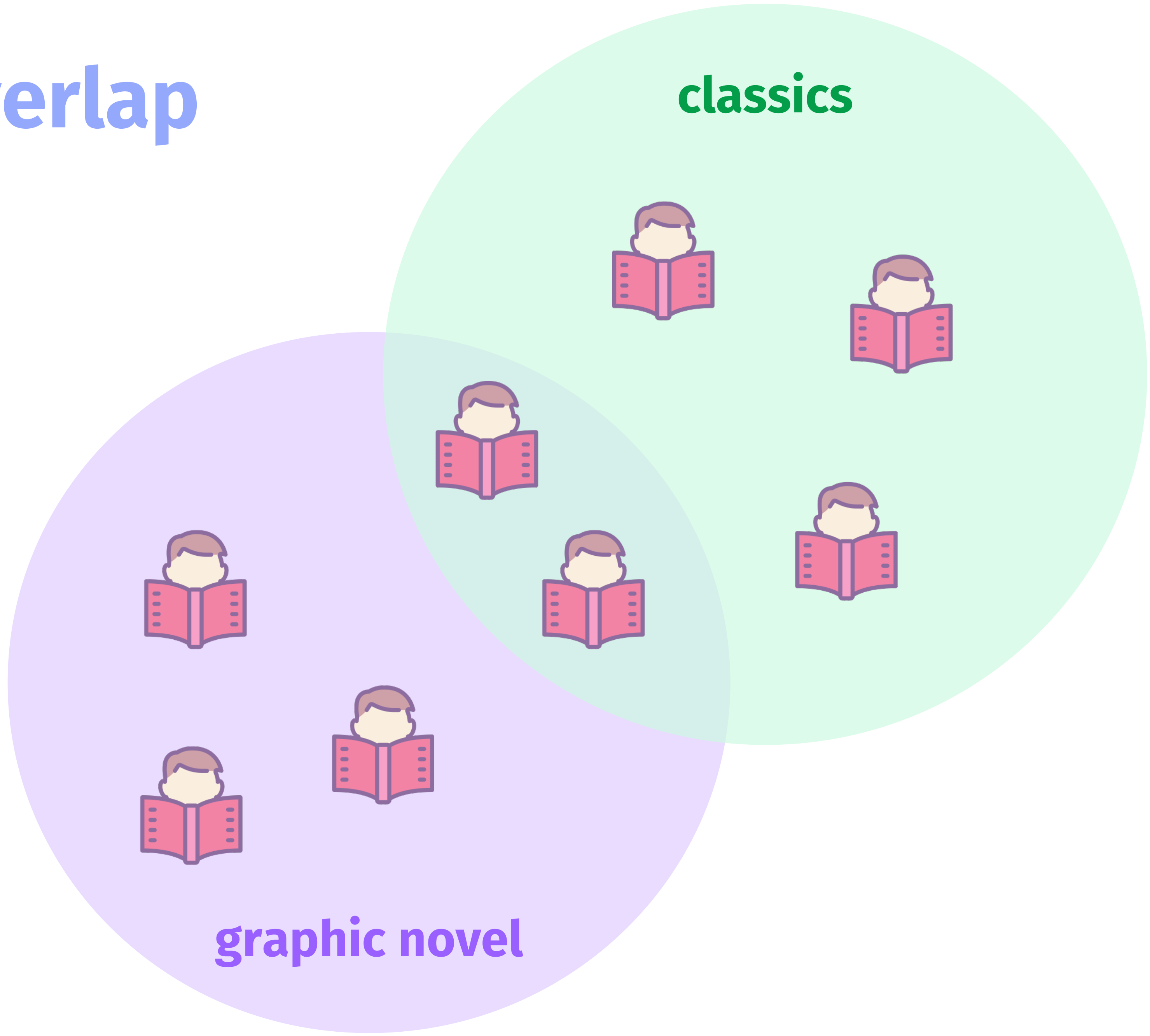


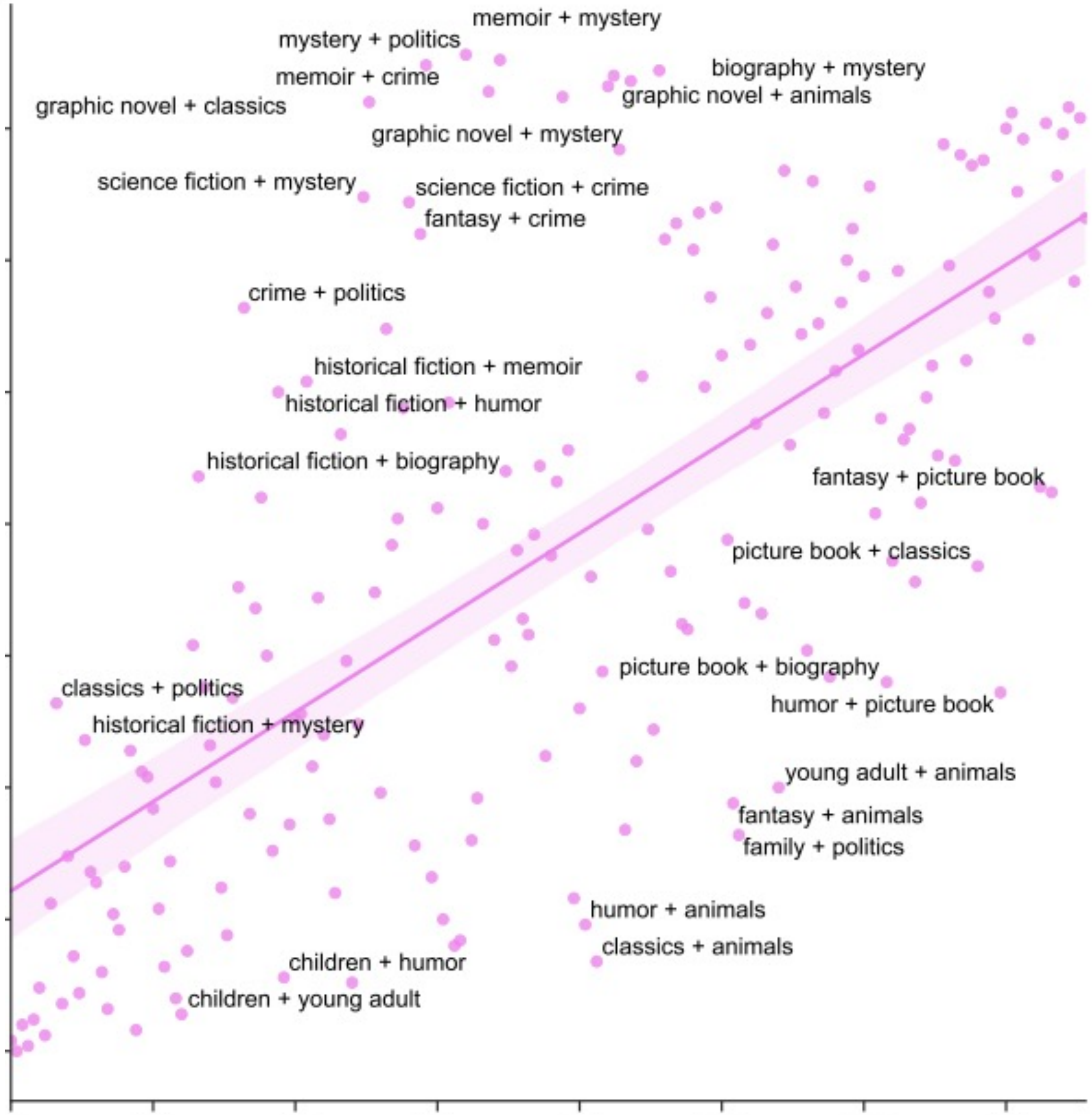
- How much **overlap** of books and users is there between genre pairs?
- How distinctive are the **review texts** for this genre?
- How similar are the tagging habits of a genre’s **reviewers**?

