

Text Analysis for Social Scientists and Leaders



Class 3: Embeddings & Similarity

Prof. Michael Yeomans

Dimension Reduction

Sparse Representation

"This is a sentence"
"This is also one sentence"
"This is a document"
"This is not a document"

Dimension Reduction

Sparse Representation

"This is a sentence"
"This is also one sentence"
"This is a document"
"This is not a document"

This	is	a	sentence	also	one	document	not	wolf	star	...
1	1	1	1	0	0	0	0	0	0	0
1	1	0	1	1	1	0	0	0	0	0
1	1	1	0	0	0	1	0	0	0	0
1	1	1	0	0	0	1	1	0	0	0

Dimension Reduction

Sparse Representation

"This is a sentence"
"This is also one sentence"
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This	is	a	sentence	also	one	document	not	wolf	star	...
1	1	1	1	0	0	0	0	0	0	0
1	1	0	1	1	1	0	0	0	0	0
1	1	1	0	0	0	1	0	0	0	0
1	1	1	0	0	0	1	1	0	0	0

Dense Representations

Dimension Reduction

Sparse Representation

"This is a sentence"
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"This is a document"
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This is a sentence										also	one	document	not	wolf	star	...
1	1	1		1	0	0	0	0	0	0	0	0	0	0	0	
1	1	0		1	1	1	0	0	0	0	0	0	0	0	0	
1	1	1		0	0	0	1	0	0	0	0	0	0	0	0	
1	1	1		0	0	0	1	1	0	0	0	0	0	0	0	

Dense Representations

Price	ft ²	Bedrooms	zone	Parking?
1800	440	3	3	yes
1400	610	1	1	No
1100	575	2	4	No
2200	800	2	2	Yes

Dimension Reduction

Sparse Representation

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1	1	1	0	0	0	1	0	0	0	0
1	1	1	0	0	0	1	1	0	0	0

Dense Representations

Lower dimensionality -> easier to estimate

Dimension Reduction

Sparse Representation

"This is a sentence"
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This	is	a	sentence	also	one	document	not	wolf	star	...
1	1	1	1	0	0	0	0	0	0	0
1	1	0	1	1	1	0	0	0	0	0
1	1	1	0	0	0	1	0	0	0	0
1	1	1	0	0	0	1	1	0	0	0

Dense Representations

Lower dimensionality -> easier to estimate
Captures “similarity”
- different words have similar meanings

Dimension Reduction

What words are similar to one another?

Dimension Reduction

What words are similar to one another?

Cat vs Lion

Dimension Reduction

What words are similar to one another?

Cat vs Lion

Cat vs Mouse

Dimension Reduction

What words are similar to one another?

Cat vs Lion

Cat vs Mouse

King vs Lion

Dimension Reduction

What words are similar to one another?

Cat vs Lion

Cat vs Mouse

King vs Lion

Red vs Green

Dimension Reduction

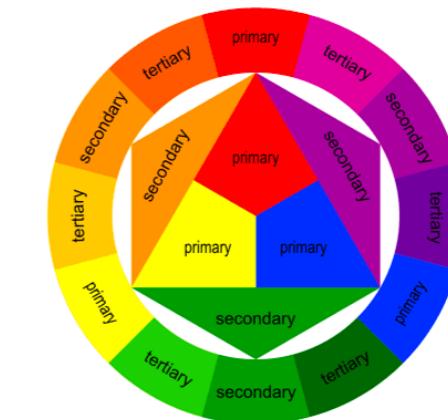
What words are similar to one another?

Cat vs Lion

Cat vs Mouse

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Dimension Reduction

What words are similar to one another?

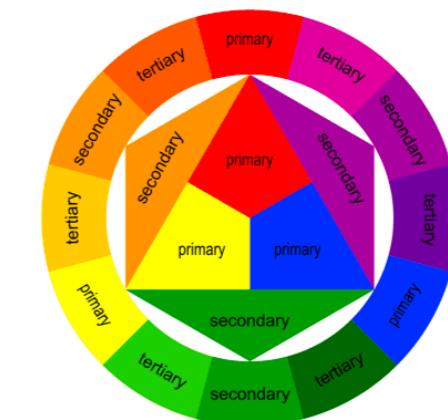
Cat vs Lion

Cat vs Mouse

King vs Lion

Red vs Green

Mouse vs Keyboard



Dimension Reduction

What words are similar to one another?

Cat vs Lion

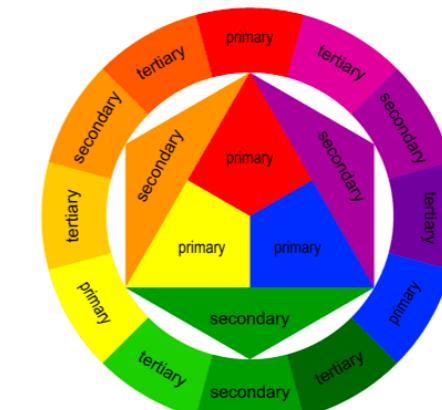
Cat vs Mouse

King vs Lion

Red vs Green

Mouse vs Keyboard

Cat vs Keyboard



Dimension Reduction

What words are similar to one another?

Similarity is high-dimensional!

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Synonyms: same meaning in all senses

Probably no true examples....

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Big/large

Dimension Reduction

What words are similar to one another?

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Synonyms: same meaning in all senses

Probably no true examples....

Big/large - my large sister != my big sister

Dimension Reduction

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Antonyms: opposite along one dimension, otherwise similar

Hot/cold, in/out, tall/short, long/short

Dimension Reduction

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Similarity is high-dimensional!

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Probably no true examples....

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Antonyms: opposite along one dimension, otherwise similar

Hot/cold, in/out, tall/short, long/short

Homonyms: different meanings for same character string

River bank / National bank

Dimension Reduction

Theory-Driven - “*We'll tell you what a word means*”

Dimension Reduction

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Dictionaries

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Theory-Driven - “*We'll tell you what a word means*”
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Data-Driven - “*You will know a word by the company it keeps*”

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Two senses of similarity:

Dimension Reduction

Theory-Driven - “*We’ll tell you what a word means*”
Dictionaries

Data-Driven - “*You will know a word by the company it keeps*”

Two senses of similarity:

Syntagmatic - often found in the same documents

“GDP”, “inflation”, “economy”, “currency”

e.g. topic models (LDA), Latent Semantic Analysis

Dimension Reduction

Theory-Driven - “*We’ll tell you what a word means*”
Dictionaries

Data-Driven - “*You will know a word by the company it keeps*”

Two senses of similarity:

Syntagmatic - often found in the same documents
“GDP”, “inflation”, “economy”, “currency”
e.g. topic models (LDA), Latent Semantic Analysis

Paradigmatic - often have the same neighbours
“wrote”, “remarked”, “said”, “added”
e.g. word2vec, GloVe, BERT, GPT-1/2/3

Dictionaries

Dictionaries

Every word has its own score (from raters)

Dictionaries

Every word has its own score (from raters)

	Word	Score	Word	Score
Valence	love	1.000	toxic	0.008
	happy	1.000	nightmare	0.005
Arousal	elated	0.960	mellow	0.069
	frenzy	0.965	napping	0.046
Dominance	powerful	0.991	weak	0.045
	leadership	0.983	empty	0.081

(Osgood et al., 1957; Mohammad, 2018)

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Every word in a category has the same score

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(Osgood et al., 1957; Mohammad, 2018)

Every word in a category has the same score

LIWC

(Tausczik & Pennebaker, 2010)

"a+"	"abound"	"abounds"	"achievement"
"abundance"	"abundant"	"accessible"	"acumen"
"accessible"	"acclaim"	"acclaimed"	"adequate"
"acclamation"	"accolade"	"accolades"	"achievements"
"accommodative"	"accommodative"	"accomplish"	"adaptable"
"accomplished"	"accomplishment"	"accomplishment"	"adjustable"

Dictionaries

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Advantages

Easy to implement

Some dictionaries are validated

Limitations

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No use of word order. e.g. “bad” vs. “not bad”

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Interpretation can be muddy e.g. “authenticity” dictionary

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Assumes context universality

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Advantages

Easy to implement

Some dictionaries are validated

Limitations

No use of word order. e.g. “bad” vs. “not bad”

Interpretation can be muddy e.g. “authenticity” dictionary

Assumes context universality

Blurry distinction between style vs. content

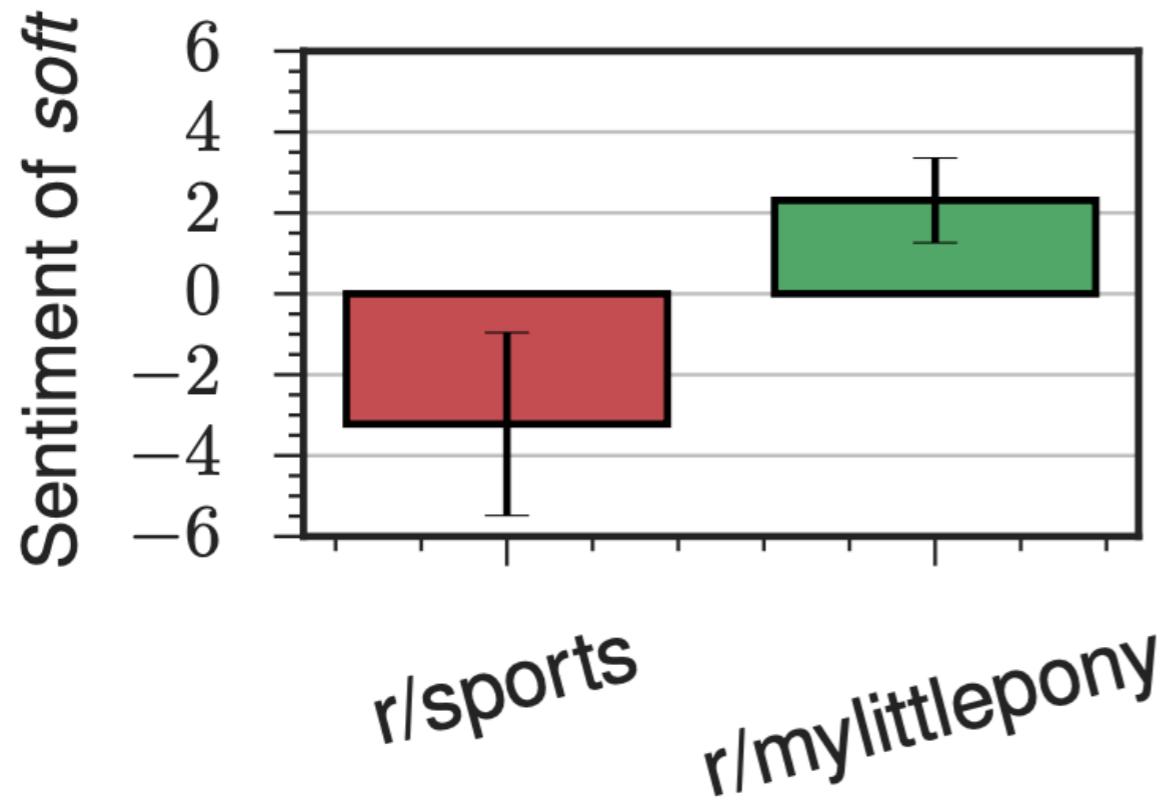
Sentiment

Context Specificity

“Inducing Domain-Specific Sentiment Lexicons from Unlabeled Corpora”
(Hamilton et al., 2016)

Sentiment

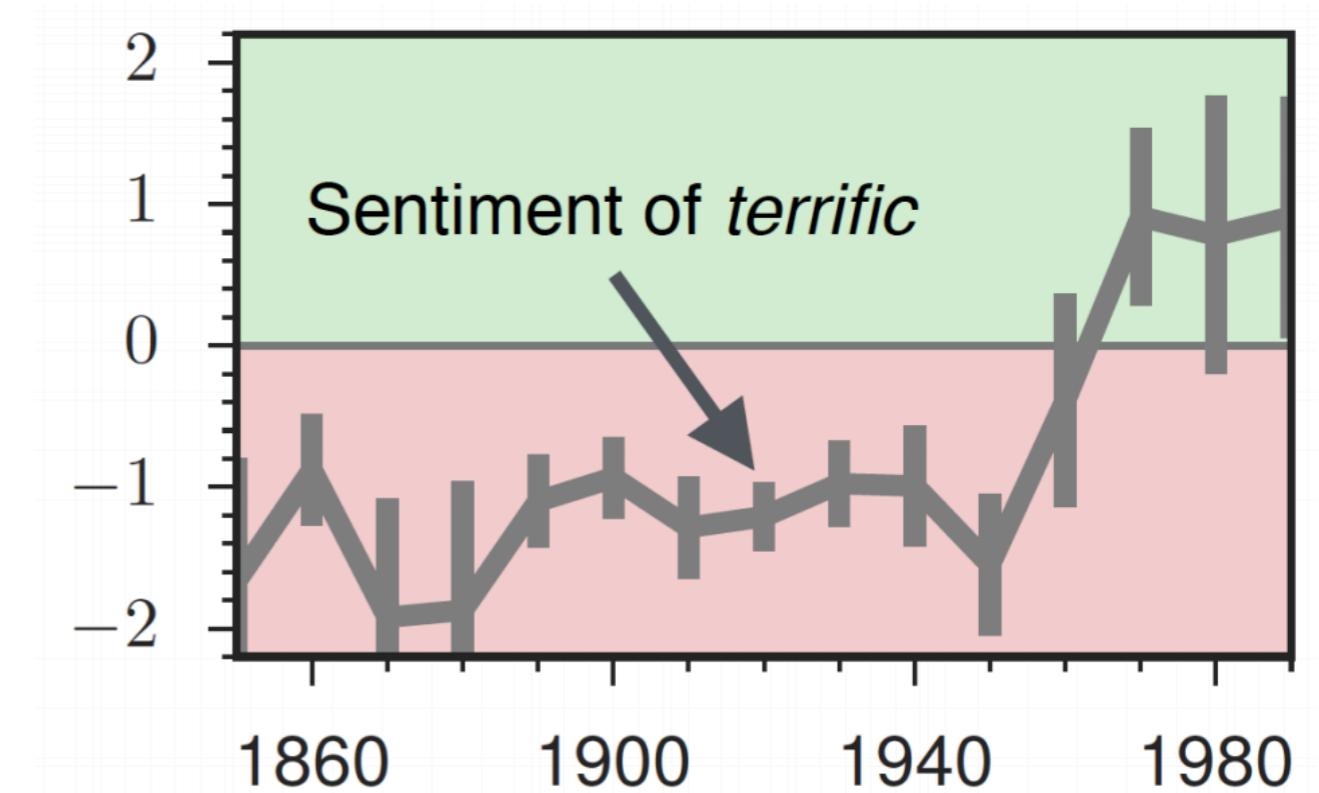
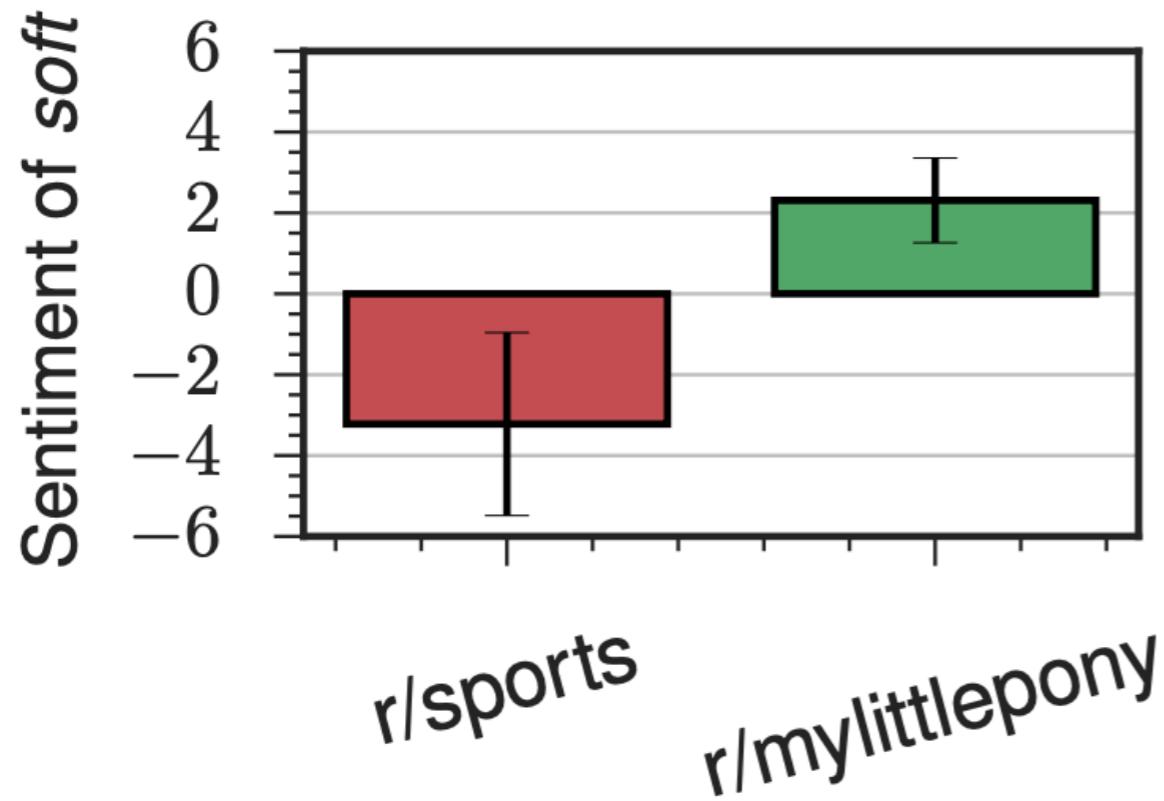
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Context Specificity



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Sentiment

Context Specificity

Random Forest (supervised ngram model)

Loughran Macdonald (finance-specific)

Harvard PsychoSocial dictionary (domain-general)

“Disclosure Sentiment: Machine Learning vs. Dictionary Methods”
(Frankel, Jennings & Lee, 2022)

Sentiment

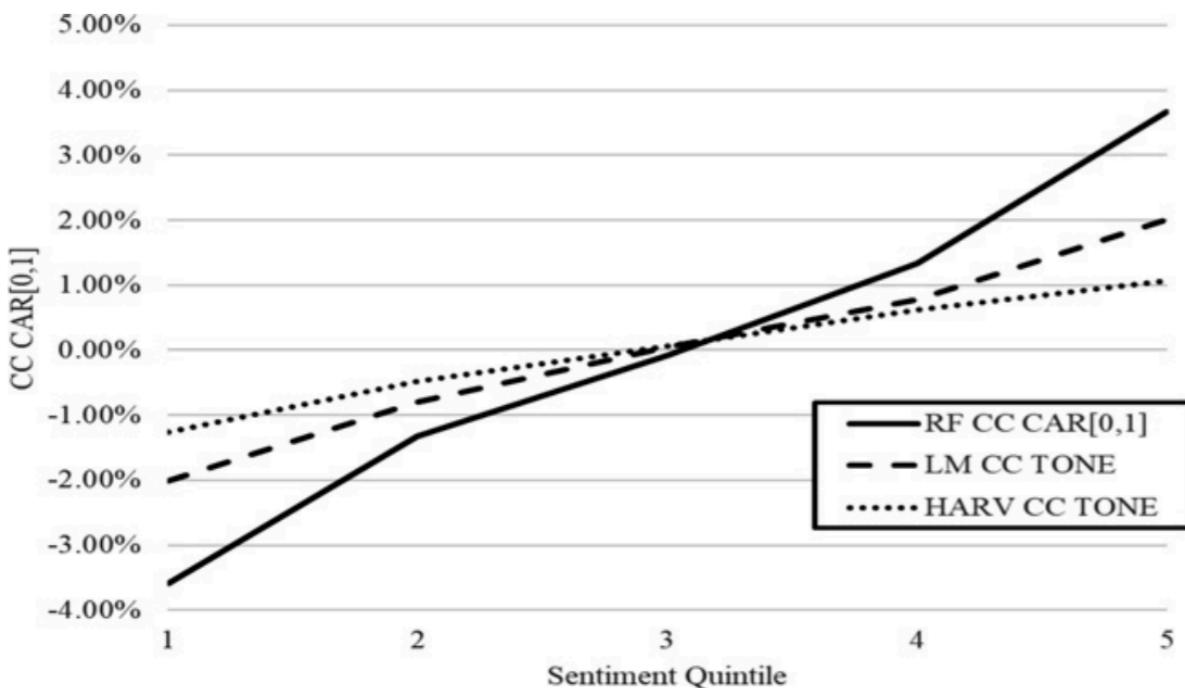
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Figure 2. Conference Call Returns and Sentiment



“Disclosure Sentiment: Machine Learning vs. Dictionary Methods”
(Frankel, Jennings & Lee, 2022)

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Figure 2. Conference Call Returns and Sentiment

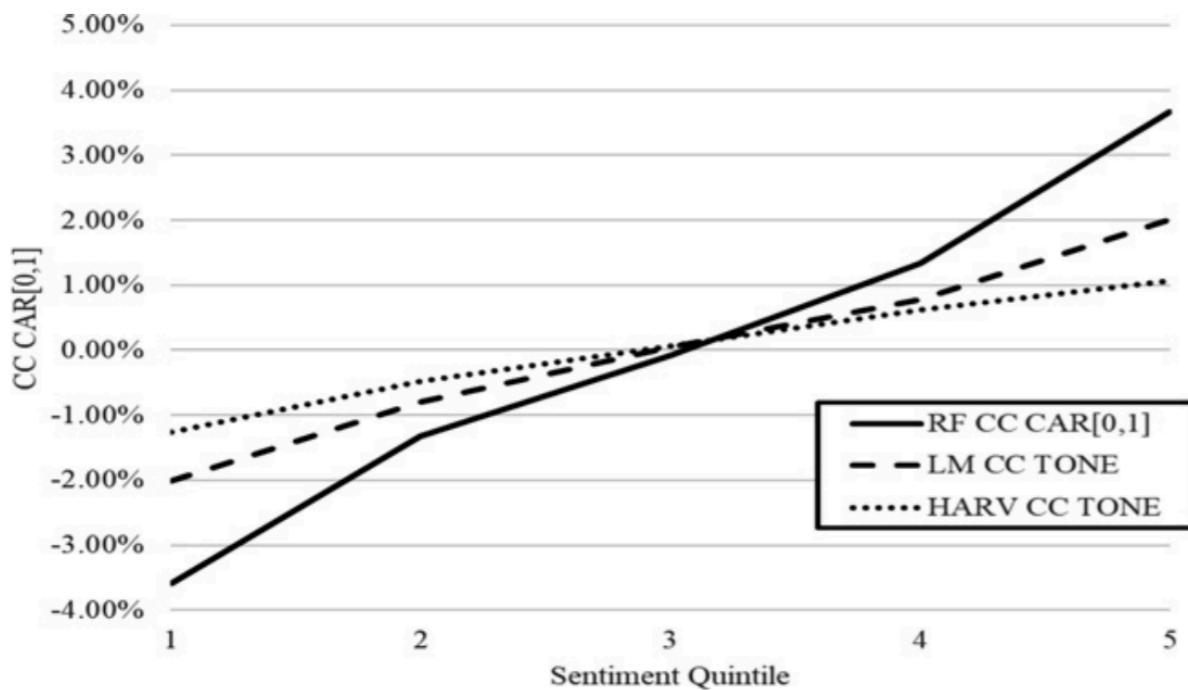
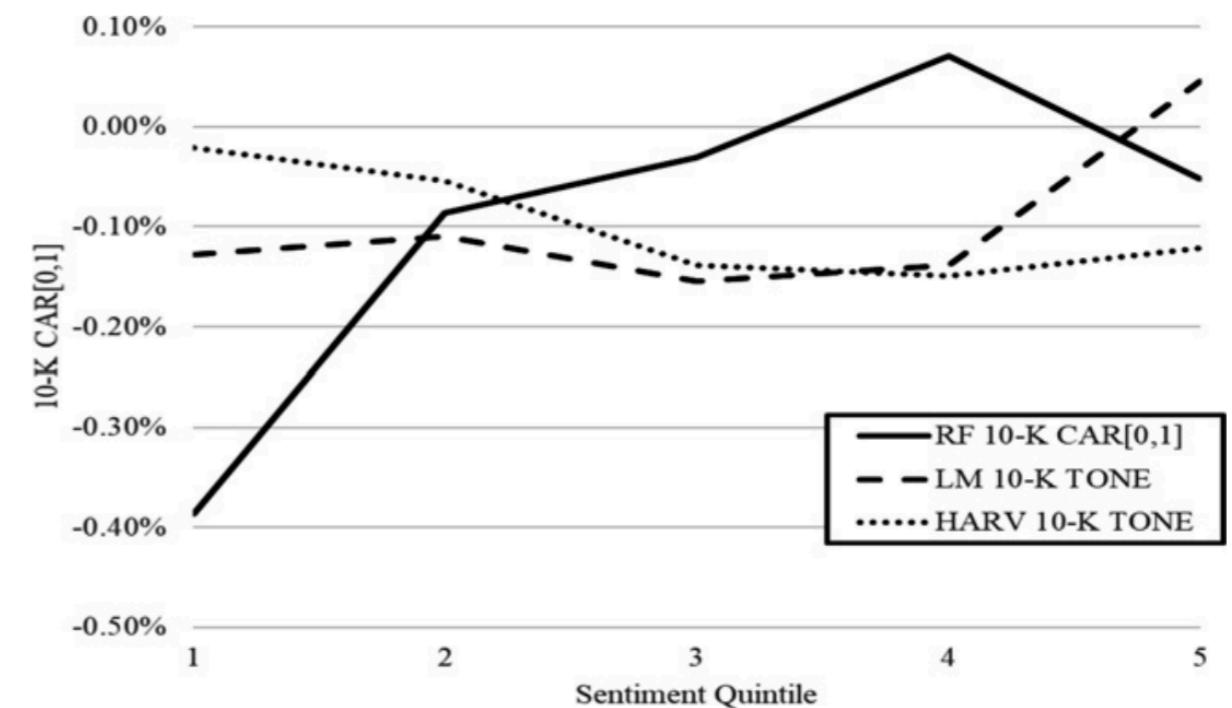


Figure 1. 10-K Filing Returns and Sentiment



“Disclosure Sentiment: Machine Learning vs. Dictionary Methods”
(Frankel, Jennings & Lee, 2022)

Sentiment

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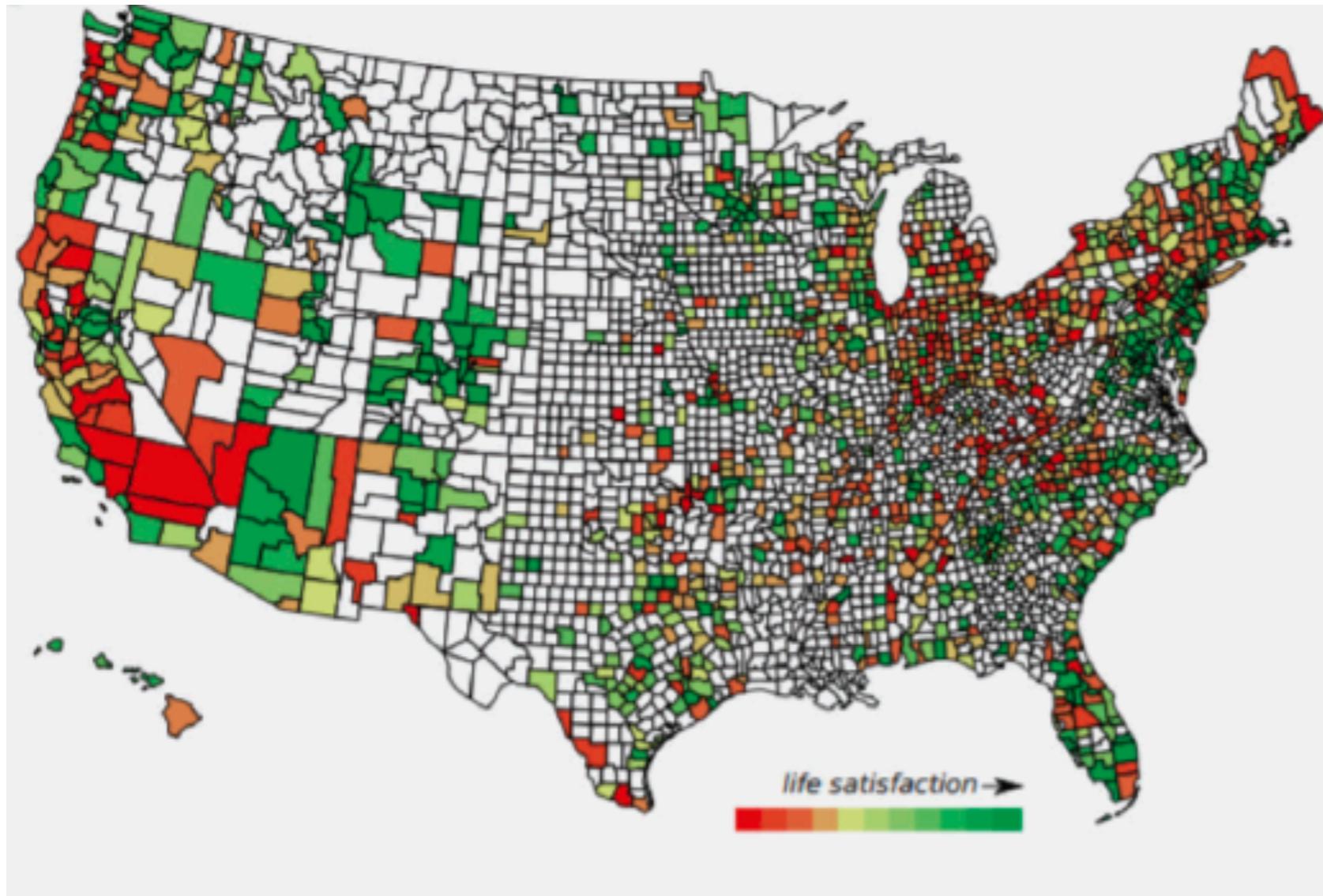
Harvard PsychoSocial dictionary (domain-general)

