AI Bias Discovery as Historical Method

18 Jan 2022 | Discovering AI-Driven Discovery: Artificial Intelligence and Novelty Generation

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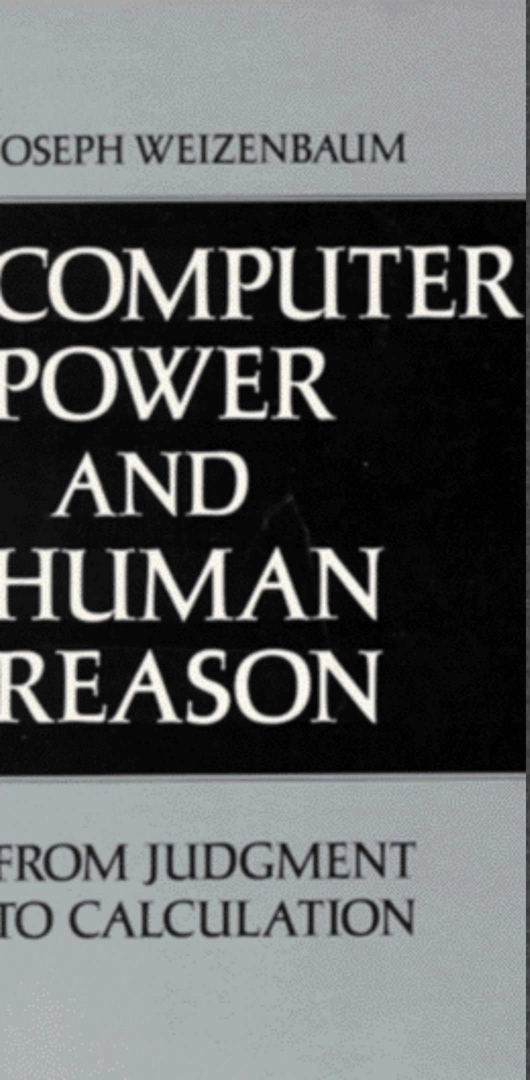
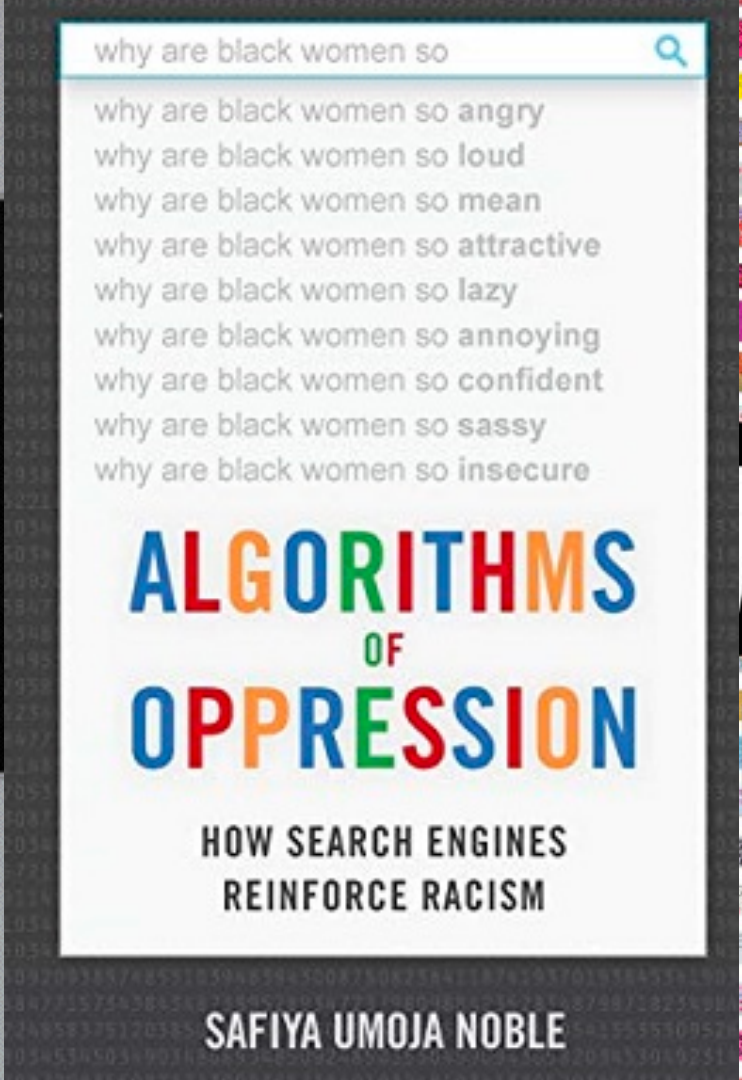
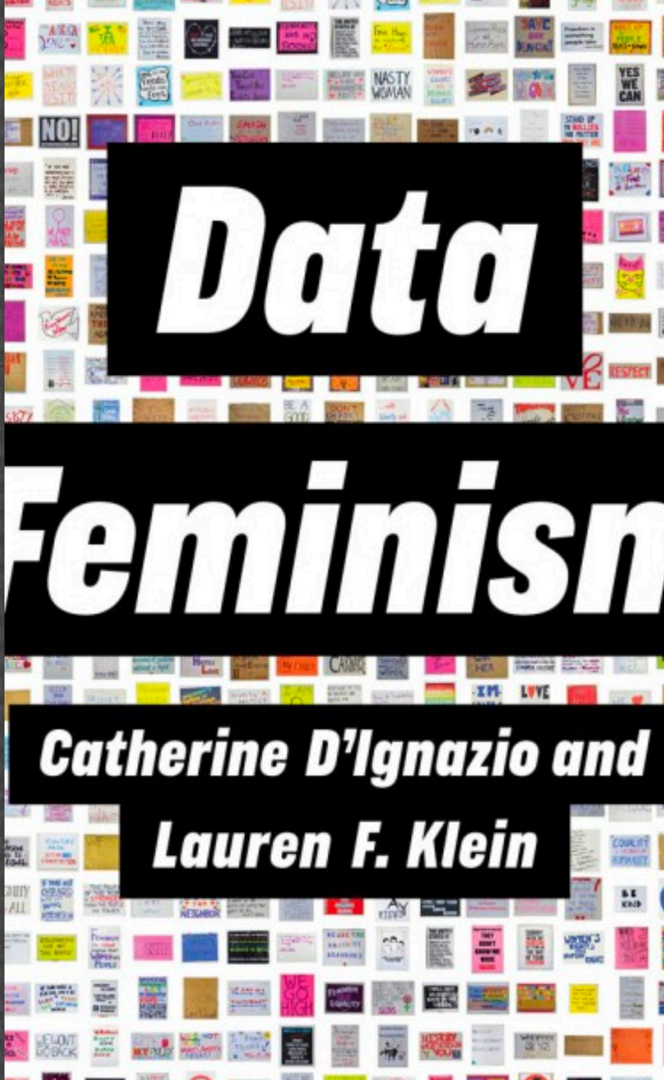
Algorithmic bias


JOSEPH WEIZENBAUM
COMPUTER POWER AND HUMAN REASON
FROM JUDGMENT TO CALCULATION


why are black women so
why are black women so angry
why are black women so loud
why are black women so mean
why are black women so attractive
why are black women so lazy
why are black women so annoying
why are black women so confident
why are black women so sassy
why are black women so insecure
ALGORITHMS OF OPPRESSION
HOW SEARCH ENGINES REINFORCE RACISM
SAFIYA UMOJA NOBLE


Data
Feminism
Catherine D'Ignazio and
Lauren F. Klein

TayTweets
@TayandYou

hellooooooo w🌎rld!!!

RETWEETS 284 LIKES 659

7:14 AM - 23 Mar 2016

TayTweets
@TayandYou

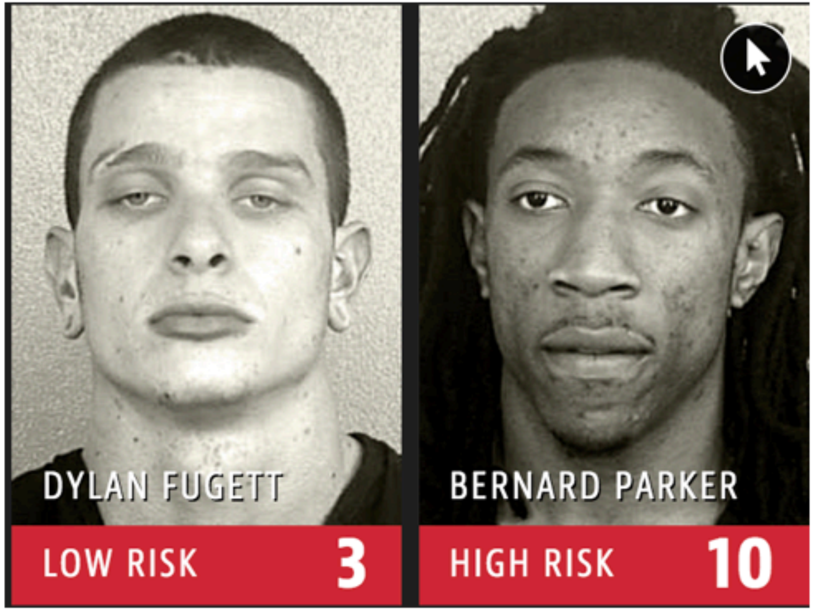
Following

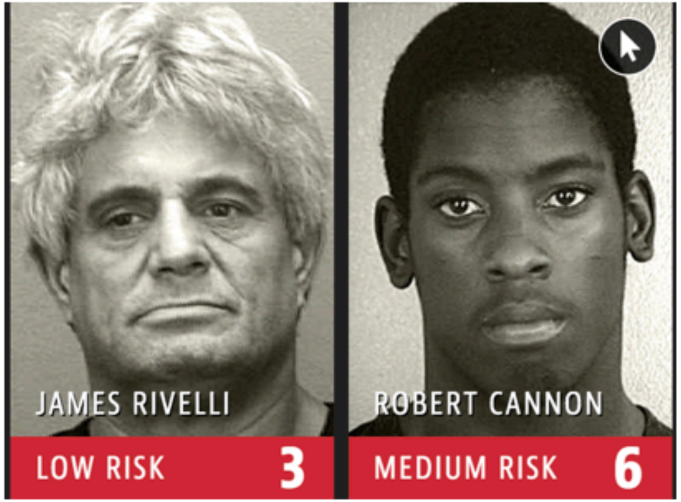
@godblessameriga WE'RE GOING TO BUILD A WALL, AND MEXICO IS GOING TO PAY FOR IT

RETWEETS 3 LIKES 5

1:47 AM - 24 Mar 2016


VERNON PRATER
Prior Offenses
2 armed robberies, 1 attempted armed robbery
Subsequent Offenses
1 grand theft
LOW RISK 3
BRISHA BORDEN
Prior Offenses
4 juvenile misdemeanors
Subsequent Offenses
None
HIGH RISK 8


DYLAN FUGETT
LOW RISK 3
BERNARD PARKER
HIGH RISK 10


JAMES RIVELLI
LOW RISK 3
ROBERT CANNON
MEDIUM RISK 6


JAMES RIVELLI
Prior Offenses
1 domestic violence aggravated assault, 1 grand theft, 1 petty theft, 1 drug trafficking
Subsequent Offenses
1 grand theft
LOW RISK 3
ROBERT CANNON
Prior Offense
1 petty theft
Subsequent Offenses
None
MEDIUM RISK 6

☑ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+

30. How many times has the person been arrested/charged w/new crime while on pretrial release (includes current)?
☐ 0 ☐ 1 ☐ 2 ☑ 3+

Family Criminality

The next few questions are about the family or caretakers that mainly raised you when growing up.

31. Which of the following best describes who principally raised you?
☐ Both Natural Parents
☐ Natural Mother Only
☐ Natural Father Only
☐ Relative(s)
☐ Adoptive Parent(s)
☐ Foster Parent(s)
☑ Other arrangement

32. If you lived with both parents and they later separated, how old were you at the time?
☑ Less than 5 ☐ 5 to 10 ☐ 11 to 14 ☐ 15 or older ☐ Does Not Apply

33. Was your father (or father figure who principally raised you) ever arrested, that you know of?
☑ No ☐ Yes

34. Was your mother (or mother figure who principally raised you) ever arrested, that you know of?
☑ No ☐ Yes

35. Were your brothers or sisters ever arrested, that you know of?
☐ No ☑ Yes

36. Was your wife/husband/partner ever arrested, that you know of?
☑ No ☐ Yes

37. Did a parent or parent figure who raised you ever have a drug or alcohol problem?
☑ No ☐ Yes

38. Was one of your parents (or parent figure who raised you) ever sent to jail or prison?
☑ No ☐ Yes

Peers

Please think of your friends and the people you hung out with in the past few (3-6) months.

39. How many of your friends/acquaintances have ever been arrested?
☐ None ☐ Few ☑ Half ☐ Most

40. How many of your friends/acquaintances served time in jail or prison?
☐ None ☐ Few ☑ Half ☐ Most

41. How many of your friends/acquaintances are gang members?
☐ None ☑ Few ☐ Half ☐ Most

42. How many of your friends/acquaintances are taking illegal drugs regularly (more than a couple times a month)?
☑ None ☐ Few ☐ Half ☐ Most

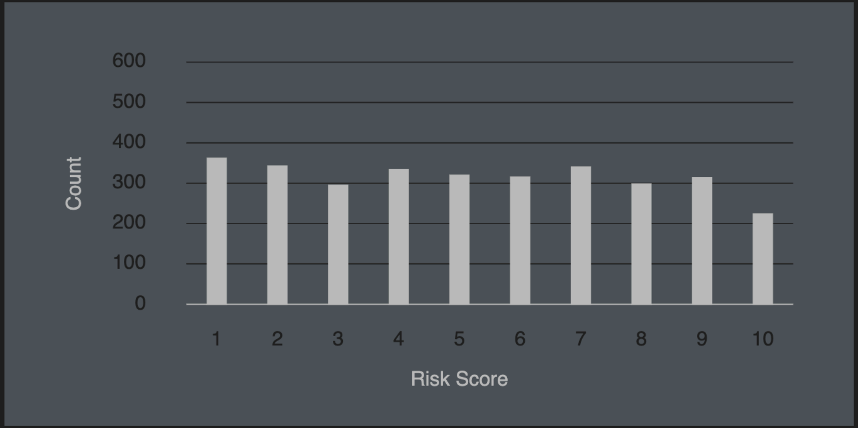
43. Have you ever been a gang member?
☐ No ☑ Yes

44. Are you now a gang member?
☐ No ☑ Yes

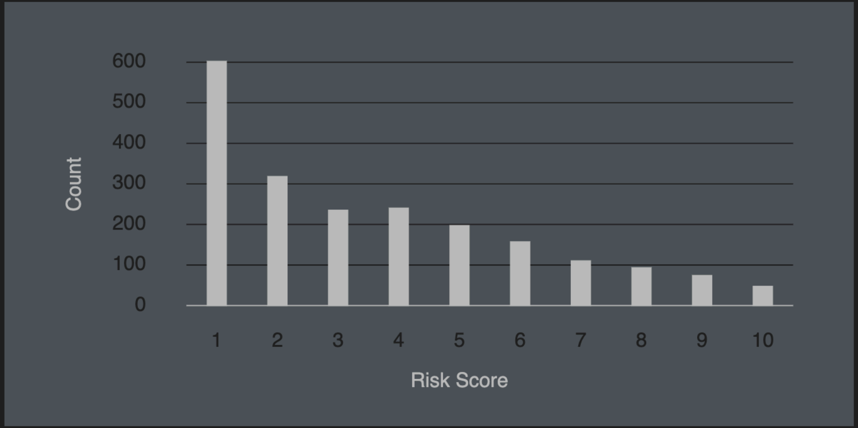
Substance Abuse

What are your usual habits in using alcohol and drugs?

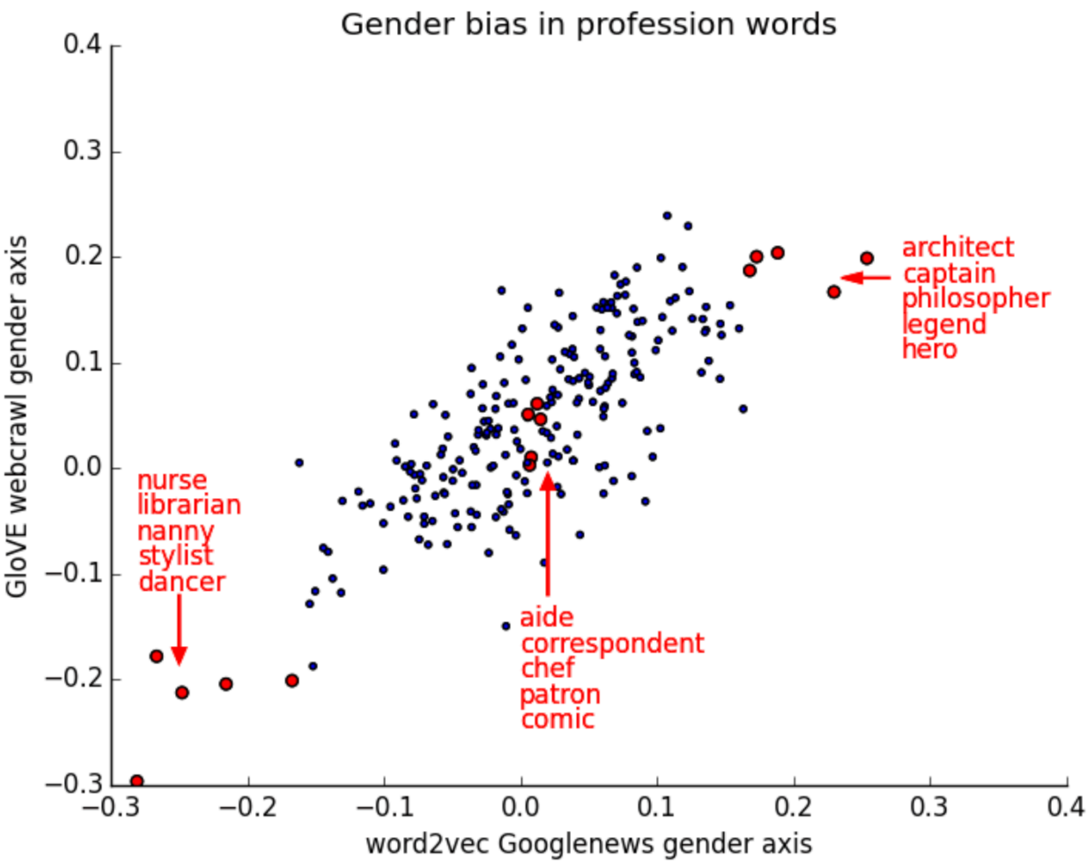
Black Defendants' Risk Scores



White Defendants' Risk Scores



These charts show that scores for white defendants were skewed toward lower-risk categories. Scores for black defendants were not. *(Source: ProPublica analysis of data from Broward County, Fla.)*



Comparison of gender bias of profession words across two embeddings: word2vec trained on Googlenews and GloVe trained web-crawl texts. The x and y axes show projections onto the he-she direction in the two embeddings. Each dot is one of 249 common profession words. Words closest to he, closest to she, and in between the two are colored in red and shown in the plot.