Book Overlap



User Overlap



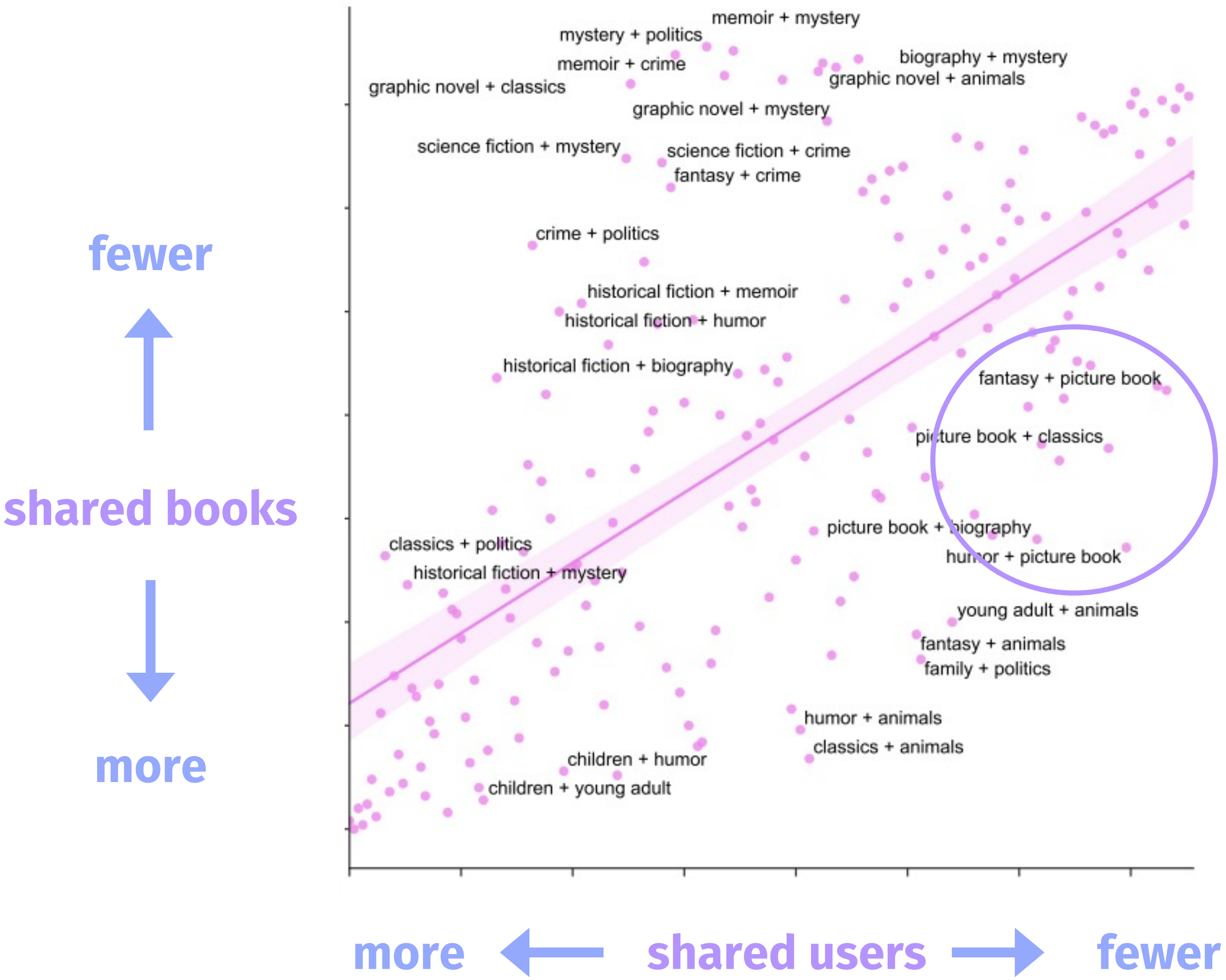


fewer

shared books

more

more ← shared users → fewer

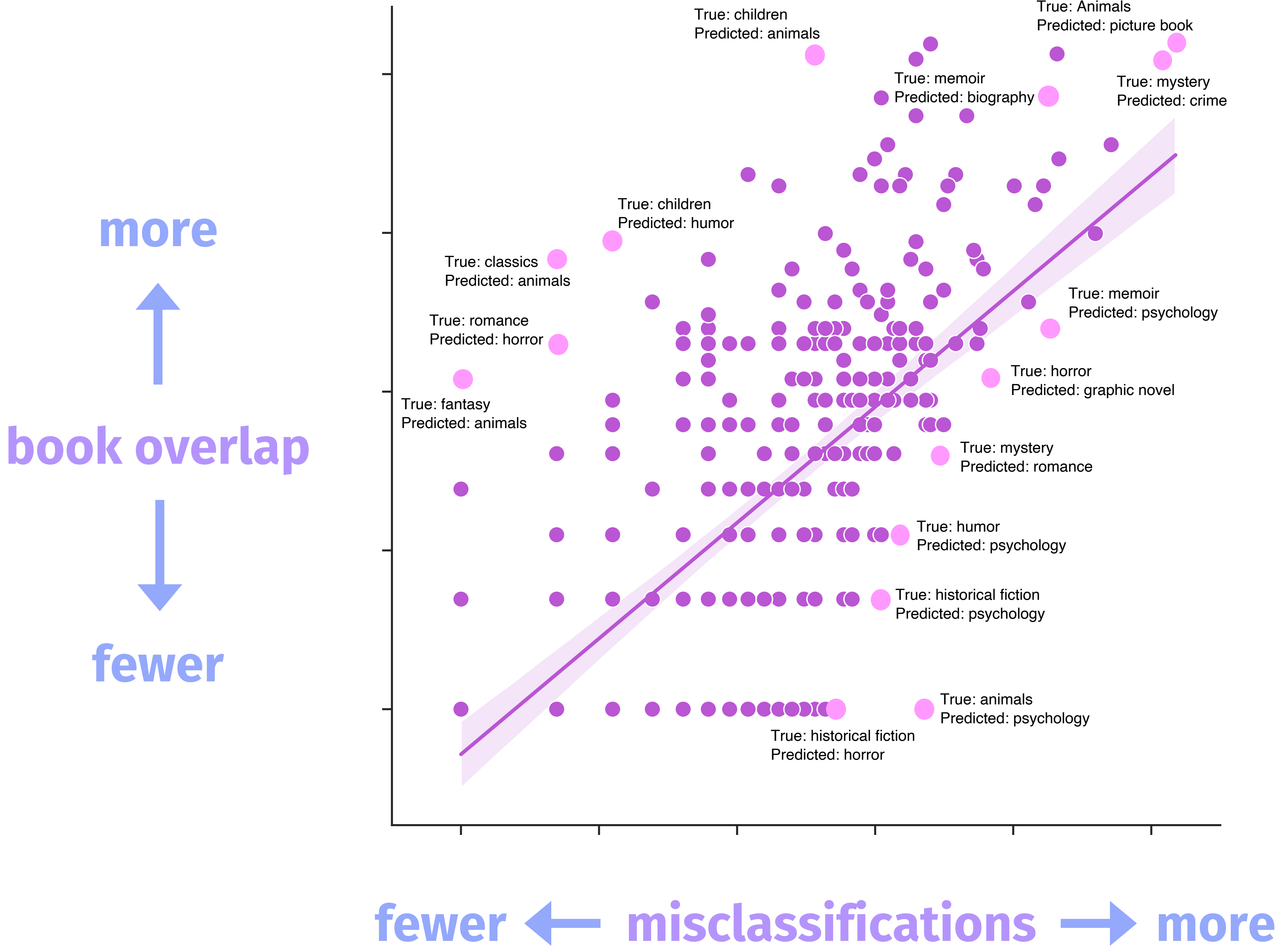

fewer
shared books
more
memoir + mystery
mystery + politics
memoir + crime
biography + mystery
graphic novel + animals
graphic novel + classics
graphic novel + mystery
science fiction + mystery
science fiction + crime
fantasy + crime
crime + politics
historical fiction + memoir
historical fiction + humor
historical fiction + biography
fantasy + picture book
picture book + classics
picture book + biography
humor + picture book
classics + politics
historical fiction + mystery
young adult + animals
fantasy + animals
family + politics
humor + animals
classics + animals
children + humor
children + young adult
more
shared users
fewer

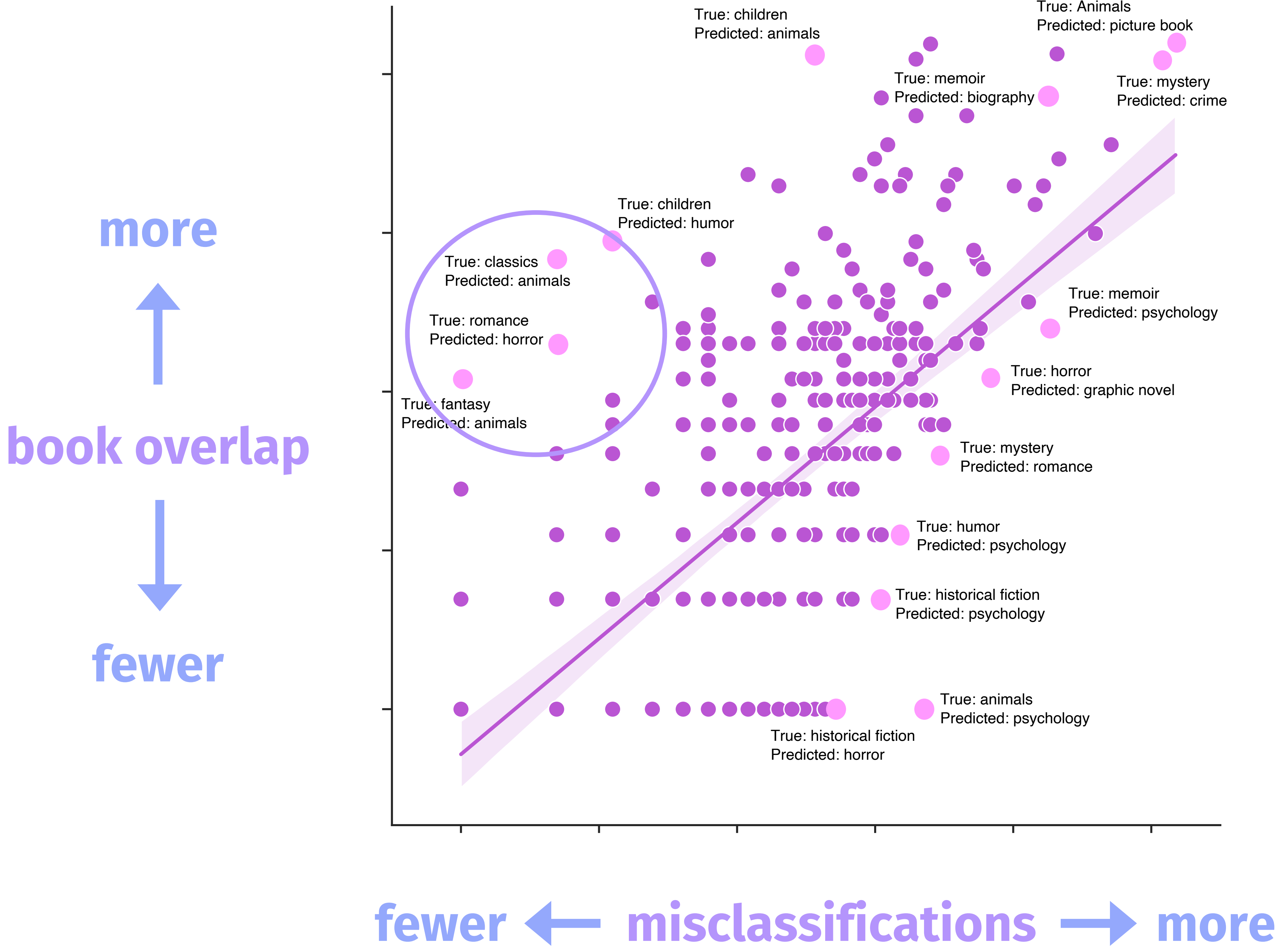

fewer
shared books
more
memoir + mystery
mystery + politics
memoir + crime
biography + mystery
graphic novel + animals
graphic novel + classics
graphic novel + mystery
science fiction + mystery
science fiction + crime
fantasy + crime
crime + politics
historical fiction + memoir
historical fiction + humor
historical fiction + biography
fantasy + picture book
picture book + classics
picture book + biography
humor + picture book
classics + politics
historical fiction + mystery
young adult + animals
fantasy + animals
family + politics
humor + animals
classics + animals
children + humor
children + young adult
more
shared users
fewer

Genre Classification “Mistakes”

“There were some moments though where I had to wonder about the historical accuracy of some of the attitudes and that broke the reading spell for me. Pretty predictable but I enjoyed the ride. Almost a 4 read for me but not quite.”