Positive	Negative
Conclusive	Evaded
Resolve	Condone
Versatile	Confess
Vibrant	Deadlocks
Invent	Costly

“Disclosure Sentiment: Machine Learning vs. Dictionary Methods”
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Sentiment

Topic vs Style

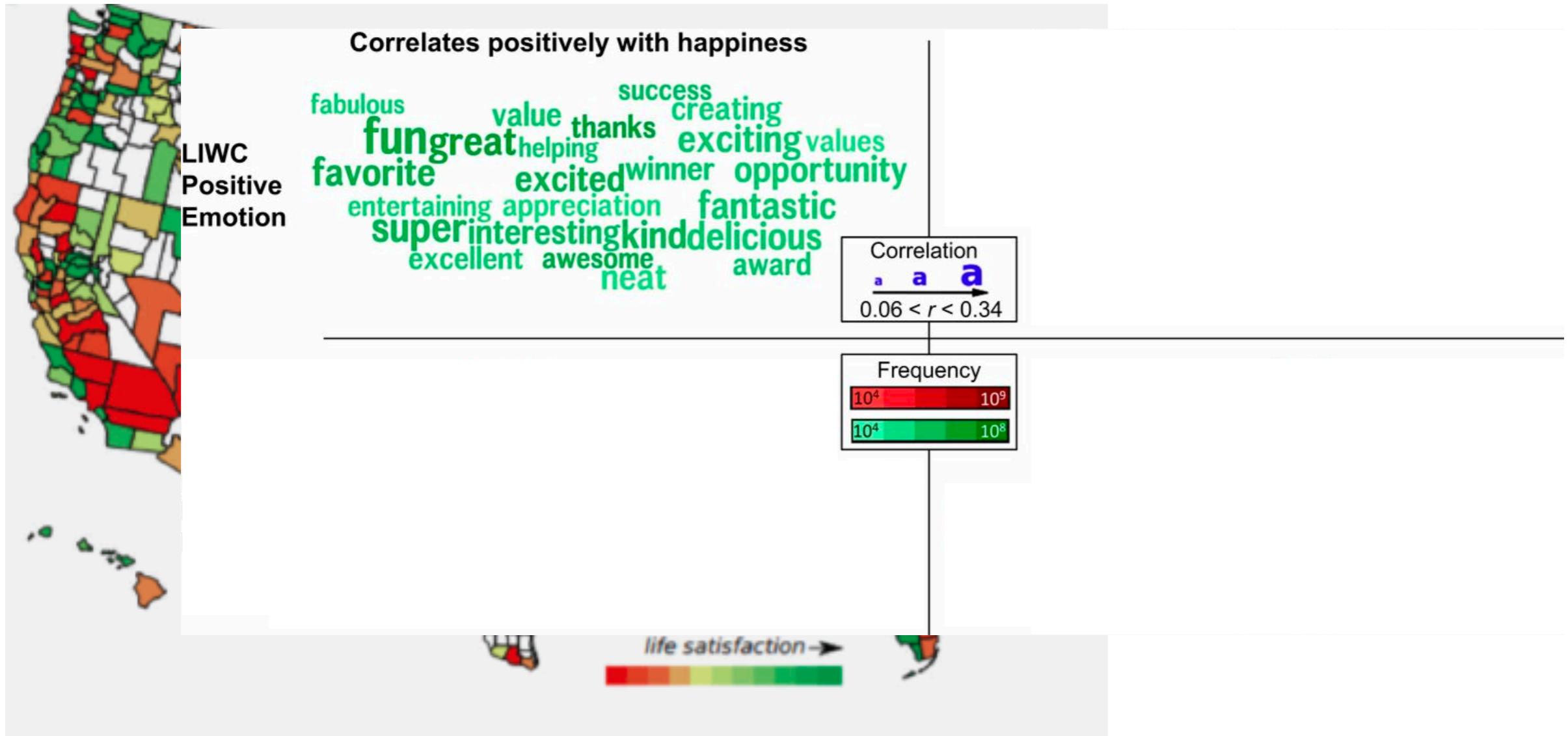


“Estimating geographic subjective well-being from Twitter”

(Jaidka et al., 2020)

Sentiment

Topic vs Style

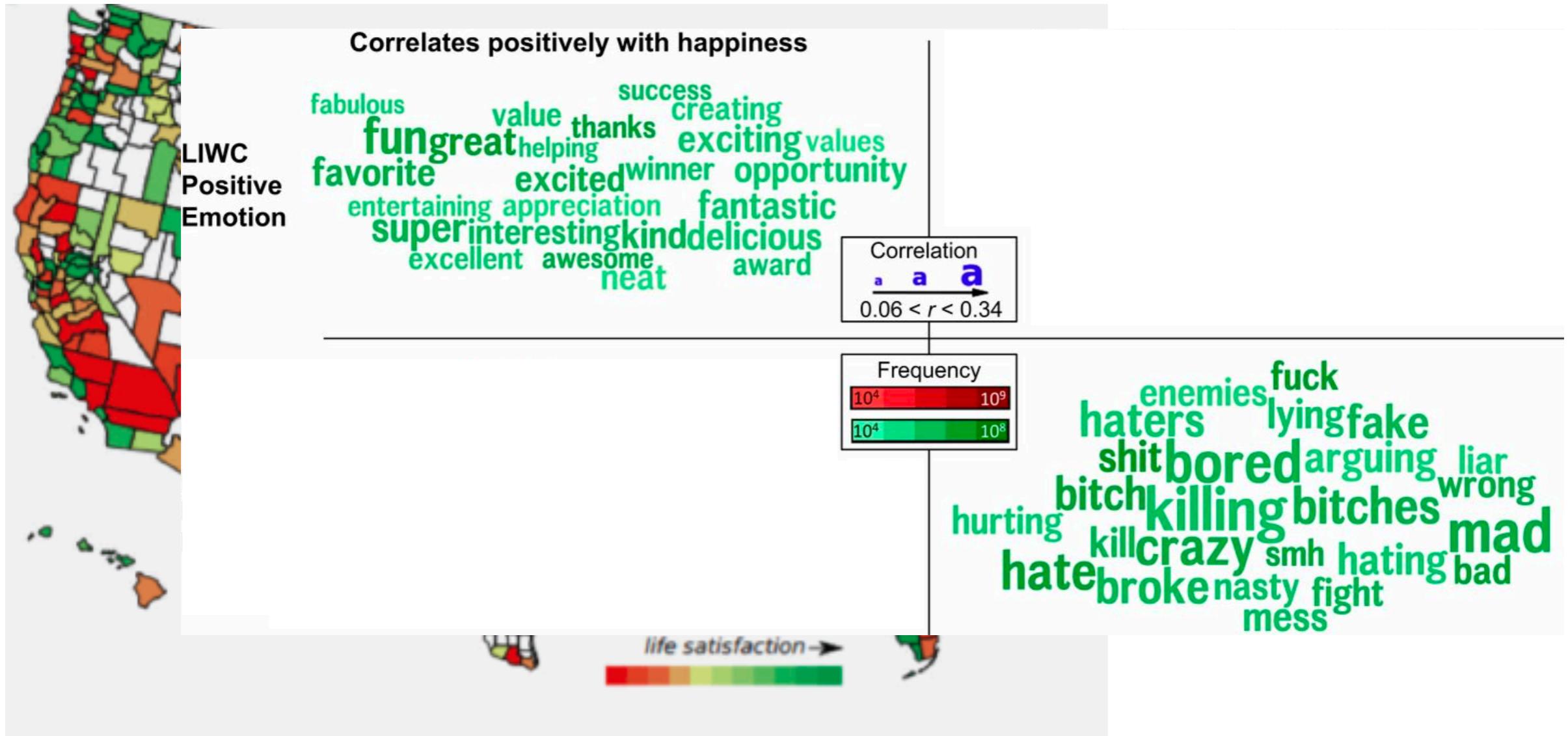


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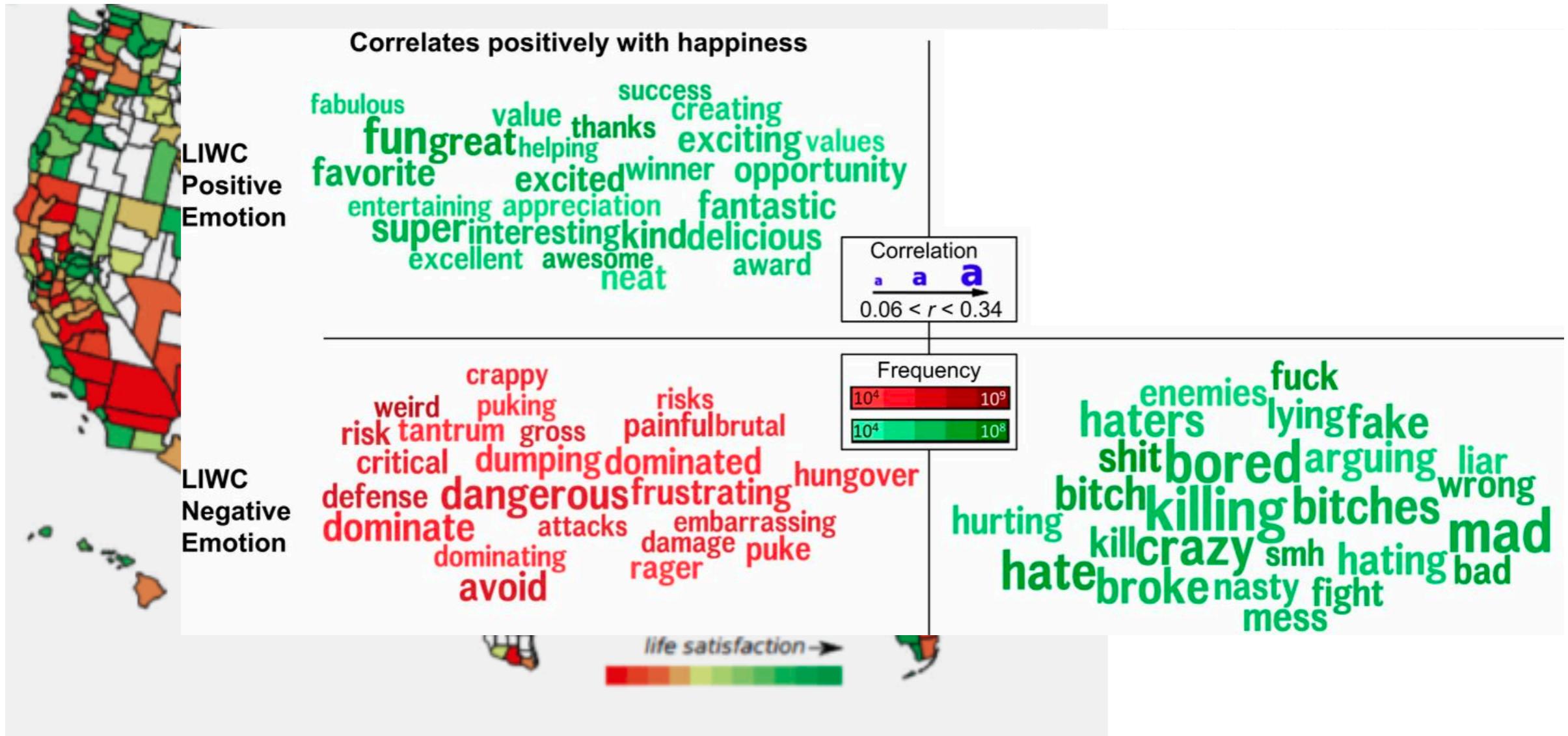


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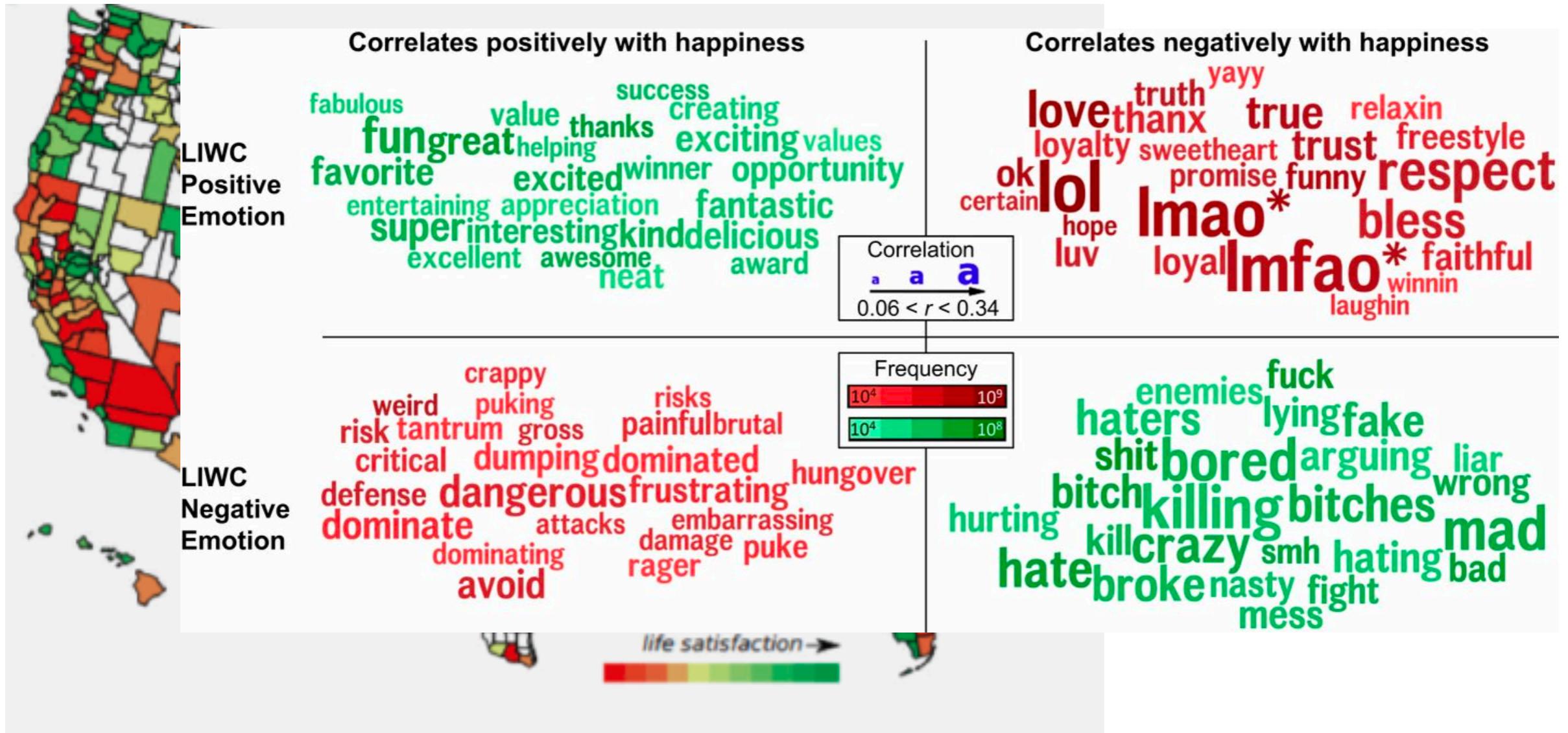


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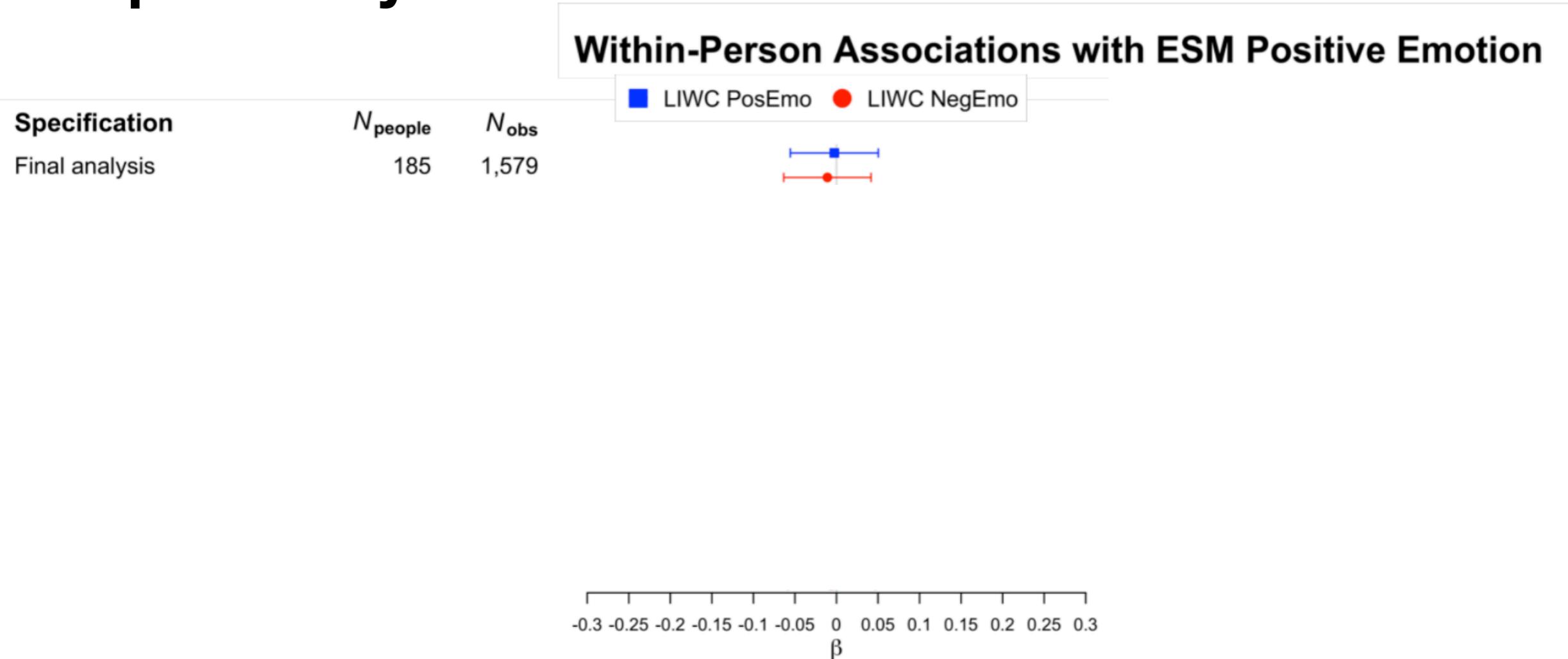


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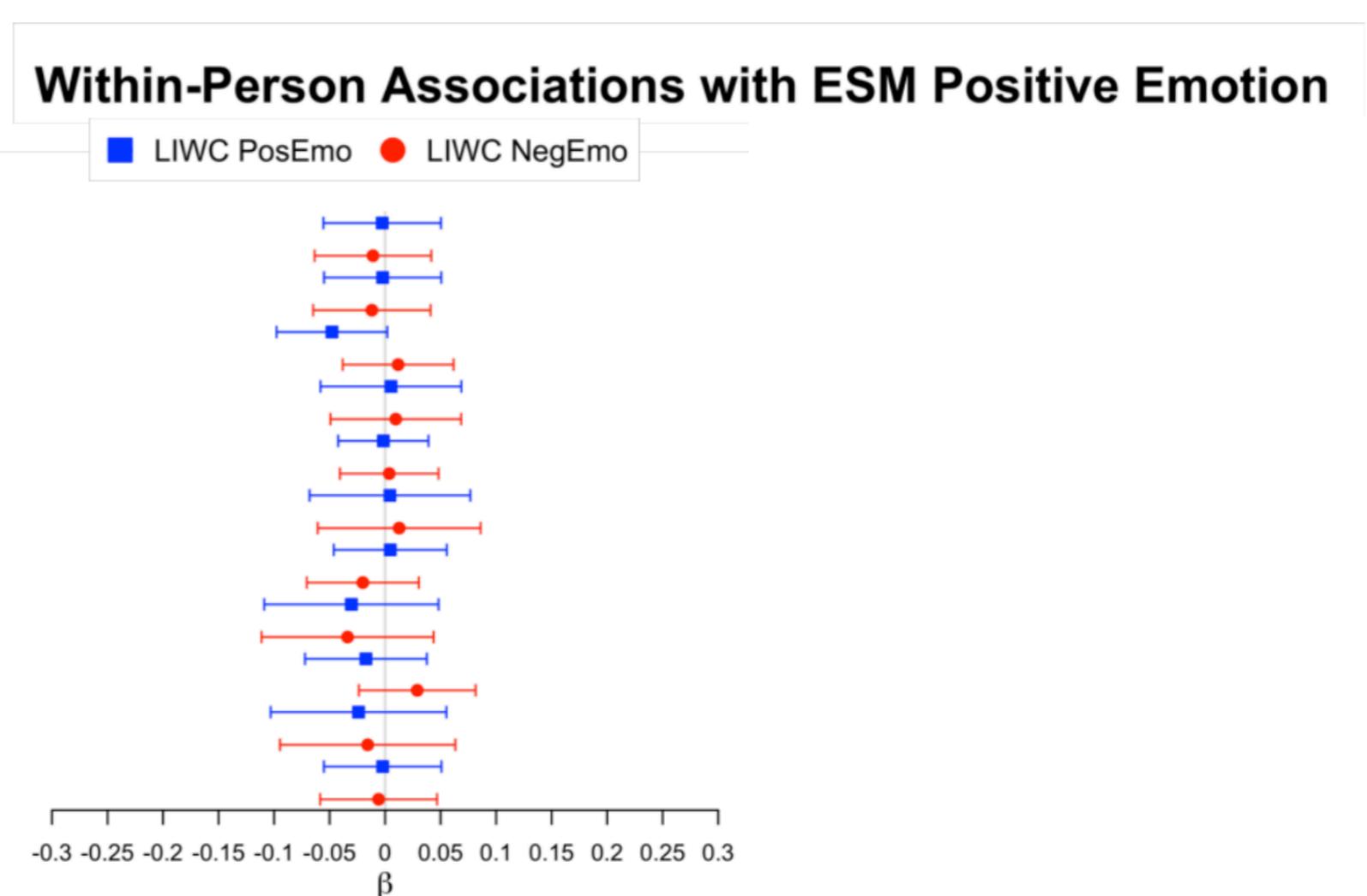


“Emotion Fluctuations and Everyday Speech”
(Sun et al., 2019)

Sentiment

Topic vs Style

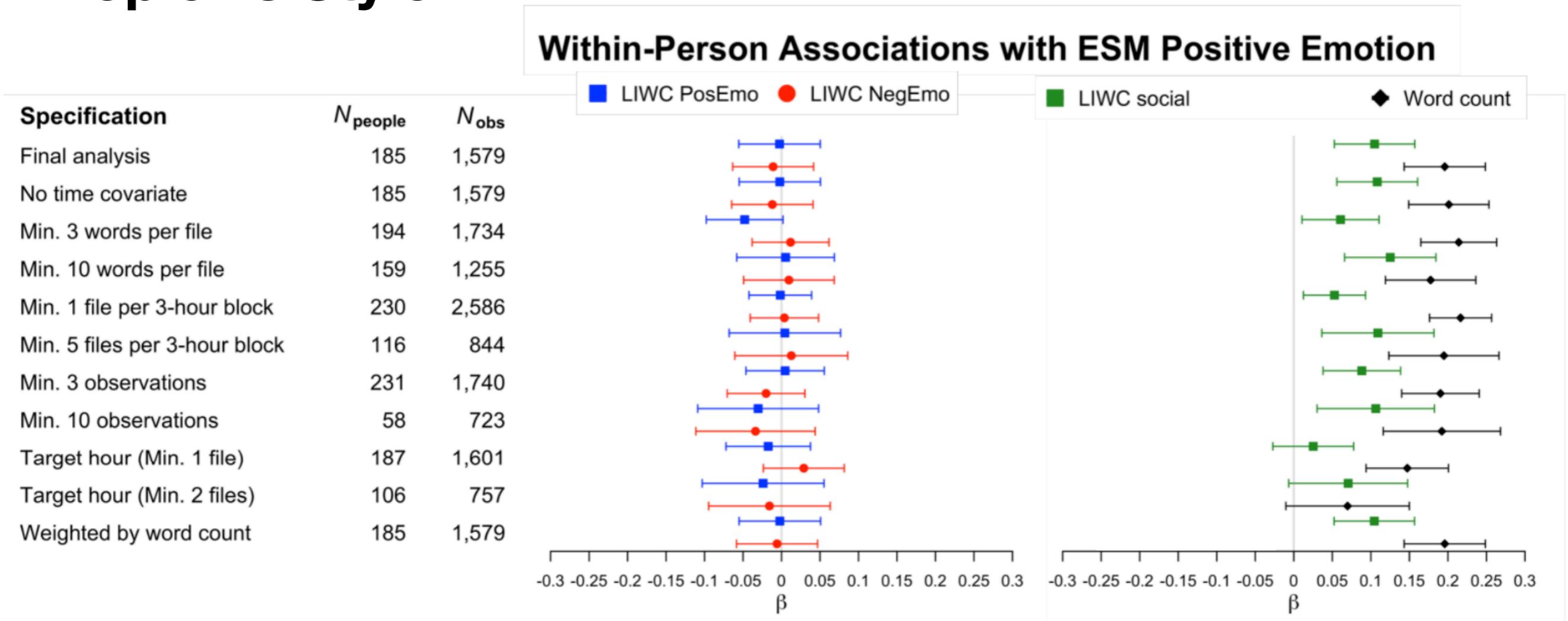
Specification	N_{people}	N_{obs}
Final analysis	185	1,579
No time covariate	185	1,579
Min. 3 words per file	194	1,734
Min. 10 words per file	159	1,255
Min. 1 file per 3-hour block	230	2,586
Min. 5 files per 3-hour block	116	844
Min. 3 observations	231	1,740
Min. 10 observations	58	723
Target hour (Min. 1 file)	187	1,601
Target hour (Min. 2 files)	106	757
Weighted by word count	185	1,579



"Emotion Fluctuations and Everyday Speech"
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Sentiment

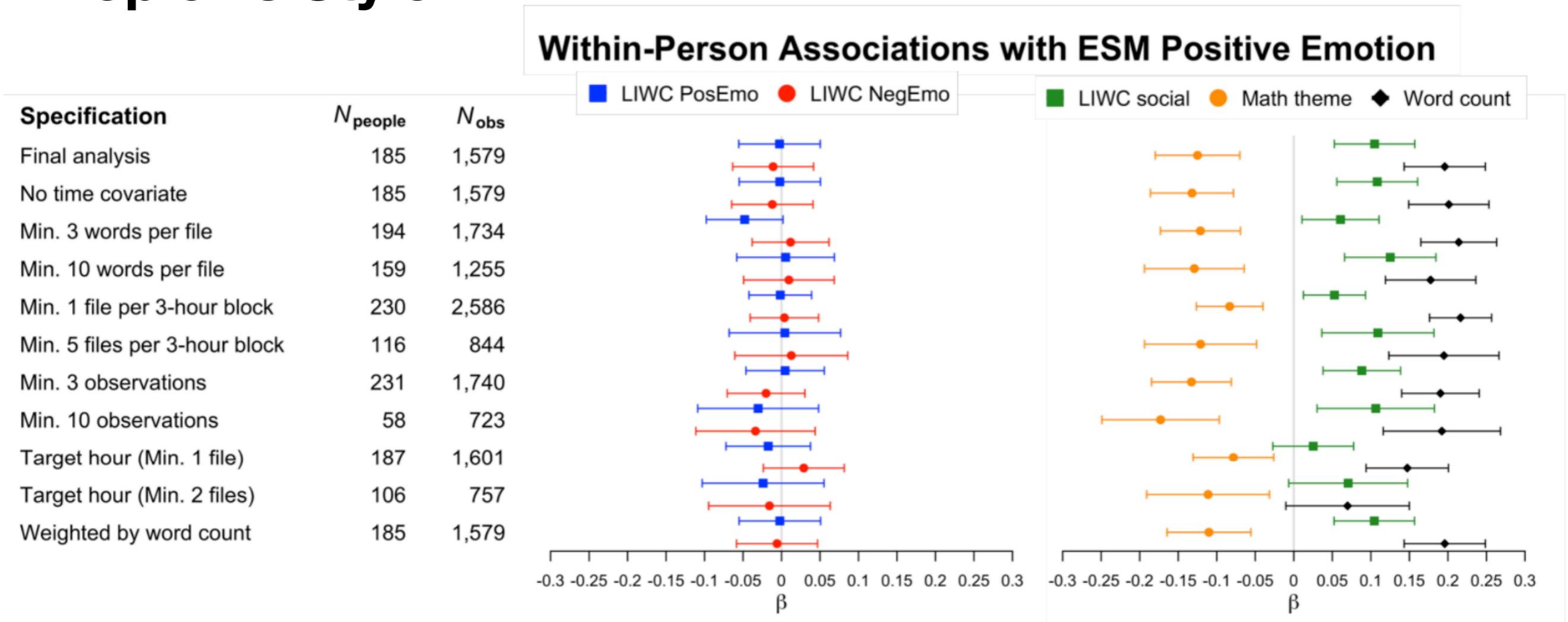
Topic vs Style



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Sentiment

Topic vs Style



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Sentiment

Best case scenario: descriptions of things

Sentiment

Best case scenario: descriptions of things



Travis M.