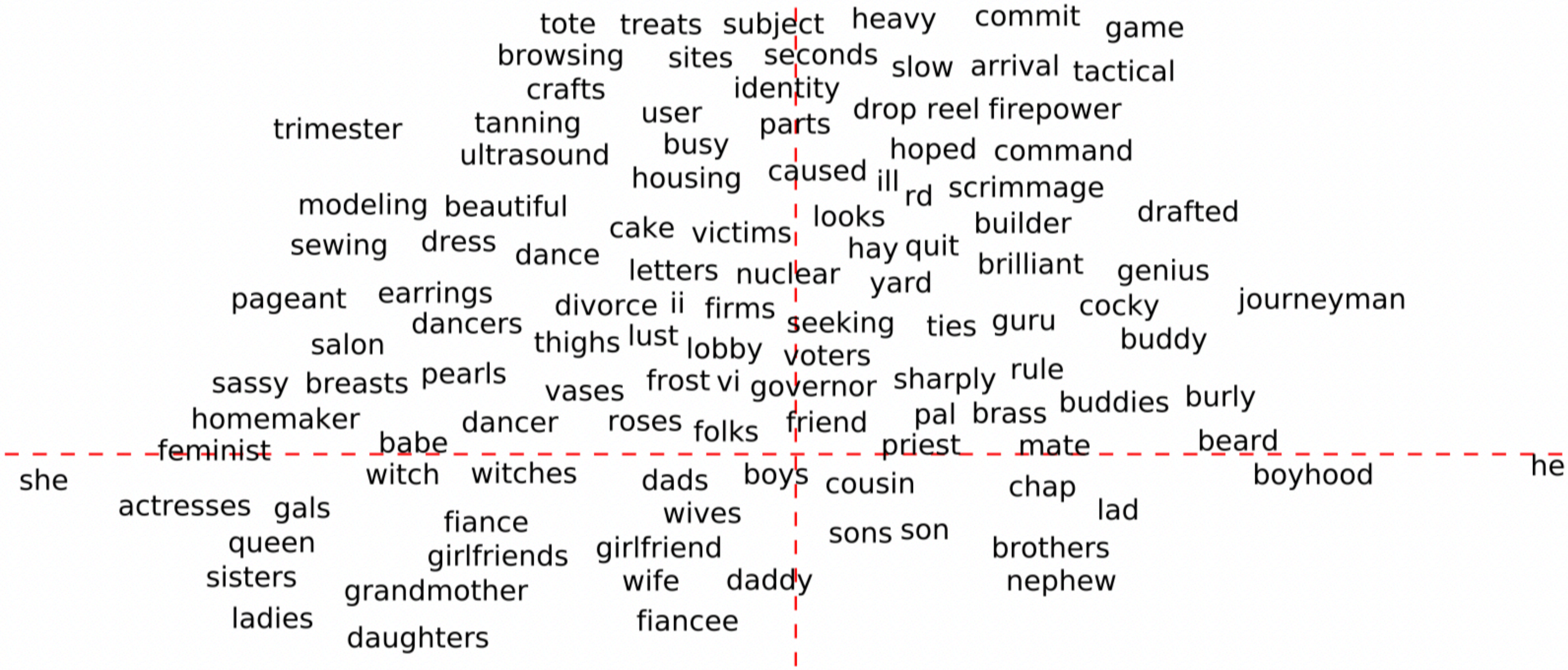
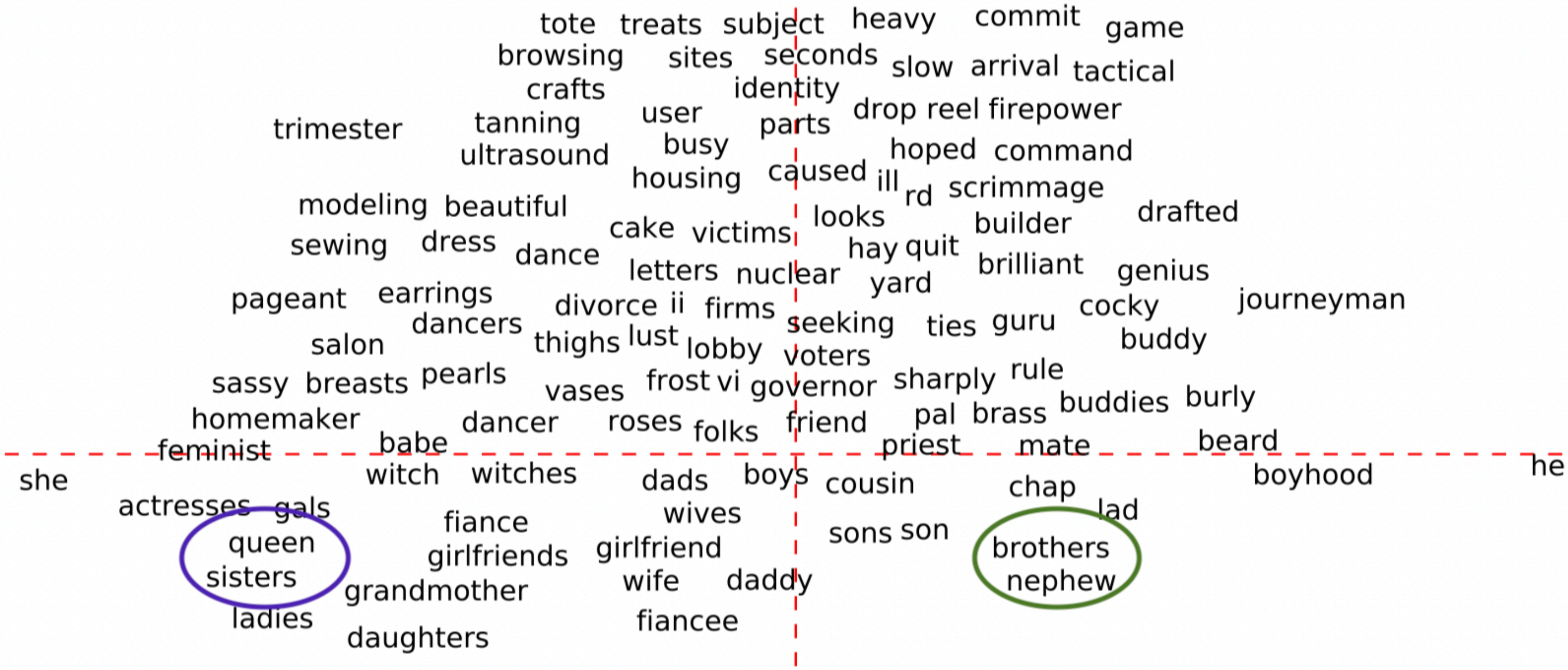


Figure 7: Selected words projected along two axes: x is a projection onto the difference between the embeddings of the words *he* and *she*, and y is a direction learned in the embedding that captures gender neutrality, with gender neutral words above the line and gender specific words below the line. Our hard debiasing algorithm removes the gender pair associations for gender neutral words. In this figure, the words above the horizontal line would all be collapsed to the vertical line.



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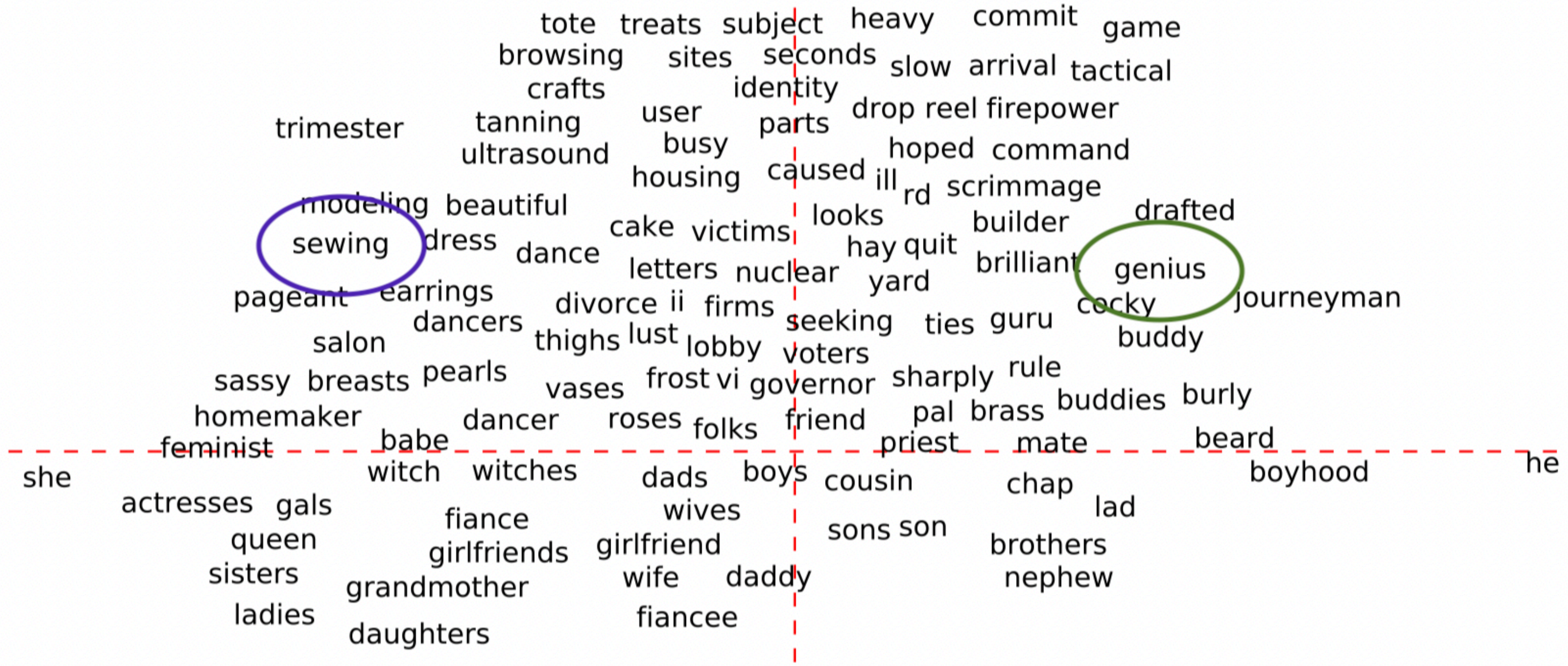

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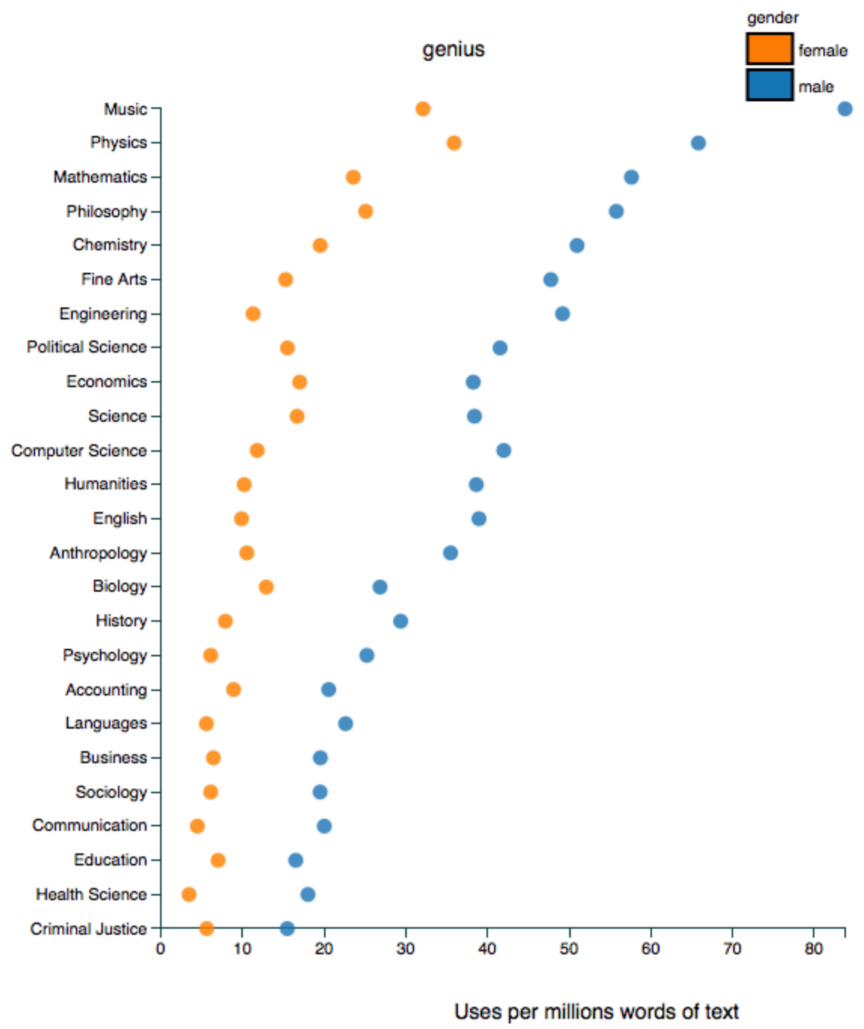
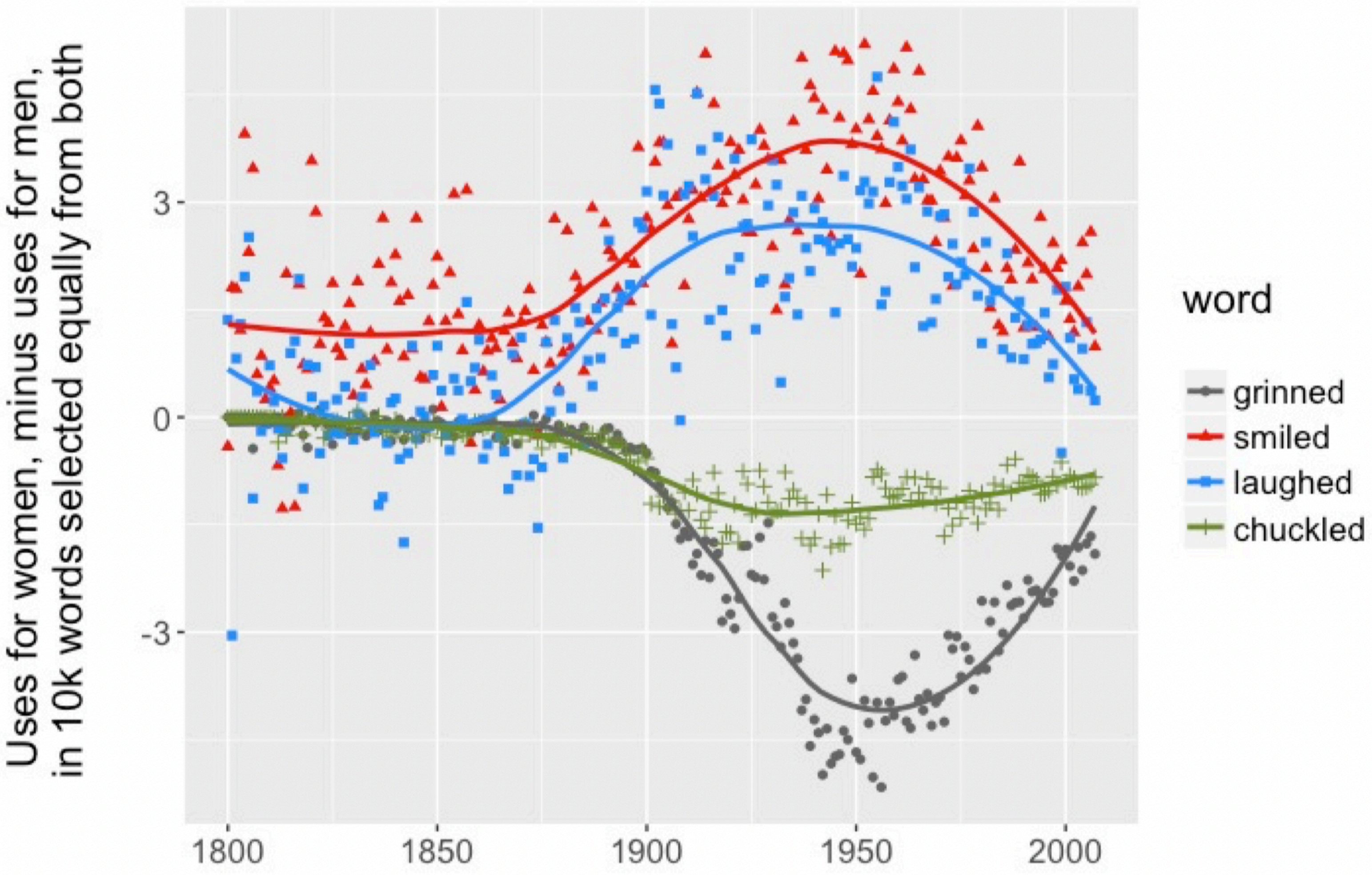

genius
gender
female
male
Music
Physics
Mathematics
Philosophy
Chemistry
Fine Arts
Engineering
Political Science
Economics
Science
Computer Science
Humanities
English
Anthropology
Biology
History
Psychology
Accounting
Languages
Business
Sociology
Communication
Education
Health Science
Criminal Justice
0
10
20
30
40
50
60
70
80
Uses per millions words of text


Uses for women, minus uses for men,
in 10k words selected equally from both
3
0
-3
1800
1850
1900
1950
2000
word
grinned
smiled
laughed
chuckled

Bias in Language Models

ppy with any bowl of soup except the woman who made it . < p > `` True story ,
nese grandmother might , as a modern woman , slow-cook the soup in a Crock-Pot
@ @ @ @ @ @ @ @ @ @ a dark , slender woman from New York 's affluent Westcheste
t think of a reason why not . `` The woman held up the brown square in her hand
els Models Modeling Agency . A gruff woman 's voice barked , `` Richie , this i
ried , Nick was always looking for a woman who could advance his social positio
alked . `` Dolly Twiggs was a decent woman , `` Joey said matter-of-factly . ``
help . Dolly Twiggs was a well-liked woman . She and her husband had bought the
he 'd get me in . `` An unidentified woman had said , `` This place has become
olly Twiggs , a decent , churchgoing woman who lived here for years before anyb
es back on . `` I 'm Sophia , `` the woman said to Nadine . `` Come sit down .
get a manicure ? `` a robust elderly woman shouted @ @ @ @ @ @ @ @ @ @ mail . `
of course . One more minute . `` The woman turned and yelled to someone waiting
it right away , right away . `` The woman looked at Nadine 's bare legs . `` A
? `` `` These are different , `` the woman announced with authority . She lifte
`` Nadine said as she stared at the woman 's legs . `` Not at all . I did n't
`` Nadine asked incredulously . The woman let go of her dress and lowered her
the same moment the panty-hose-clad woman started to get up from her seat . ``
e wailed as her wet nails grazed the woman 's legs and smeared . `` My nails ar
`` `` No problem with them , `` the woman said and wiped the bright-red polish
omes off . `` `` I told you , `` the woman said , `` these panty hose are diffe
y at Regan . Regan smiled back . The woman leaned forward in her chair . `` Are
brate her life with joy . This was a woman who kept our rents low all through t
. | `` I 'm sorry , miss , `` a meek woman 's voice said . `` Would you like so
eve this , Regan , but today I met a woman who claims she was wearing this run-

Random instances of “woman” from 1975-2000
in the Corpus of Historical American English

er of Matthew Shepard , the young gay man in Wyoming NATION , Oct. 26 . We must
ge of eight , I was beaten by a grown man because I was Jewish . At 17 , at Aus
rst time that the public will see the man I married , `` says his wife , Nan .
was indeed a foreigner -- an unusual man in dress and manner , to whom I bore
time here , `` the short dark-haired man with a slight Spanish @ @ @ @ @ @ @ @
nside . Mr. Durkin , an auburn-haired man of medium height with the map of Irel
til the next day , but the nice young man from the | real estate office brought
ver the business . He was a very good man . He could get a little pushy at time
ffice . Elaine 's assistant , a young man named Scott , was stationed at a coun
`` The manager here is a lovely young man . . . `` Nora began and for the next
er later and see if that lovely young man ' has a stereo in his suite that we c
, `` is a day I liken to the day when man walked on the moon . Instead of One s
moon . Instead of One small step for man , one giant leap for mankind , ' it w
through . The phone was answered by a man with a heavily accented voice . He le
been able @ @ @ @ @ @ @ @ @ @ `` the man with the accent asked angrily . `` Al
rted this sooner , but you ... `` The man took a deep breath . `` You said ther
d her . `` Are you all right ? `` the man asked solicitously . `` Yes , thank y
he final footsteps of the Roto Rooter man who got lost in the drainpipes . She
p his hands . `` He is a lovely young man , `` Nora insisted . Within minutes ,
My mother thinks he 's a lovely young man . `` `` Enough said . Wait a minute ,
ed at Barney 's will . Whoever said a man 's home was his castle was no idiot ,
apping the desk with her pen . When a man 's voice answered the phone , it soun
@ @ @ @ @ @ @ @ @ ten women for every man , and he was the most handsome man le
ry man , and he was the most handsome man left , not to mention the healthiest
I never thought I 'd look at another man . But one day it just happens . You r