—wyvernfriend, review of *Simply Unforgettable*

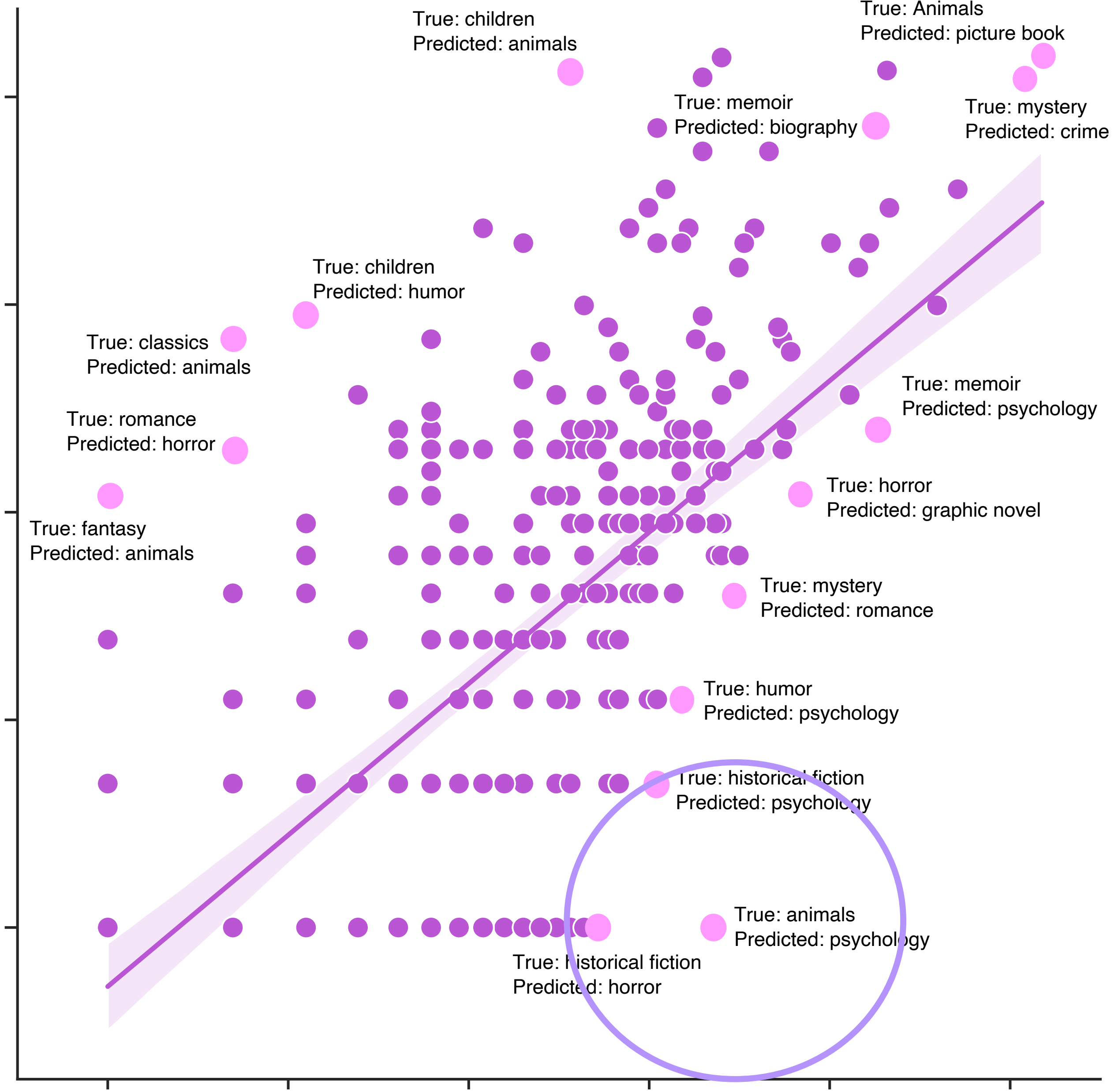

True: children
Predicted: animals
True: Animals
Predicted: picture book
True: memoir
Predicted: biography
True: mystery
Predicted: crime
True: children
Predicted: humor
True: classics
Predicted: animals
True: memoir
Predicted: psychology
True: romance
Predicted: horror
True: horror
Predicted: graphic novel
True: fantasy
Predicted: animals
True: mystery
Predicted: romance
True: humor
Predicted: psychology
True: historical fiction
Predicted: psychology
True: animals
Predicted: psychology
True: historical fiction
Predicted: horror
more
book overlap
fewer
fewer
misclassifications
more


more
book overlap
fewer
True: children
Predicted: animals
True: Animals
Predicted: picture book
True: memoir
Predicted: biography
True: mystery
Predicted: crime
True: children
Predicted: humor
True: classics
Predicted: animals
True: romance
Predicted: horror
True: fantasy
Predicted: animals
True: memoir
Predicted: psychology
True: horror
Predicted: graphic novel
True: mystery
Predicted: romance
True: humor
Predicted: psychology
True: historical fiction
Predicted: psychology
True: animals
Predicted: psychology
True: historical fiction
Predicted: horror
fewer
misclassifications
more