**Sherman Heights, San
Diego, CA**

0 friends

1 review



12/31/2018

Got seated immediately which is rare here. But after we sat down it took 20 minutes to be waited on. Another 20 for our drink order. And nearly an hour after that we were still waiting on our appetizer. We cancelled our whole order and are now at a jack in the box just to get some decent service

Sentiment

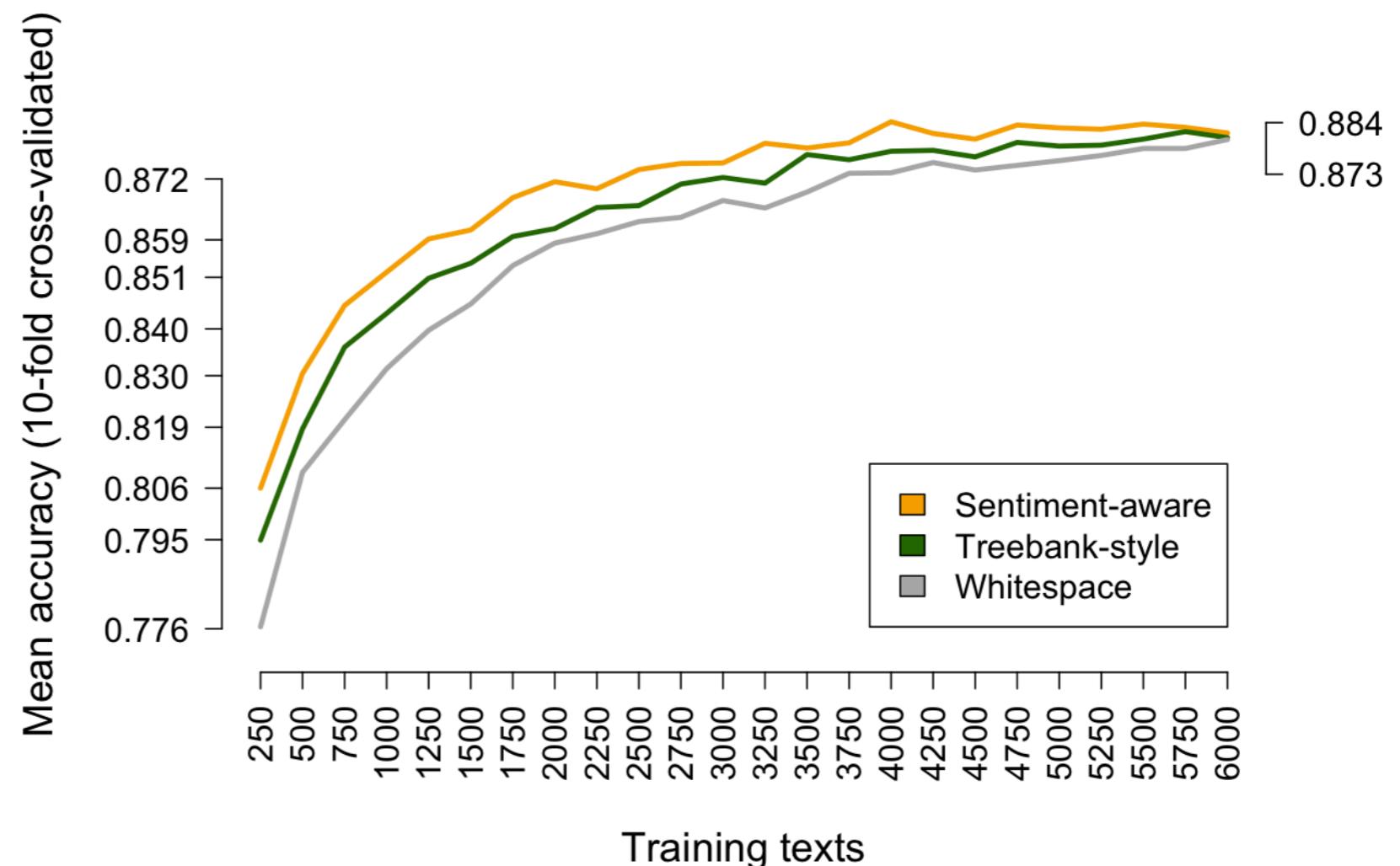
Other improvements

“Sentiment Analysis Symposium” Potts, 2011

Sentiment

Other improvements

Separate tokens for all caps [WOW], punctuation [!], emoticons [:])

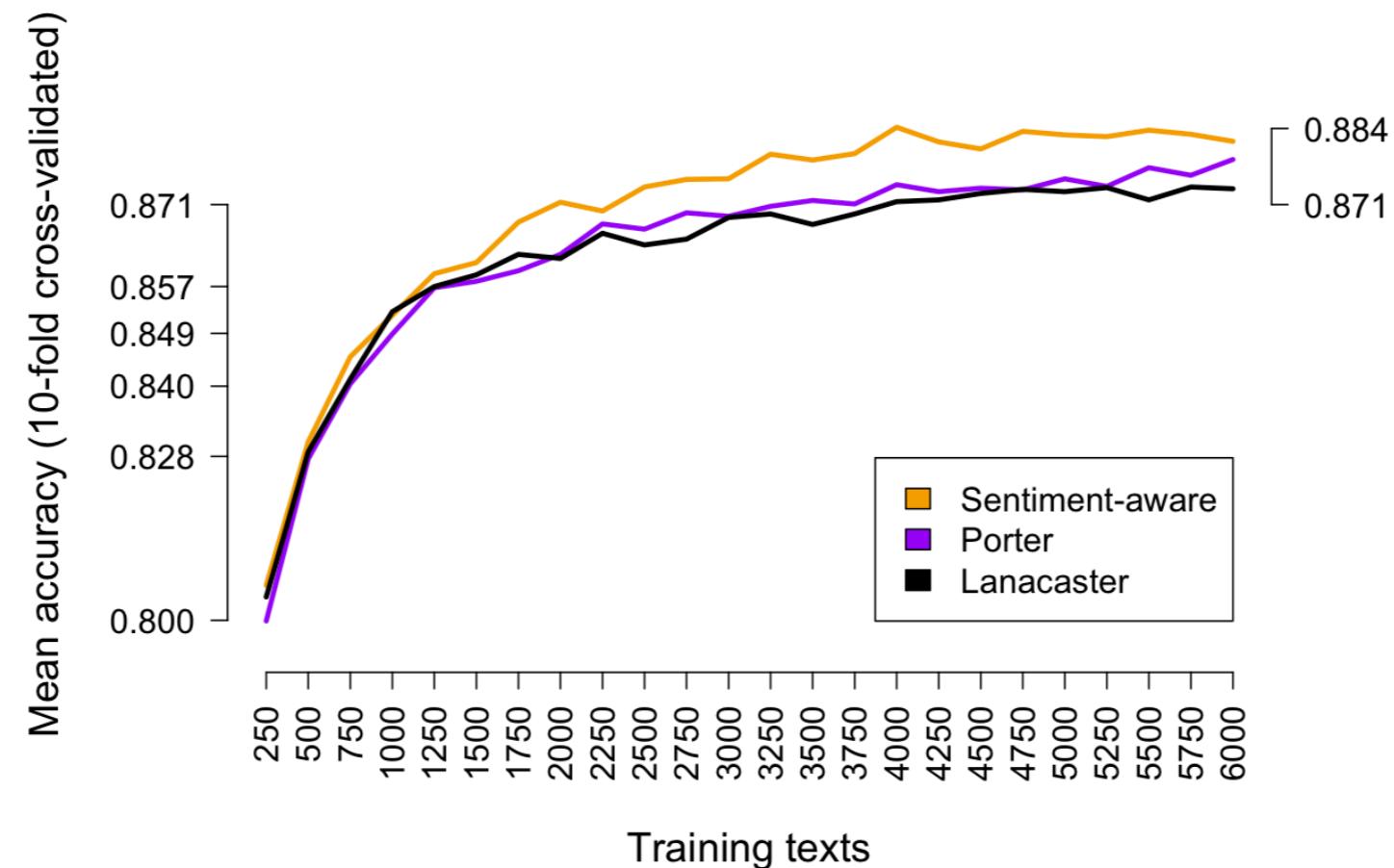


Sentiment

Other improvements

Separate tokens for all caps [WOW], punctuation [!], emoticons [:])

Stemming only tends to help at low sample sizes



Sentiment

Other improvements

Negation scoping

“It was that bad.” becomes: [“it”, “was”, “that”, “bad”, “.”]

Sentiment

Other improvements

Negation scoping

“It was that bad.” becomes: [“it”, “was”, “that”, “bad”, “.”]
“It was not that bad, honestly.”

Sentiment

Other improvements

Negation scoping

“It was that bad.” becomes: [“it”, “was”, “that”, “bad”, “.”]

“It was not that bad, honestly.” becomes:

[“it”, “was”, “not”, “that_NEG”, “bad_NEG”, “”, “honestly”, “.”]

Sentiment

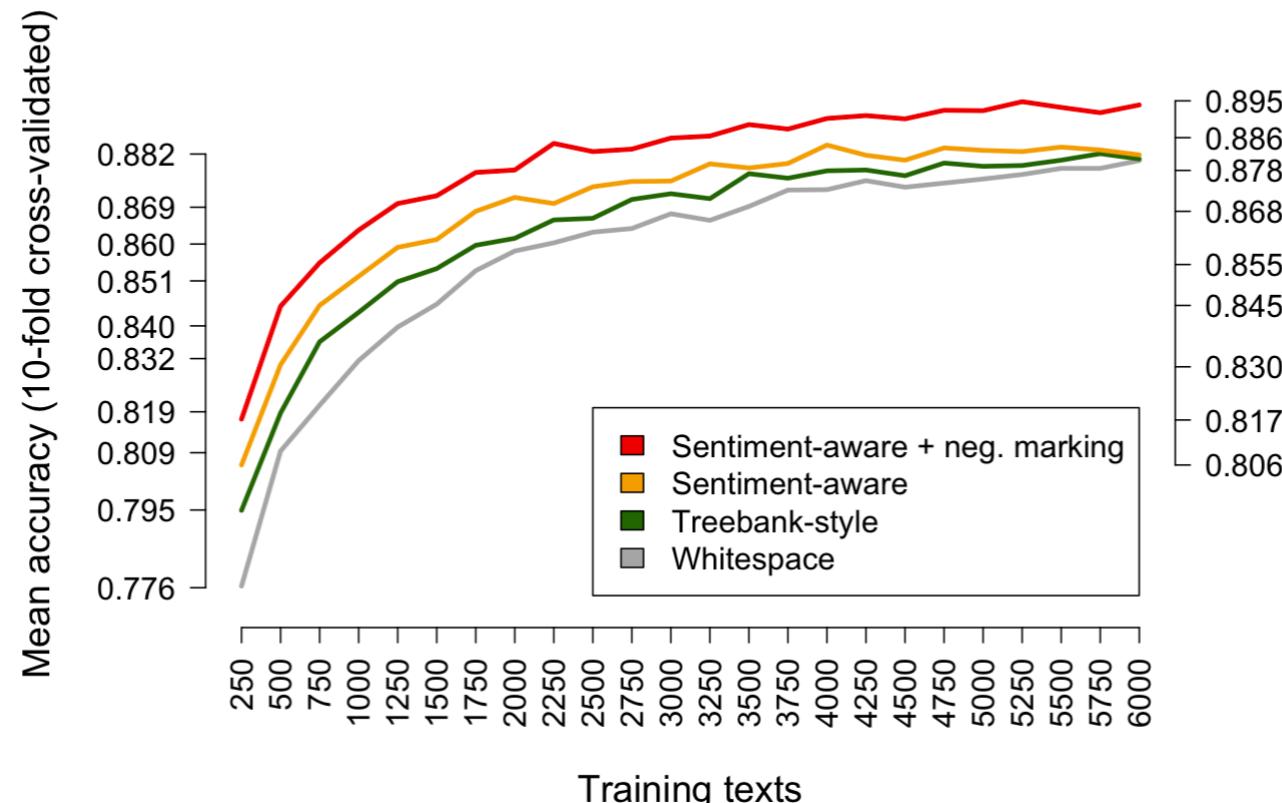
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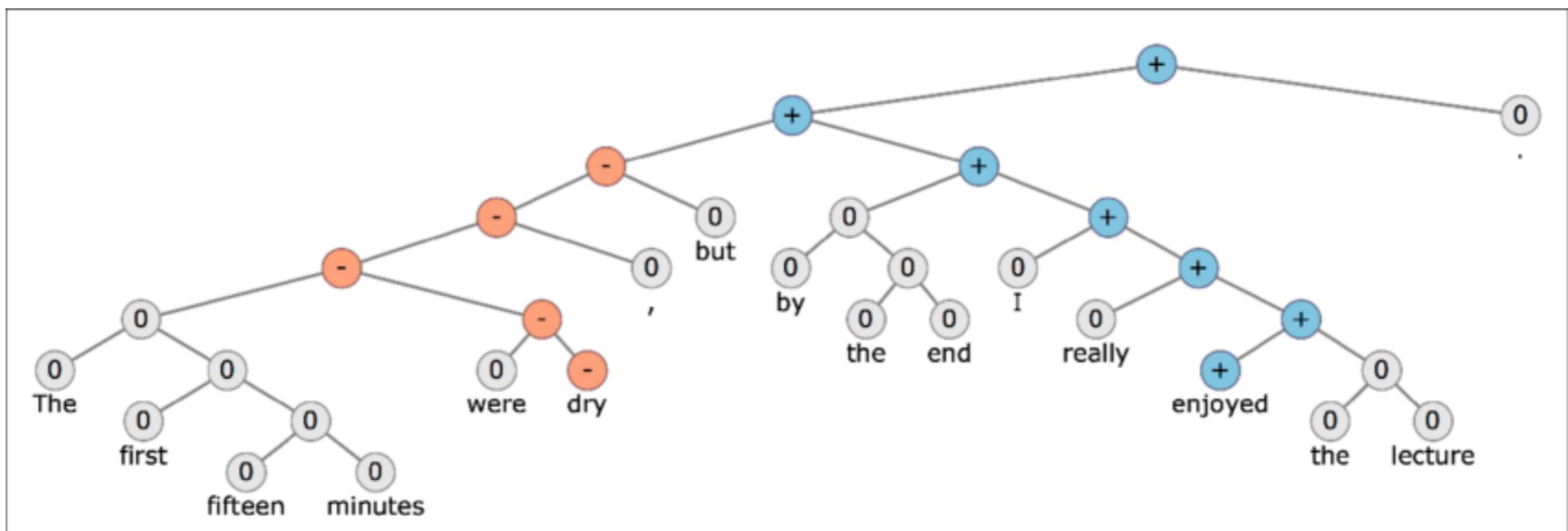
[“it”, “was”, “not”, “that_NEG”, “bad_NEG”, “”, “honestly”, “.”]



“Sentiment Analysis Symposium” Potts, 2011

Sentiment

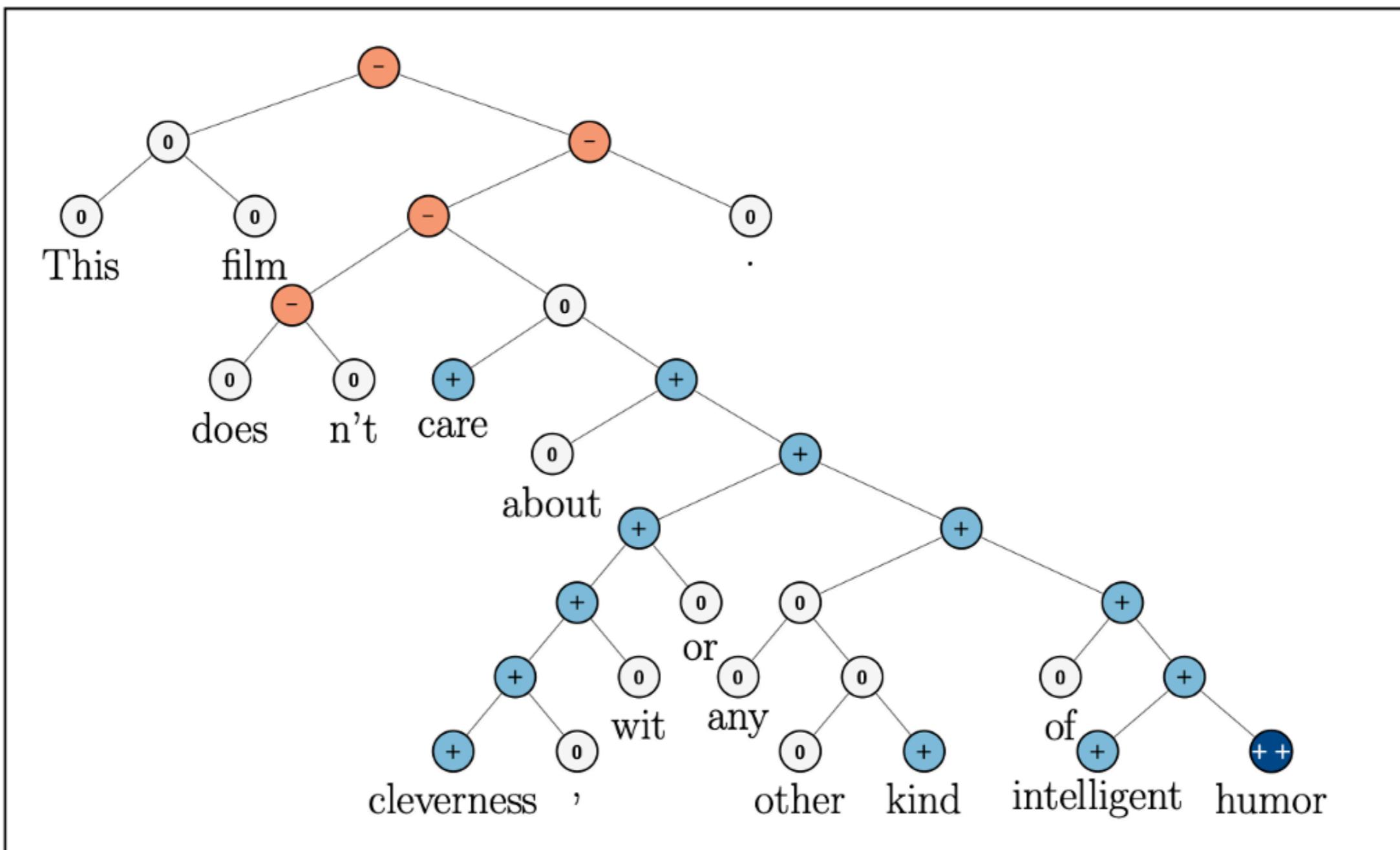
State of the art - Stanford Sentiment treebank



Socher et al., 2013

Sentiment

State of the art - Stanford Sentiment treebank



Socher et al., 2013

Sentiment

Good enough for most: VADER, sentimentr...

Word Sentiment

This

is

not

good

news

,

it

is

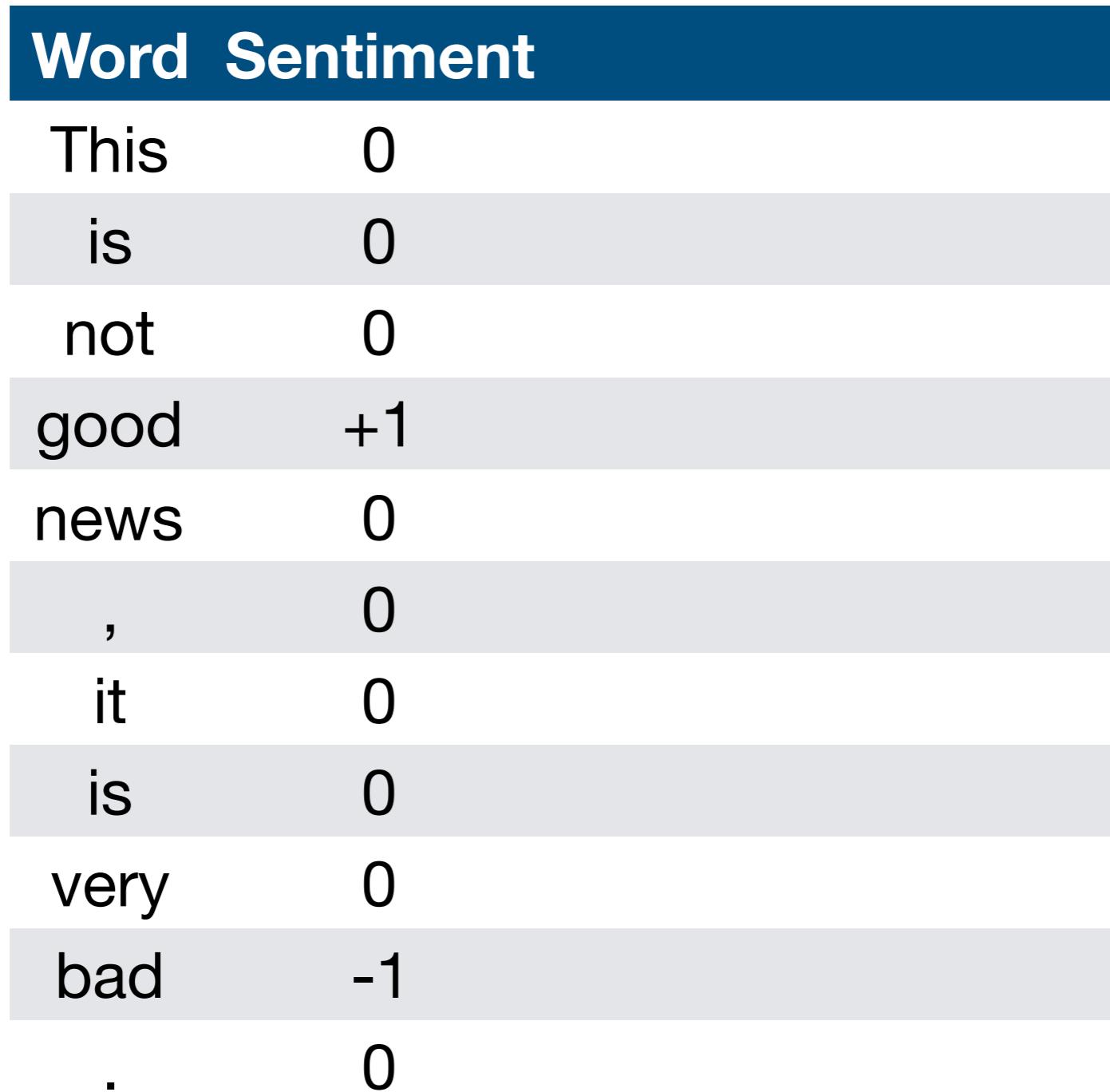
very

bad

.

Sentiment

Good enough for most: VADER, sentimentr...



Sentiment

Good enough for most: VADER, sentimentr...

Word	Sentiment	Modifier
This	0	
is	0	
not	0	
good	+1	
news	0	
,	0	
it	0	
is	0	
very	0	
bad	-1	
.	0	

Sentiment

Good enough for most: VADER, sentimentr...

Word	Sentiment	Modifier
This	0	
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is	0	
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Sentiment

Good enough for most: VADER, sentimentr...

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news	0	*(-1)
,	0	
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is	0	
very	0	Intensifier
bad	-1	*(2)
.	0	

Sentiment

Good enough for most: VADER, sentimentr...

Word	Sentiment	Modifier	Score
This	0		0
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good	+1	*(-1)	-1
news	0	*(-1)	0
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it	0		0
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,	0		0
it	0		0
is	0		0
very	0	Intensifier	0
bad	-1	*(2)	-2
.	0		0
			-4

Concreteness



(Yeomans, OBDHP, 2021)

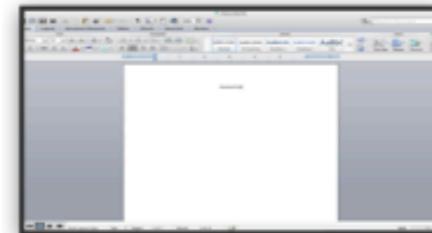
Concreteness



High Construal

*Abstract Focus
Future Decisions
(e.g., outlining)*

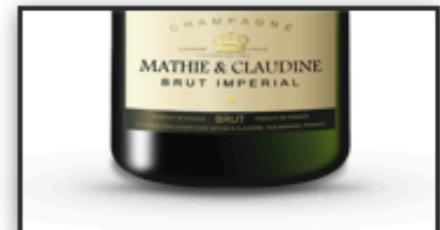
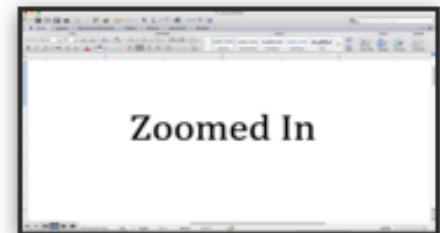
Zoom Out



Low Construal

*Narrow Focus
Immediate Decisions
(e.g., proofreading)*

Zoom In



The Data

Giving Advice

Domain: People writing advice for others

6 contexts, 3,289 observations

Concreteness: human-annotated specificity

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Concreteness: human-annotated specificity

Making Plans

Domain: Pre-course surveys at HarvardX

7 classes, 5,172 observations

Concreteness: Manipulated distance (short/long)

Concreteness: Annotated specificity ($\alpha = .68$)

The Data

Giving Advice

Domain: People writing advice for others

6 contexts, 3,289 observations

Concreteness: human-annotated specificity

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Domain: Pre-course surveys at HarvardX

7 classes, 5,172 observations

Concreteness: Manipulated distance (short/long)

Concreteness: Annotated specificity ($\alpha = .68$)

Descriptions

Domain: Lab studies where participants describe things

3 studies, 1,319 observations

Concreteness: Manipulated distance (close/far, why/how)

The Measures

Word-Level

- Empirical word ratings by humans
- Many words, individual scores

The Measures

Word-Level

	<u>Original</u> <u>MRC</u>	<u>mTurk</u> <u>Ratings</u>	<u>Bootstrapped</u> <u>MRC</u>
This	240	2.14	212.36
example	--	3.03	335.35
sentence	--	3.57	397.16
has	267	2.18	272.31
both	322	2.97	256.11
concrete	562	4.59	506.81
and	220	1.52	277.14
abstract	--	1.45	373.73
words.	--	3.56	389.48

Size	~1,000	~40,000	~80,000
Source	Colthart, 1981	Brysbaert et al, 2014	Paetzold & Specia, 2017

The Measures

Word-Level

- Empirical word ratings by humans
- Many words, individual scores

Categorical

- Theoretically-driven word categories
- Few categories, simple weights

The Measures

Word-Level

- Empirical word ratings by humans
- Many words, individual scores

Categorical

"Linguistic Category Model"

<u>Part of Speech</u>	<u>Score</u>
Descriptive Action Verbs	5
Interpretive Action Verbs	4
State Verbs	3
Adjectives	2
Nouns	1

"Immediacy"

<u>LIWC Category</u>	<u>Valence</u>
1st Person Singular	1
Present-Tense Verbs	1
Discrepancies	1
Words >6 Letters	-1
Articles	-1

A Concrete Mega-Analysis

12 measures of concreteness

17 datasets across four domains

9,780 documents

Zero = < .03	Medium = .2 - .4
Very Low = .03 - .1	High = .4 - .6
Low = .1 - .2	Very High = >.6

Name of Measure	Measurement Validity			
	Advice	Plan Distance	Plan Specificity	Describing
mTurk Ratings				
Original MRC				
Bootstrap MRC				
Immediacy				
Larrimore- LIWC				
Pan-LIWC				
Part-of- Speech LCM				
Syntax LCM				
DICTION				

Word-Level

Categorical

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Name of Measure	Measurement Validity			
	Advice	Plan Distance	Plan Specificity	Describing
mTurk Ratings	Low	Low	Low	Low
Original MRC	Low	Low	Very Low	Medium
Bootstrap MRC	Low	Low	Low	Low
Immediacy	Zero	Very Low	Zero	Medium
Larrimore- LIWC	Very Low	Very Low	Very Low	Zero
Pan-LIWC	Zero	Very Low	Very Low	Zero
Part-of- Speech LCM	Zero	Very Low	Zero	Medium
Syntax LCM	Zero	Zero	Very Low	Low
DICTION	Very Low	Zero	Zero	Very Low