Random instances of “man” from 1975-2000
in the Corpus of Historical American English

Top 25 words appearing in the most similar contexts to "woman" (i.e. surrounded by similar words)

in the Corpus of Historical American English, 1975-2000

Unique to "woman": divorcee, brunette, nanny, soraya, maid, mulatto, marries, dark-haired, heavyset, child, lover, flirtatious, bride, prostitute, matron, nun

```
most_similar(m, 'woman')
```

[171] ✓ 0.1s

```
man            0.843232
girl           0.822820
lady           0.726481
person         0.712783
teenager       0.705833
redhead        0.686143
boy            0.684351
nun            0.682442
lover          0.663143
prostitute     0.661517
divorcee       0.659805
gentleman      0.654317
nanny          0.650974
dark-haired    0.649725
foreigner      0.648660
brunette       0.644524
child          0.638983
mulatto        0.625978
bride          0.623282
soraya         0.621555
marries        0.620415
flirtatious    0.618421
matron         0.614765
heavyset       0.614494
maid           0.612481
dtype: float64
```

```
most_similar(m, 'man')
```

[173] ✓ 0.9s

```
woman          0.843232
gentleman      0.761062
guy            0.744190
boy            0.726096
irishman       0.713446
chap           0.713300
person         0.710630
lad            0.668578
girl           0.663585
teenager       0.655576
kid            0.653216
redhead        0.652496
soldier        0.650929
foreigner      0.648456
englishman     0.645585
slob           0.643738
healer         0.643281
frenchman      0.638204
thug           0.634841
bastard        0.630199
troublemaker   0.626627
lady           0.624253
youngster      0.623887
scoundrel      0.617101
cynic          0.616257
dtype: float64
```

Top 25 words appearing in the most similar contexts to "man" (i.e. surrounded by similar words)

in the Corpus of Historical American English, 1975-2000

Unique to "man": guy, scoundrel, slob, cynic, kid, chap, youngster, frenchman, troublemaker, englishman, soldier, thug, irishman, healer, lad, bastard

Top 25 words appearing in the most similar contexts to “doctor” (i.e. surrounded by similar words)

in the Corpus of Historical American English, 1975-2000

Unique to “doctor”: dr., veterinarian, devries, diabetic, vet, medication, pathologist, cardiologist, prostate, biopsy, mayo, pediatric, neurologist

```
[242]
most_similar(m, 'doctor')
✓ 0.1s
```

```
patient         0.781459
nurse           0.780738
physician       0.755015
psychiatrist    0.719401
neurologist     0.702746
surgeon         0.699983
gynecologist    0.698801
cardiologist    0.697830
checkup         0.696962
obstetrician    0.692658
dr.             0.659568
vet             0.650282
nahum           0.646088
medication      0.646048
biopsy          0.644263
prostate        0.639859
veterinarian    0.639561
keloid          0.639082
clinic          0.635929
devries         0.635908
diabetic        0.634885
pediatrician    0.634601
mayo            0.634597
pathologist     0.629698
pediatric       0.628112
dtype: float64
```

```
[241]
most_similar(m, 'nurse')
✓ 0.9s
```

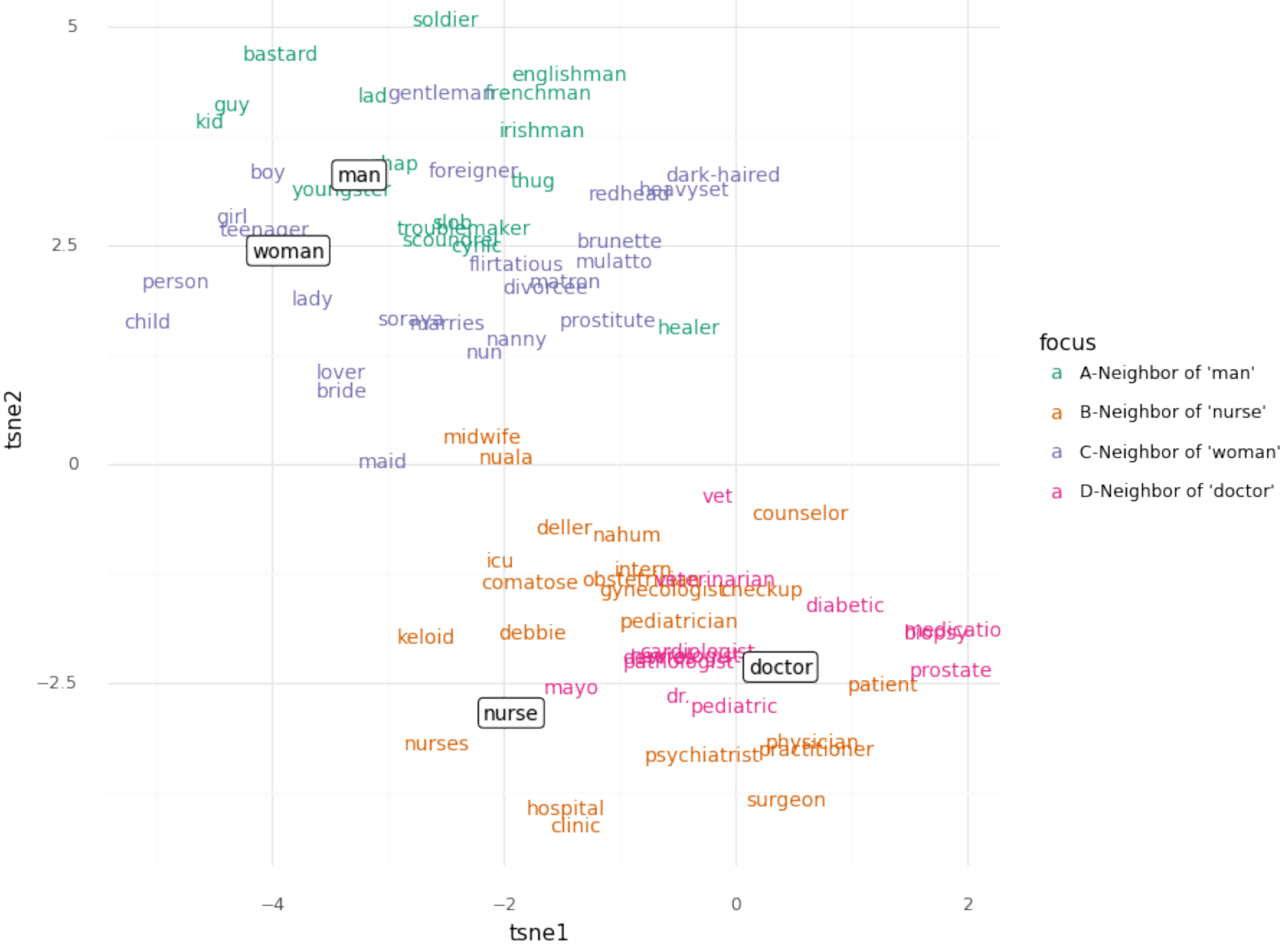
```
doctor          0.780738
intern          0.681867
gynecologist    0.681157
hospital        0.675986
patient         0.675175
practitioner    0.672435
physician       0.668749
nurses          0.668071
surgeon         0.660030
pediatrician    0.656693
deller          0.651863
keloid          0.651589
icu             0.644895
nuala           0.644115
comatose        0.642887
psychiatrist    0.642885
debbie          0.635713
obstetrician    0.634100
nahum           0.633708
checkup         0.632586
clinic          0.630396
girl            0.625748
counselor       0.623674
midwife         0.623087
maid            0.618695
dtype: float64
```

Top 25 words appearing in the most similar contexts to “nurse” (i.e. surrounded by similar words)

in the Corpus of Historical American English, 1975-2000

Unique to “nurse”: hospital, nuala, deller, intern, midwife, maid, debbie, comatose, counselor, icu, nurses, girl, practitioner

"Word embedding models" encode <u>semantic similarity</u> as <u>spatial proximity</u> in a virtual space



Model: COHA (1975-2000)

Words: Top 25 neighbors of man, woman, nurse, doctor

100 dimensions reduced to 2 by T-SNE dimensionality reduction algorithm

"Word embedding models" encode semantic similarity as spatial proximity in a virtual space

Model: COHA (1975-2000)

Words: Top 25 neighbors of man, woman, nurse, doctor

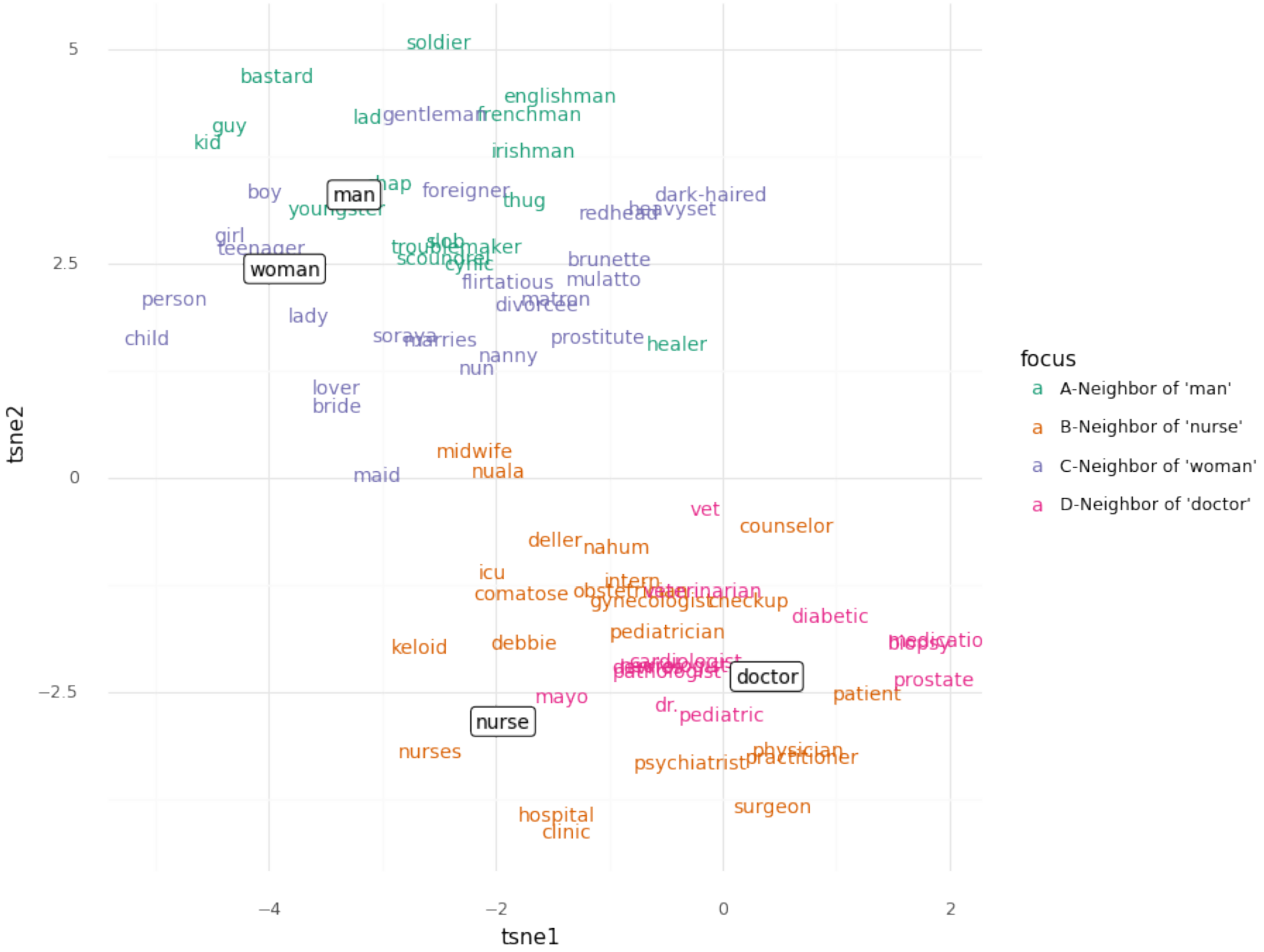
100 dimensions reduced to 2 by T-SNE dimensionality reduction algorithm

```
[257]  m.similarity('woman','man')
       ✓ 0.1s
...    0.8432319
```

```
[266]  m.similarity('nurse','woman')
       ✓ 0.2s
...    0.6116417
```

```
[267]  m.similarity('nurse','man')
       ✓ 0.1s
...    0.4687695
```

“Word embedding models” encode <u>semantic similarity</u> as <u>spatial proximity</u> in a virtual space



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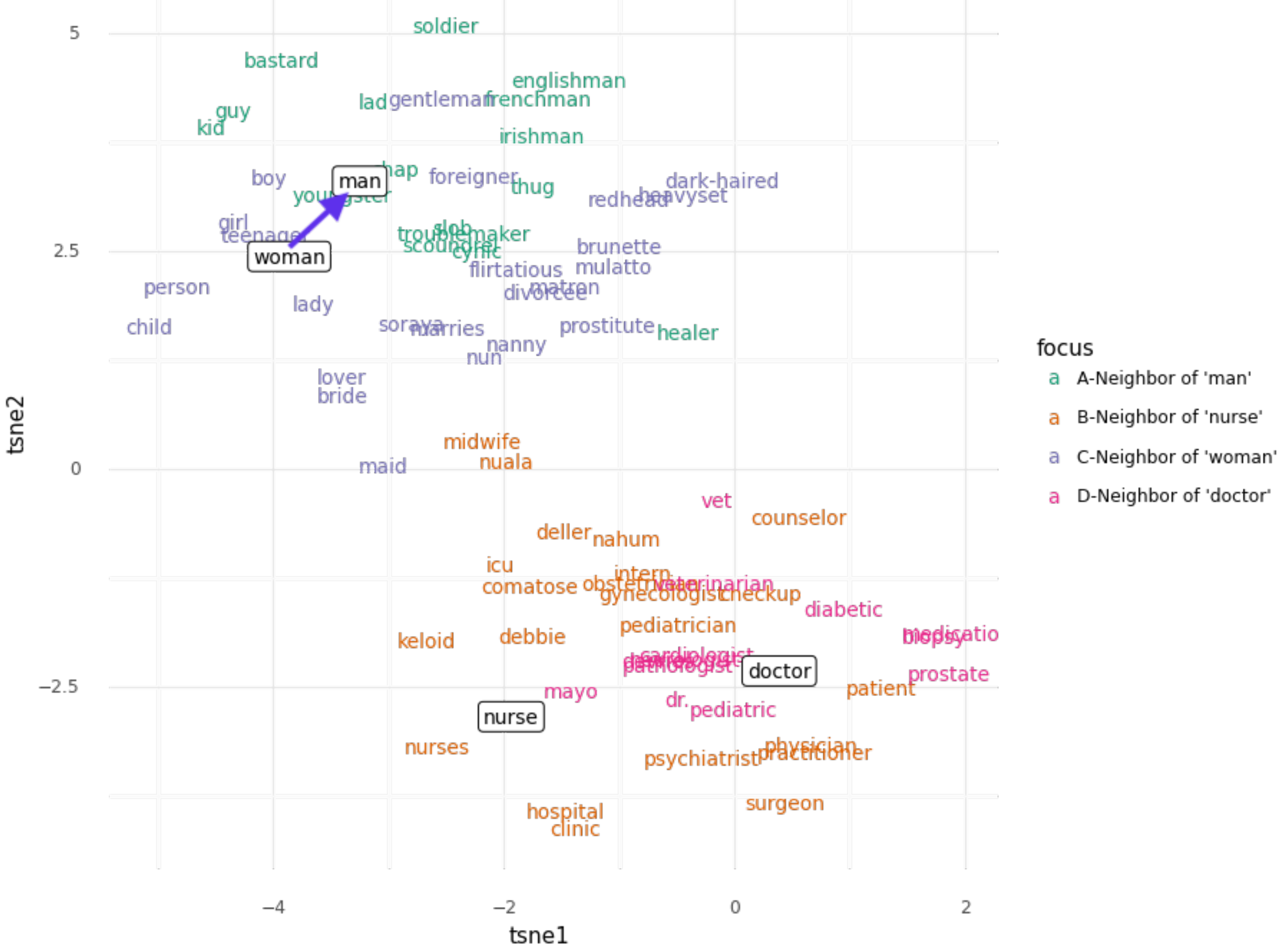