more

book overlap

fewer



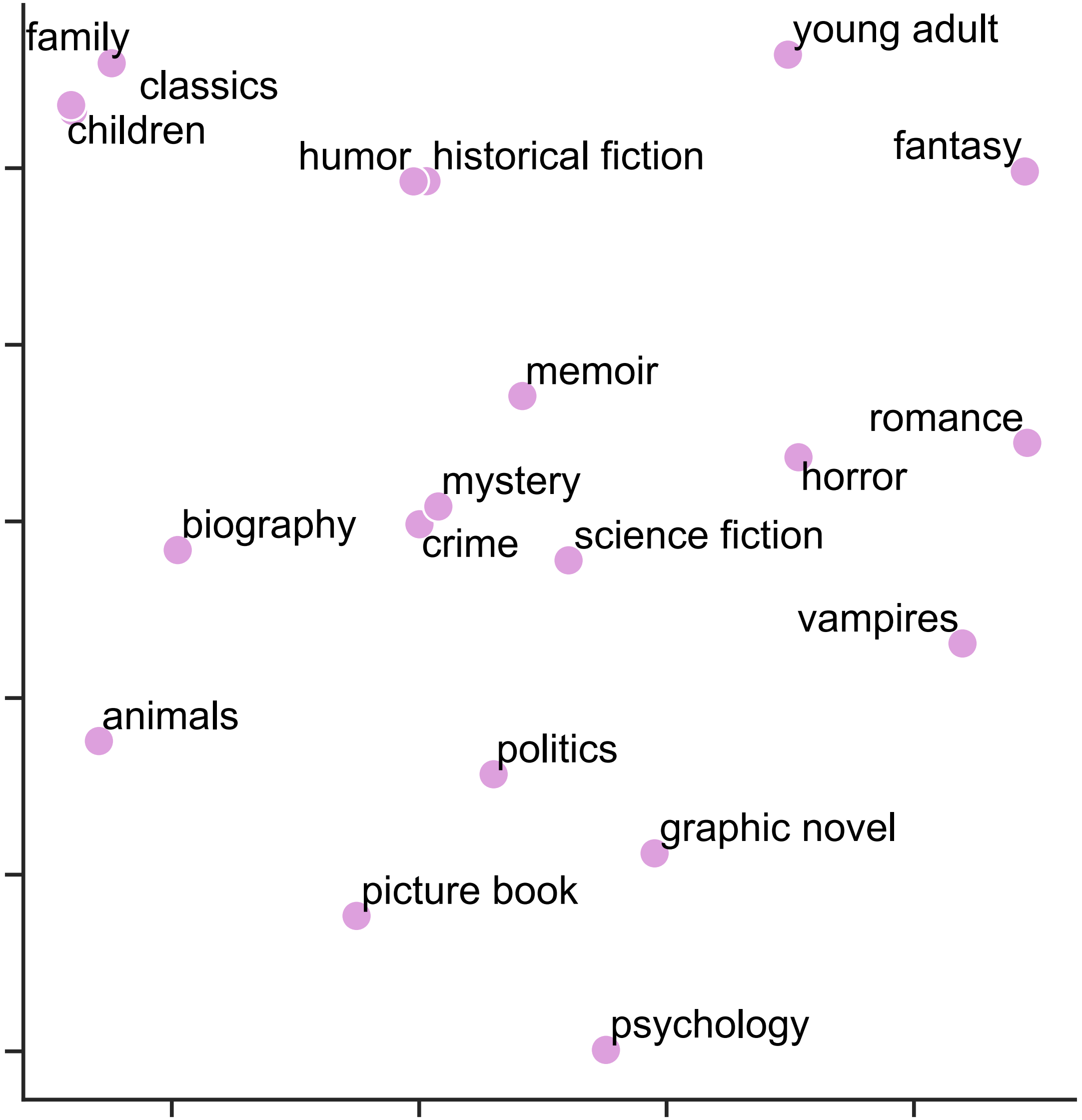
fewer ← misclassifications → more

Reviewer Homogeneity

Do these users have similar tagging (reading) habits?

	history	biography	memoir	historical fiction	romance	crime
User 1	12	3	6	3	0	2
User 2	10	2	11	15	55	0