Word-Level

Categorical

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Word-Level

\$95 for LIWC

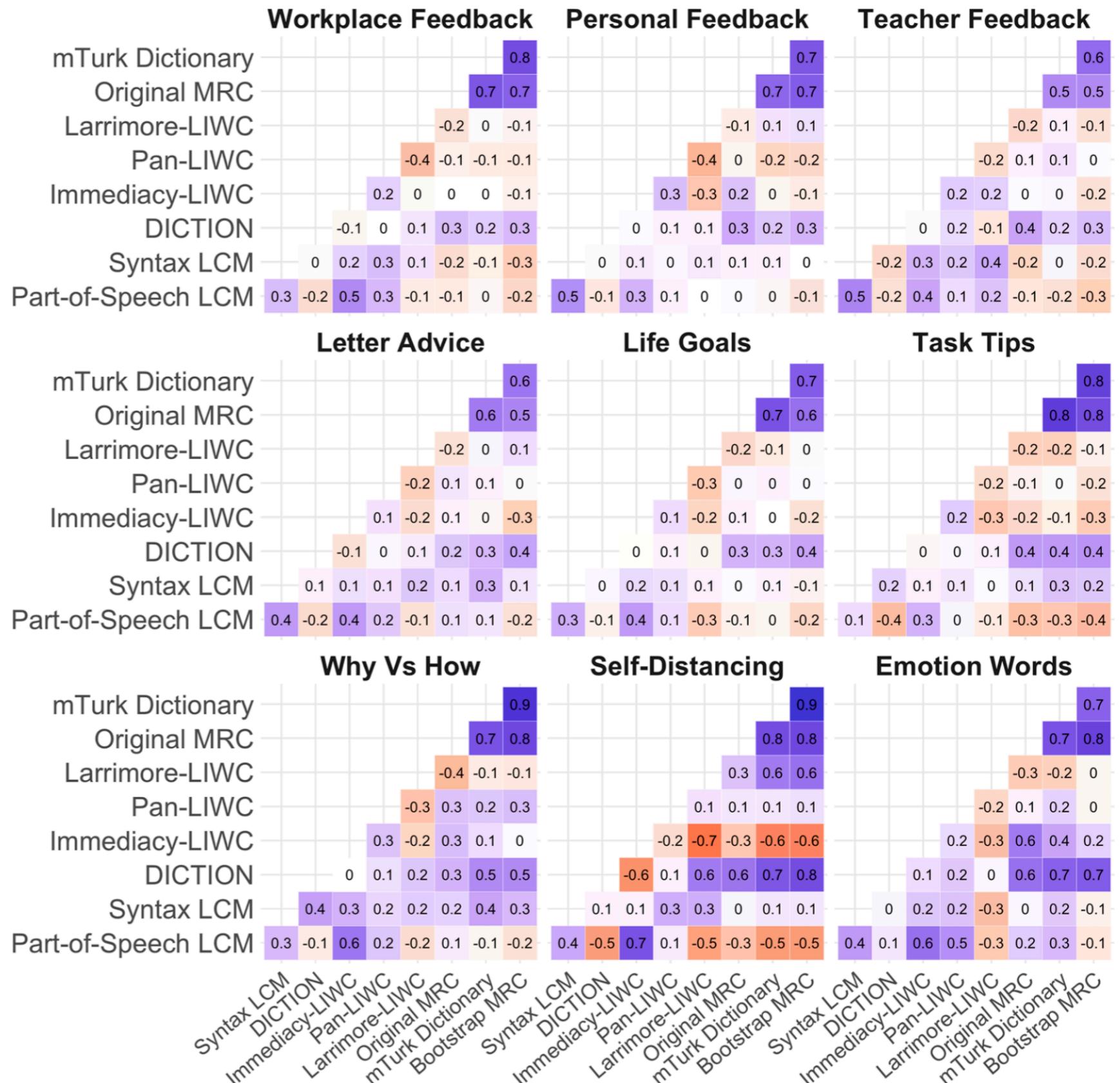
Categorical

\$219 for DICTION

Name of Measure	Measurement Validity			
	Advice	Plan Distance	Plan Specificity	Describing
mTurk Ratings	Low	Low	Low	Low
Original MRC	Low	Low	Very Low	Medium
Bootstrap MRC	Low	Low	Low	Low
Immediacy	Zero	Very Low	Zero	Medium
Larrimore- LIWC	Very Low	Very Low	Very Low	Zero
Pan-LIWC	Zero	Very Low	Very Low	Zero
Part-of-Speech LCM	Zero	Very Low	Zero	Medium
Syntax LCM	Zero	Zero	Very Low	Low
DICTION	Very Low	Zero	Zero	Very Low

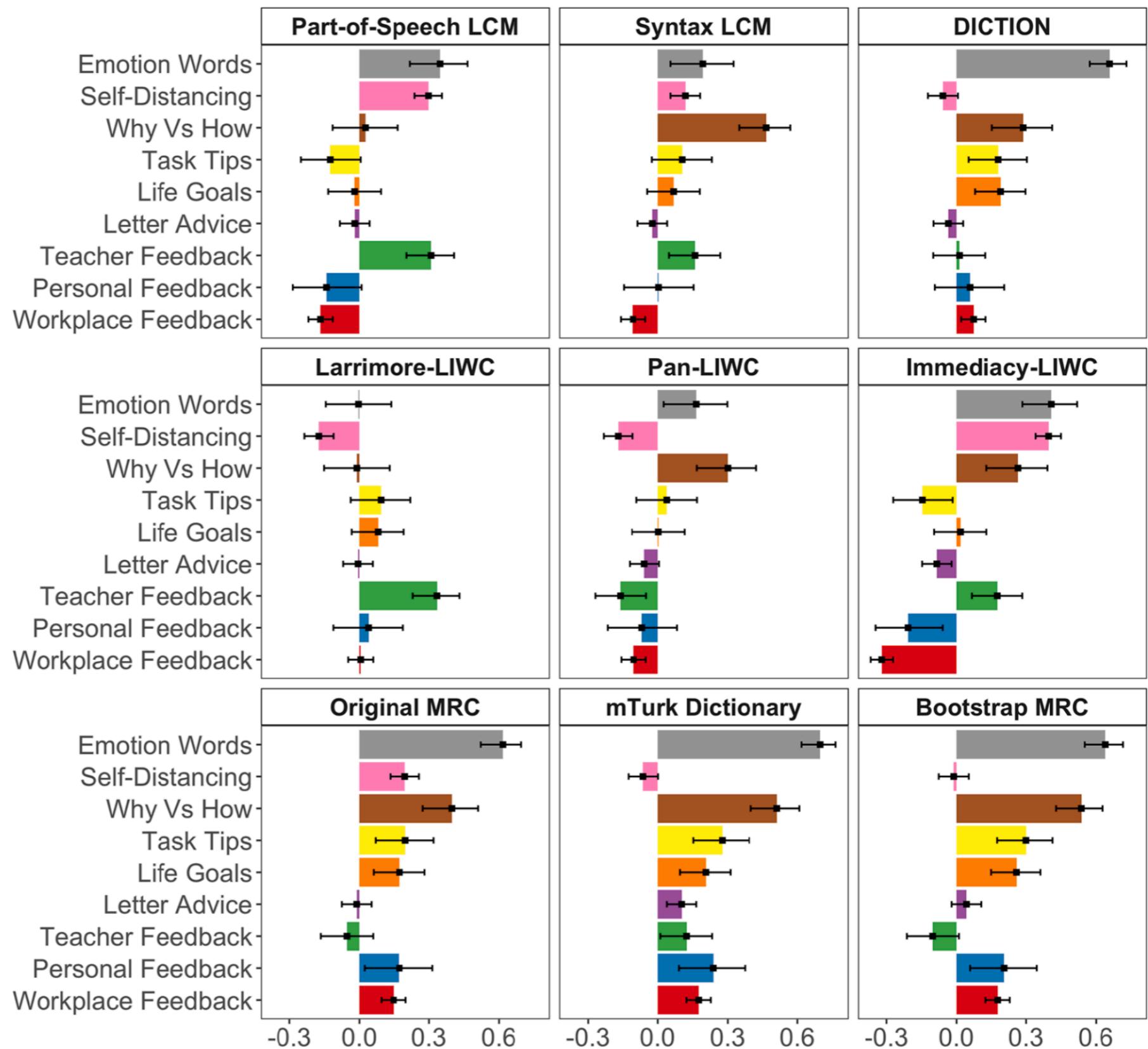
A Concrete Mega-Analysis

Concreteness
dictionaries do
not correlate
with each other



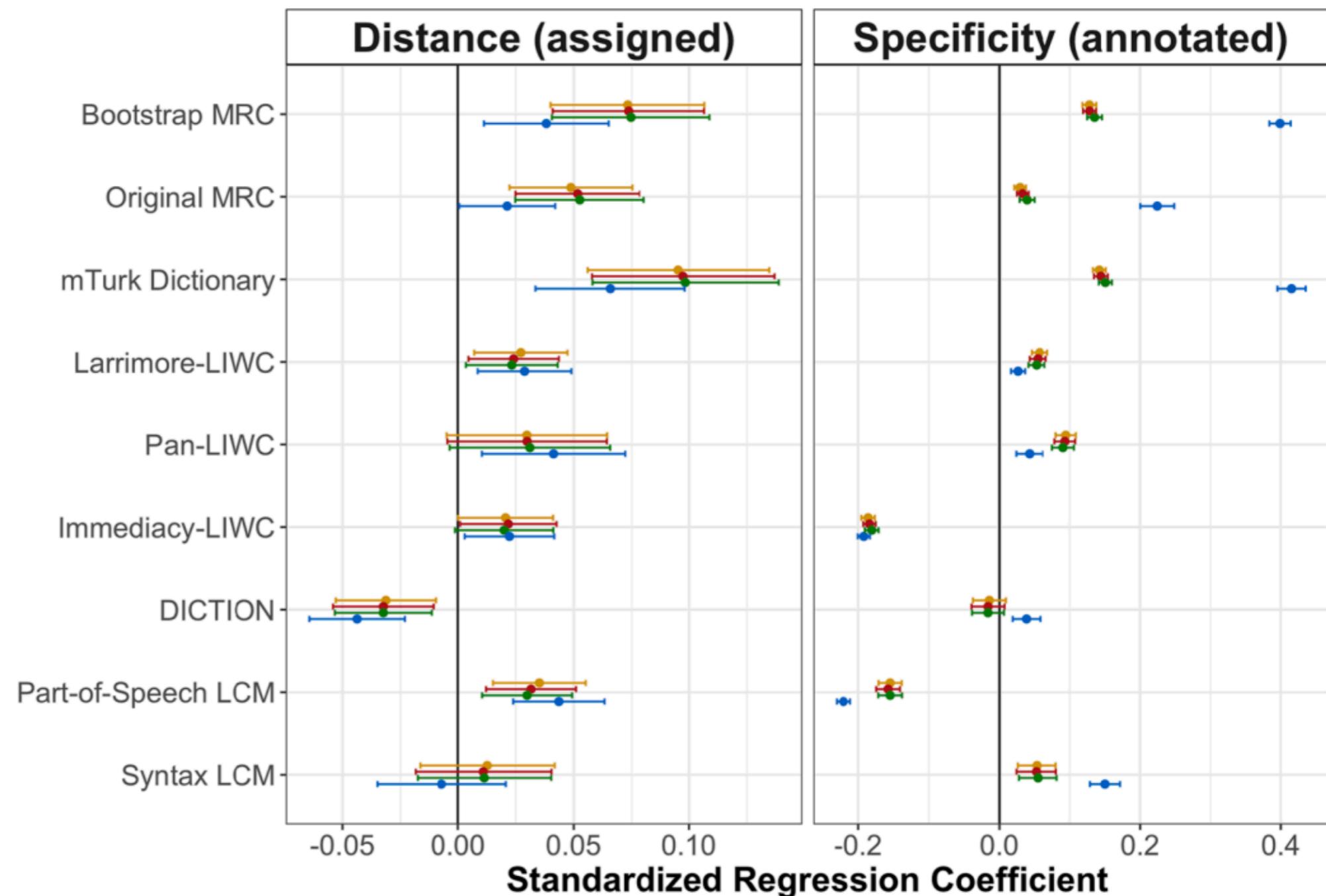
A Concrete Mega-Analysis

Concreteness
dictionaries don't
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A Concrete Mega-Analysis

Concreteness
dictionaries don't
correlate with
concreteness



Machine Learning



Machine Learning

Abstractly: let the data decide

Concretely: supervised learning



Supervised NLP

Supervised NLP

	Test Dataset
Training Dataset	Advice
Advice	.228 [.195, .260]
Plan Distance	
Plan Specificity	
Describing	

Supervised NLP

	Test Dataset
Training Dataset	Advice
Advice	.228 [.195, .260]
Plan Distance	.022 [-.012, .056]
Plan Specificity	.191 [.158, .224]
Describing	.119 [.085, .152]

Supervised NLP

		Test Dataset		
Training Dataset		Advice	Plan Distance	Plan Specificity
Advice	Advice	.228 [.195, .260]		
	Plan Distance	.022 [-.012, .056]	.339 [.315, .363]	
Plan Specificity	Plan Specificity	.191 [.158, .224]		.733 [.720, .745]
	Describing	.119 [.085, .152]		

Supervised NLP

		Test Dataset		
Training Dataset		Advice	Plan Distance	Plan Specificity
Advice	.228	.004	.258	
	[.195, .260]	[-.024, .031]	[.232, .283]	
Plan Distance	.022	.339	.026	
	[-.012, .056]	[.315, .363]	[-.001, .053]	
Plan Specificity	.191	.038	.733	
	[.158, .224]	[.011, .065]	[.720, .745]	
Describing	.119	.012	.417	
	[.085, .152]	[-.015, .039]	[.394, .439]	

Supervised NLP

	Test Dataset		
Training Dataset	Advice	Plan Distance	Plan Specificity
Advice	.228 [.195, .260]	.004 [-.024, .031]	.258 [.232, .283]
Plan Distance	.022 [-.012, .056]	.339 [.315, .363]	.026 [-.001, .053]
Plan Specificity	.191 [.158, .224]	.038 [.011, .065]	.733 [.720, .745]
Describing	.119 [.085, .152]	.012 [-.015, .039]	.417 [.394, .439]

Best Previous	.155 [.122, .188]	.047 [.020, .075]	.488 [.466, .510]
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Supervised NLP

	Test Dataset			
Training Dataset	Advice	Plan Distance	Plan Specificity	Describing
Advice	.228 [.195, .260]	.004 [-.024, .031]	.258 [.232, .283]	
Plan Distance	.022 [-.012, .056]	.339 [.315, .363]	.026 [-.001, .053]	
Plan Specificity	.191 [.158, .224]	.038 [.011, .065]	.733 [.720, .745]	
Describing	.119 [.085, .152]	.012 [-.015, .039]	.417 [.394, .439]	.092 [.038, .145]

Best Previous	.155 [.122, .188]	.047 [.020, .075]	.488 [.466, .510]
---------------	----------------------	----------------------	----------------------

Supervised NLP

	Test Dataset			
Training Dataset	Advice	Plan Distance	Plan Specificity	Describing
Advice	.228 [.195, .260]	.004 [-.024, .031]	.258 [.232, .283]	
Plan Distance	.022 [-.012, .056]	.339 [.315, .363]	.026 [-.001, .053]	
Plan Specificity	.191 [.158, .224]	.038 [.011, .065]	.733 [.720, .745]	
Describing	.119 [.085, .152]	.012 [-.015, .039]	.417 [.394, .439]	.092 [.038, .145]

Best Previous	.155 [.122, .188]	.047 [.020, .075]	.488 [.466, .510]	.363 [.315, .409]
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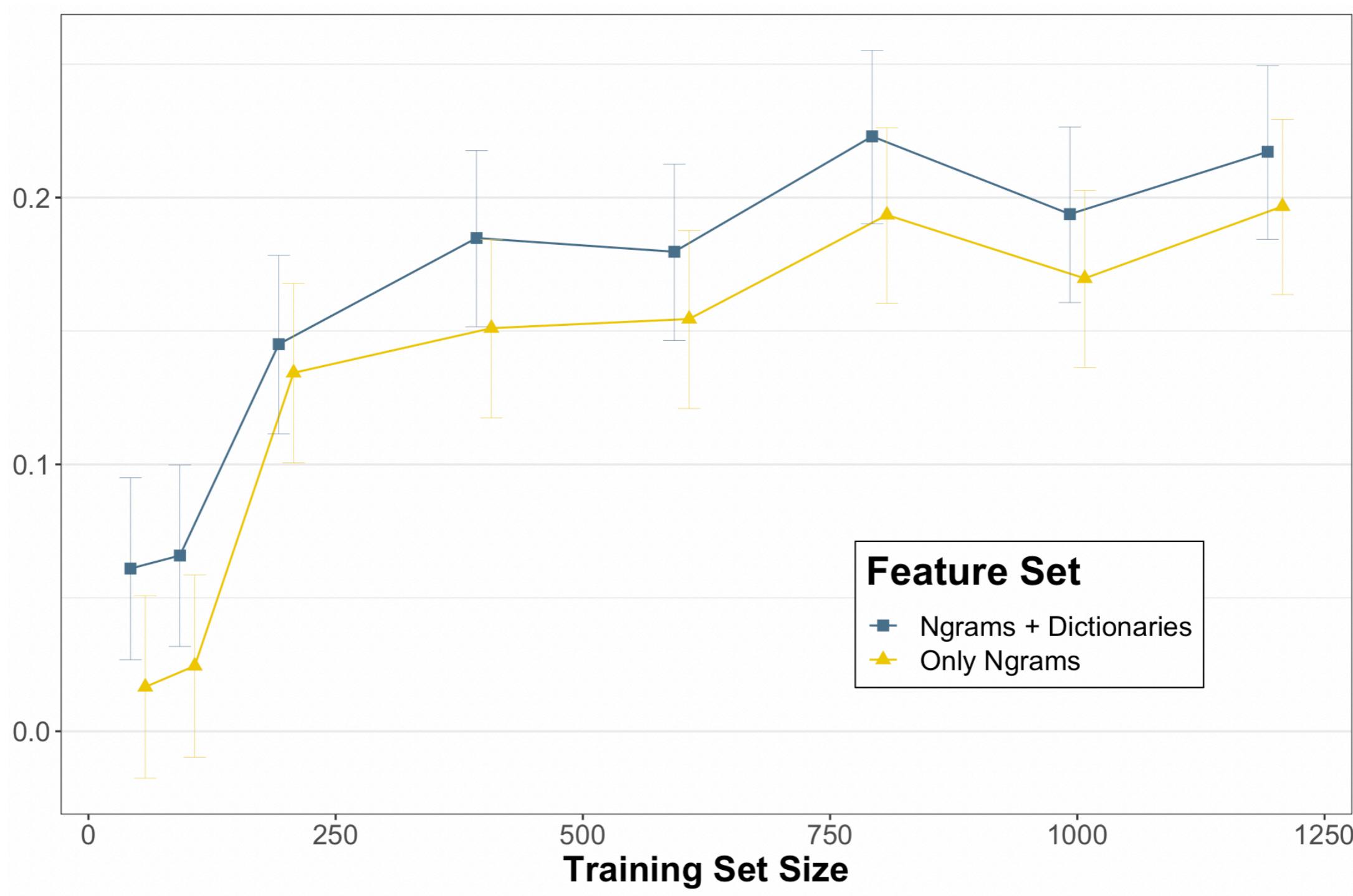
Supervised NLP

	Test Dataset			
Training Dataset	Advice	Plan Distance	Plan Specificity	Describing
Advice	.228 [.195, .260]	.004 [-.024, .031]	.258 [.232, .283]	-.113 [-.166, -.059]
Plan Distance	.022 [-.012, .056]	.339 [.315, .363]	.026 [-.001, .053]	-.012 [-.066, .042]
Plan Specificity	.191 [.158, .224]	.038 [.011, .065]	.733 [.720, .745]	-.032 [-.086, .022]
Describing	.119 [.085, .152]	.012 [-.015, .039]	.417 [.394, .439]	.092 [.038, .145]

Best Previous	.155 [.122, .188]	.047 [.020, .075]	.488 [.466, .510]	.363 [.315, .409]
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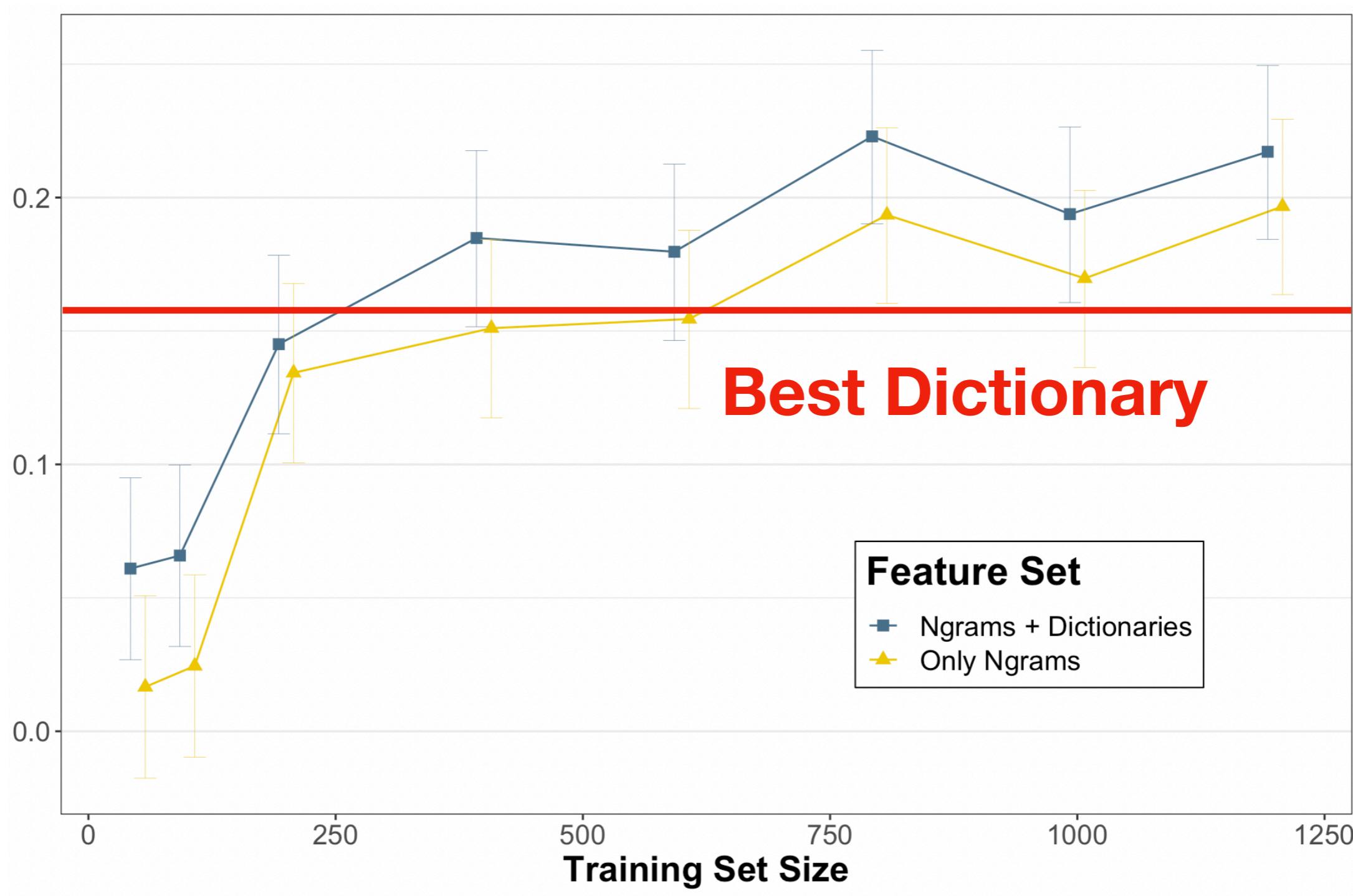
How Many Annotations?

Advice Specificity



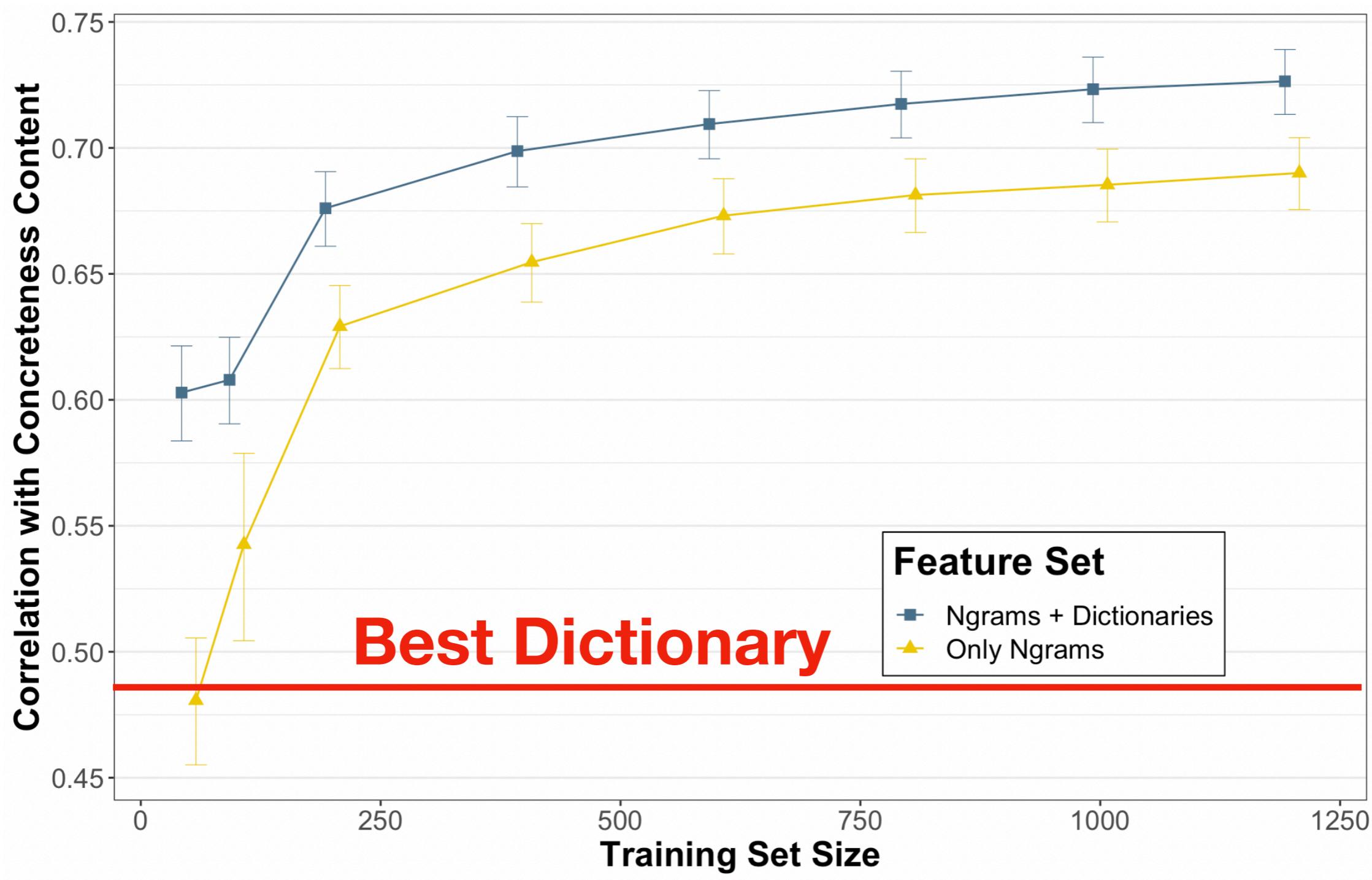
How Many Annotations?

Advice Specificity

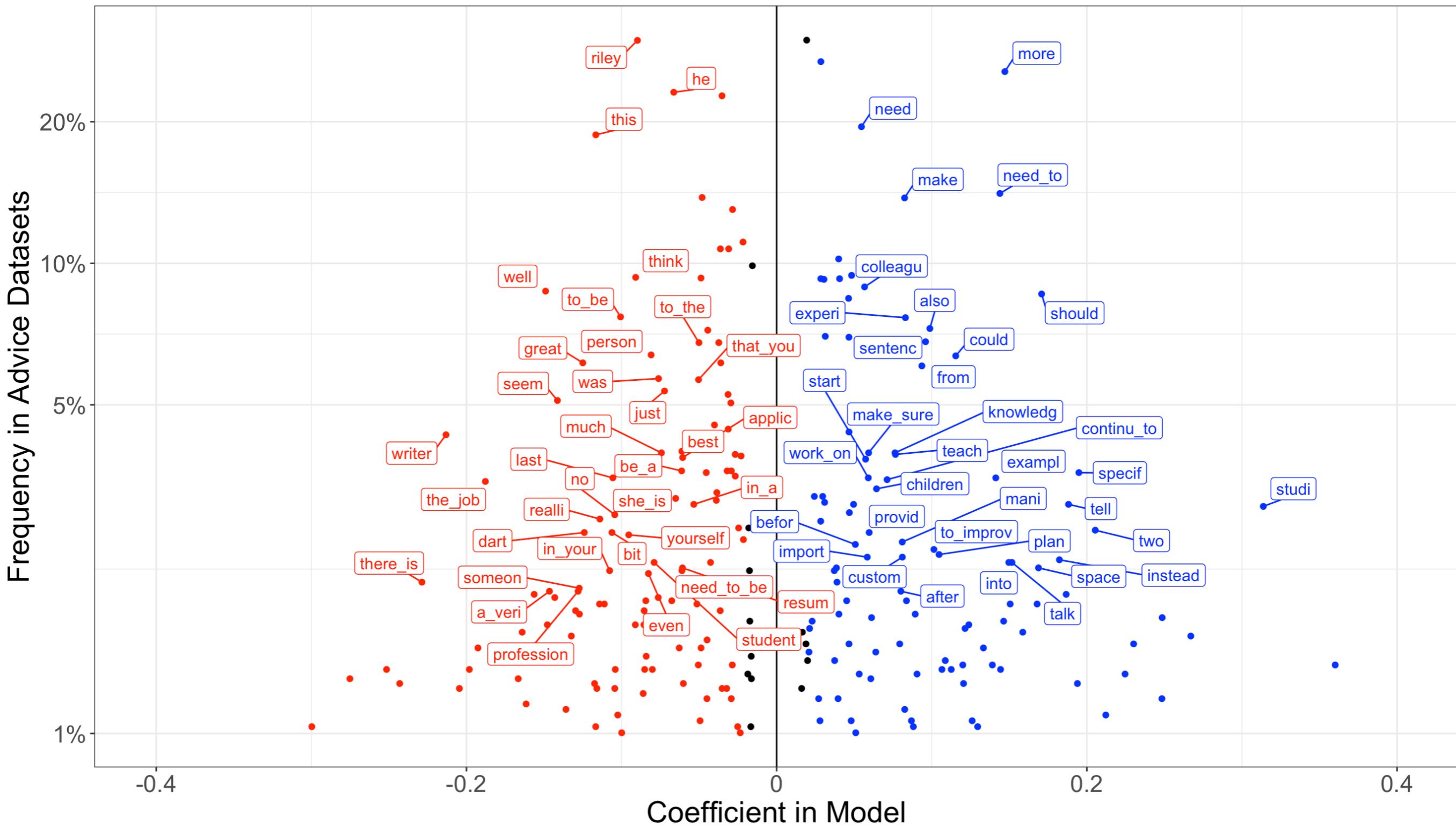


How Many Annotations?