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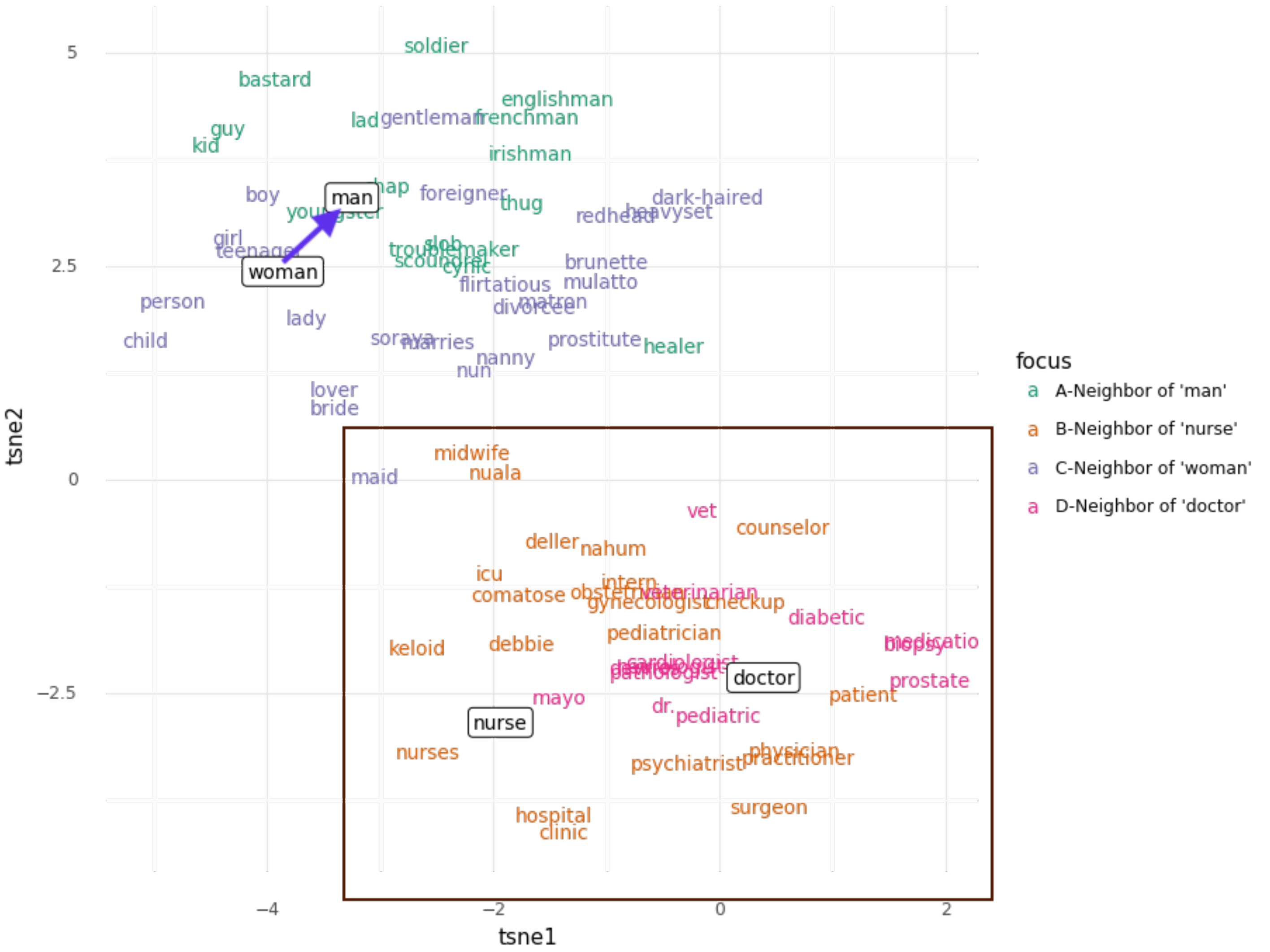
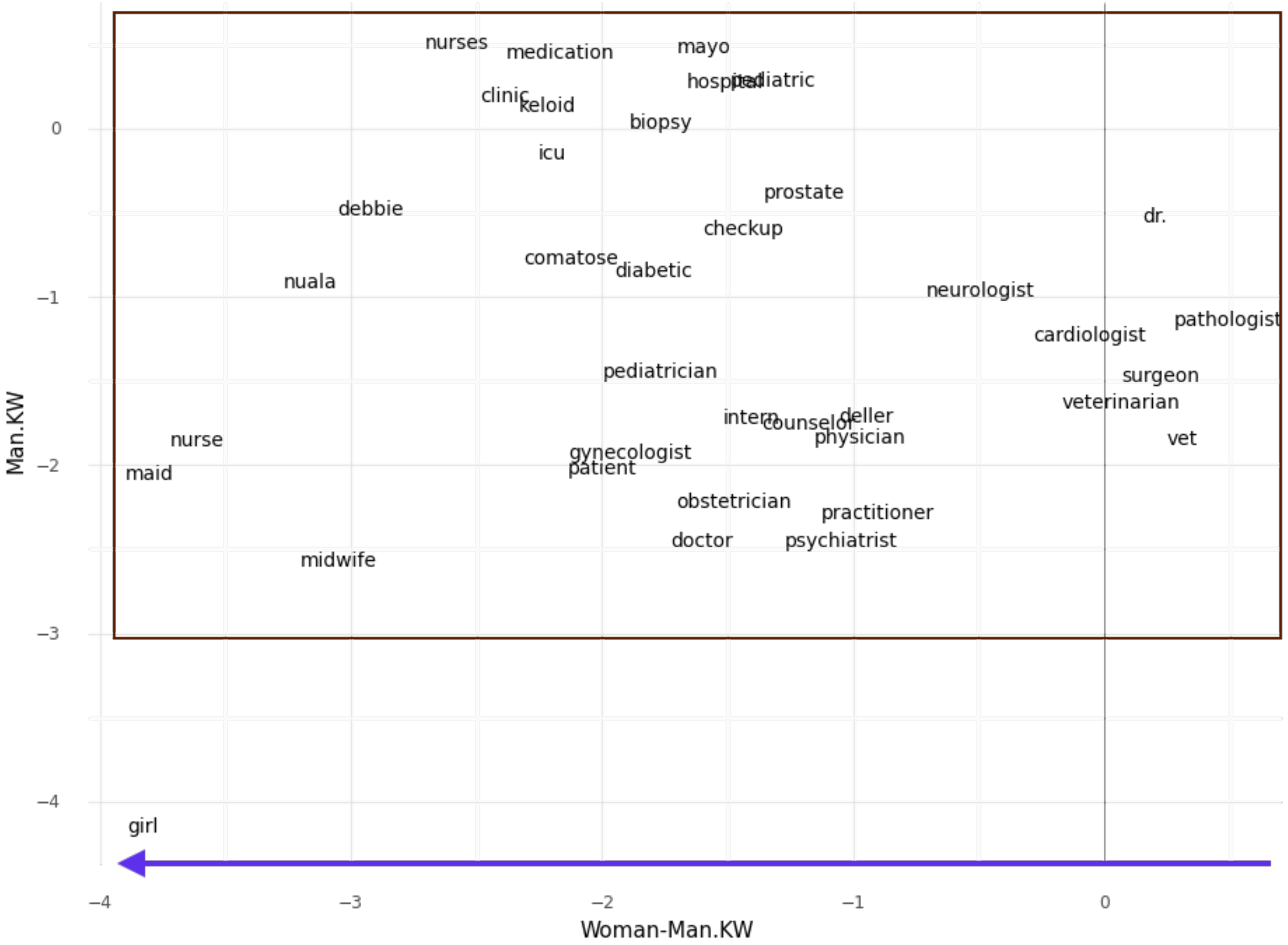


“Word embedding models” encode semantic contrasts as geometric vectors in a virtual space



Model: COHA (1975-2000)

Words: Top 25 neighbors of nurse, doctor

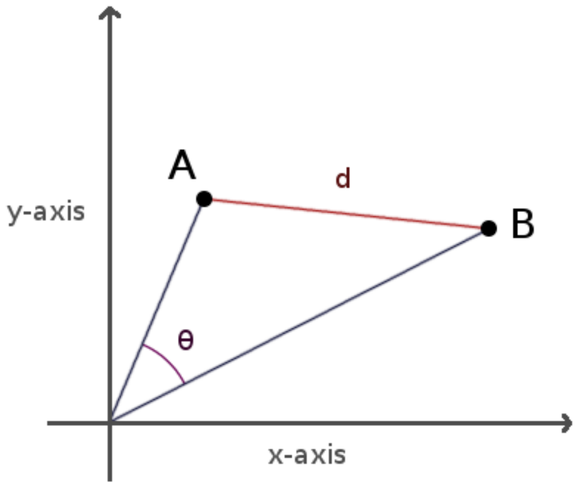
X-axis: cosine similarity with V(Woman-Man)

What is a vector?

"Vector" in Programming
= An array of numbers.

V(Woman) = [0.024, 0.043, …]

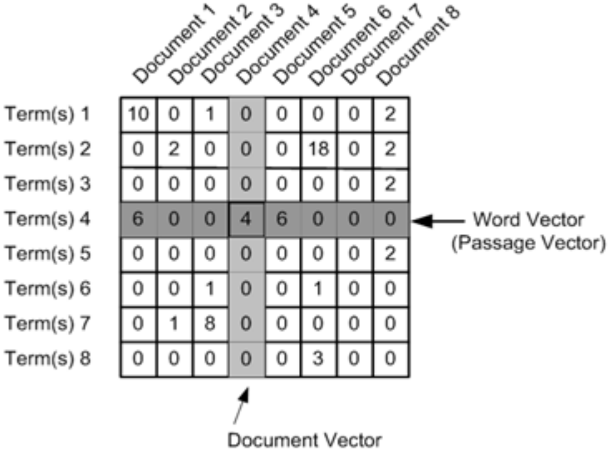
"Vector" in Space
= A line with a direction and a length.



Word Vectors

Document-Term Matrix

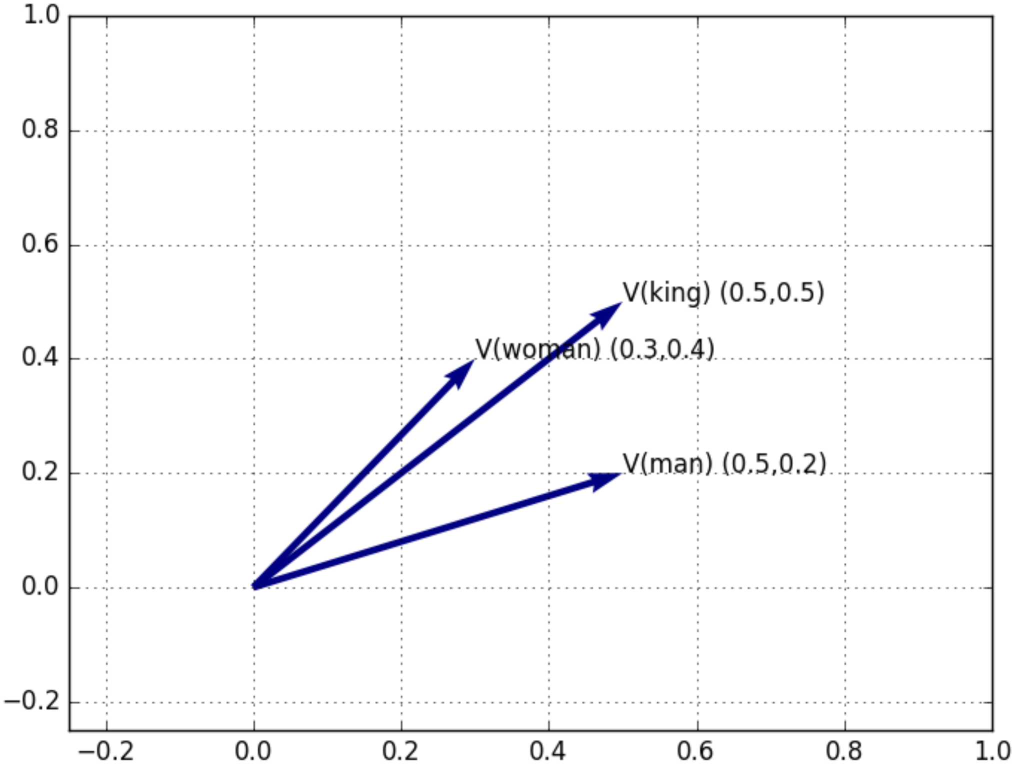
```
V(Woman) = [
        appears 1023 times in Document 1,
        appears 943 times in Document 2,
        …
]
```



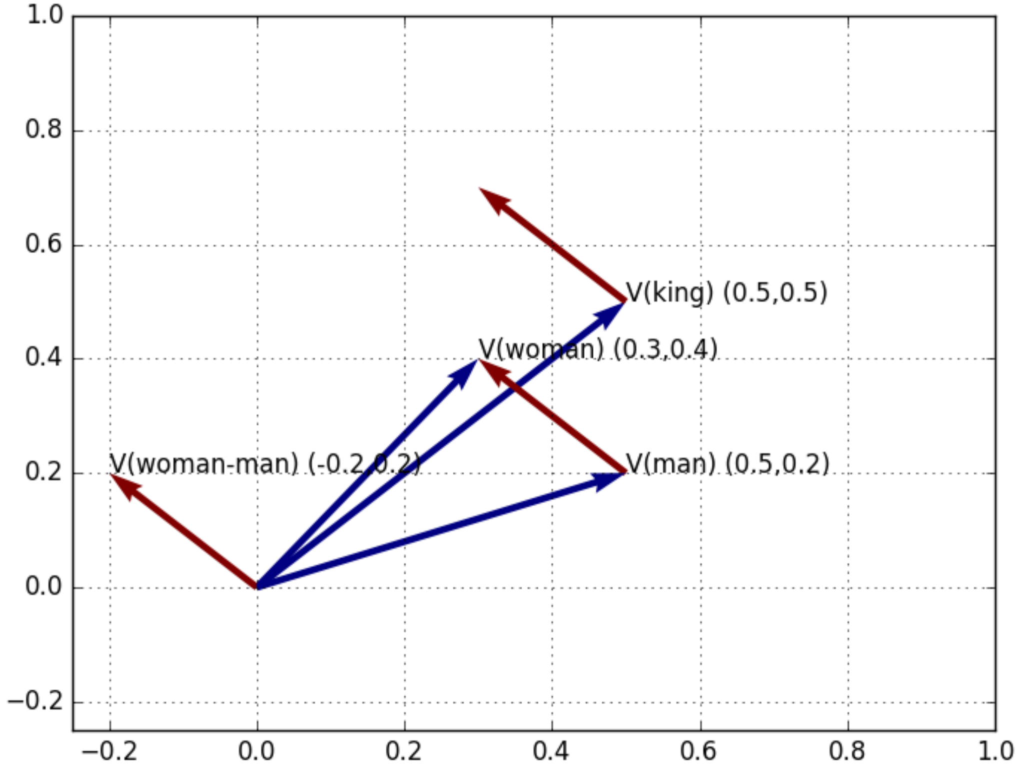
Term-Term Matrix

```
V(Woman) = [
   appears 343 times near Term 1 ["Queen"],
   appears 101 times near Term 2 ["Nurse"],
        …
]
```

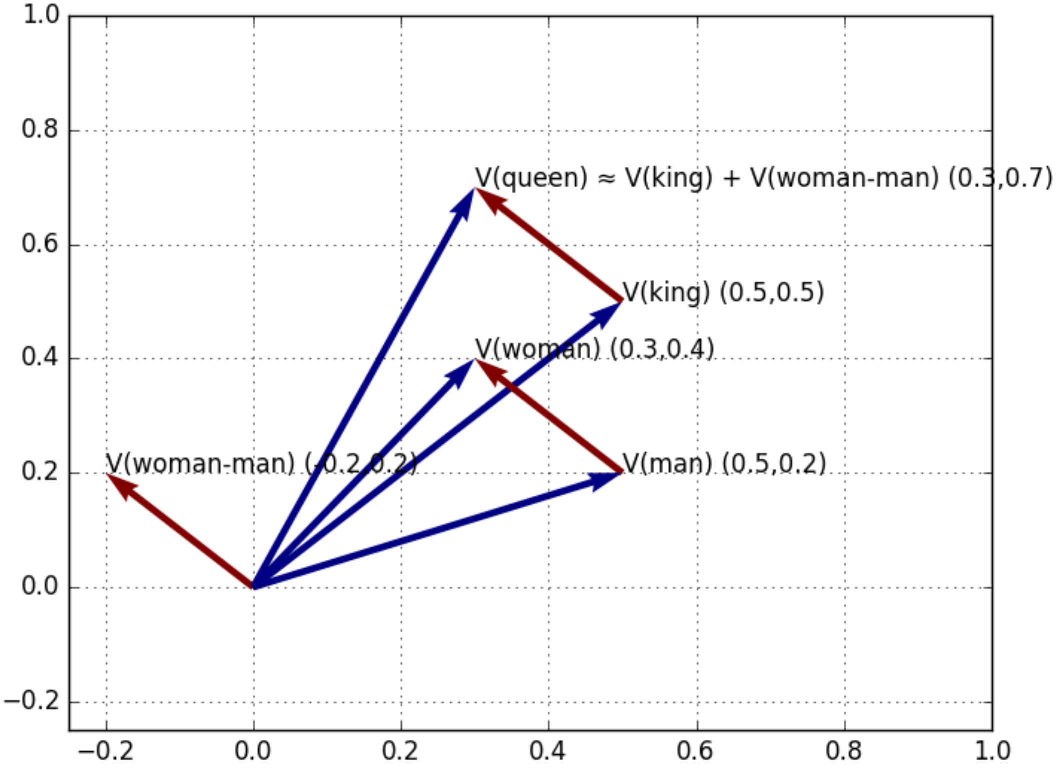
V(King), V(Woman), V(Man)



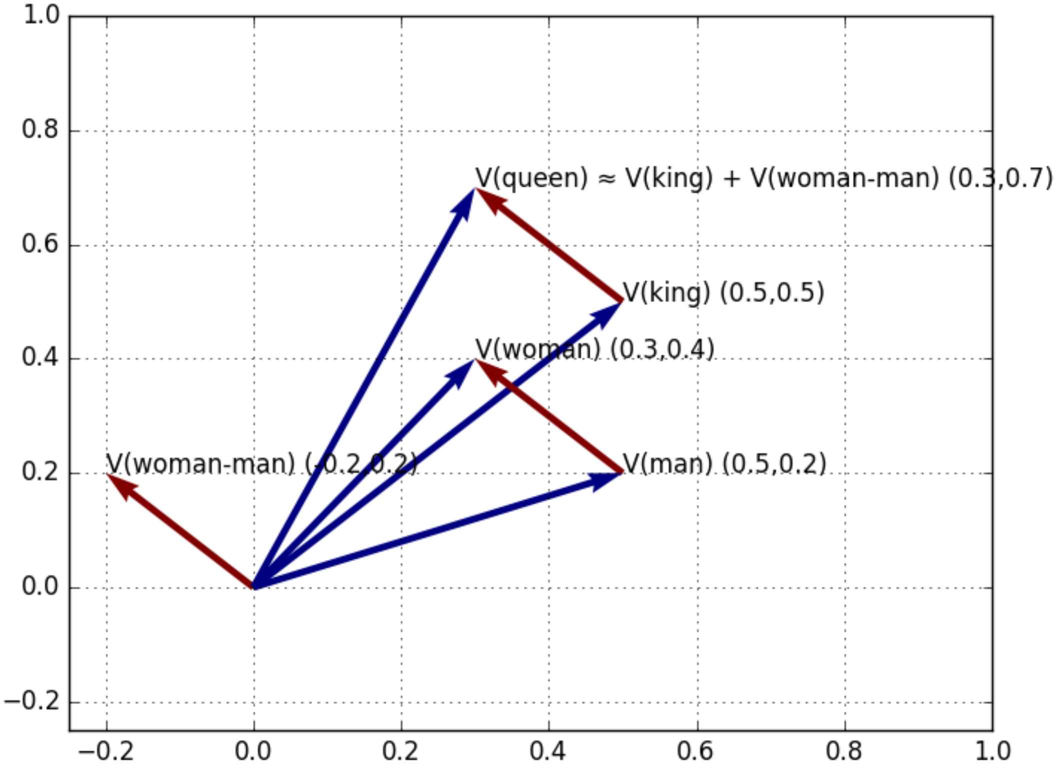
‘Man’ is to ‘Woman’ as ‘King’ is to … ?



‘Man’ is to ‘Woman’ as ‘King’ is to ‘Queen’



$$V(Queen) = V(King) + V(Woman) - V(Man)$$



V(Woman) – V(Man)

V(Woman) = [0.001, 0.12, -0.15, 0.1, …]
V(Man) = [0.0012, 0.13, 0.14, 0.1, ...]

V(Woman-Man) = [-0.0002, -0.01, -0.29, …]

V(Woman)	Human being	Adult	Female	Noun
- V(Man)	Human being	Adult	Male	Noun
= V(Woman) - V(Man)	0	0	Female-Male	0

V(Queen) – V(King)

V(Queen) = [0.001, 0.5, -0.15, 0.1, …]
V(King) = [0.0012, 0.51, 0.14, 0.1, ...]

V(Queen-King) = [-0.0002, -0.01, -0.29, ...]