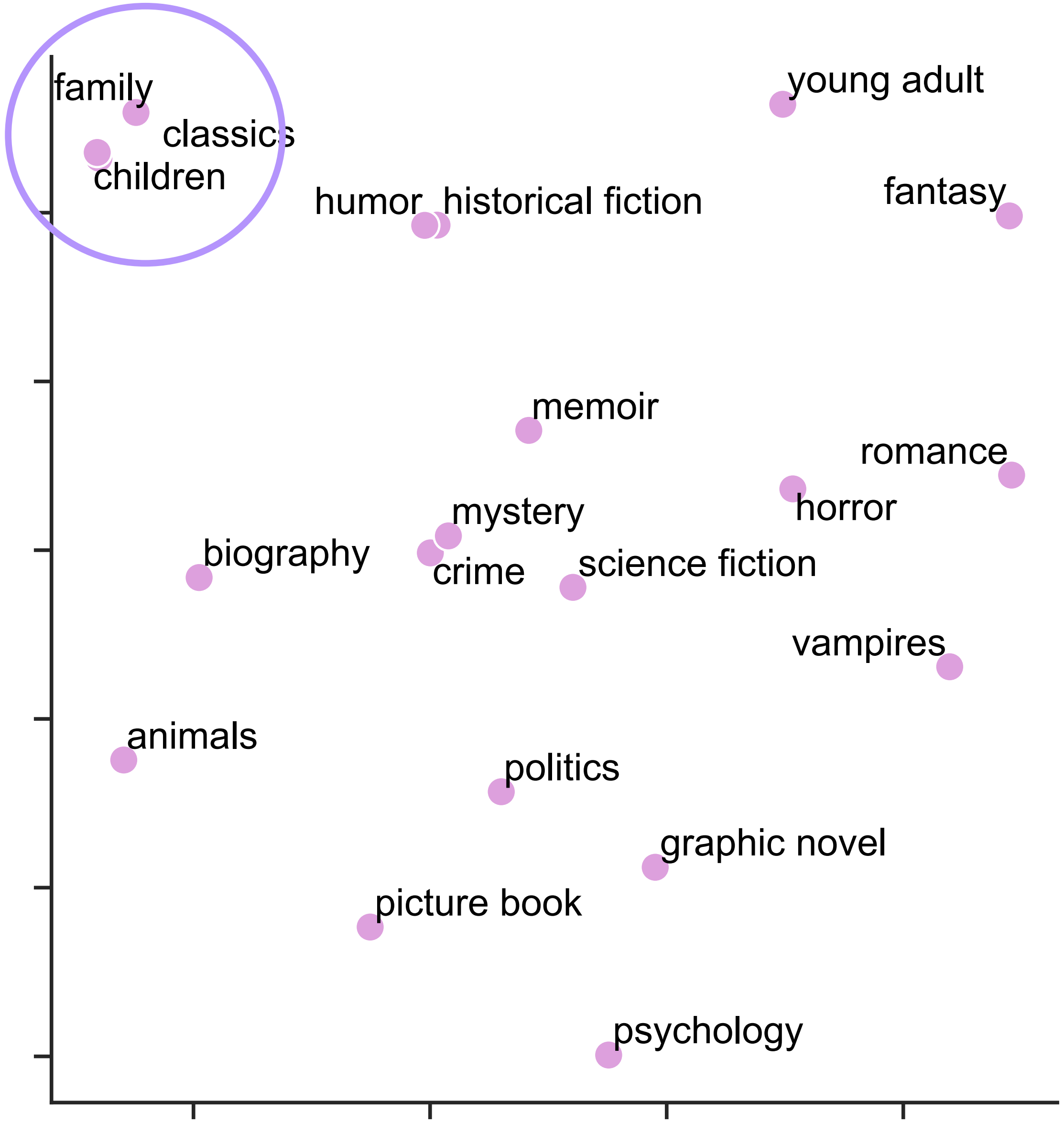
classification
is harder



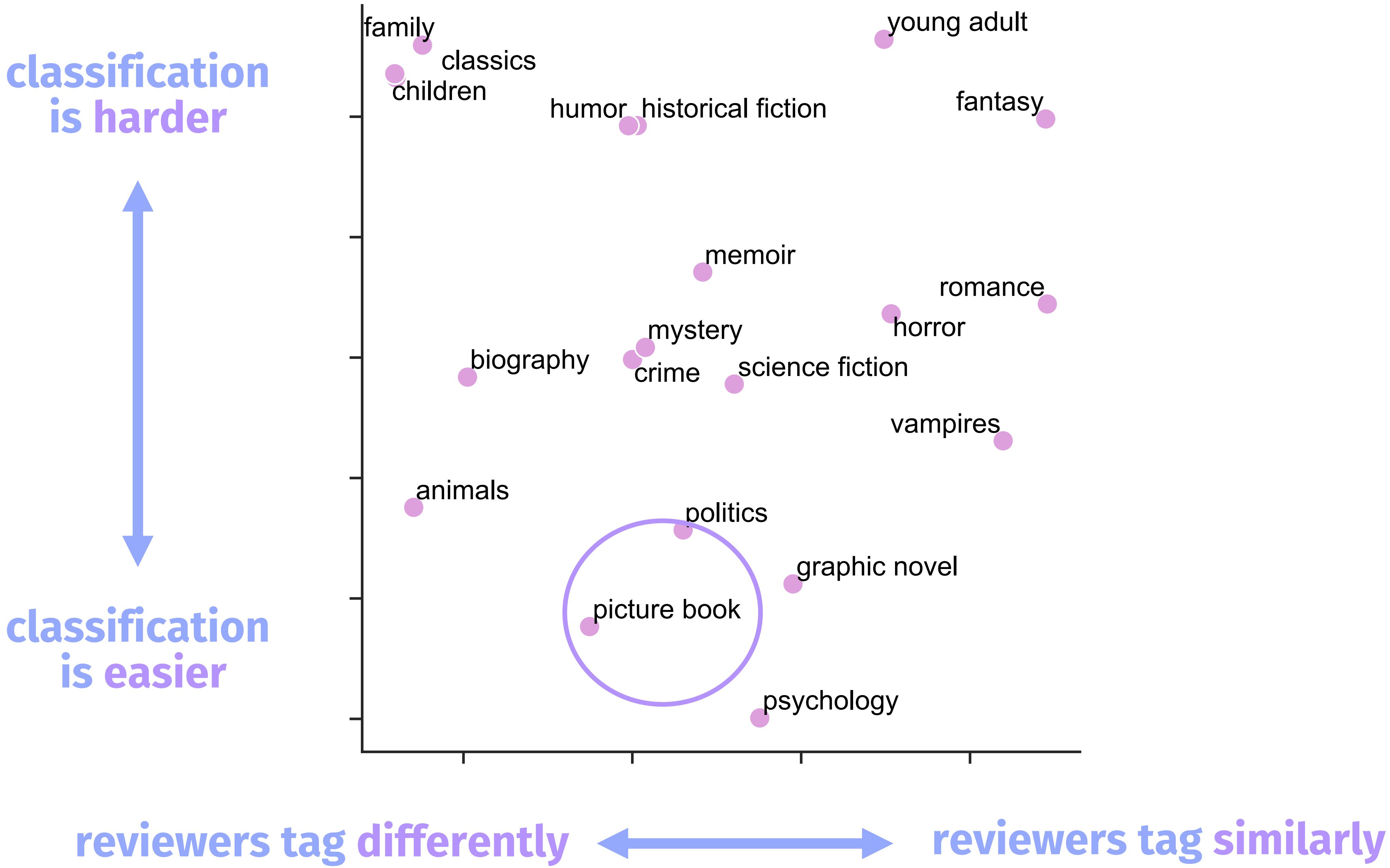
classification
is easier

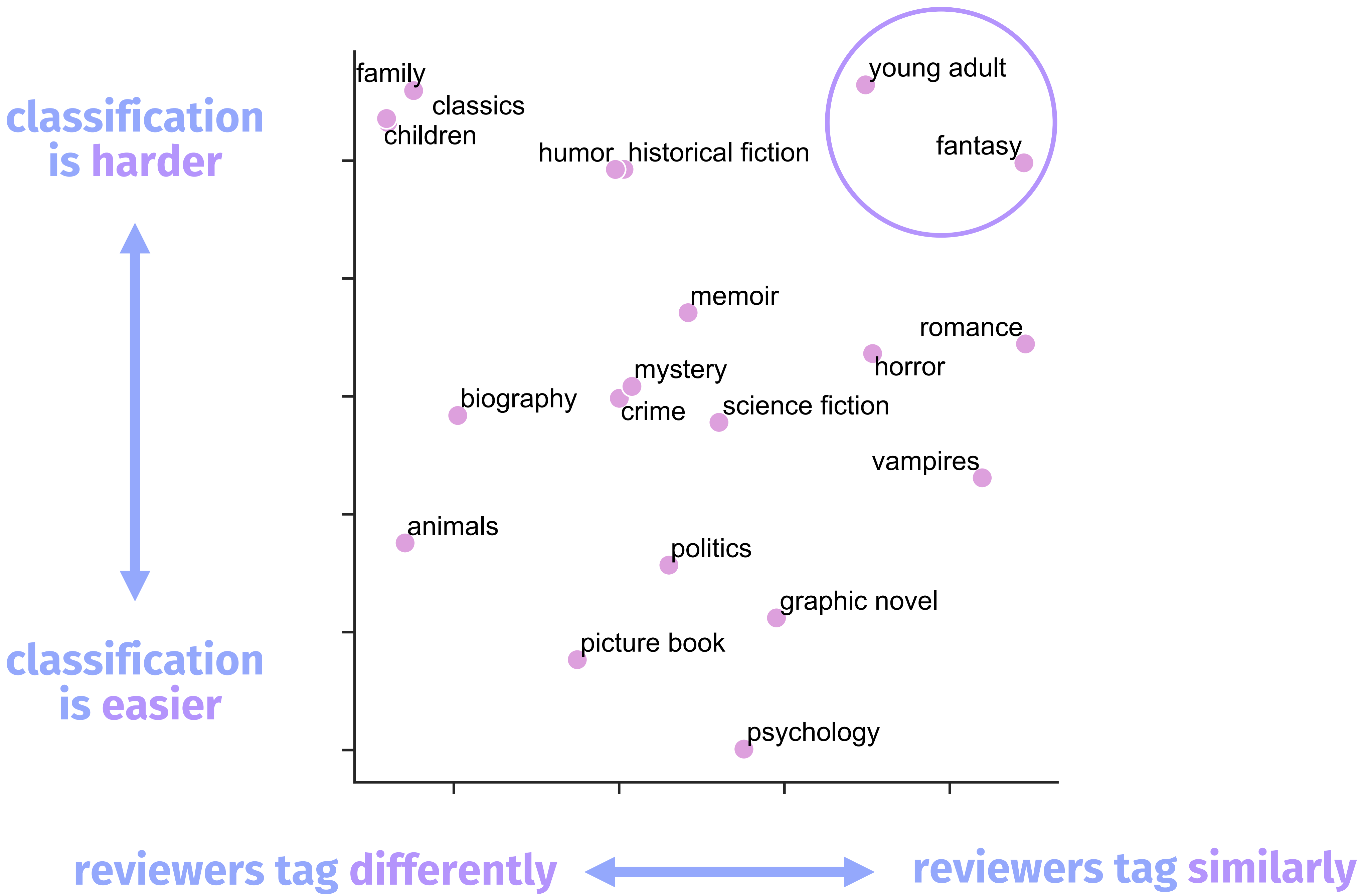
reviewers tag differently ⟷ reviewers tag similarly classification is harder

classification is easier



reviewers tag differently ↔ reviewers tag similarly


classification
is harder
classification
is easier
family
classics
children
young adult
humor
historical fiction
fantasy
memoir
romance
horror
mystery
biography
crime
science fiction
vampires
animals
politics
graphic novel
picture book
psychology
reviewers tag differently
reviewers tag similarly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biography
crime
science fiction
vampires
animals
politics
graphic novel
picture book
psychology

Take Aways from LibraryThing

- Genres differ by their surprisal, reviewer homogeneity, topics, and book and user overlap with other genres

- Free-form tagging gives individuals **creative license** to diverge from traditional catalogs

- Goodreads and LibraryThing help shape literary reception—and **reviewers' tags are directly shaping your bookstores and libraries**

My Research Goals

Use NLP methods to study the sharing of personal experiences online

- Birth communities: power and narrative in birth stories (CSCW, 2019)
- Expressing pain through similes (Frontiers in Neuroscience, 2019)
- Literary genres in online reading communities (Cultural Analytics, 2021; CSCW, 2021)

Probe the reliability of NLP methods for cultural analytics applications