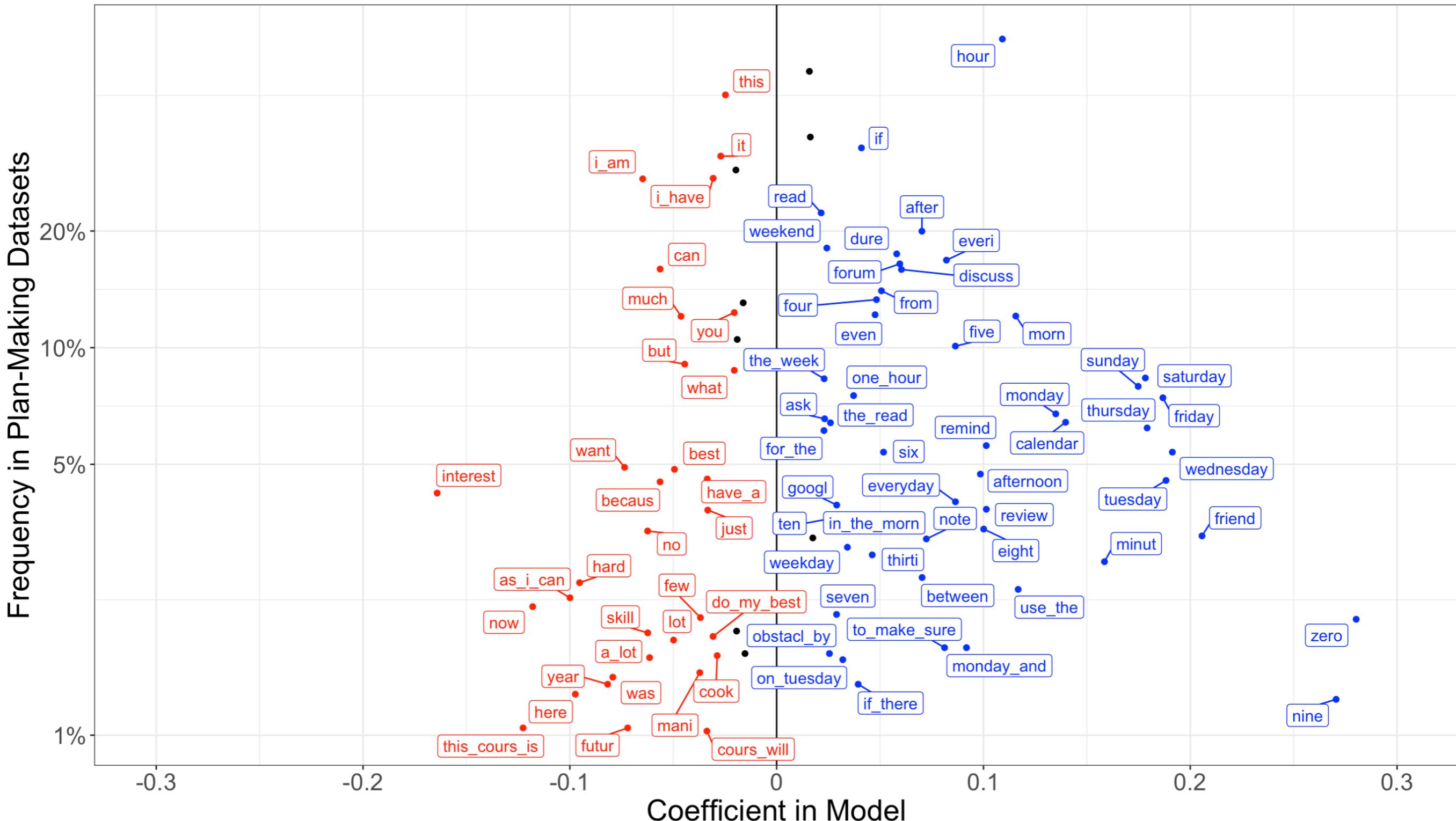
Planning Specificity



Advice Model



Plan Specificity Model



Dimension Reduction

Theory-Driven - “*We’ll tell you what a word means*”
Dictionaries

Data-Driven - “*You will know a word by the company it keeps*”

Two senses of similarity:

Syntagmatic - often found in the same documents
“GDP”, “inflation”, “economy”, “currency”
e.g. topic models (LDA), Latent Semantic Analysis

Paradigmatic - often have the same neighbours
“wrote”, “remarked”, “said”, “added”
e.g. word2vec, GloVe, BERT, GPT-1/2/3

Word Similarity

Many words have similar meanings or functions

How to reduce?

You will know a word by the company it keeps

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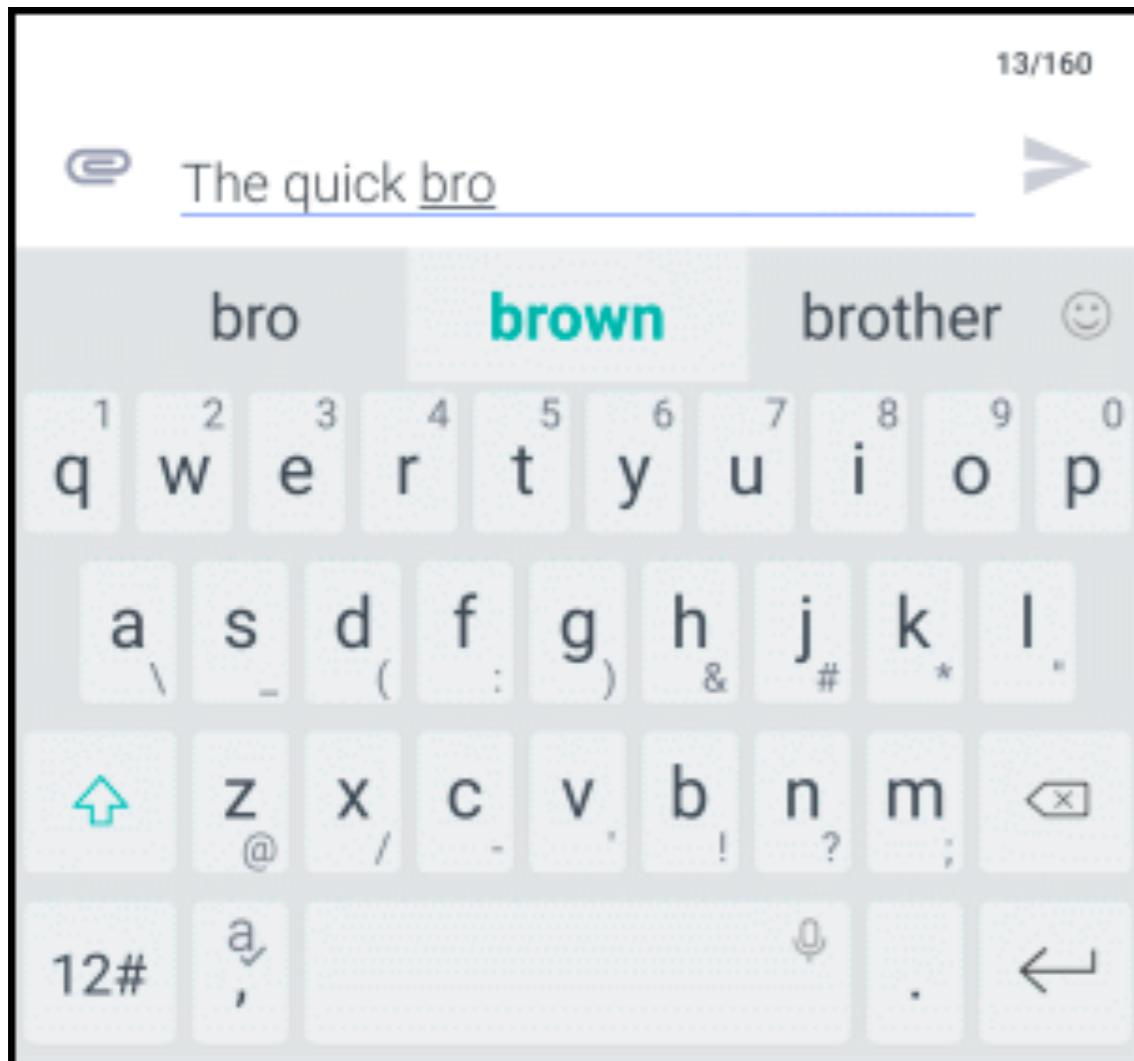
Paradigmatic - often have the same neighbours

“wrote”, “remarked”, “said”, “added”

e.g. word2vec, GloVe

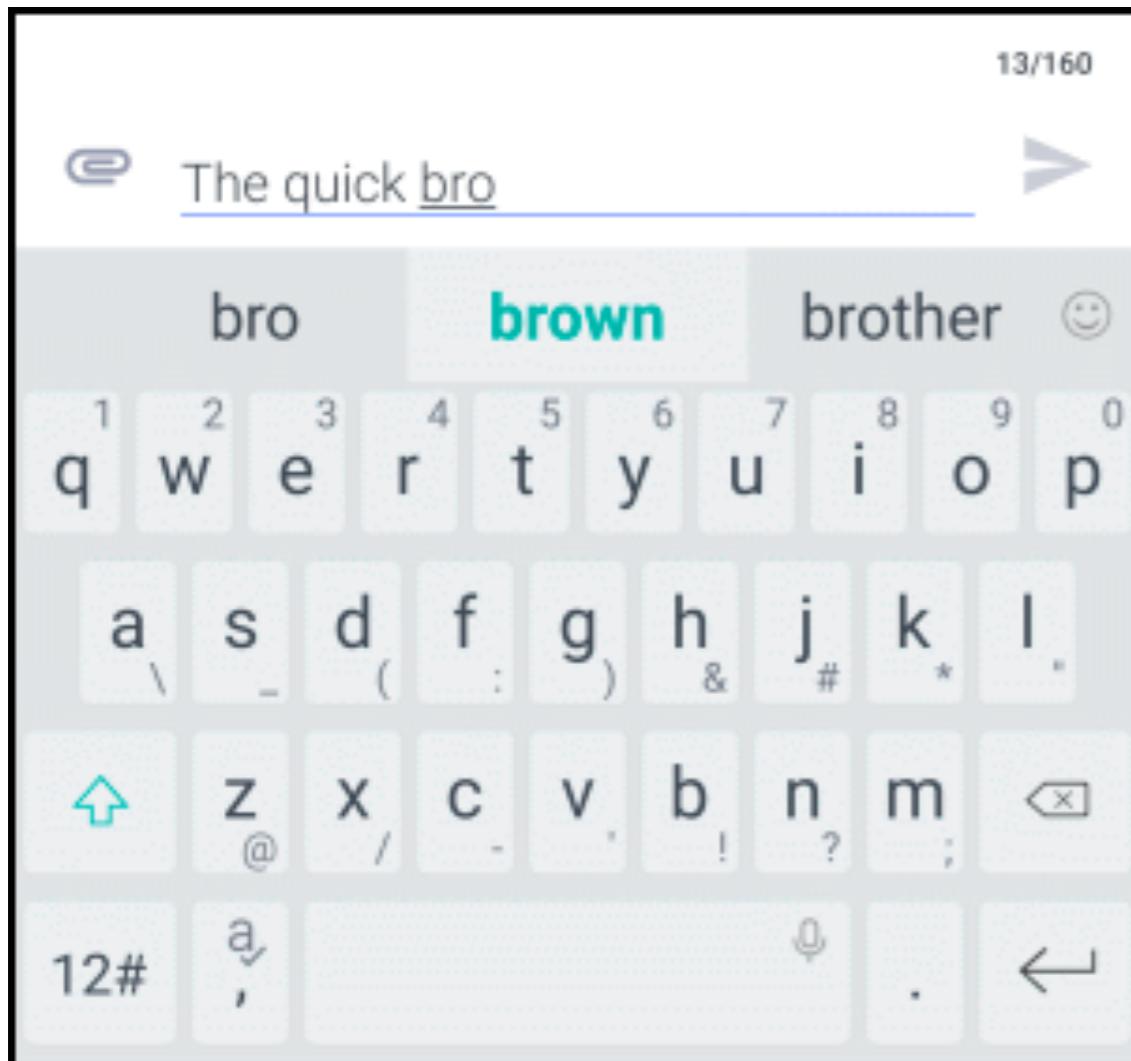
Language Modeling Task

Predictive Text



Language Modeling Task

Predictive Text



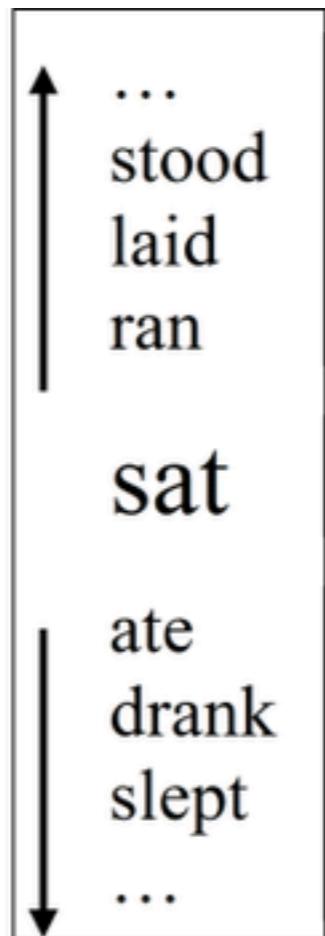
- what is the next
- what is the next **holiday**
- what is the next **marvel movie**
- what is the next **warriors game**
- what is the next **full moon**
- what is the next **holiday coming up**
- what is the next **generation called**
- what is the next **marvel show**
- what is the next **covid variant**
- what is the next **bitcoin**
- what is the next **spiderman movie**

Language Modeling Task

Continuous Bag of Words

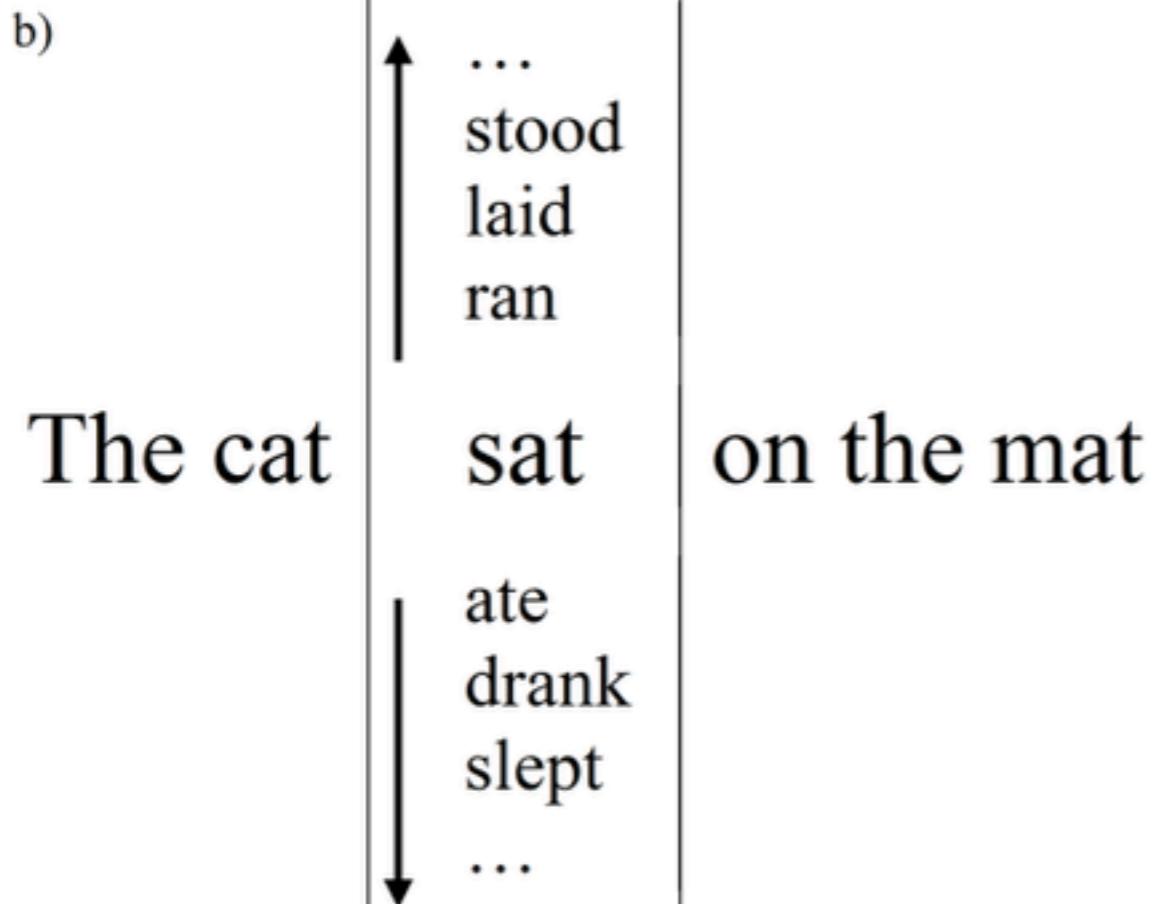
b)

The cat sat on the mat



Language Modeling Task

Continuous Bag of Words



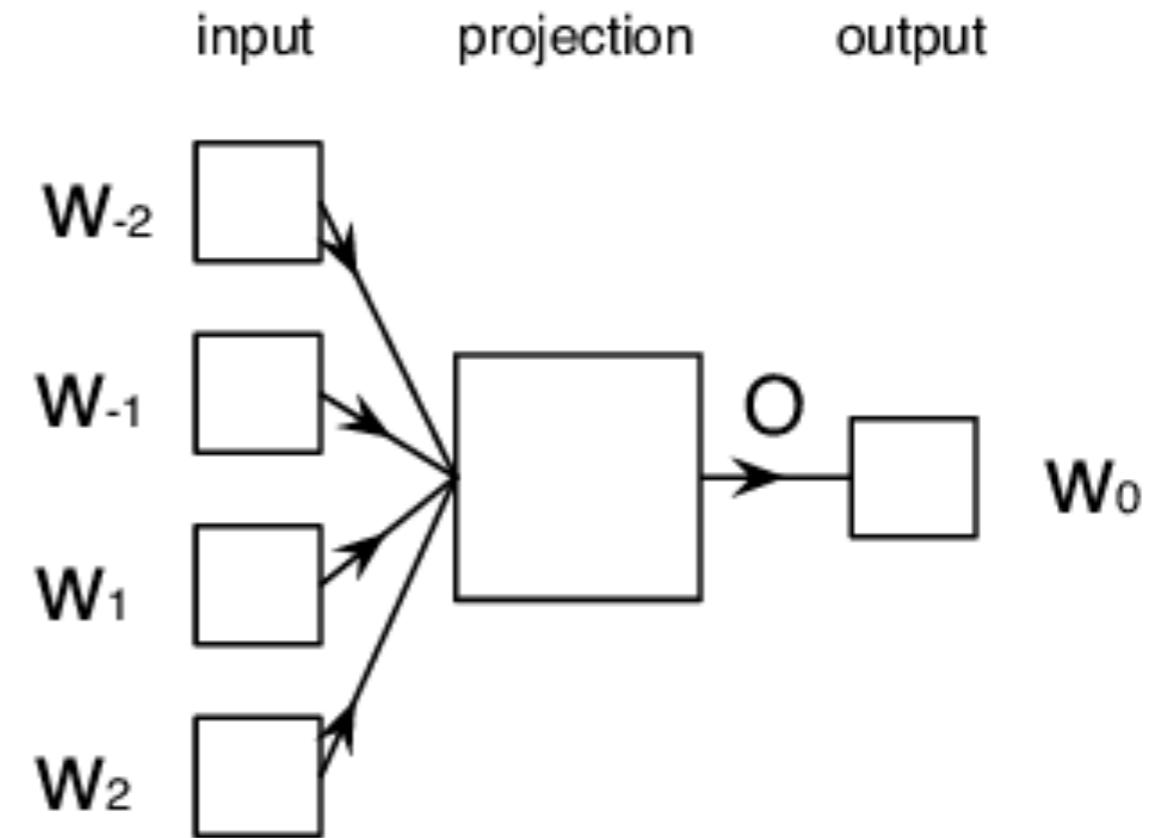
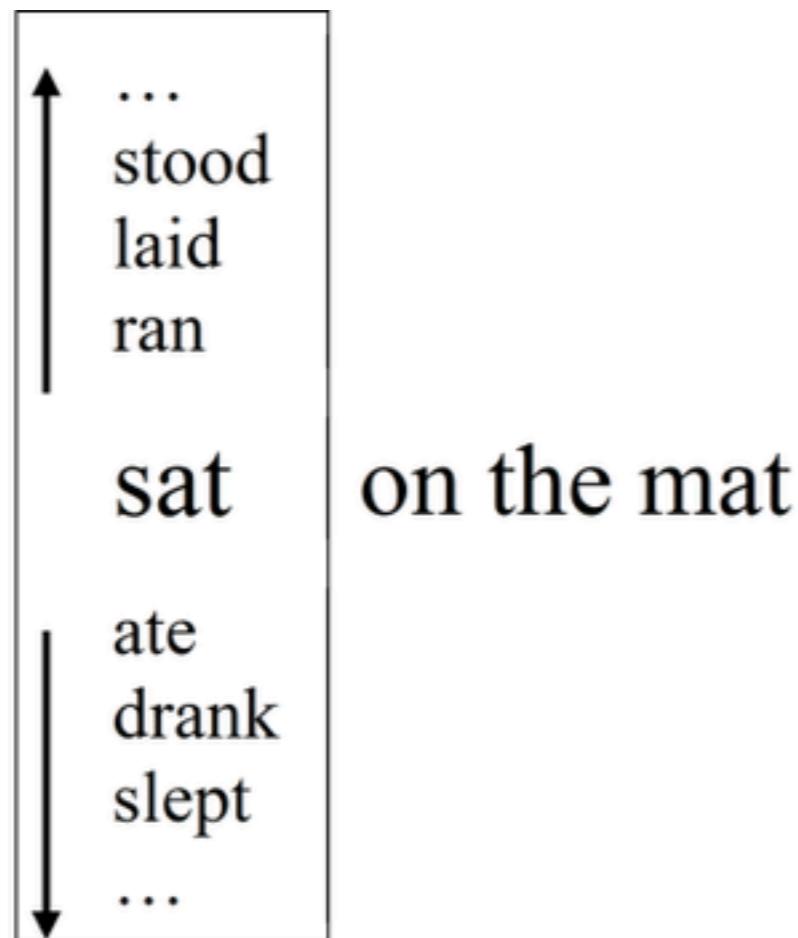
Predict the context words using the masked word
"Self-Supervised Learning"

Language Modeling Task

Continuous Bag of Words

b)

The cat sat on the mat



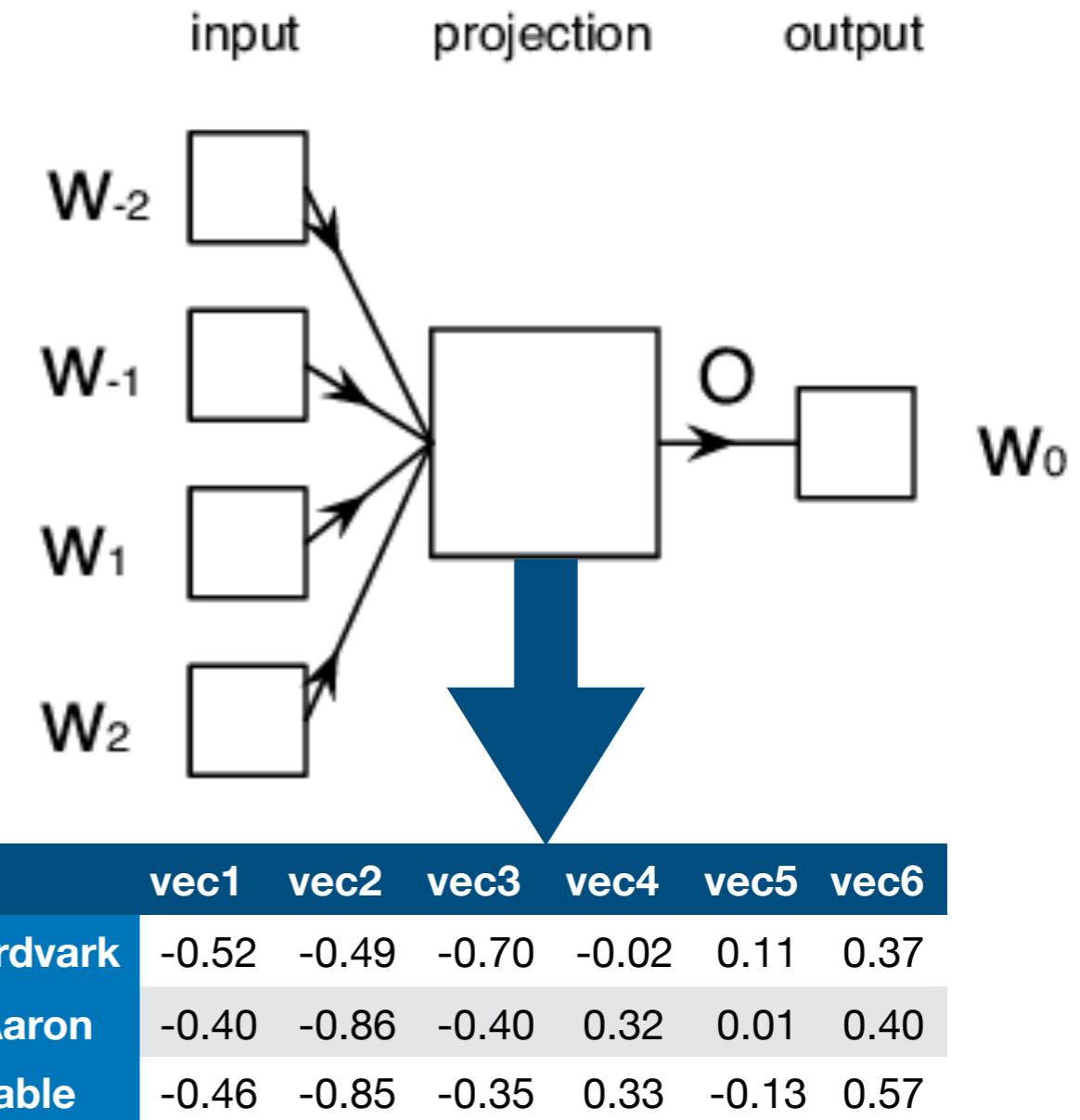
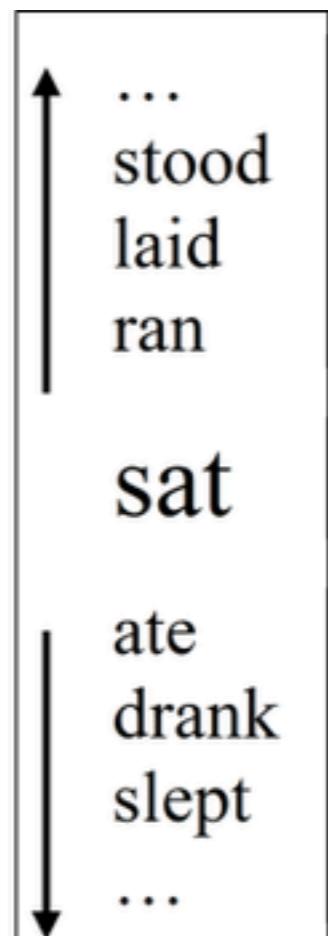
Predict the context words using the masked word
"Self-Supervised Learning"

Language Modeling Task

Continuous Bag of Words

b)