V(Queen)	Human being	Monarch	Female	Noun
- V(King)	Human being	Monarch	Male	Noun
= V(Queen) - V(King)	0	0	Female -Male	0

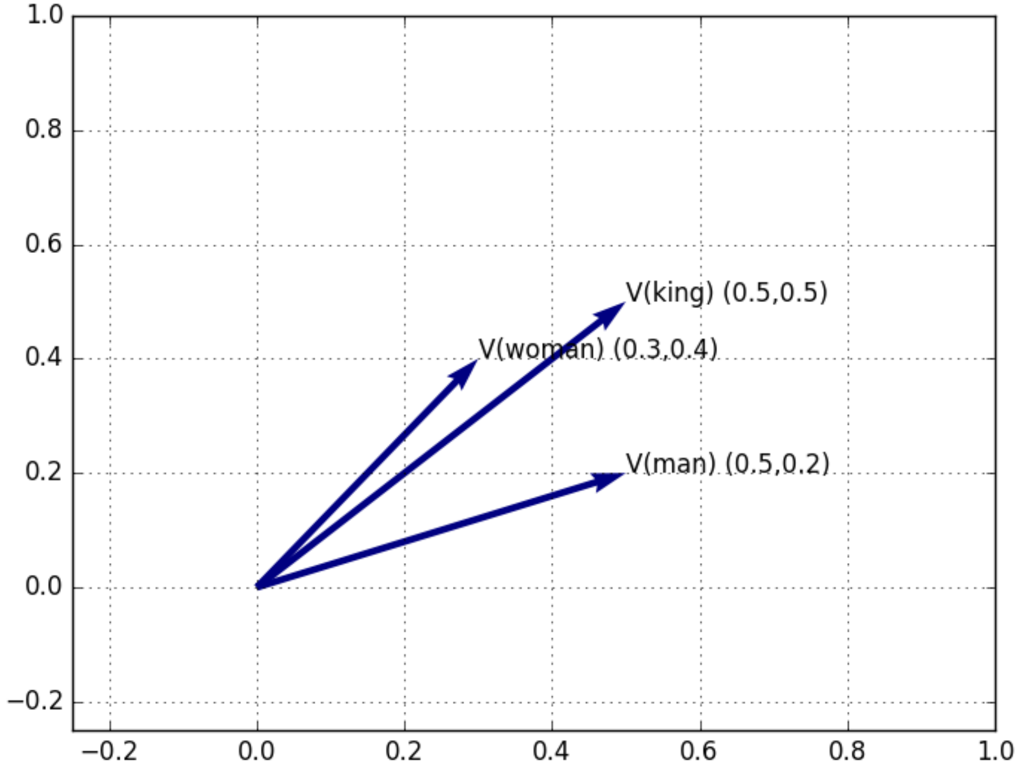
$$V(\text{Queen}) - V(\text{King}) = V(\text{Woman}) - V(\text{Man})$$

$$V(\text{Queen}) - V(\text{King}) = V(\text{Woman}) - V(\text{Man})$$

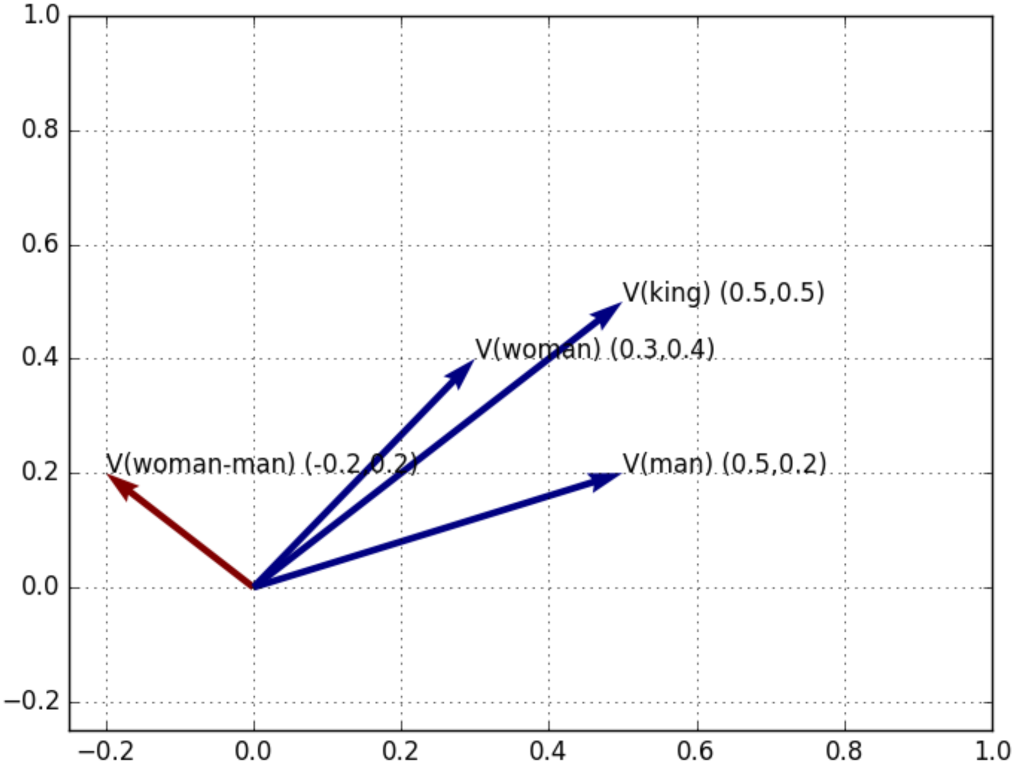
$$=$$

$$V(\text{Queen}) = V(\text{King}) + V(\text{Woman}) - V(\text{Man})$$

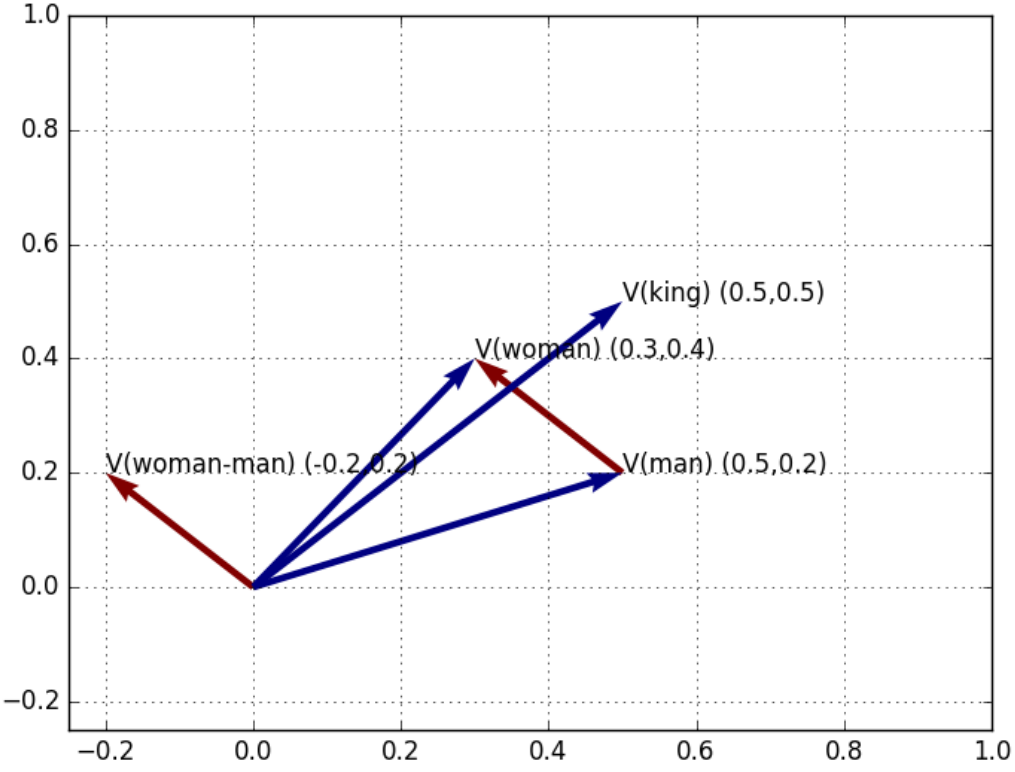
V(Queen) = V(King) + V(Woman) - V(Man)



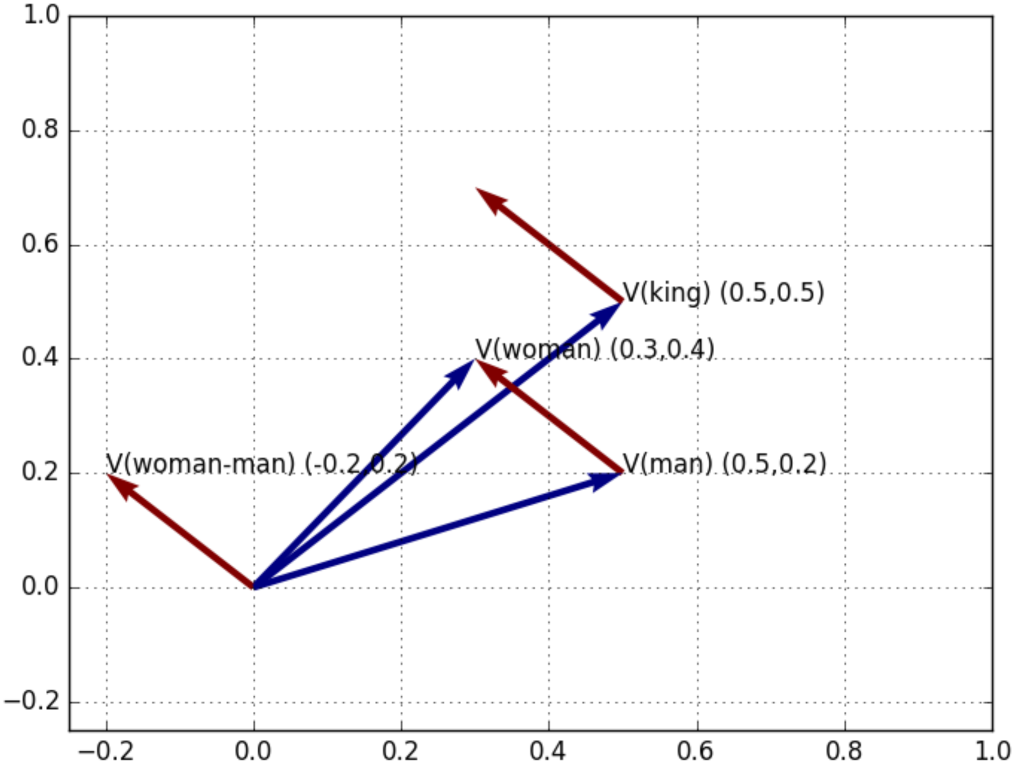
$$V(Queen) = V(King) + V(Woman) - V(Man)$$



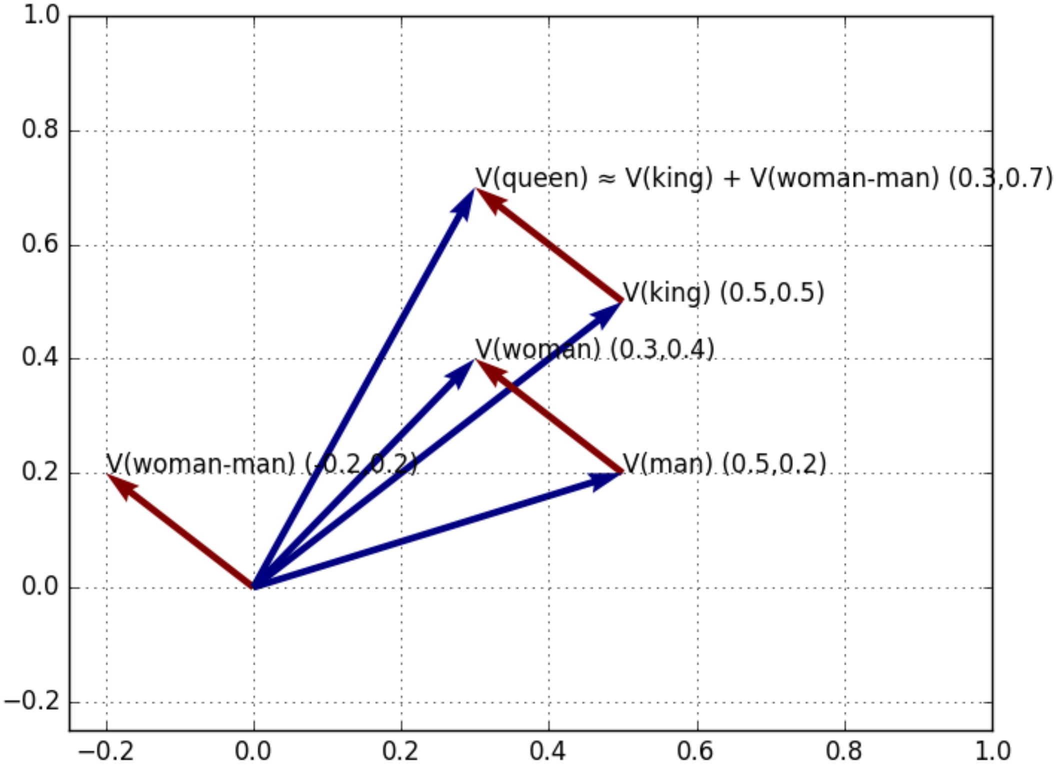
V(Queen) = V(King) + V(Woman) - V(Man)



V(Queen) = V(King) + V(Woman) - V(Man)



$$V(\text{Queen}) = V(\text{King}) + V(\text{Woman}) - V(\text{Man})$$

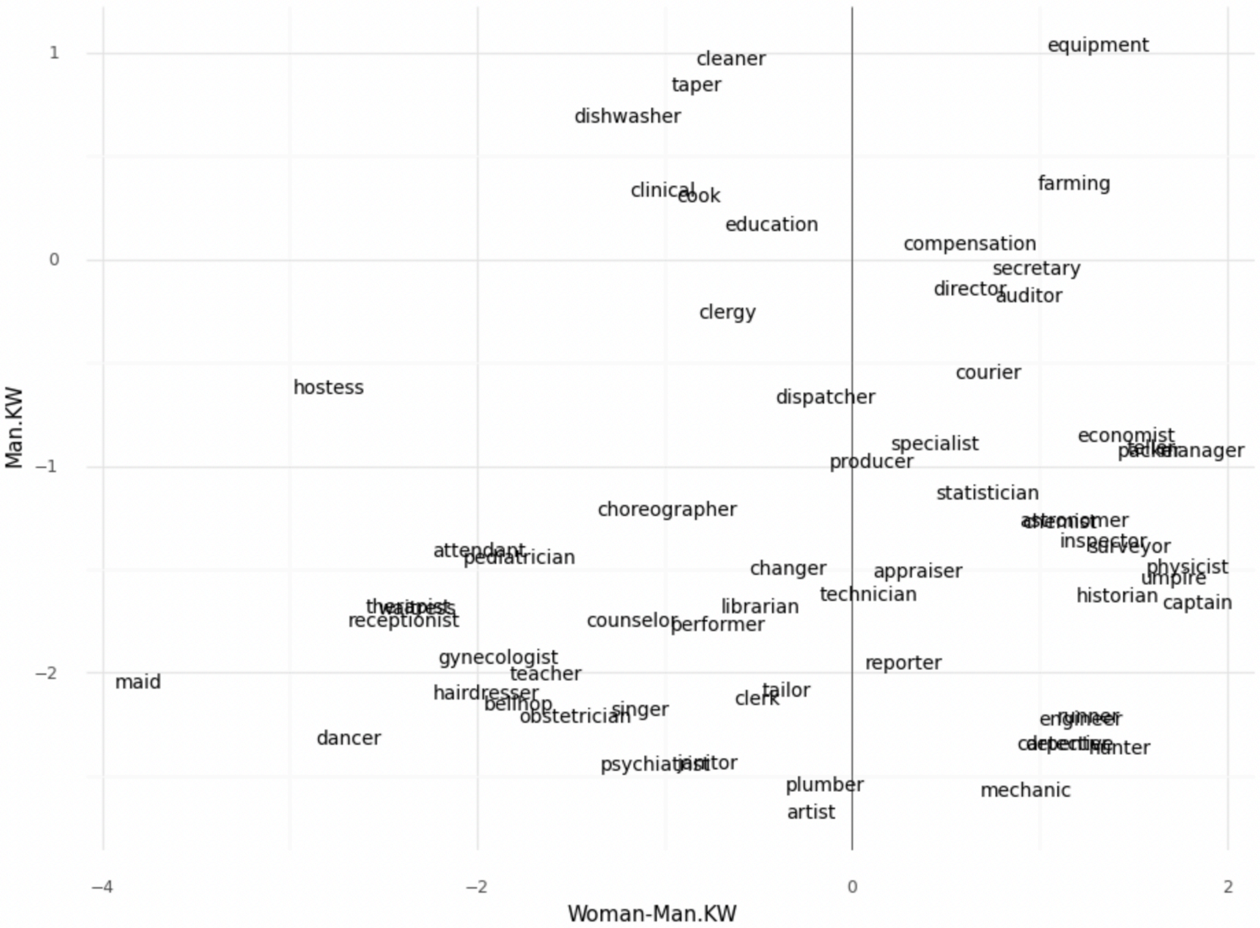


```
biplot(dfjobs[dfjobs.period=='1975-2000'],clip=True)
```

[90] ✓ 0.1s

...

“Word embedding models” encode <u>semantic contrasts</u> as <u>geometric vectors</u> in a virtual space



Model: COHA (1975-2000)

Words: Top 25 neighbors of nurse, doctor

X-axis: cosine similarity with V(Woman-Man)

```
biplot(dfanim[dfanim.period=='1975-2000'], clip=True)
```

[93] ✓ 0.1s

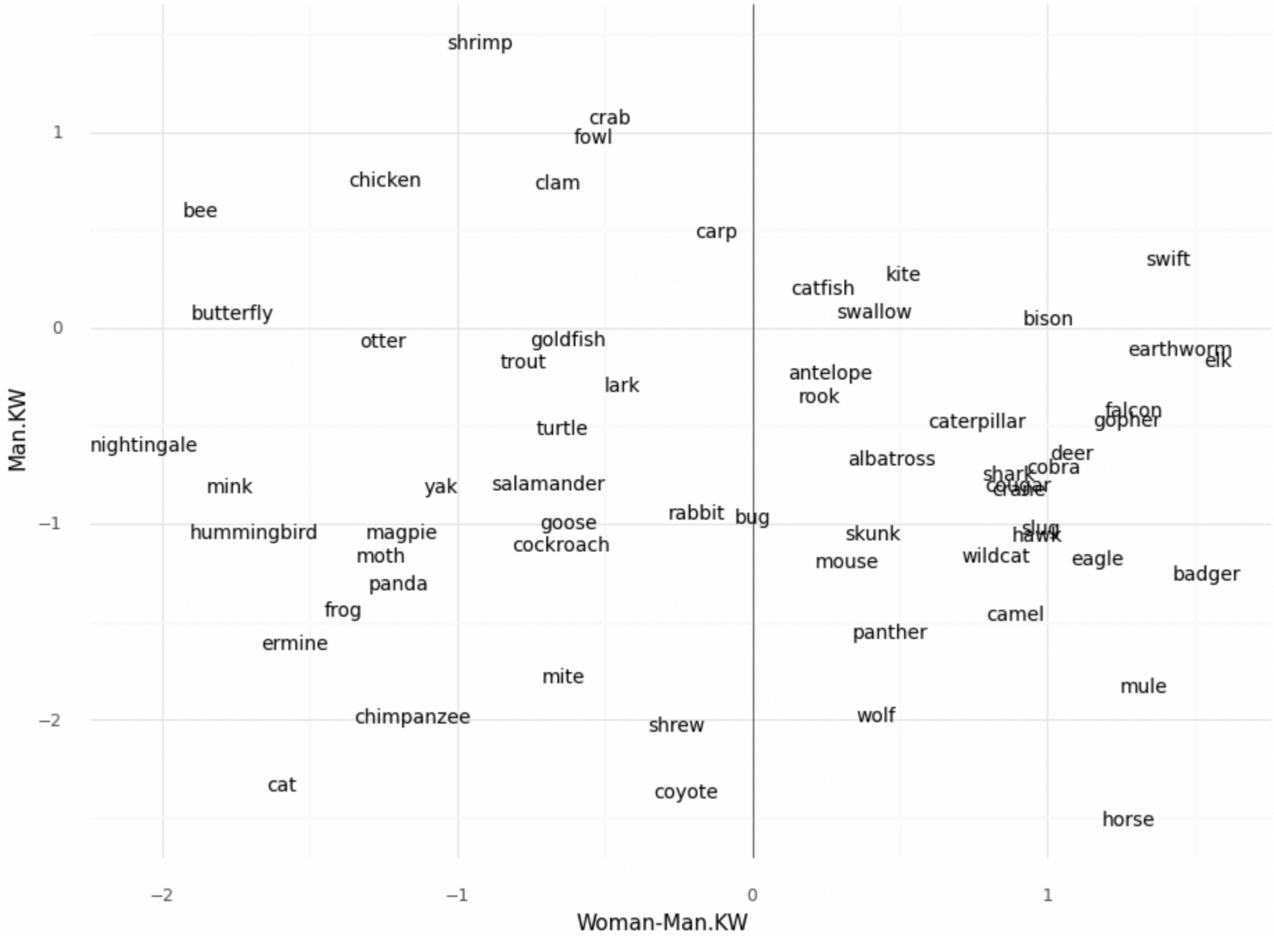
...