- Instability of cosine similarities for word embeddings (TACL, 2018)
- Seed selection can affect bias measurement (ACL, 2021)
- BERT for Humanists (public tutorials, 2021; ACH, 2021; ICWSM, 2022)

Modeling Personal Experiences Shared in Online Communities

NLP tools are usually designed for **downstream** use cases; but considering **upstream** use cases yields lessons about **biases** and **instability.**

Communities can be windows into **personal stories** and experiences; **grounded** communities make computational analysis more feasible.

We can do this work with **care**; sample carefully, consider data ethics, give back to the community, work on illuminating issues with social and humanist significance.

Future Work

- Online communities that “**collaborate without consensus**”
- Online communities grounded in a **shared** cultural or healthcare experience
- Emphasize **voices** of patients, readers, gamers—rather than publishers, medical professionals, researchers

Susan Leigh Star. “The Structure of Ill-Structured Solutions: Boundary Objects and Heterogeneous Distributed Problem Solving.” *Distributed Artificial Intelligence*, 1989.

Research doesn't happen alone!

My Committee: David Mimno, Lillian Lee, Jeff Rzeszotarski, Richard Jean So

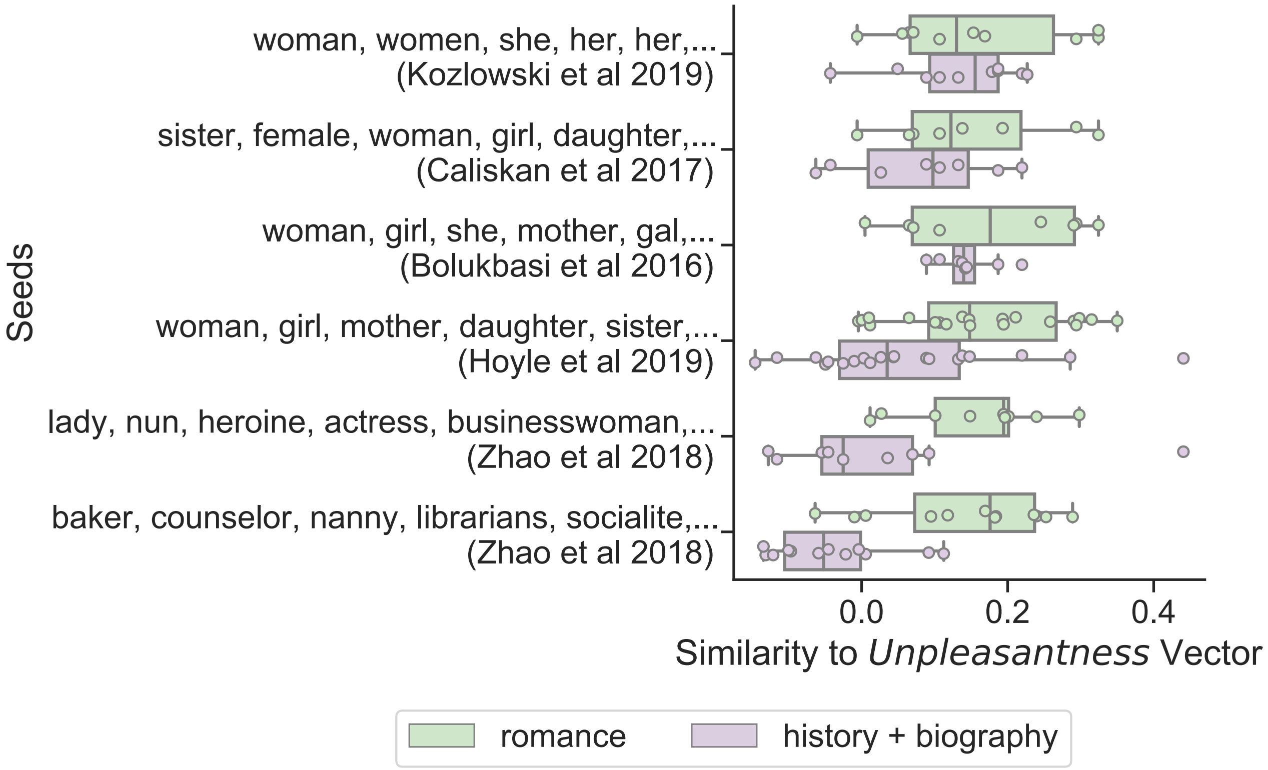
My Collaborators: Karen Levy, Melanie Walsh, LeAnn McDowall, Alexandra Olteanu, Asia Biega, Fernando Diaz, A. Feder Cooper, Robert Griffin, Marten van Schijndel, Matthew Wilkens, Sharifa Sultana, Long Le-Khac