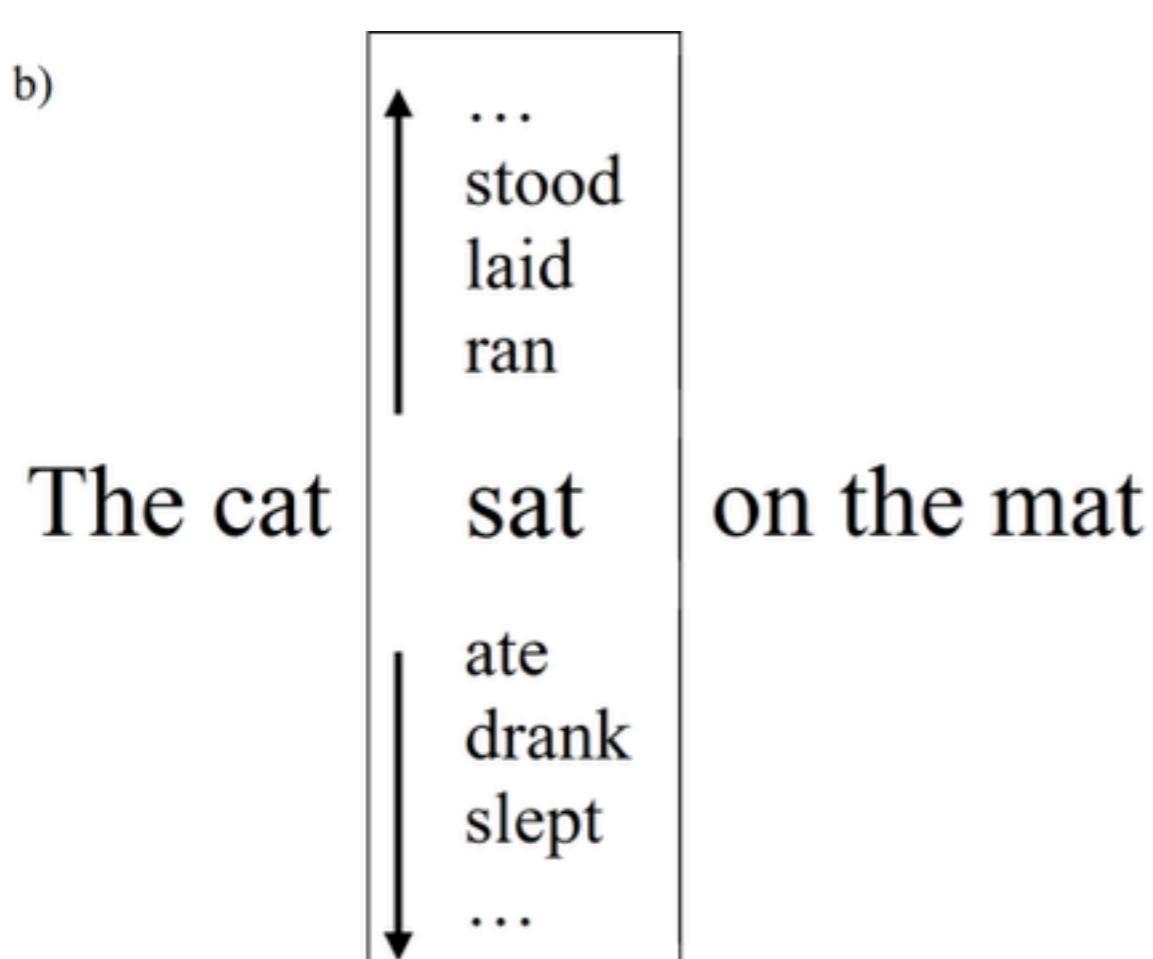
The cat sat on the mat



Predict the context words using the masked word
"Self-Supervised Learning"

Language Modeling Task

Skip-grams



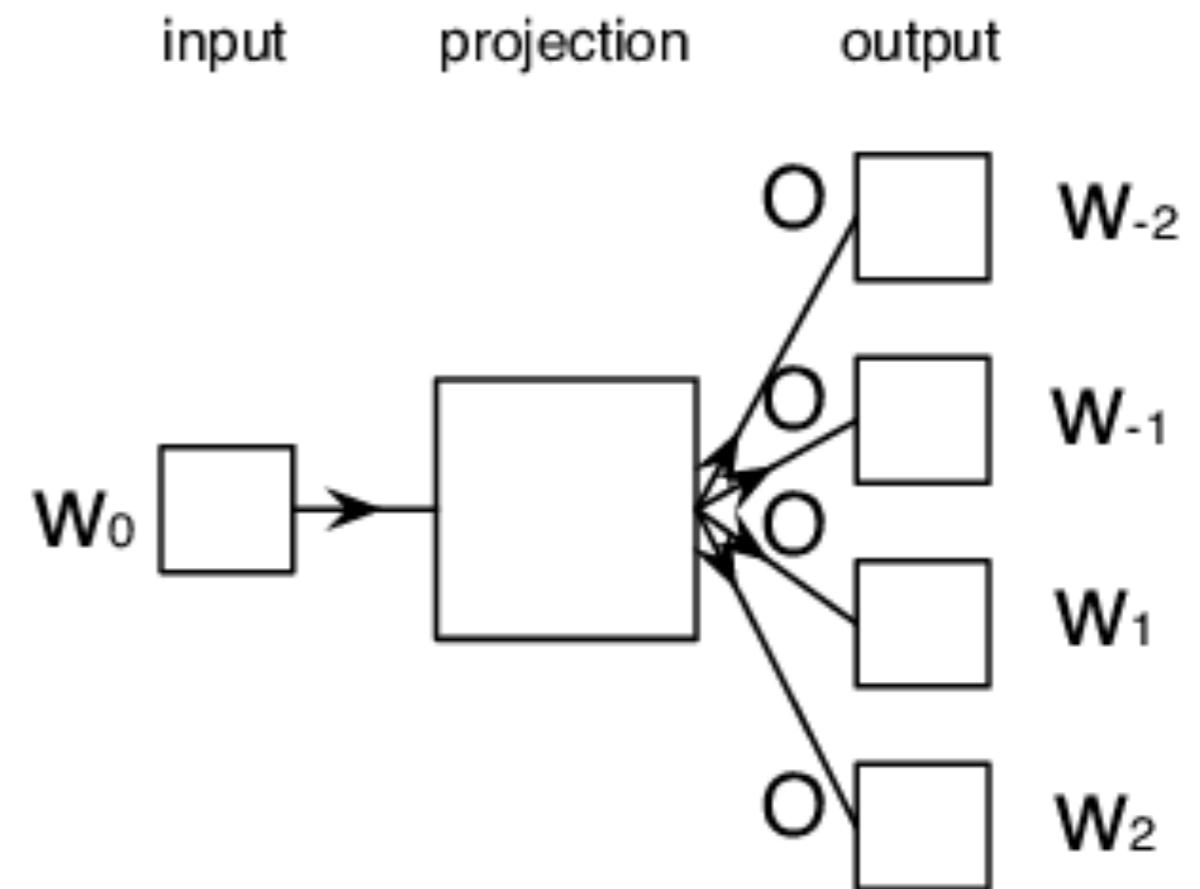
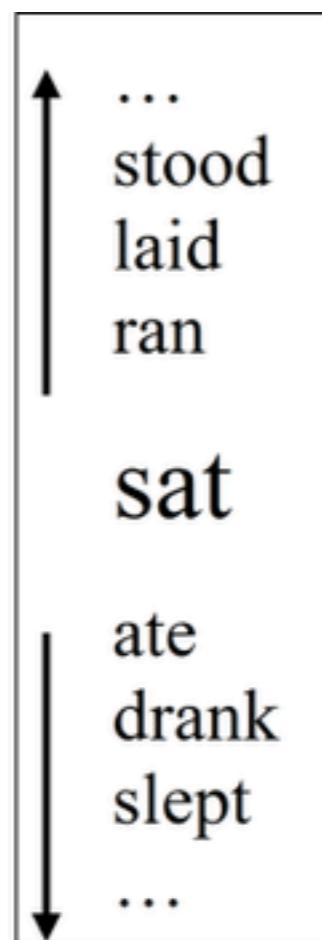
Predict the context words using the masked word
"Self-Supervised Learning"

Language Modeling Task

Skip-grams

b)

The cat sat on the mat



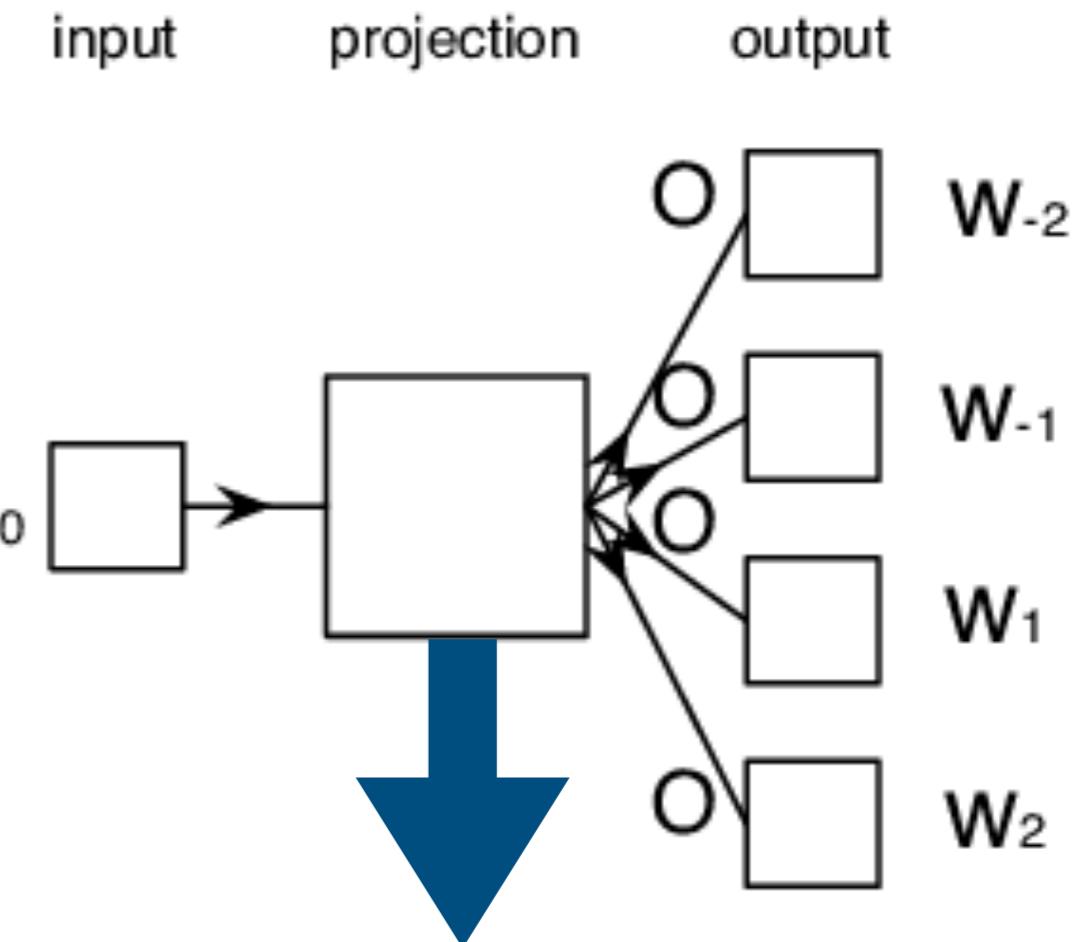
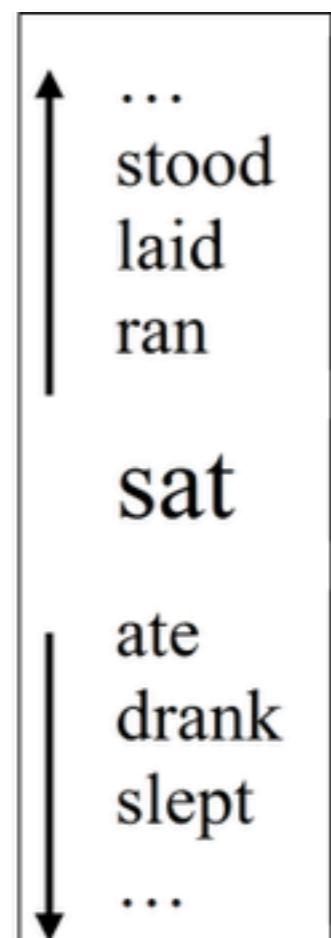
Predict the context words using the masked word
"Self-Supervised Learning"

Language Modeling Task

Skip-grams

b)

The cat sat on the mat



	vec1	vec2	vec3	vec4	vec5	vec6
aardvark	-0.52	-0.49	-0.70	-0.02	0.11	0.37
Aaron	-0.40	-0.86	-0.40	0.32	0.01	0.40
able	-0.46	-0.85	-0.35	0.33	-0.13	0.57

Predict the context words using the masked word
"Self-Supervised Learning"

Negative Sampling

The cat [sat] on the mat

Masked Word	Context Word	In data
sat	the	1
sat	cat	1
sat	on	1
sat	the	1

Negative Sampling

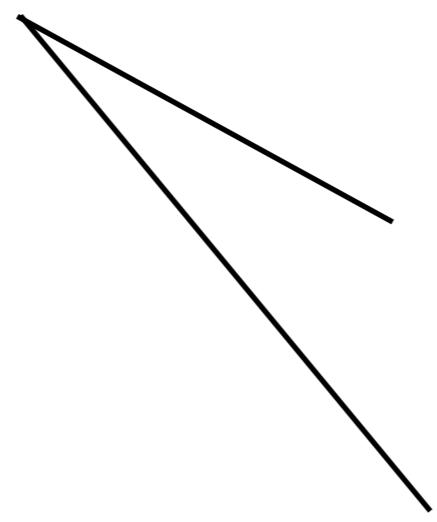
The cat [sat] on the mat

Masked Word	Context Word	In data
sat	the	1
sat	cat	1
sat	on	1
sat	the	1
sat	horse	0
sat	flower	0
sat	running	0
sat	nice	0

Negative Sampling

The cat [sat] on the mat

random other words
not from context

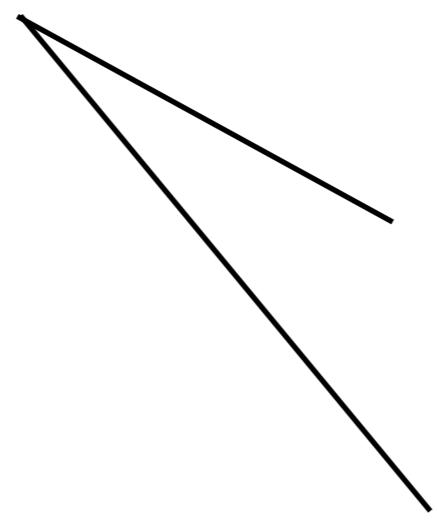


Masked Word	Context Word	In data
sat	the	1
sat	cat	1
sat	on	1
sat	the	1
sat	horse	0
sat	flower	0
sat	running	0
sat	nice	0

Negative Sampling

The cat [sat] on the mat

random other words
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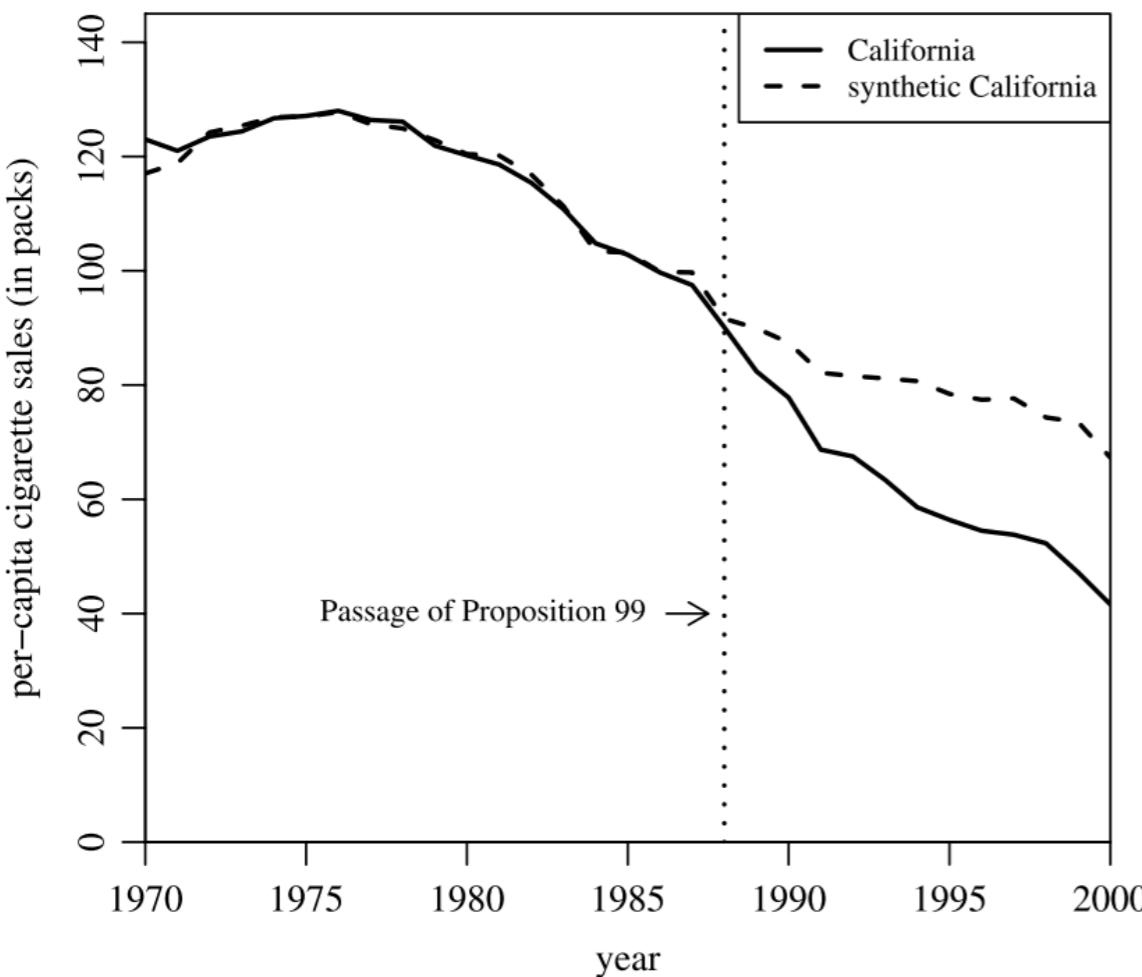
Masked Word	Context Word	In data
sat	the	1
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sat	running	0
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Similar to synthetic control
- generate comparison set

Negative Sampling

The cat [sat] on the mat

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Masked Word	Context Word	In data
sat	the	1
sat	cat	1
sat	on	1
sat	the	1
sat	horse	0
sat	flower	0
sat	running	0
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Similar to synthetic control
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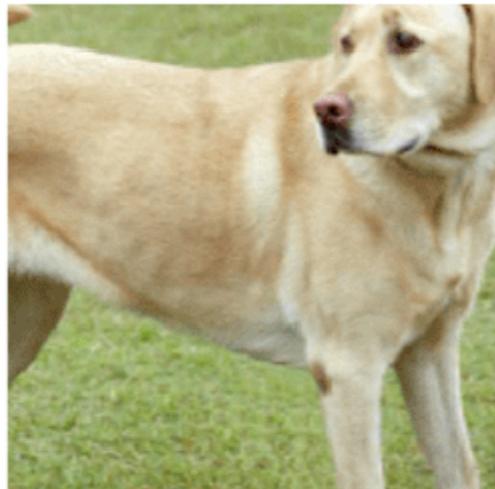
Self-Supervised Image Learning



(a) Original



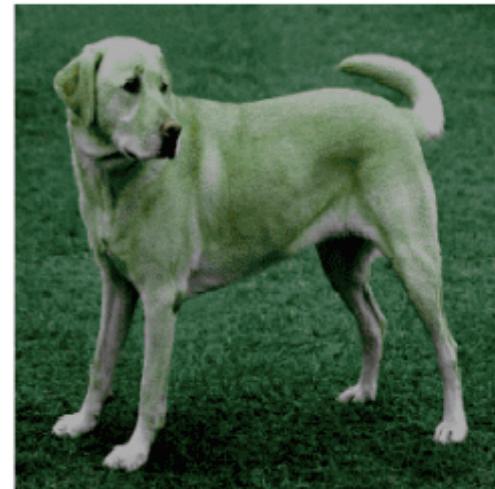
(b) Crop and resize



(c) Crop, resize (and flip)



(d) Color distort. (drop)



(e) Color distort. (jitter)



(f) Rotate $\{90^\circ, 180^\circ, 270^\circ\}$



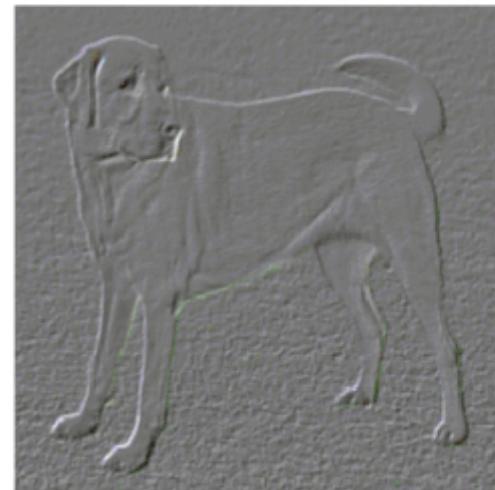
(g) Cutout



(h) Gaussian noise



(i) Gaussian blur

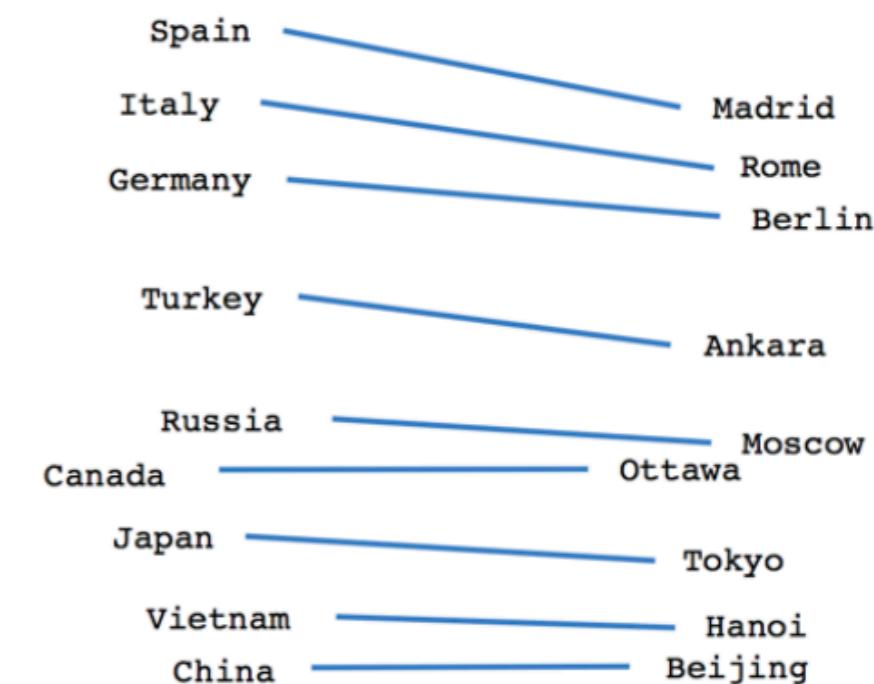
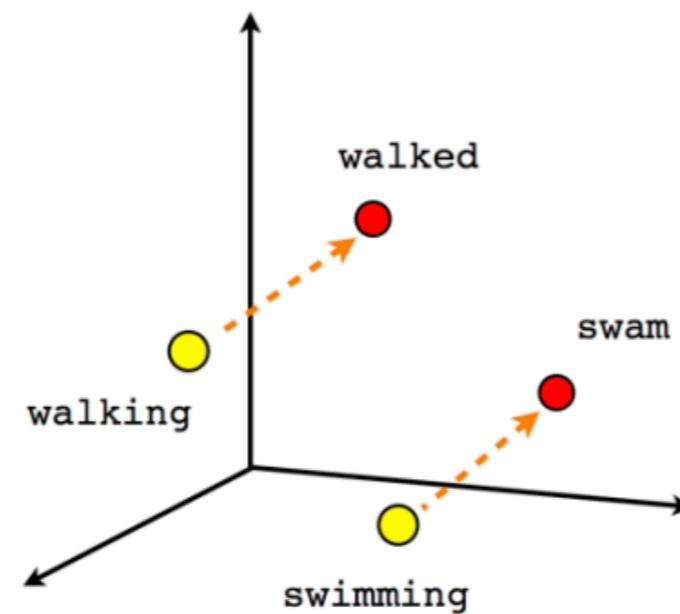
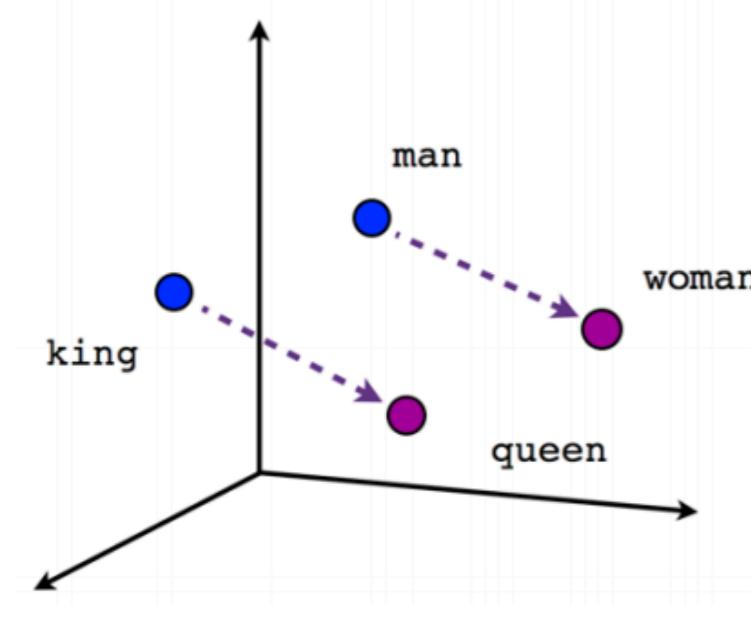


(j) Sobel filtering

Chen et al., 2020

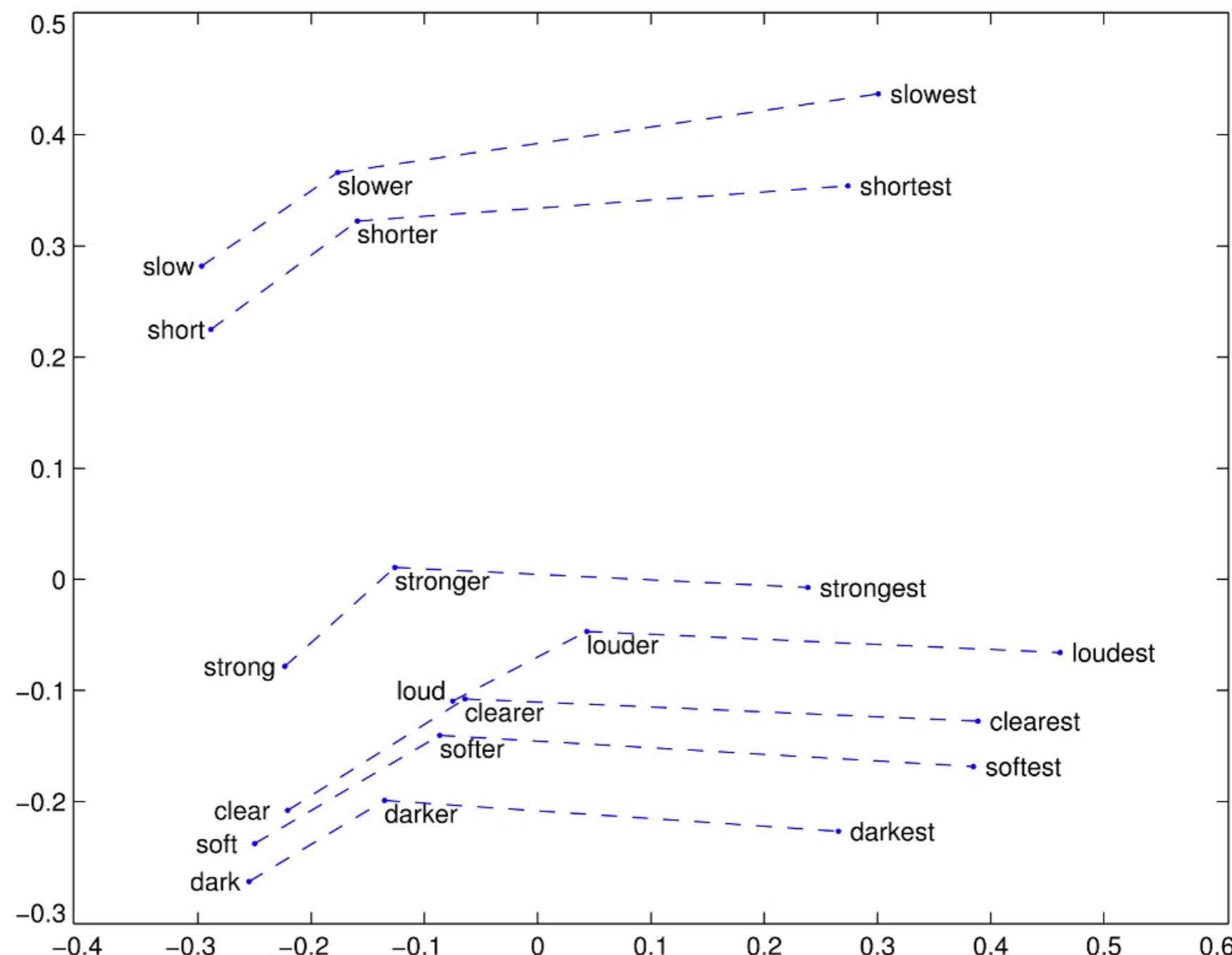
Embedding Spaces

What does meaning look like?