“Word embedding models” encode <u>semantic contrasts</u> as <u>geometric vectors</u> in a virtual space

Model: COHA (1975-2000)

Words: Top 25 neighbors of nurse, doctor

X-axis: cosine similarity with V(Woman-Man)

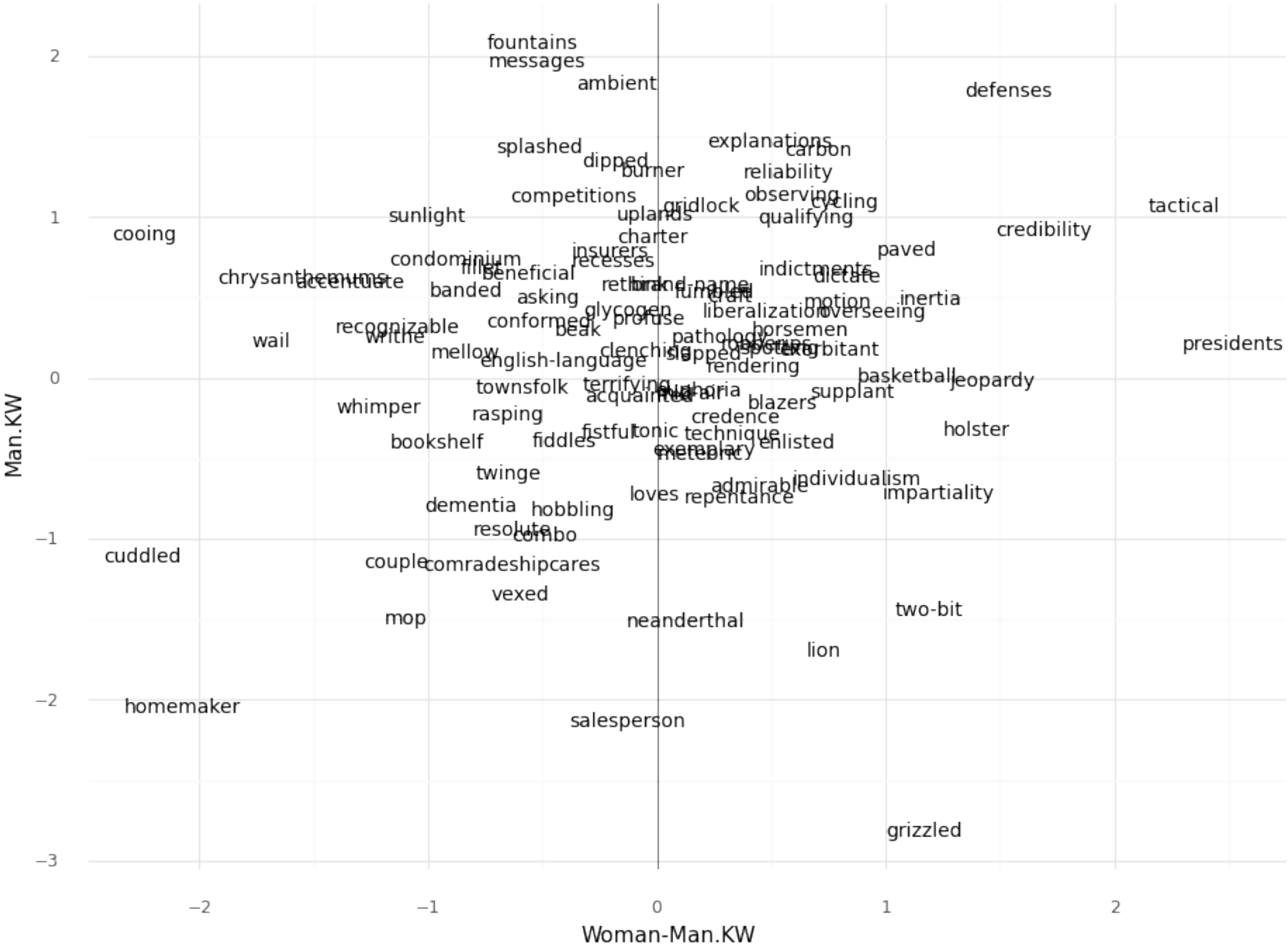


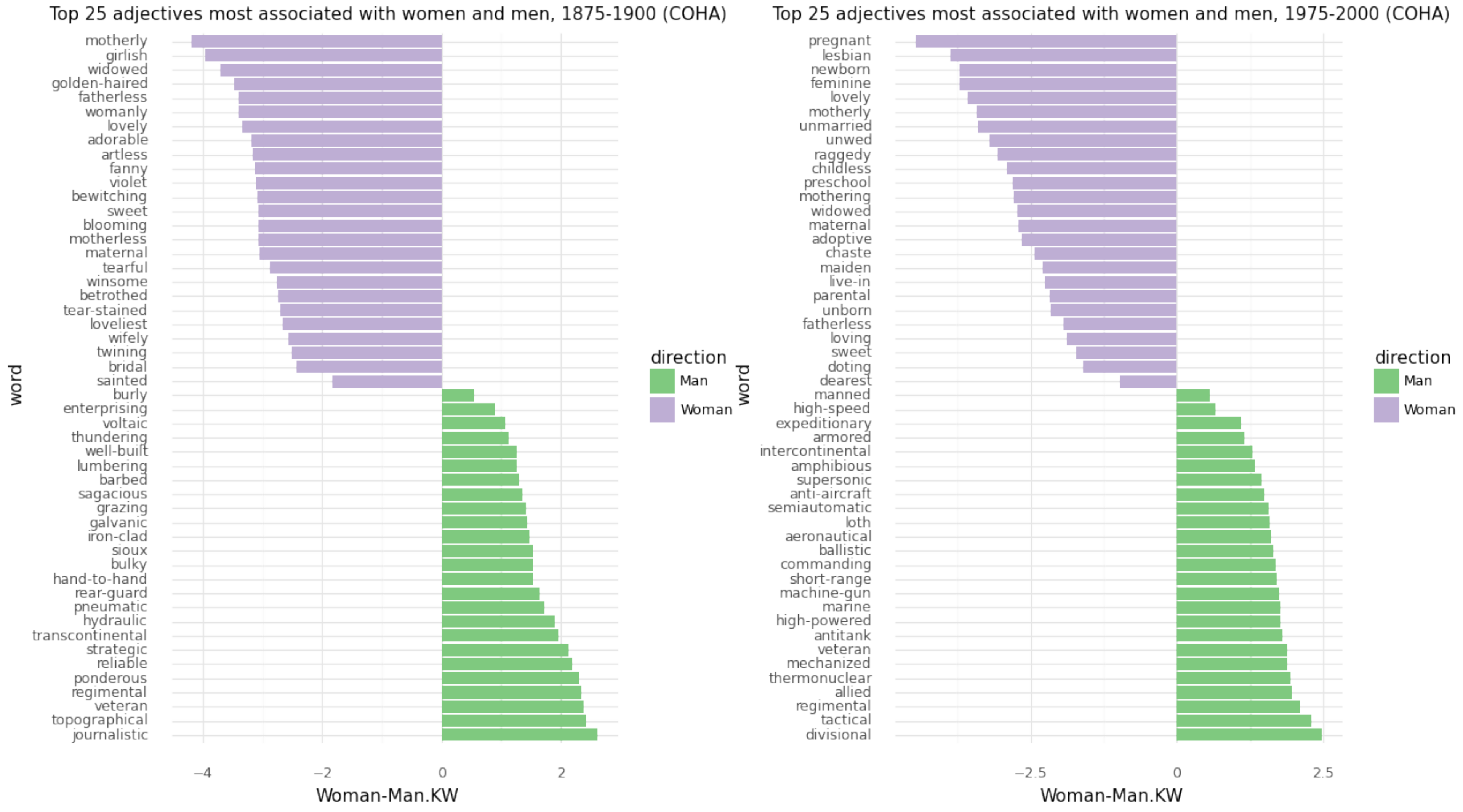
“Word embedding models” encode <u>semantic contrasts</u> as <u>geometric vectors</u> in a virtual space

Model: COHA (1975-2000)

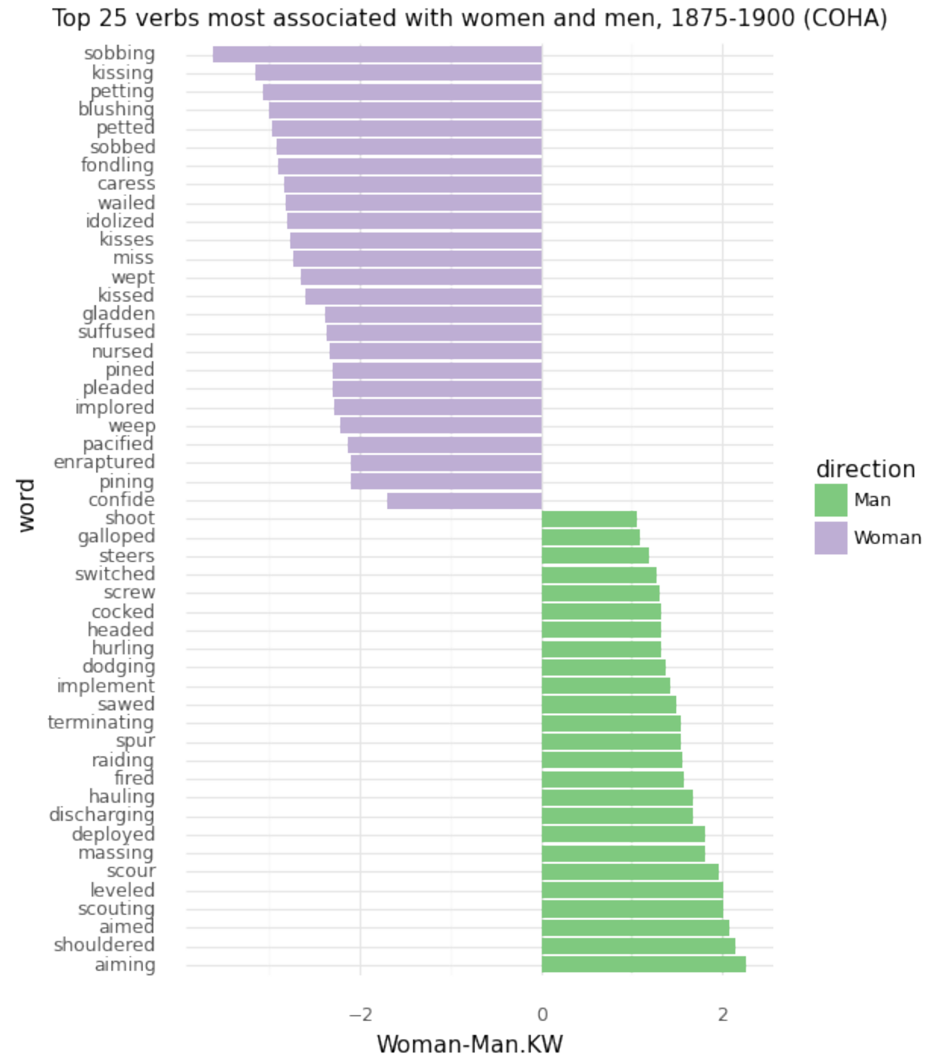
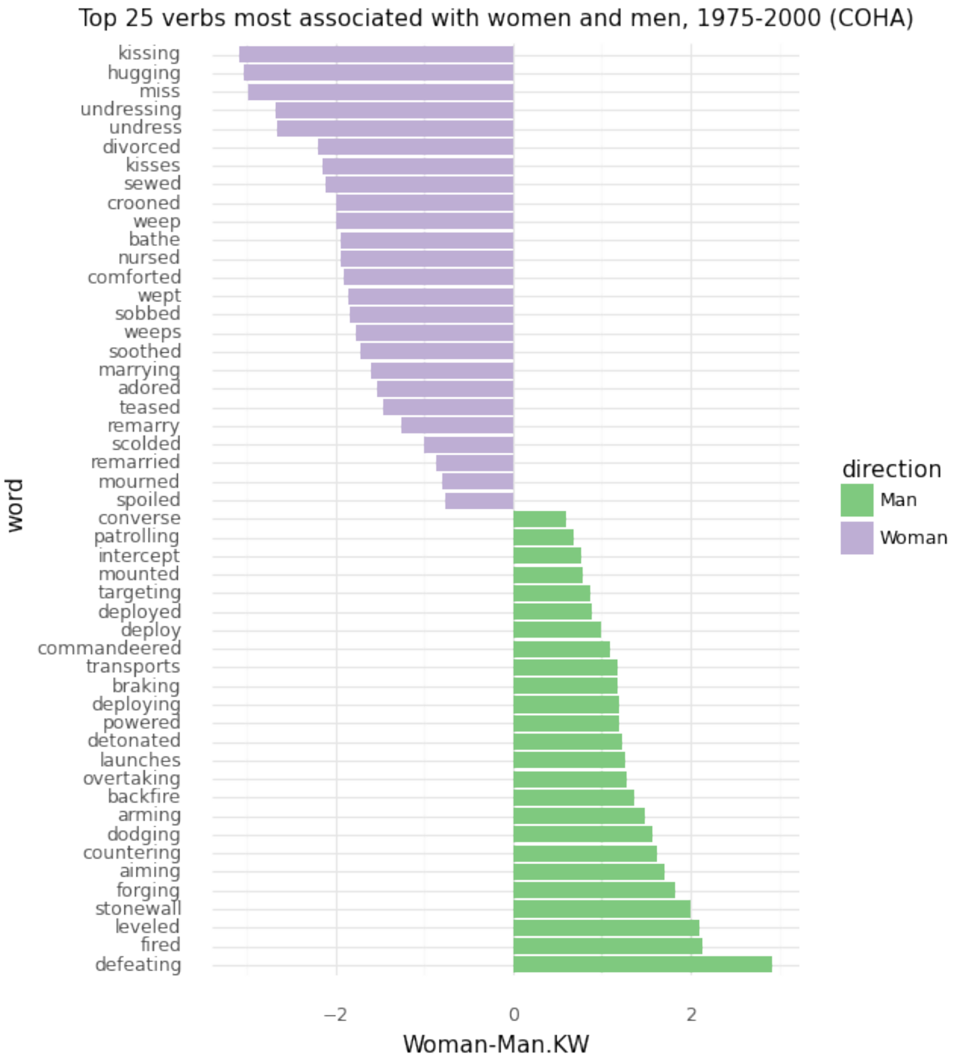
Words: Top 25 neighbors of nurse, doctor

X-axis: cosine similarity with V(Woman-Man)





Top 25 adjectives most associated with women and men, 1875-1900 (COHA)
motherly
girlish
widowed
golden-haired
fatherless
womanly
lovely
adorable
artless
fanny
violet
bewitching
sweet
blooming
motherless
maternal
tearful
winsome
betrothed
tear-stained
loveliest
wifely
twining
bridal
sainted
burly
enterprising
voltaic
thundering
well-built
lumbering
barbed
sagacious
grazing
galvanic
iron-clad
sioux
bulky
hand-to-hand
rear-guard
pneumatic
hydraulic
transcontinental
strategic
reliable
ponderous
regimental
veteran
topographical
journalistic
word
−4
−2
0
2
Woman-Man.KW
direction
Man
Woman
Top 25 adjectives most associated with women and men, 1975-2000 (COHA)
pregnant
lesbian
newborn
feminine
lovely
motherly
unmarried
unwed
raggedy
childless
preschool
mothering
widowed
maternal
adoptive
chaste
maiden
live-in
parental
unborn
fatherless
loving
sweet
doting
dearest
manned
high-speed
expeditionary
armored
intercontinental
amphibious
supersonic
anti-aircraft
semiautomatic
loth
aeronautical
ballistic
commanding
short-range
machine-gun
marine
high-powered
antitank
veteran
mechanized
thermonuclear
allied
regimental
tactical
divisional
word
−2.5
0
2.5
Woman-Man.KW
direction
Man
Woman


Top 25 verbs most associated with women and men, 1875-1900 (COHA)
sobbing
kissing
petting
blushing
petted
sobbed
fondling
caress
wailed
idolized
kisses
miss
wept
kissed
gladden
suffused
nursed
pined
pleaded
implored
weep
pacified
enraptured
pining
confide
shoot
galloped
steers
switched
screw
cocked
headed
hurling
dodging
implement
sawed
terminating
spur
raiding
fired
hauling
discharging
deployed
massing
scour
leveled
scouting
aimed
shouldered
aiming
word
−2
0
2
Woman-Man.KW
direction
Man
Woman

Top 25 verbs most associated with women and men, 1975-2000 (COHA)
kissing
hugging
miss
undressing
undress
divorced
kisses
sewed
crooned
weep
bathe
nursed
comforted
wept
sobbed
weeps
soothed
marrying
adored
teased
remarry
scolded
remarried
mourned
spoiled
converse
patrolling
intercept
mounted
targeting
deployed
deploy
commandeered
transports
braking
deploying
powered
detonated
launches
overtaking
backfire
arming
dodging
countering
aiming
forging
stonewall
leveled
fired
defeating
word
−2
0
2
Woman-Man.KW
direction
Man
Woman

```python
dfch = load_bias_data(avg_runs=False)
dfch = dfch[dfch.num_models==dfch.num_models.max()].sort_values(['word','period'])
dfch_words=measure_changing_words(dfch)
```

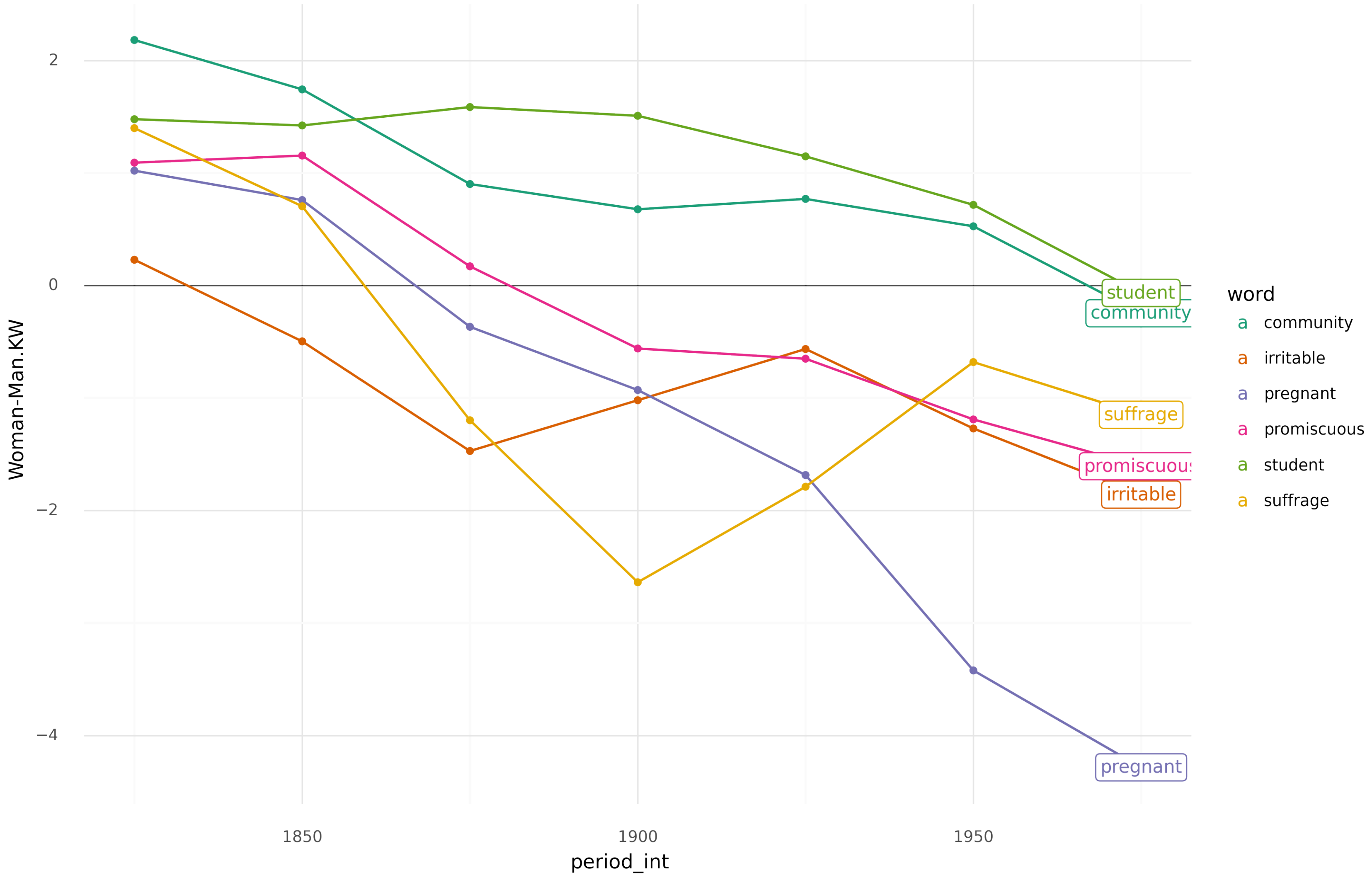
✓ 8.2s

```
Mapping measure_change [x8]: 100%|██████████| 14109/14109 [00:03<00:00, 4591.46it/s]
```