My Labmates: Moontae Lee, Xanda Schofield, Jack Hessel, Laure Thompson, Gregory Yauney, Rosamond Thalken, Katherine Lee, Federica Bologna (and extended labmates Justine Zhang, Liye Fu, Jonathan Chang)

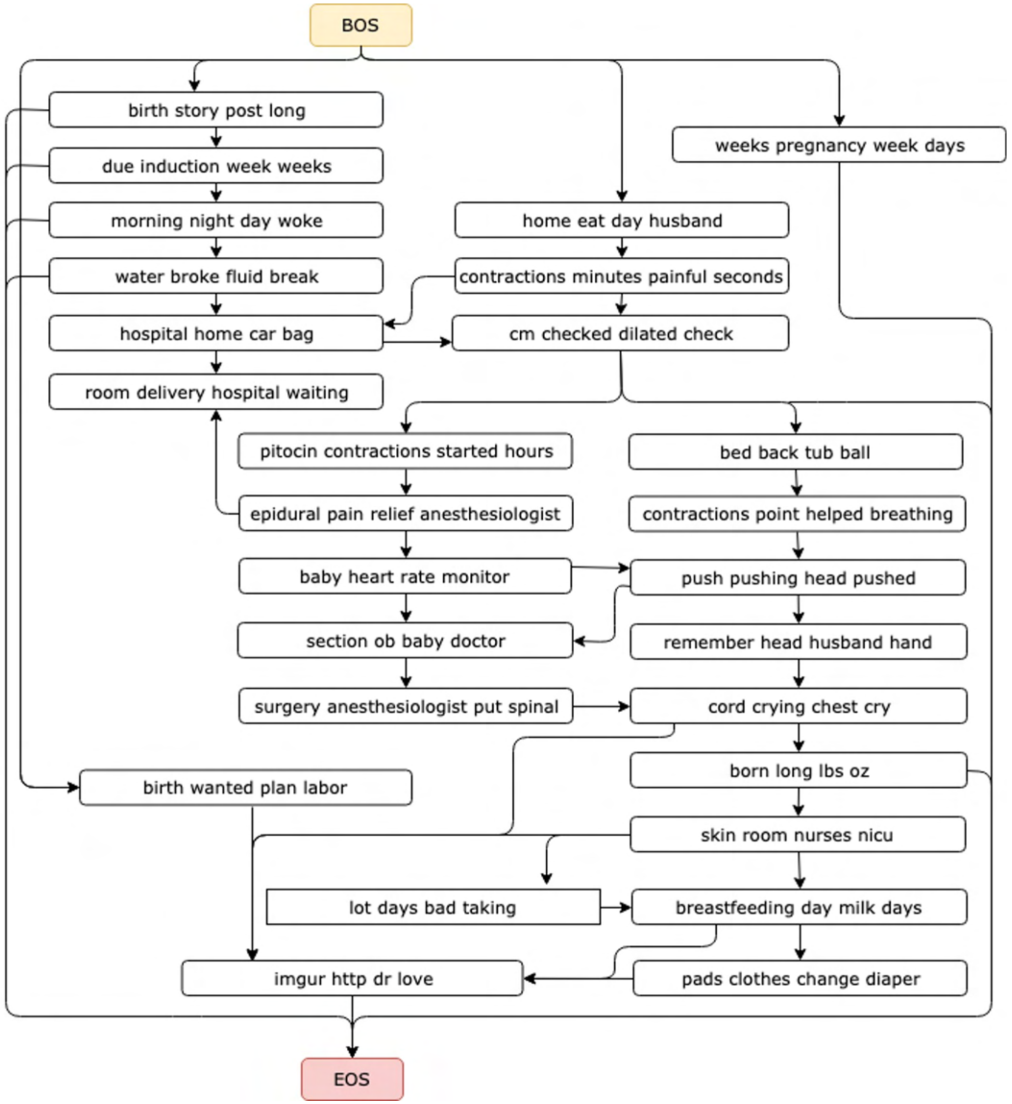
Feedback, Brainstorming, Conversation, Inspiration: Lauren Kilgour, Emily Tseng, Sindhu Ernala, Xiao Ma, Jen Liu, Briana Vecchione, Os Keyes, Rishi Bommasani, Forrest Davis, etc. etc.

And many, many more at Cornell, at internships, in NLP Seminar, GSGIC, and elsewhere!

Questions?



Seeds
woman, women, she, her, her,...
(Kozlowski et al 2019)
sister, female, woman, girl, daughter,...
(Caliskan et al 2017)
woman, girl, she, mother, gal,...
(Bolukbasi et al 2016)
woman, girl, mother, daughter, sister,...
(Hoyle et al 2019)
lady, nun, heroine, actress, businesswoman,...
(Zhao et al 2018)
baker, counselor, nanny, librarians, socialite,...
(Zhao et al 2018)
0.0
0.2
0.4
Similarity to *Unpleasantness* Vector
romance
history + biography



BOS
birth story post long
due induction week weeks
morning night day woke
water broke fluid break
hospital home car bag
room delivery hospital waiting
weeks pregnancy week days
home eat day husband
contractions minutes painful seconds
cm checked dilated check
pitocin contractions started hours
epidural pain relief anesthesiologist
baby heart rate monitor
section ob baby doctor
surgery anesthesiologist put spinal
bed back tub ball
contractions point helped breathing
push pushing head pushed
remember head husband hand
cord crying chest cry
born long lbs oz
skin room nurses nicu
breastfeeding day milk days
pads clothes change diaper
birth wanted plan labor
lot days bad taking
imgur http dr love
EOS