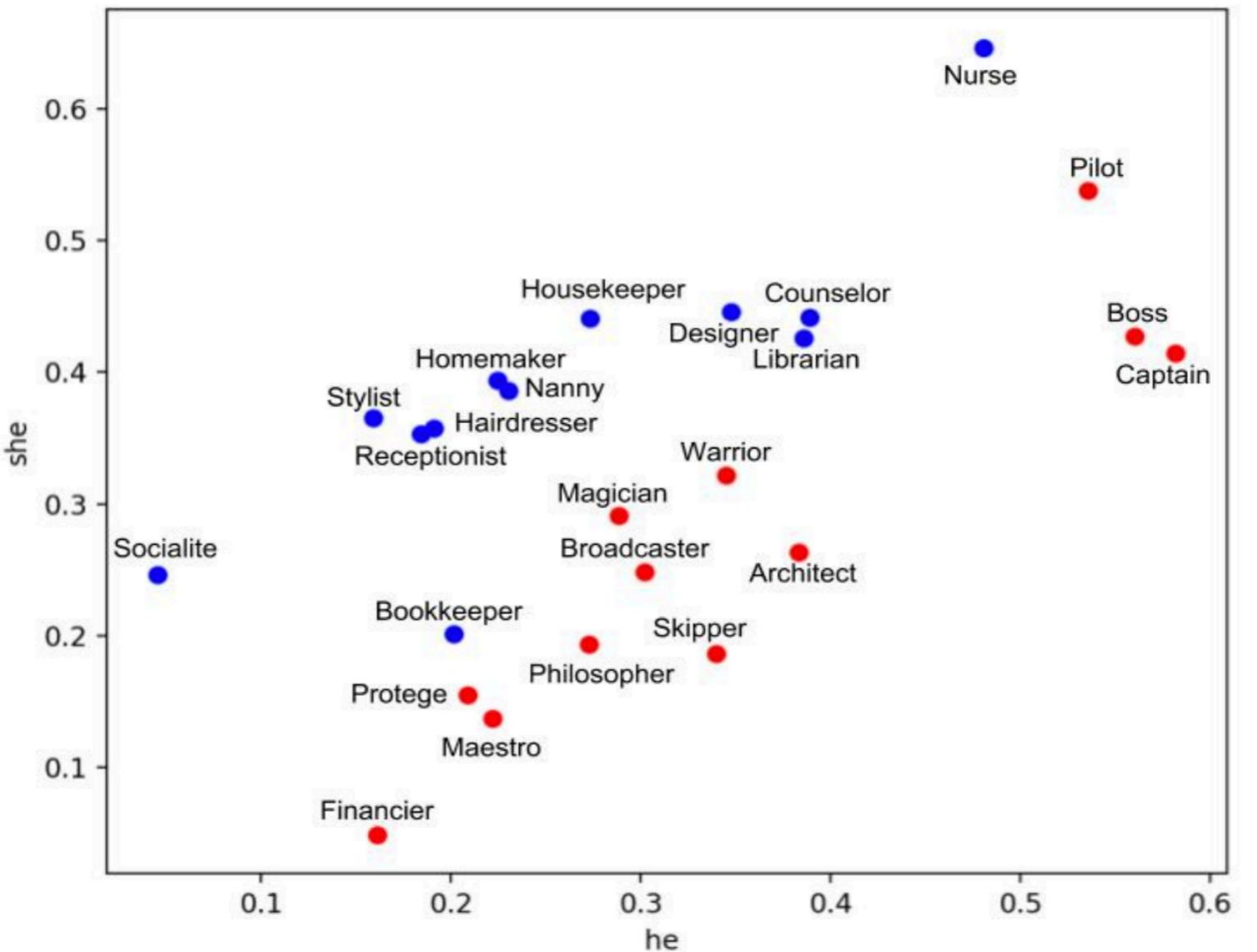
Embedding Spaces

What does meaning look like?



Embedding Spaces

What does meaning look like?

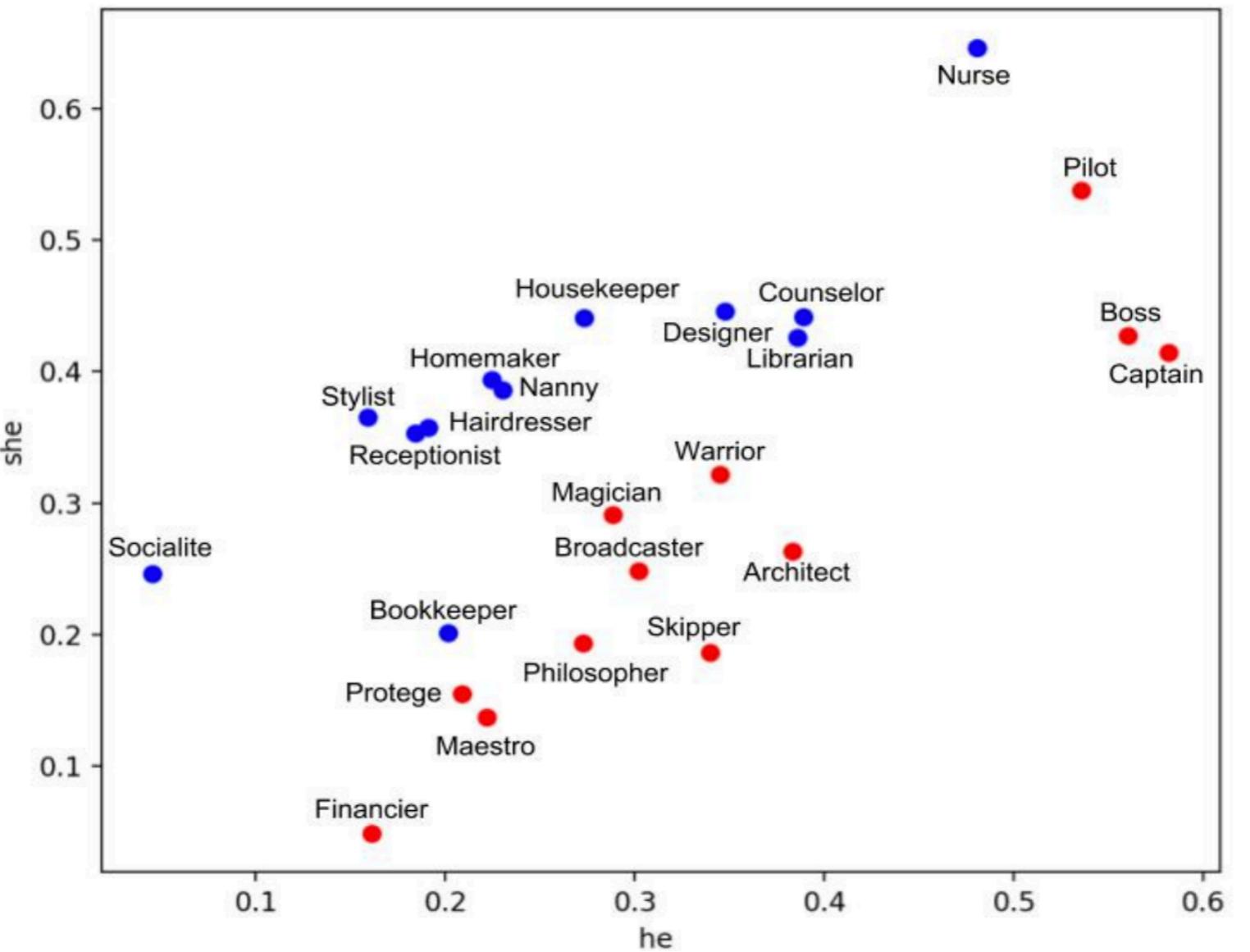


Caliskan, Bryson & Narayanan, 2017

Embedding Spaces

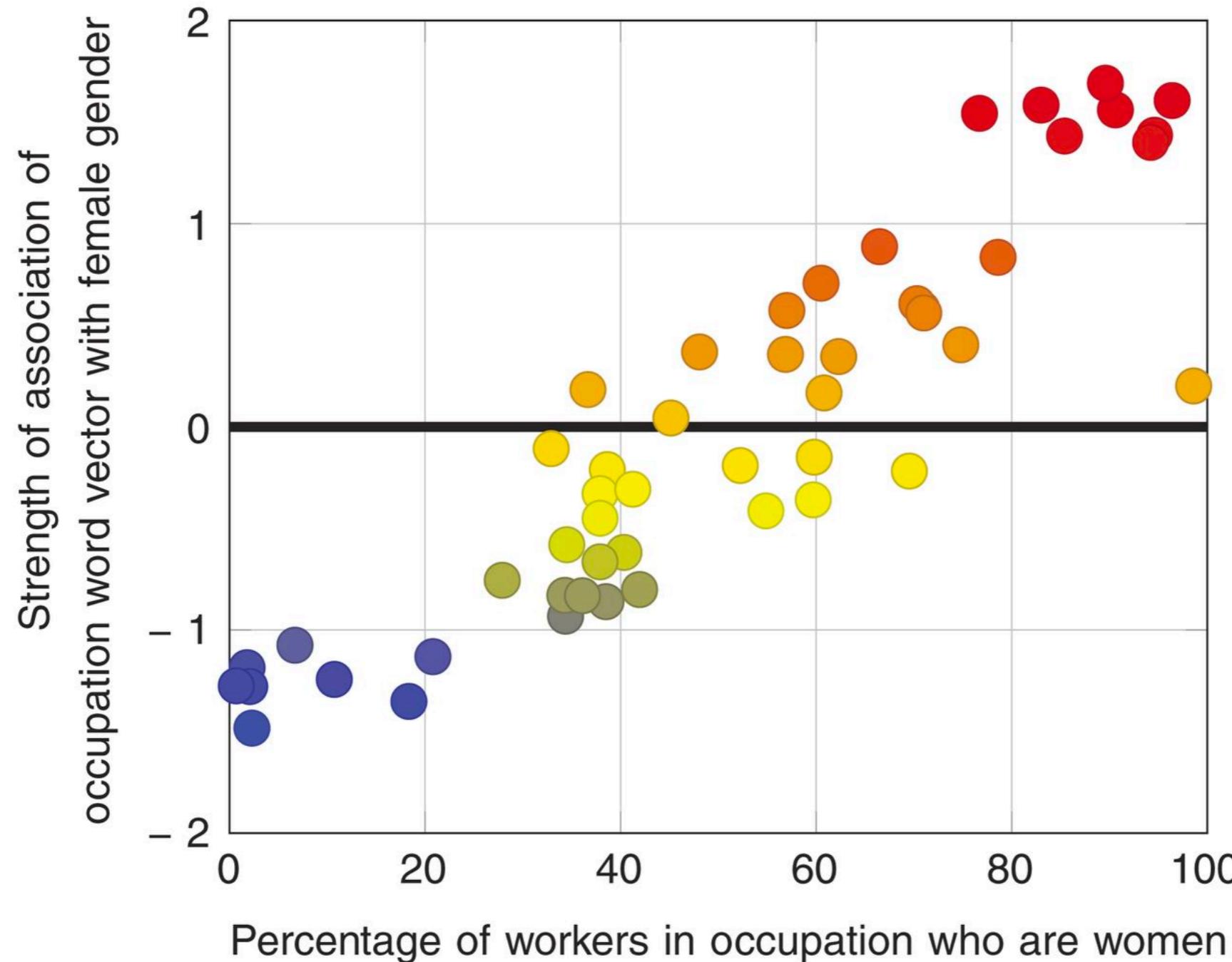
What does meaning look like?

Where is the bias?



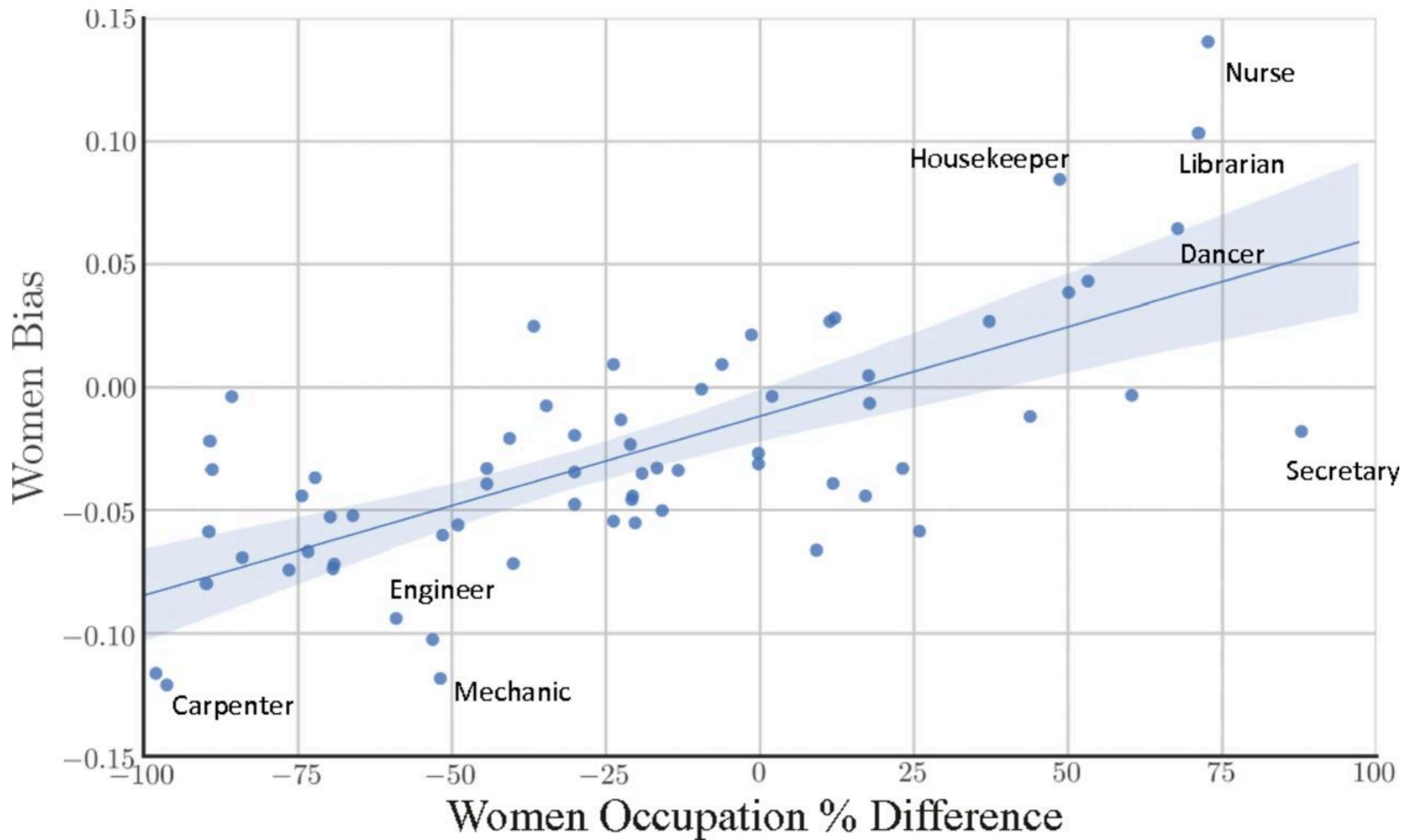
Caliskan, Bryson & Narayanan, 2017

Applications of Word Similarity



Caliskan, Bryson & Narayanan, 2017

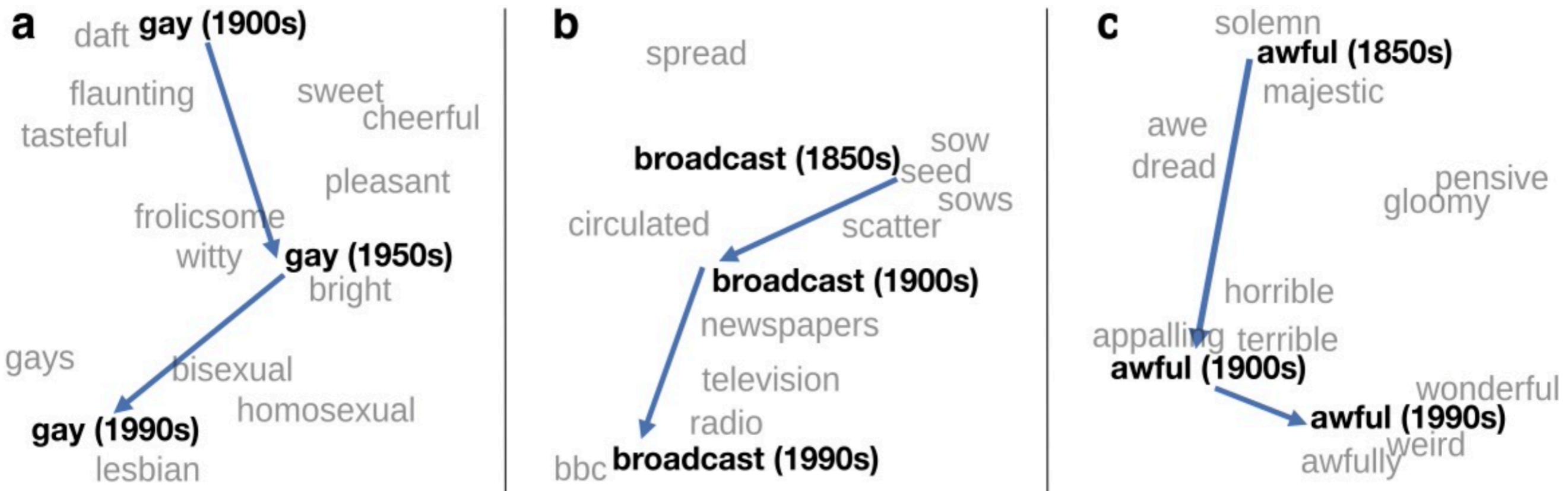
Applications of Word Similarity



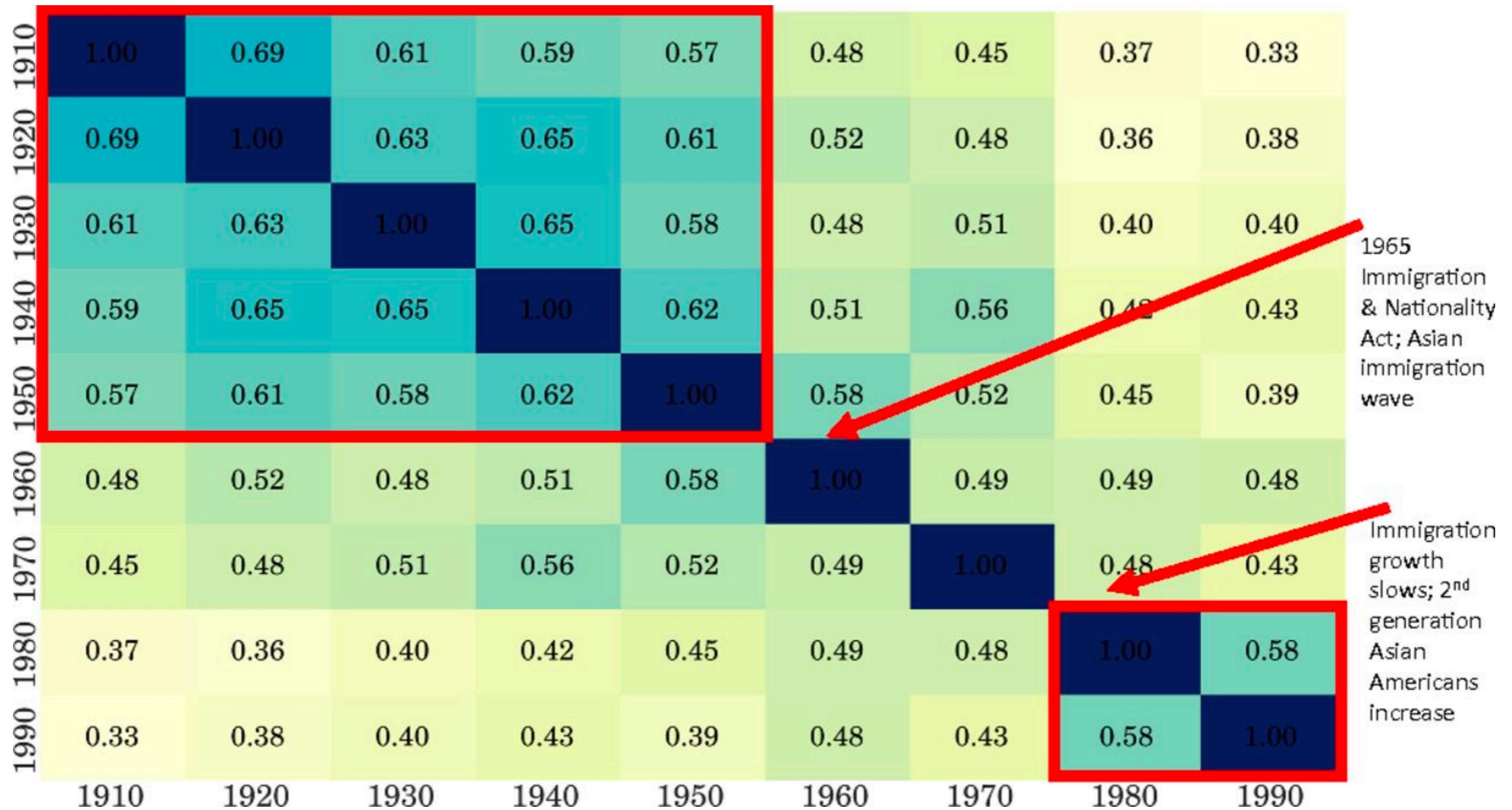
Garg et al., 2018

Applications of Word Similarity

~30 million books, 1850-1990, Google Books data



Applications of Word Similarity

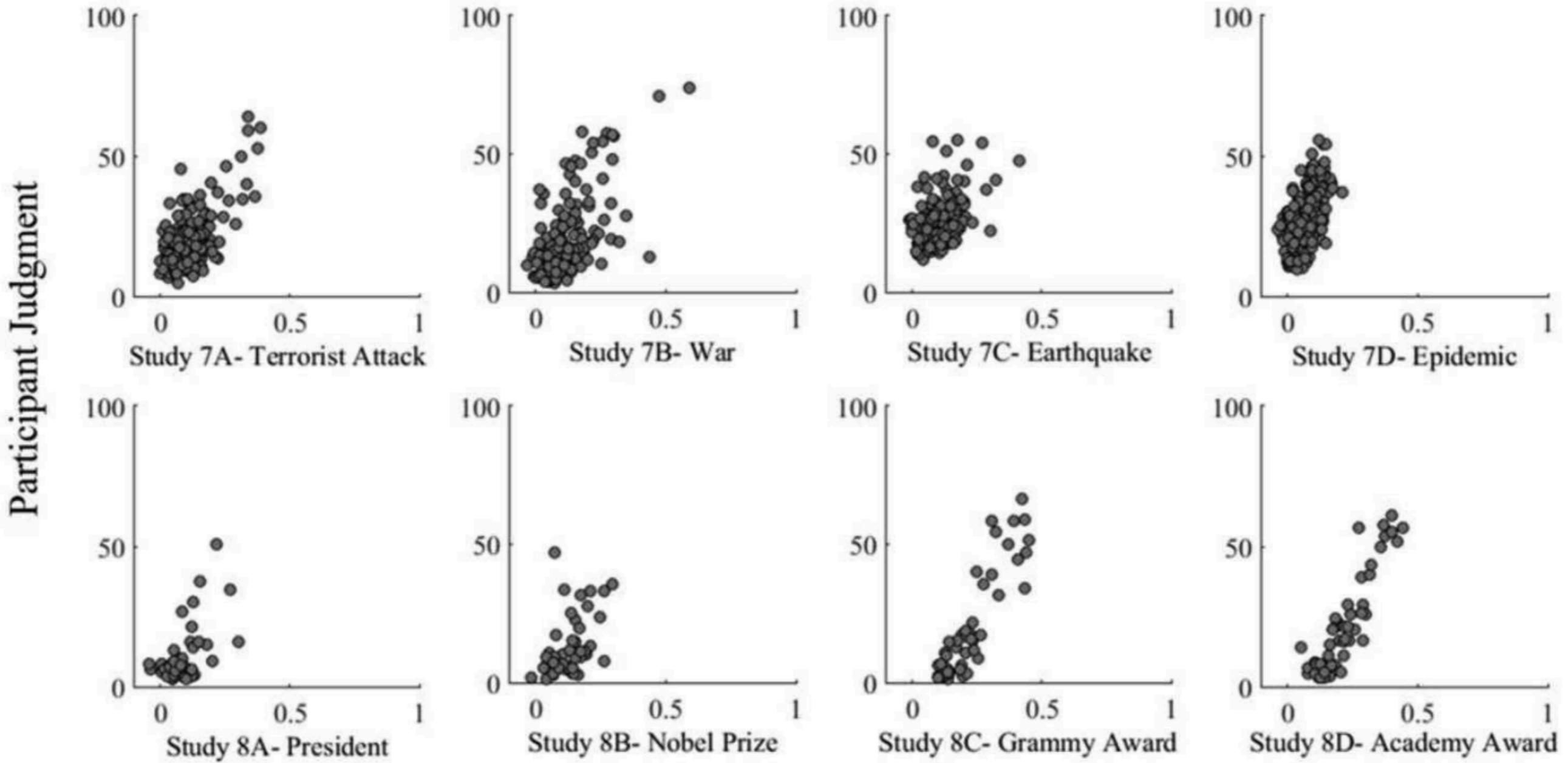


Applications of Word Similarity

Table 3. Top Asian (vs. White) adjectives in 1910, 1950, and 1990 by relative norm difference in the COHA embedding

1910	1950	1990
Irresponsible	Disorganized	Inhibited
Envious	Outrageous	Passive
Barbaric	Pompous	Dissolute
Aggressive	Unstable	Haughty
Transparent	Effeminate	Complacent
Monstrous	Unprincipled	Forceful
Hateful	Venomous	Fixed
Cruel	Disobedient	Active
Greedy	Predatory	Sensitive
Bizarre	Boisterous	Hearty