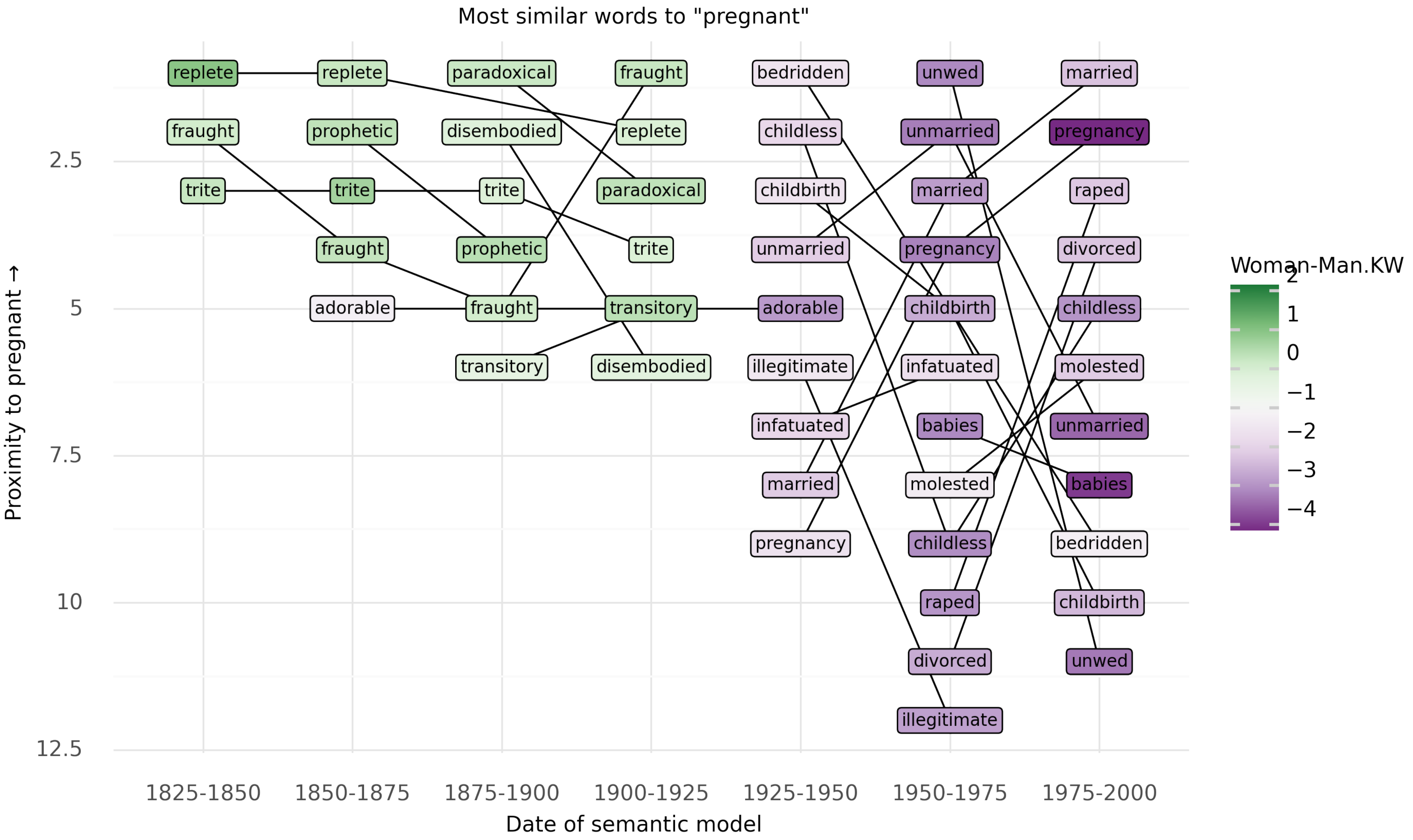
```python
# Flipped strongly from male to female
dfch_words.query('start>1 & end<-1')
```

✓ 0.4s

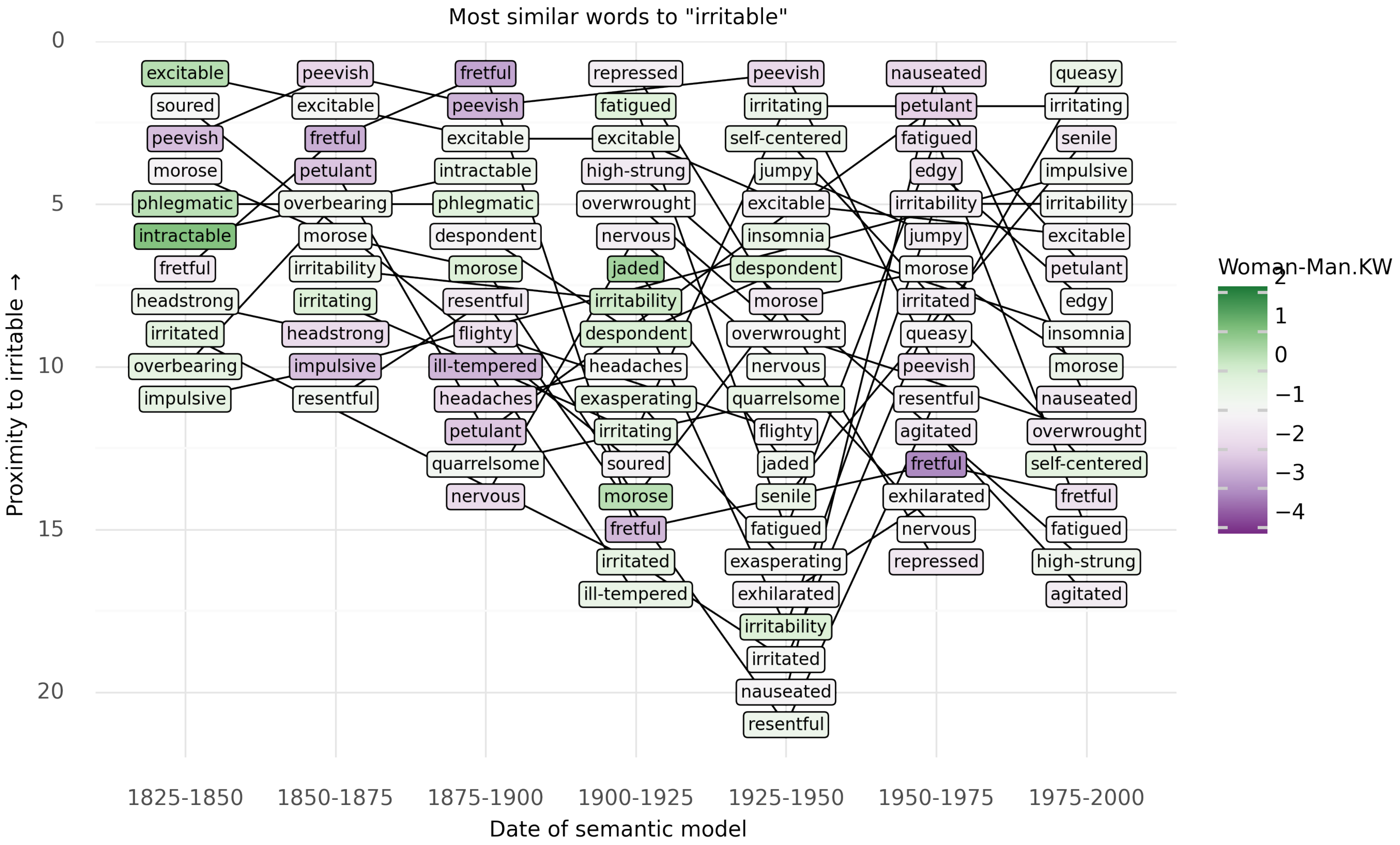
	r2	n	p	slope	min	max	magn	start	end	change	flipped
word											
pregnant	0.425397	70.0	7.191590e-10	-0.000902	-5.096402	1.474648	6.571050	1.021198	-4.466344	-5.487542	F
surveys	0.409056	70.0	1.927320e-09	0.000478	-1.934621	2.789710	4.724331	1.070980	-1.235086	-2.306066	F
transmitted	0.366967	70.0	2.176925e-08	0.000418	-1.653432	2.419716	4.073148	1.817210	-1.146560	-2.963770	F
directors	0.357096	70.0	3.759949e-08	0.000378	-1.734639	2.441559	4.176198	1.443726	-1.084106	-2.527833	F
suffrage	0.345089	70.0	7.233071e-08	-0.000525	-3.245400	1.744547	4.989947	1.399206	-1.645384	-3.044590	F
students	0.342102	70.0	8.497096e-08	0.000373	-1.681791	2.295249	3.977040	1.937452	-1.024948	-2.962401	F
workshop	0.325800	70.0	2.022156e-07	0.000292	-1.750702	1.750887	3.501589	1.307427	-1.122798	-2.430225	F
disturbing	0.309342	70.0	4.759322e-07	-0.000291	-1.935269	1.605469	3.540739	1.152357	-1.033217	-2.185574	F
sexual	0.287158	70.0	1.465778e-06	-0.000361	-2.201852	1.552307	3.754160	1.289470	-1.896934	-3.186404	F
locality	0.276380	70.0	2.503339e-06	0.000280	-1.975636	1.858252	3.833888	1.060823	-1.084801	-2.145624	F
aids	0.242696	70.0	1.275986e-05	0.000425	-2.839062	2.310006	5.149068	1.617648	-2.383460	-4.001108	F
subscribers	0.236894	70.0	1.678582e-05	0.000286	-1.753401	1.907317	3.660719	1.603851	-1.313613	-2.917465	F
enlarged	0.231979	70.0	2.114679e-05	0.000315	-1.901894	2.212753	4.114647	2.019158	-1.437638	-3.456795	F
surgical	0.220251	70.0	3.651064e-05	0.000264	-1.710502	1.708357	3.418859	1.205644	-1.136272	-2.341916	F
deficiency	0.185273	70.0	1.791568e-04	0.000231	-1.675014	1.584672	3.259686	1.004041	-1.002095	-2.006136	F
promiscuous	0.137693	70.0	1.443766e-03	-0.000246	-2.868975	1.827251	4.696226	1.092226	-1.891701	-2.983927	F



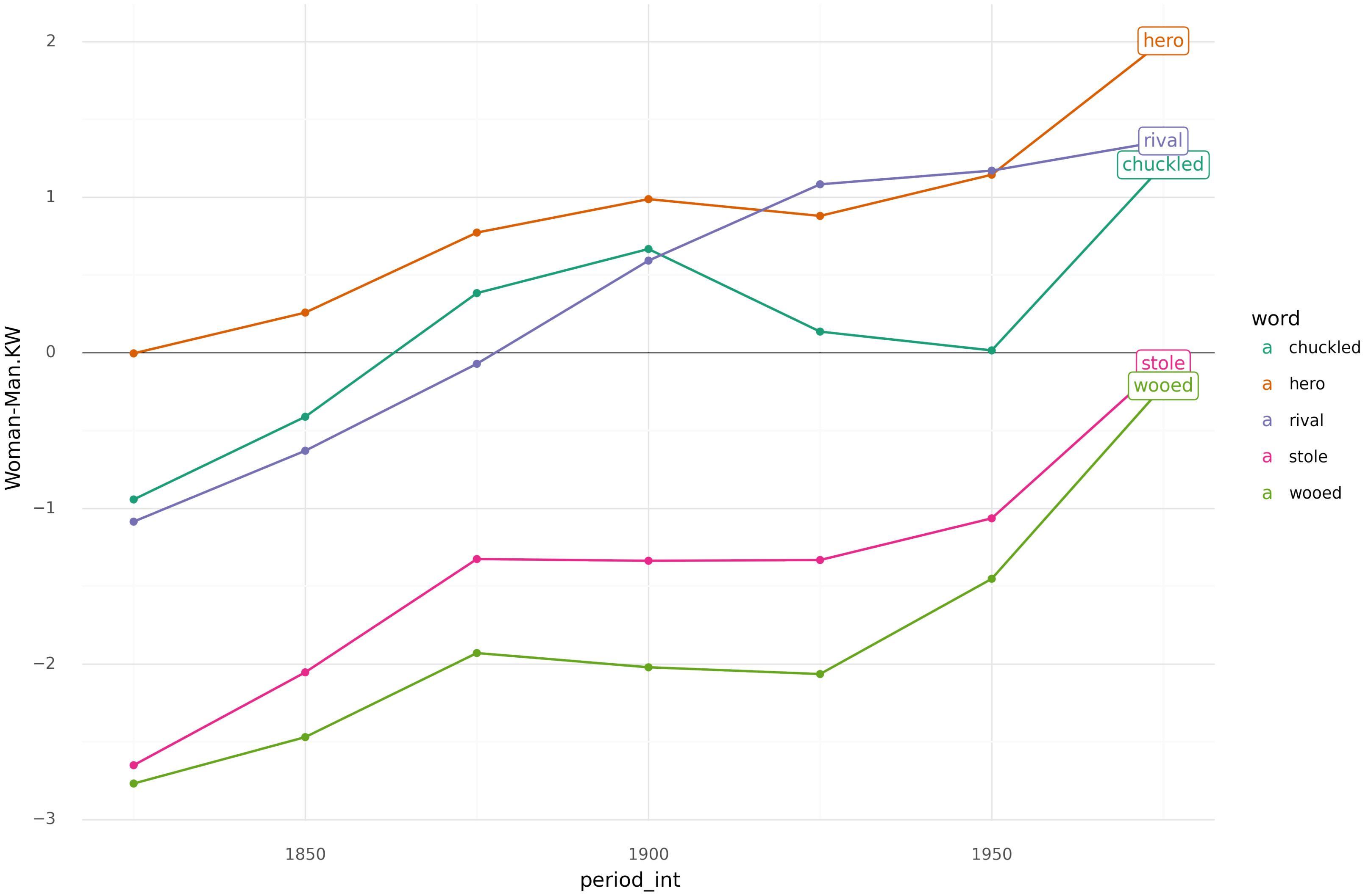
Woman-Man.KW
2
0
−2
−4
1850
1900
1950
period_int
student
community
suffrage
promiscuous
irritable
pregnant
word
community
irritable
pregnant
promiscuous
student
suffrage

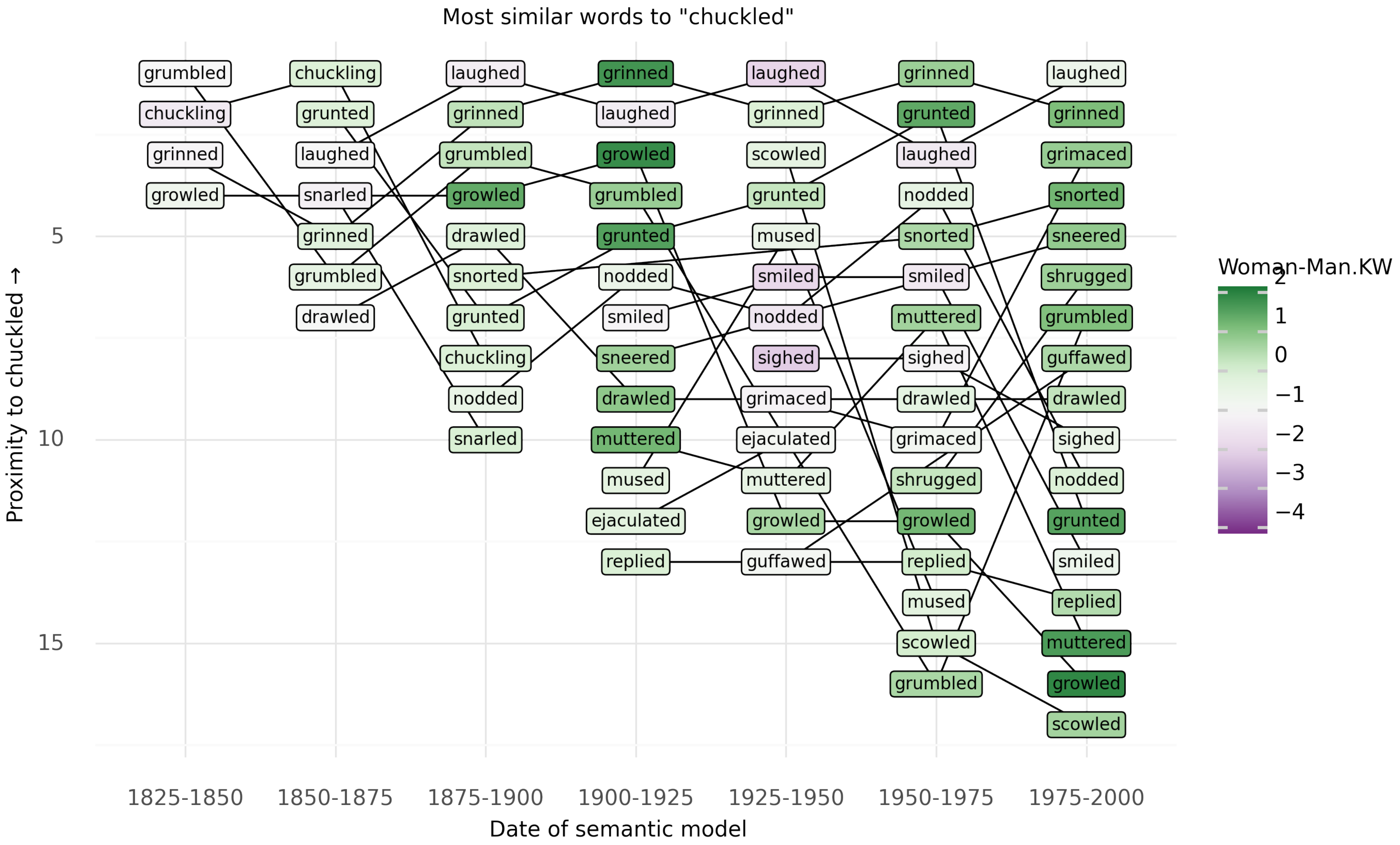


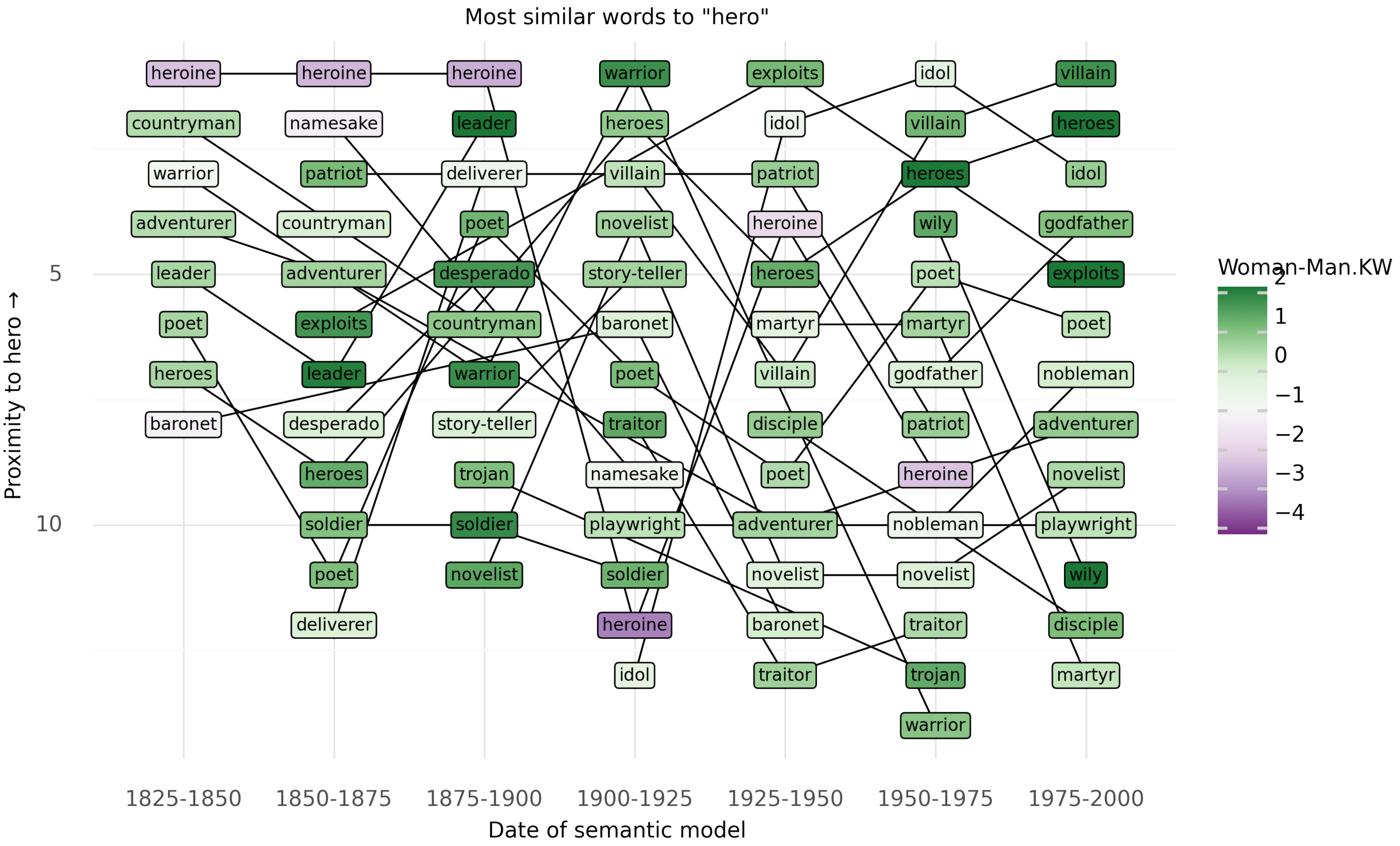
Most similar words to "pregnant"
Proximity to pregnant →
Date of semantic model
Woman-Man.KW
1825-1850
1850-1875
1875-1900
1900-1925
1925-1950
1950-1975
1975-2000
2.5
5
7.5
10
12.5
2
1
0
−1
−2
−3
−4
replete
fraught
trite
replete
prophetic
trite
fraught
adorable
paradoxical
disembodied
trite
prophetic
fraught
transitory
fraught
replete
paradoxical
trite
transitory
disembodied
bedridden
childless
childbirth
unmarried
adorable
illegitimate
infatuated
married
pregnancy
unwed
unmarried
married
pregnancy
childbirth
infatuated
babies
molested
childless
raped
divorced
illegitimate
married
pregnancy
raped
divorced
childless
molested
unmarried
babies
bedridden
childbirth
unwed



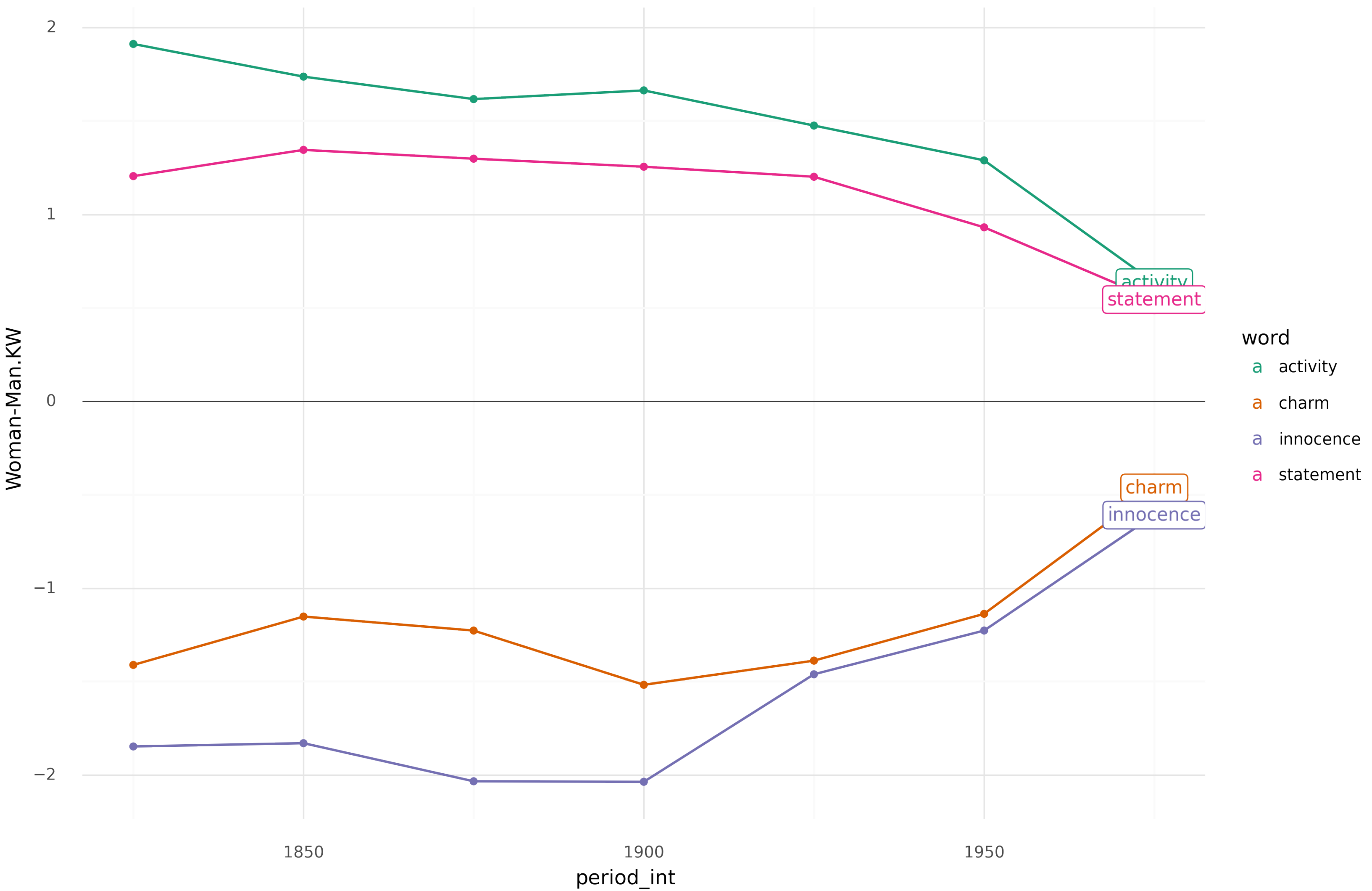
Most similar words to "irritable"
Proximity to irritable →
Date of semantic model
0
5
10
15
20
1825-1850
1850-1875
1875-1900
1900-1925
1925-1950
1950-1975
1975-2000
Woman-Man.KW
2
1
0
−1
−2
−3
−4
excitable
soured
peevish
morose
phlegmatic
intractable
fretful
headstrong
irritated
overbearing
impulsive
peevish
excitable
fretful
petulant
overbearing
morose
irritability
irritating
headstrong
impulsive
resentful
fretful
peevish
excitable
intractable
phlegmatic
despondent
morose
resentful
flighty
ill-tempered
headaches
petulant
quarrelsome
nervous
repressed
fatigued
excitable
high-strung
overwrought
nervous
jaded
irritability
despondent
headaches
exasperating
irritating
soured
morose
fretful
irritated
ill-tempered
peevish
irritating
self-centered
jumpy
excitable
insomnia
despondent
morose
overwrought
nervous
quarrelsome
flighty
jaded
senile
fatigued
exasperating
exhilarated
irritability
irritated
nauseated
resentful
nauseated
petulant
fatigued
edgy
irritability
jumpy
morose
irritated
queasy
peevish
resentful
agitated
fretful
exhilarated
nervous
repressed
queasy
irritating
senile
impulsive
irritability
excitable
petulant
edgy
insomnia
morose
nauseated
overwrought
self-centered
fretful
fatigued
high-strung
agitated


hero
rival
chuckled
stole
wooed
2
1
0
−1
−2
−3
Woman-Man.KW
1850
1900
1950
period_int
word
a chuckled
a hero
a rival
a stole
a wooed

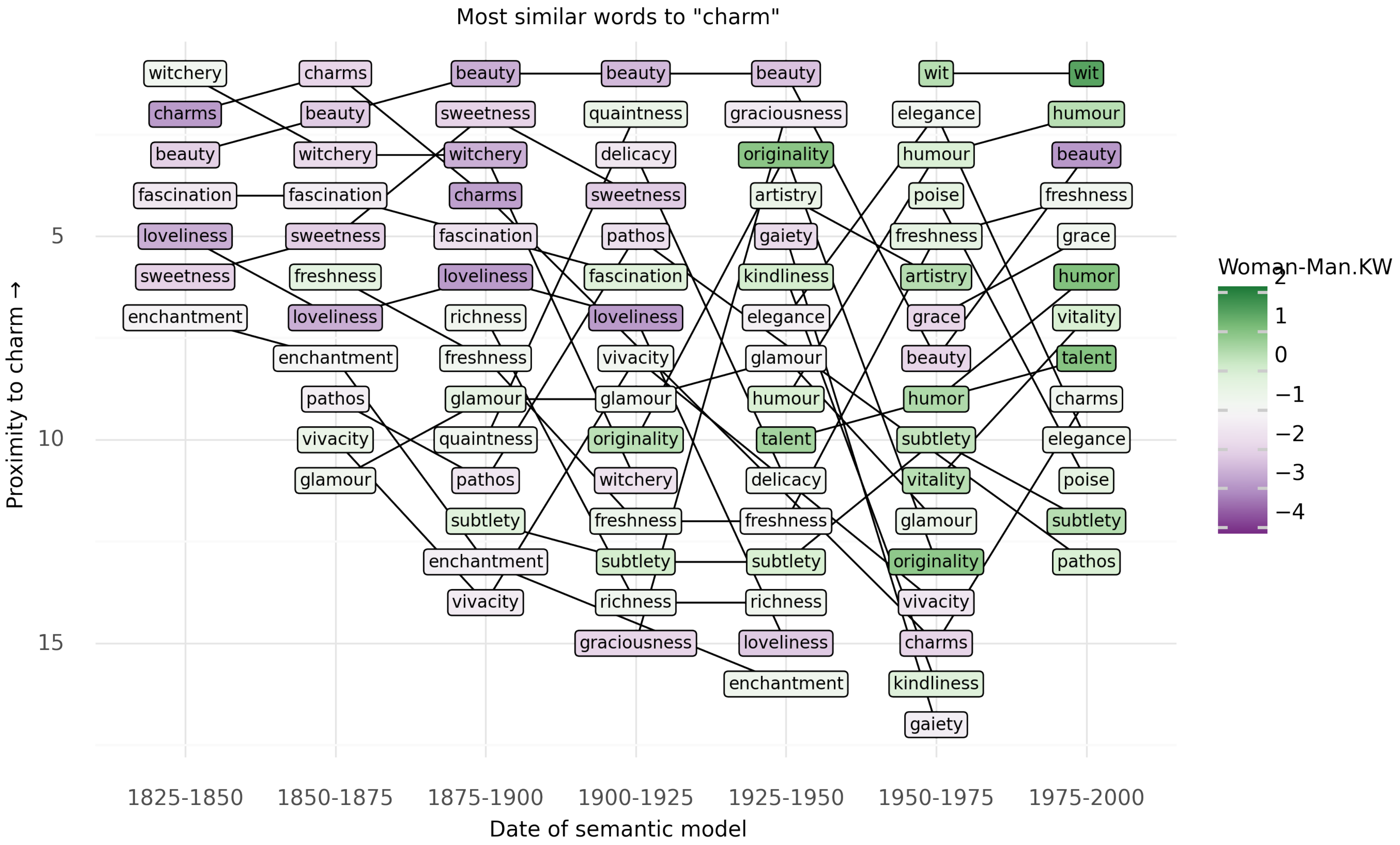

Most similar words to "chuckled"
Proximity to chuckled →
5
10
15
1825-1850
1850-1875
1875-1900
1900-1925
1925-1950
1950-1975
1975-2000
Date of semantic model
Woman-Man.KW
2
1
0
−1
−2
−3
−4
grumbled
chuckling
grinned
growled
chuckling
grunted
laughed
snarled
grinned
grumbled
drawled
laughed
grinned
grumbled
growled
drawled
snorted
grunted
chuckling
nodded
snarled
grinned
laughed
growled
grumbled
grunted
nodded
smiled
sneered
drawled
muttered
mused
ejaculated
replied
laughed
grinned
scowled
grunted
mused
smiled
nodded
sighed
grimaced
ejaculated
muttered
growled
guffawed
grinned
grunted
laughed
nodded
snorted
smiled
muttered
sighed
drawled
grimaced
shrugged
growled
replied
mused
scowled
grumbled
laughed
grinned
grimaced
snorted
sneered
shrugged
grumbled
guffawed
drawled
sighed
nodded
grunted
smiled
replied
muttered
growled
scowled

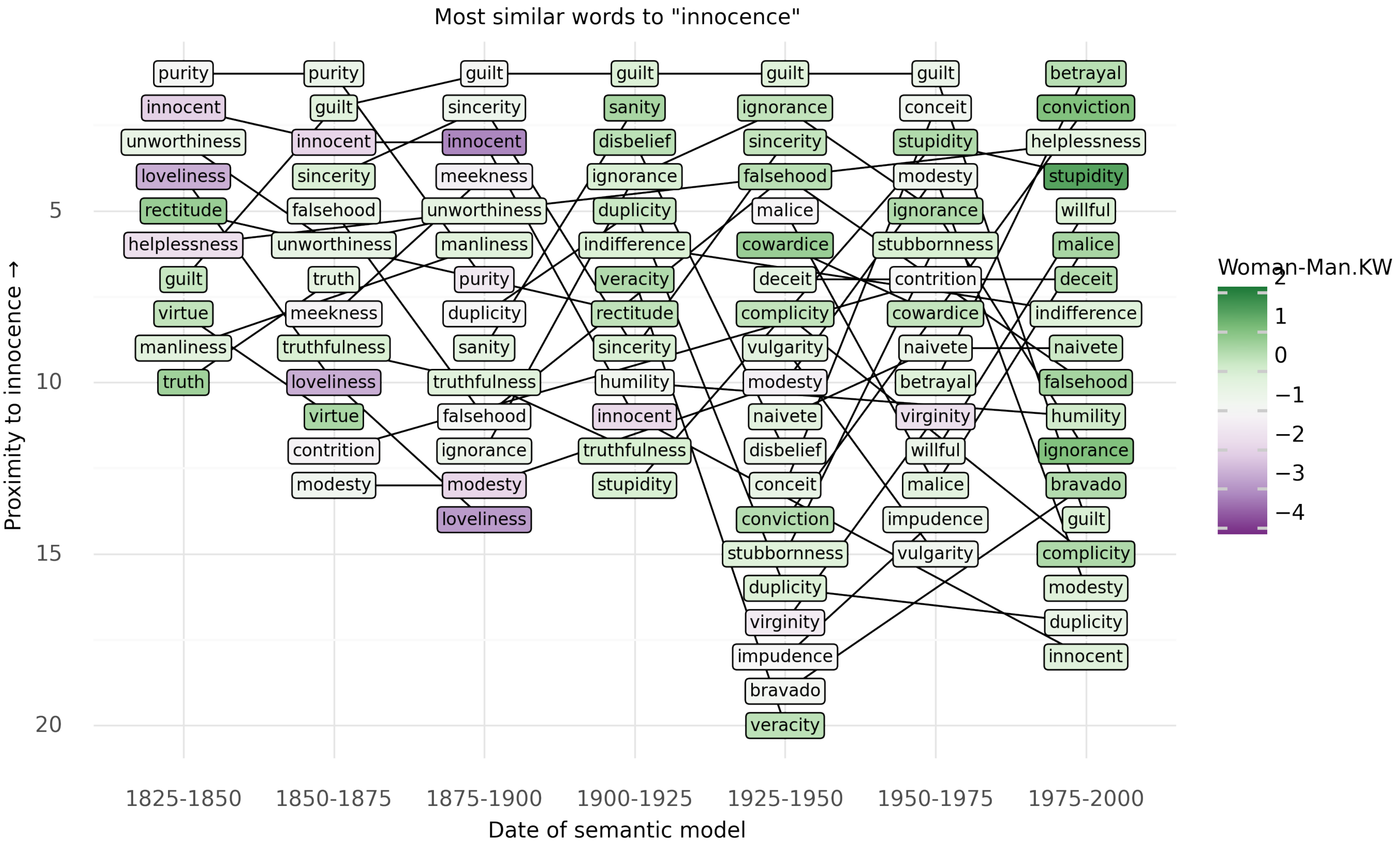


Most similar words to "hero"
Proximity to hero →
5
10
Date of semantic model
1825-1850
1850-1875
1875-1900
1900-1925
1925-1950
1950-1975
1975-2000
Woman-Man.KW
2
1
0
−1
−2
−3
−4
heroine
countryman
warrior
adventurer
leader
poet
heroes
baronet
namesake
patriot
exploits
desperado
soldier
deliverer
story-teller
trojan
novelist
villain
traitor
playwright
idol
martyr
disciple
wily
godfather
nobleman



2
1
0
−1
−2
1850
1900
1950
period_int
Woman-Man.KW
activity
statement
charm
innocence
word
a activity
a charm
a innocence
a statement


Most similar words to "charm"
Proximity to charm →
Date of semantic model
Woman-Man.KW
5
10
15
1825-1850
1850-1875
1875-1900
1900-1925
1925-1950
1950-1975
1975-2000
2
1
0
−1
−2
−3
−4
witchery
charms
beauty
fascination
loveliness
sweetness
enchantment
freshness
pathos
vivacity
glamour
richness
quaintness
subtlety
delicacy
originality
graciousness
artistry
gaiety
kindliness
elegance
humour
talent
wit
poise
grace
humor
vitality



Most similar words to "innocence"
Proximity to innocence →
Date of semantic model
1825-1850
1850-1875
1875-1900
1900-1925
1925-1950
1950-1975
1975-2000
Woman-Man.KW
2
1
0
−1
−2
−3
−4
5
10
15
20
purity
innocent
unworthiness
loveliness
rectitude
helplessness
guilt
virtue
manliness
truth
purity
guilt
innocent
sincerity
falsehood
unworthiness
truth
meekness
truthfulness
loveliness
virtue
contrition
modesty
guilt
sincerity
innocent
meekness
unworthiness
manliness
purity
duplicity
sanity
truthfulness
falsehood
ignorance
modesty
loveliness
guilt
sanity
disbelief
ignorance
duplicity
indifference
veracity
rectitude
sincerity
humility
innocent
truthfulness
stupidity
guilt
ignorance
sincerity
falsehood
malice
cowardice
deceit
complicity
vulgarity
modesty
naivete
disbelief
conceit
conviction
stubbornness
duplicity
virginity
impudence
bravado
veracity
guilt
conceit
stupidity
modesty
ignorance
stubbornness
contrition
cowardice
naivete
betrayal
virginity
willful
malice
impudence
vulgarity
betrayal
conviction
helplessness
stupidity
willful
malice
deceit
indifference
naivete
falsehood
humility
ignorance
bravado
guilt
complicity
modesty
duplicity
innocent

Thank you!

Code and slides: github.com/quadrismegistus/bias