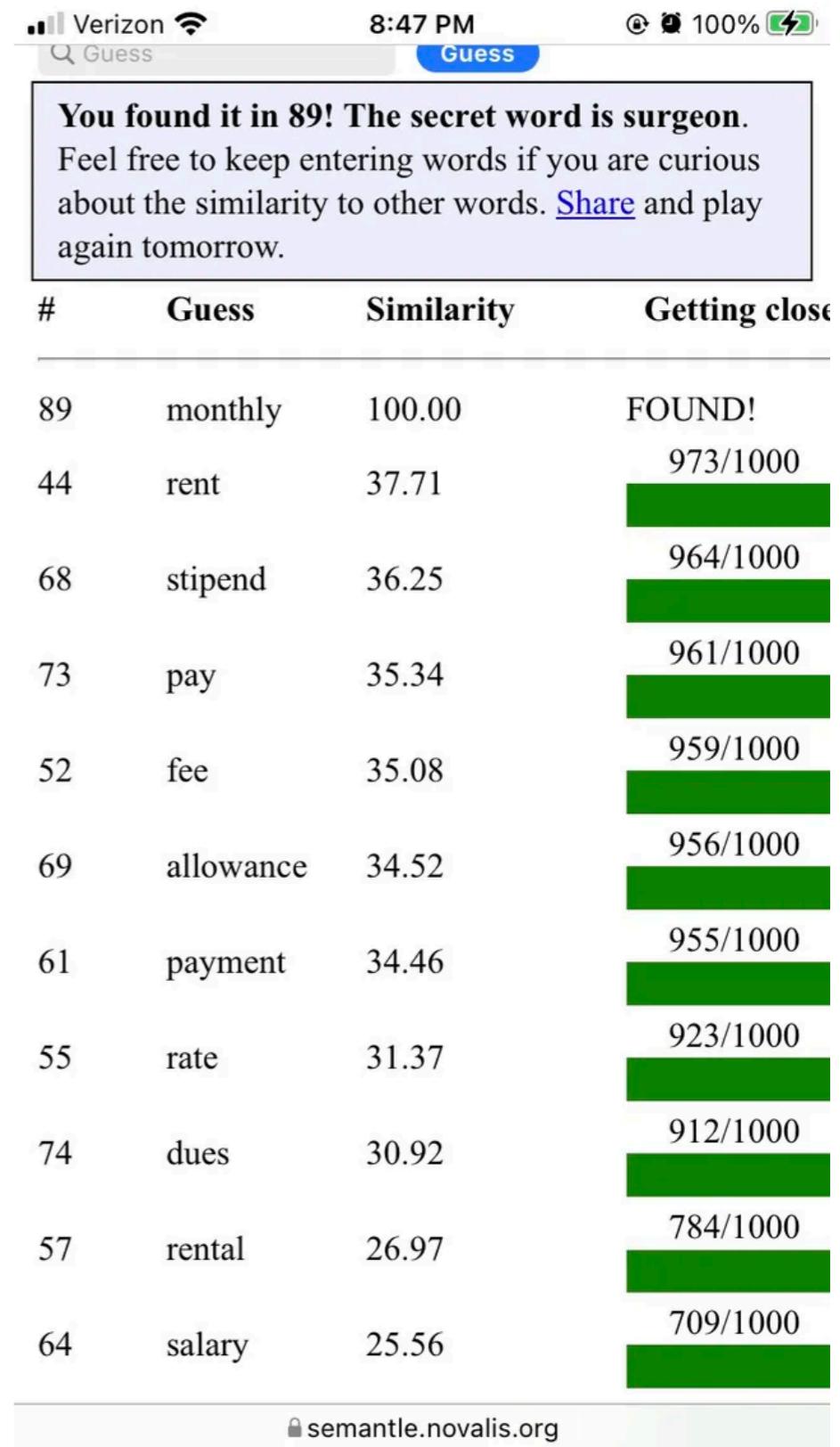
Applications of Word Similarity



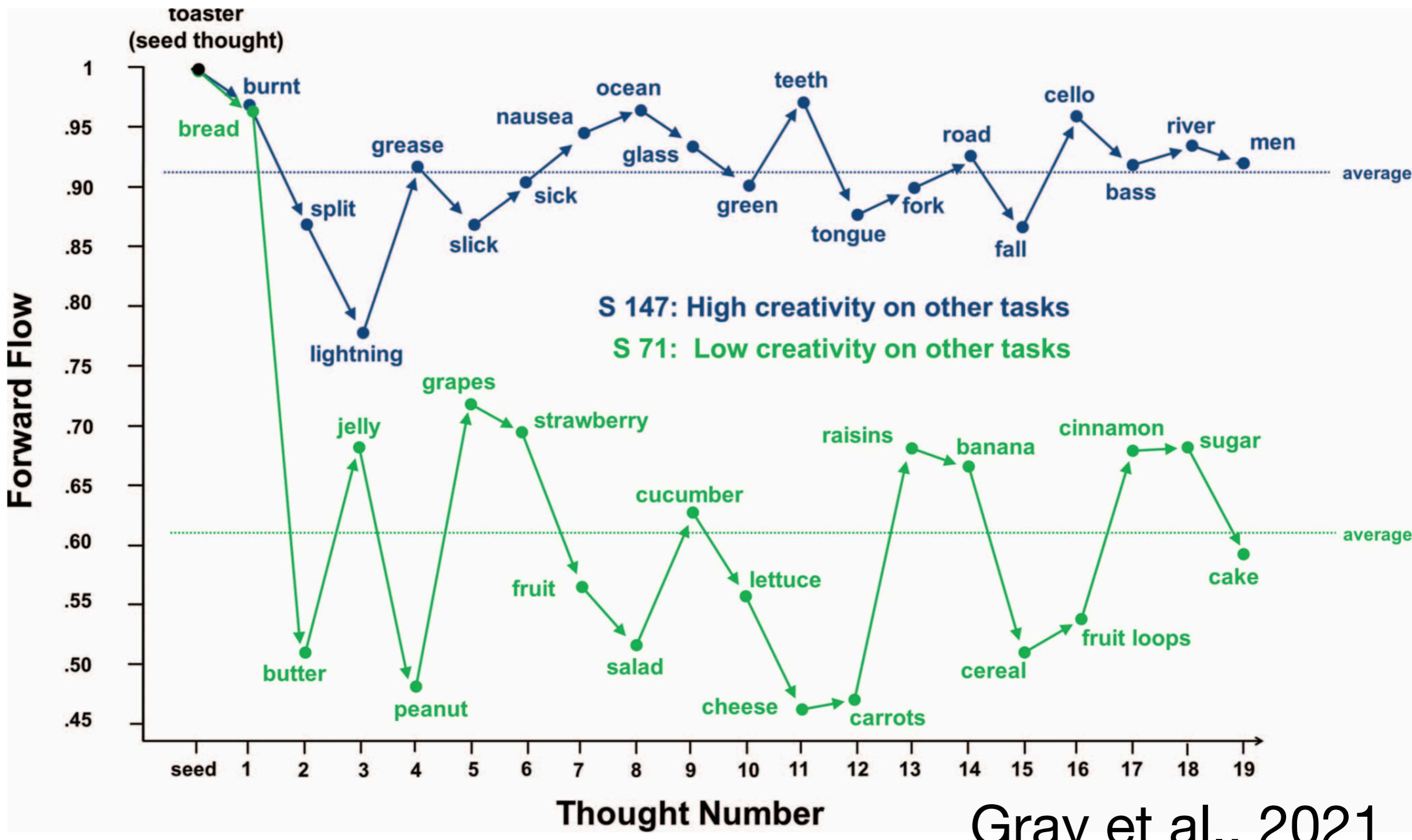
Applications of Word Similarity

<https://semantle.novalis.org/>

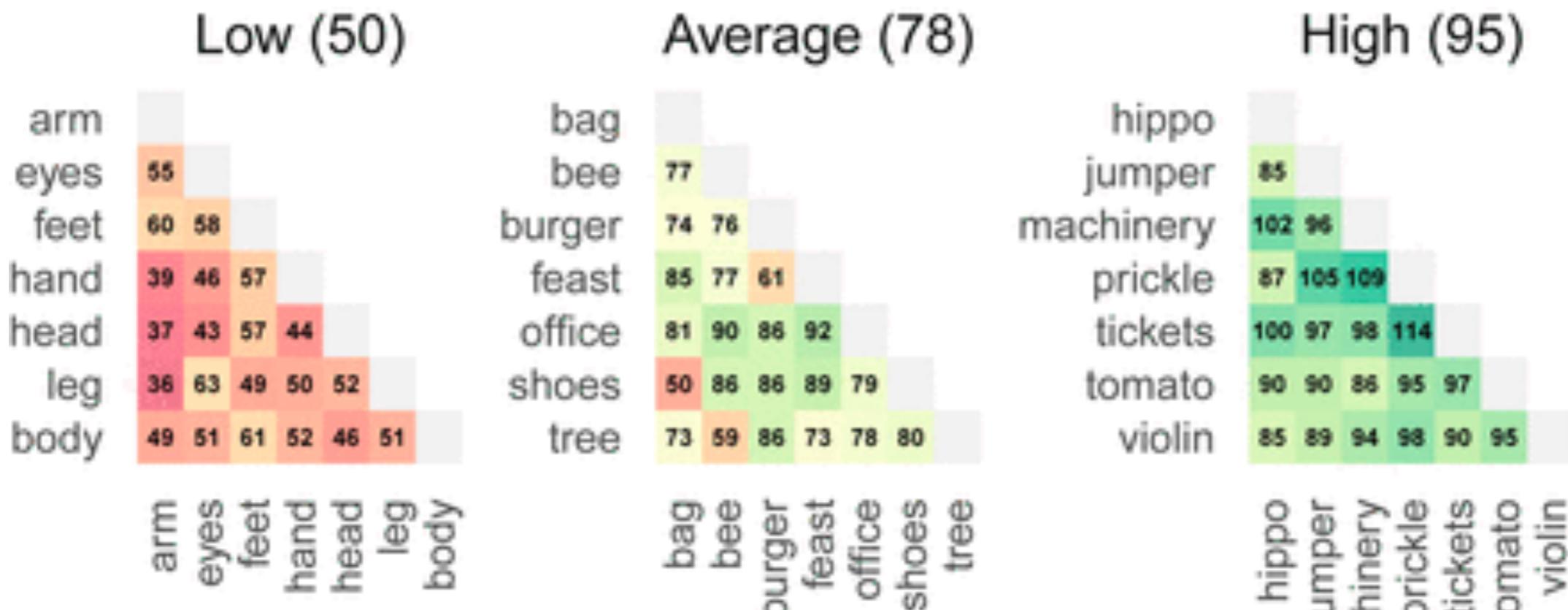
Guess the hidden word with
similarity of previous guesses



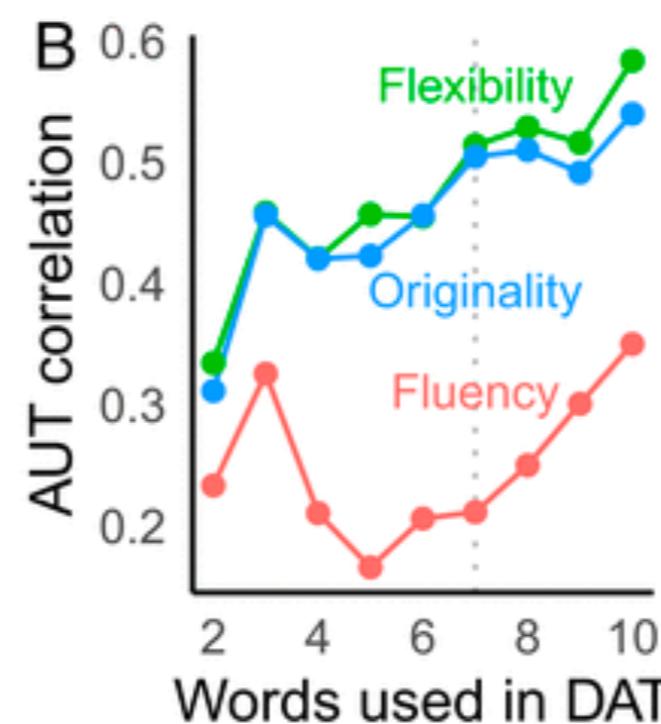
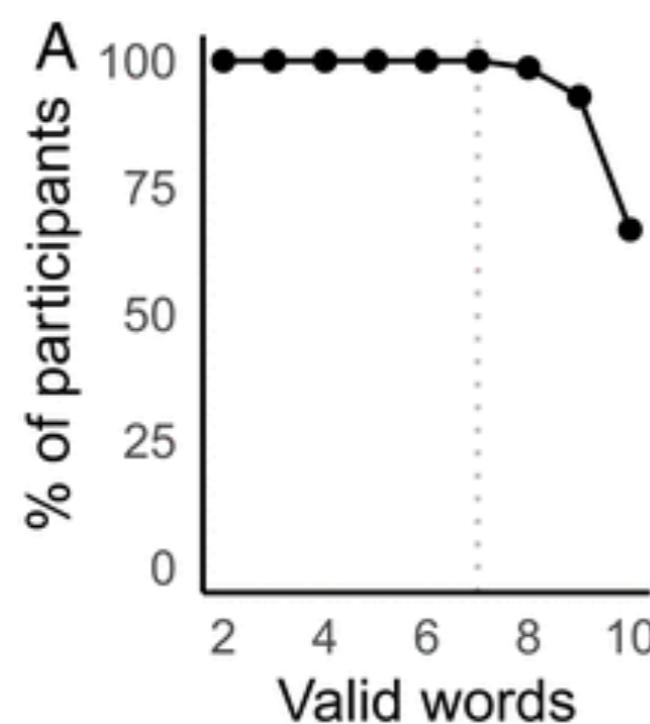
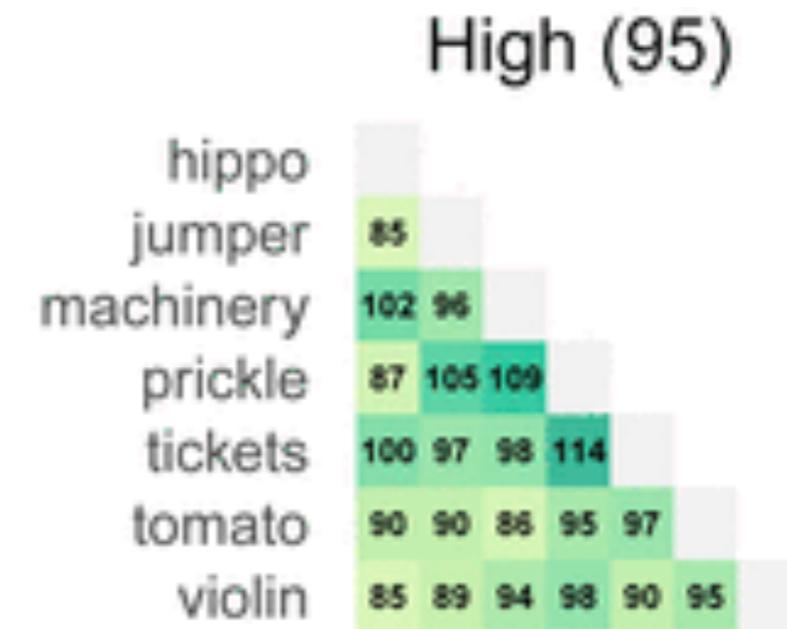
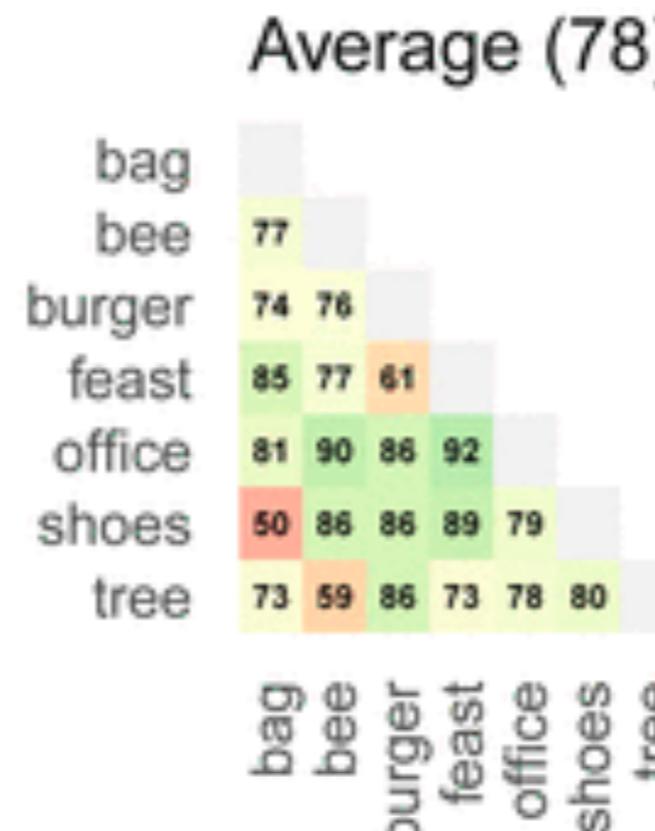
Applications of Word Similarity



Applications of Word Similarity



Applications of Word Similarity



Vector Space Model of Text

"This is bad. So bad."

"This is good"

"That is bad, very bad"

this	is	bad	good	that	very
1	1	2	0	0	0
1	1	0	1	0	0
0	1	2	0	1	1



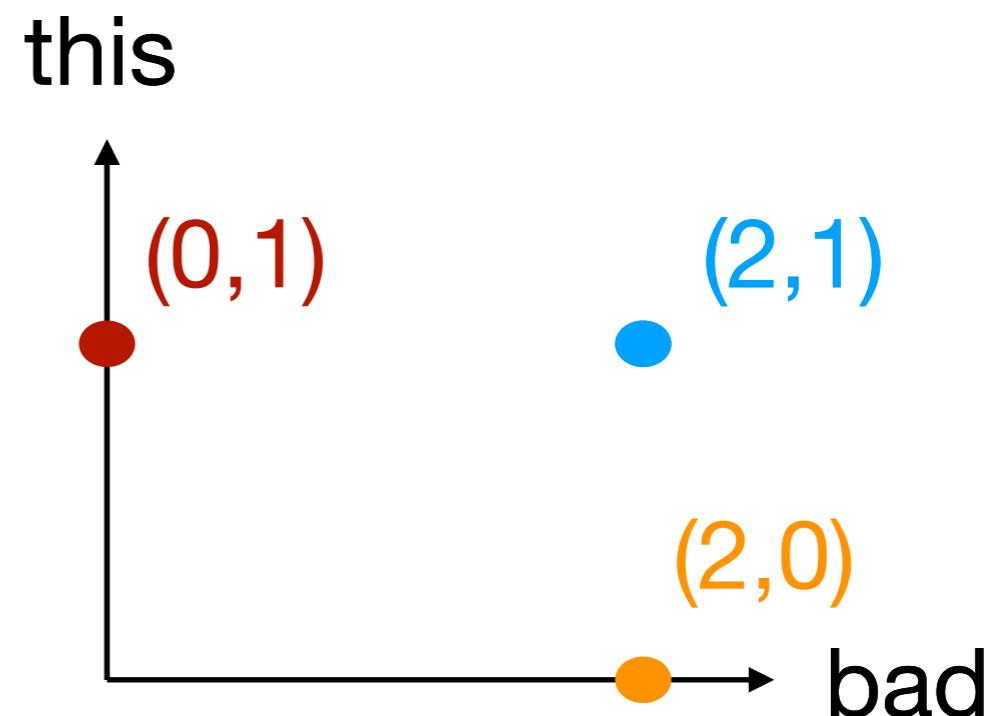
Vector Space Model of Text

"This is bad. So bad."

"This is good"

"That is bad, very bad"

this	is	bad	good	that	very
1	1	2	0	0	0
1	1	0	1	0	0
0	1	2	0	1	1



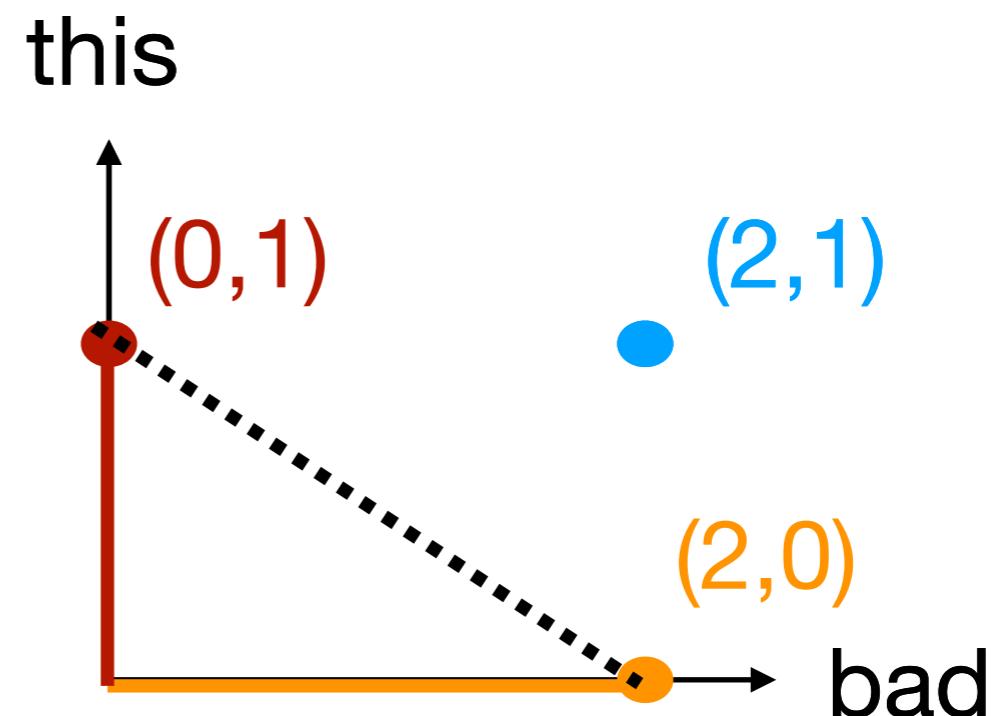
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How far is document 2 from document 3?

$$\text{Euclidian Distance } (d_2, d_3) = \sqrt{(0-2)^2 + (1-0)^2}$$

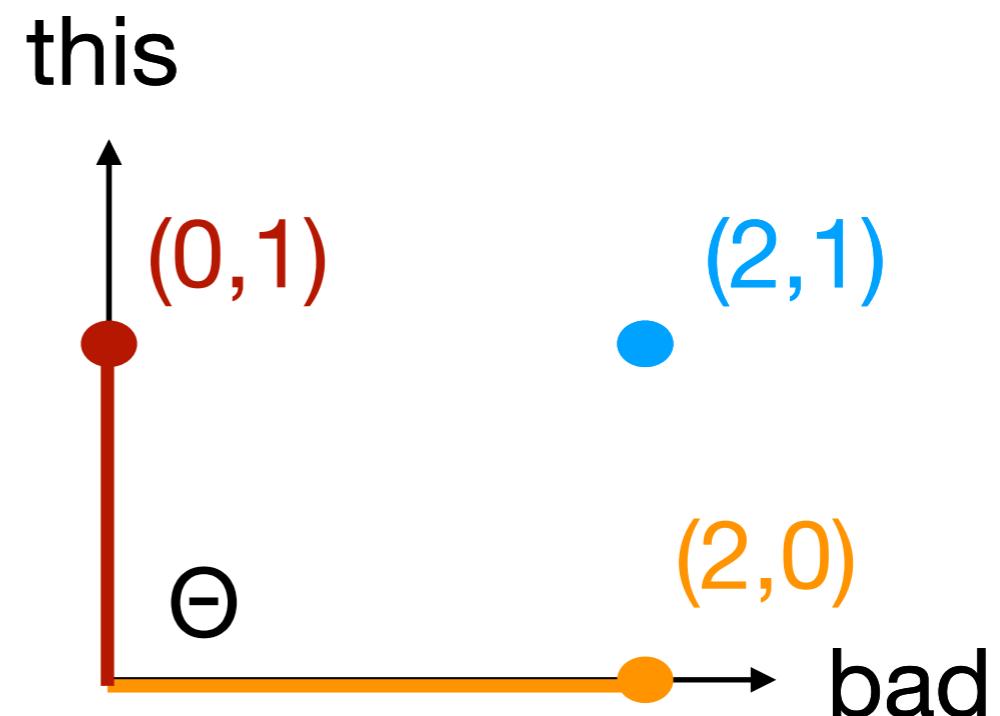
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How far is document 2 from document 3?

Euclidian Distance $(d_2, d_3) = \sqrt{(0-2)^2 + (1-0)^2}$

Cosine Distance $(d_2, d_3) = \cos(\Theta) = (d_2 \cdot d_3) / \|d_2\| * \|d_3\|$

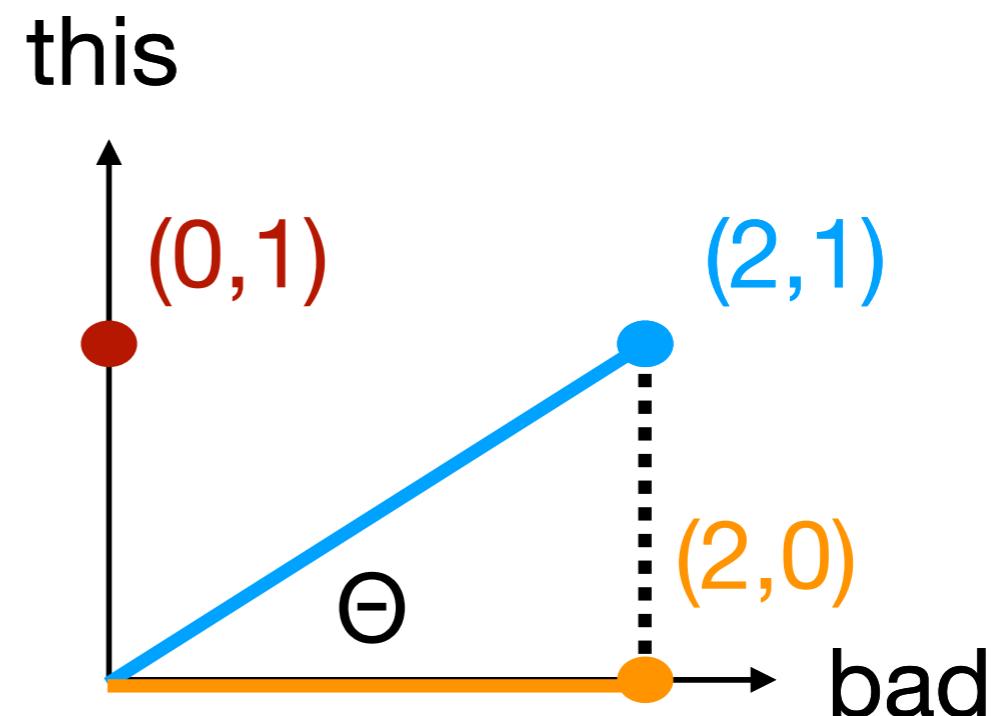
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1	1	2	0	0	0
1	1	0	1	0	0
0	1	2	0	1	1



How far is document 1 from document 3?

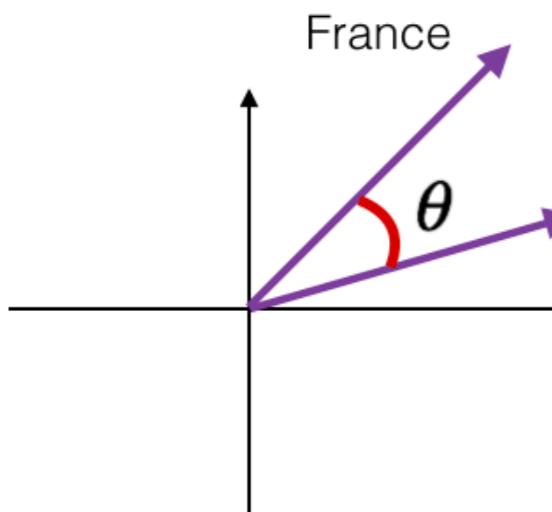
Euclidian Distance $(d_1, d_3) = \sqrt{(2-2)^2 + (1-0)^2}$

Cosine Distance $(d_1, d_3) = \cos(\Theta) = (d_1 \cdot d_3) / \|d_1\| * \|d_3\|$

Vector Space Model of Text

Cosine similarity

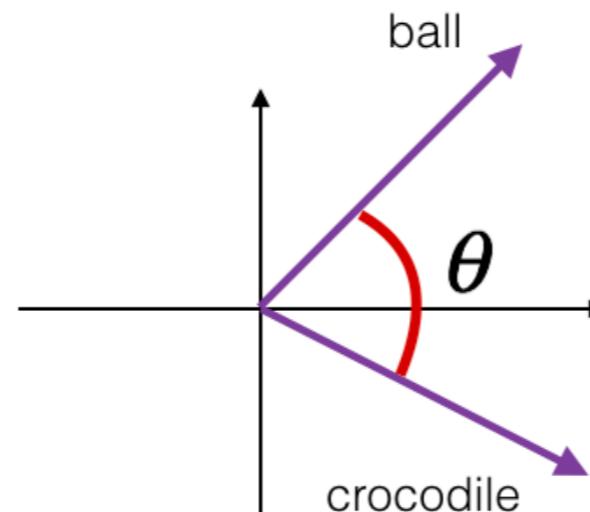
Indifferent to document length



France and Italy are quite similar

θ is close to 0°

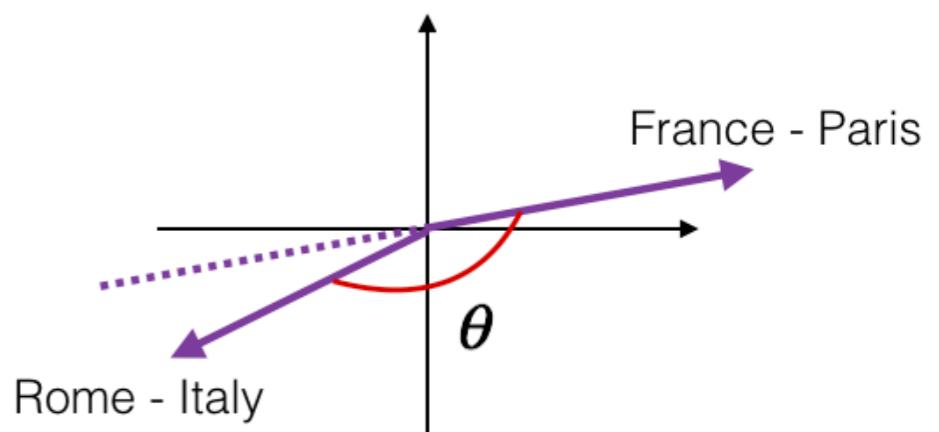
$$\cos(\theta) \approx 1$$



ball and crocodile are not similar

θ is close to 90°

$$\cos(\theta) \approx 0$$



the two vectors are similar but opposite
the first one encodes (city - country)
while the second one encodes (country - city)

θ is close to 180°

$$\cos(\theta) \approx -1$$

Embedding Models

Calculating similarity

Consider three sentences

“I am very sad”, “I am very happy”, “I am thrilled”

Which of the first two is more similar to the third?

Embedding Models

Calculating similarity

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“I am very sad”, “I am very happy”, “I am thrilled”

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According to
bag of words

Embedding Models

Calculating similarity

Consider three sentences

“I am very sad”, “I am very happy”, “I am thrilled”

Which of the first two is more similar to the third?

According to
bag of words

	i	am	veri	sad	happi	thrill
text1	1	1	1	1	0	0
text2	1	1	1	0	1	0
text3	1	1	0	0	0	1

Embedding Models

Calculating similarity

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text2	1	1	1	0	1	0
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$$\cos(t_1, t_3) = .57$$
$$\cos(t_2, t_3) = .57$$

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According to
word2vec

Embedding Models

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$$\cos(t_2, t_3) = .57$$

According to
word2vec

	vec1	vec2	vec3	vec4	vec5	vec6
text1	-0.52	-0.49	-0.70	-0.02	0.11	0.37
text2	-0.40	-0.86	-0.40	0.32	0.01	0.40
text3	-0.46	-0.85	-0.35	0.33	-0.13	0.57

Embedding Models

Calculating similarity

Consider three sentences

“I am very sad”, “I am very happy”, “I am thrilled”

Which of the first two is more similar to the third?

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bag of words

	i	am	veri	sad	happi	thrill
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text2	-0.40	-0.86	-0.40	0.32	0.01	0.40
text3	-0.46	-0.85	-0.35	0.33	-0.13	0.57

$$\cos(t_1, t_3) = .81$$
$$\cos(t_2, t_3) = .87$$

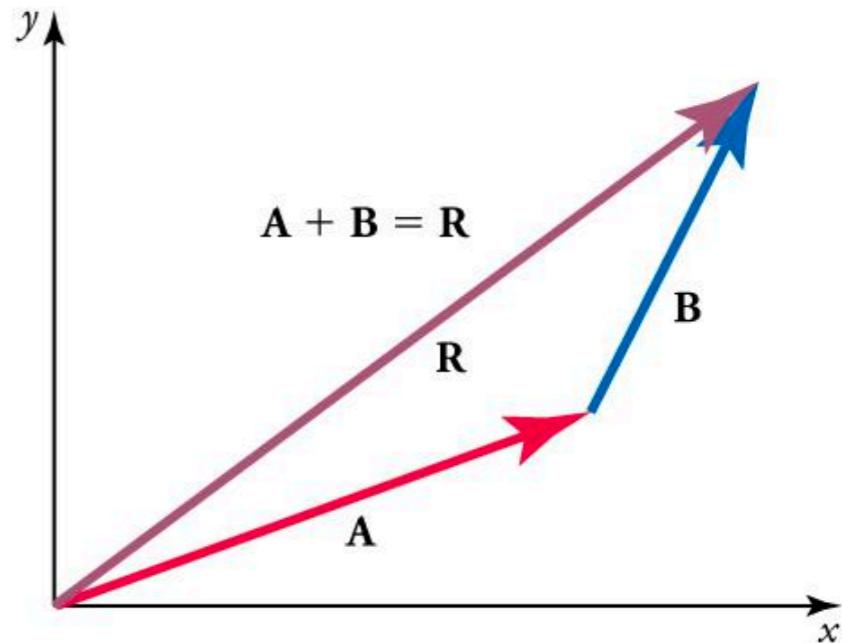
Sentence Embeddings

Simple

Sentence Embeddings

Simple

Add up the vectors of individual words



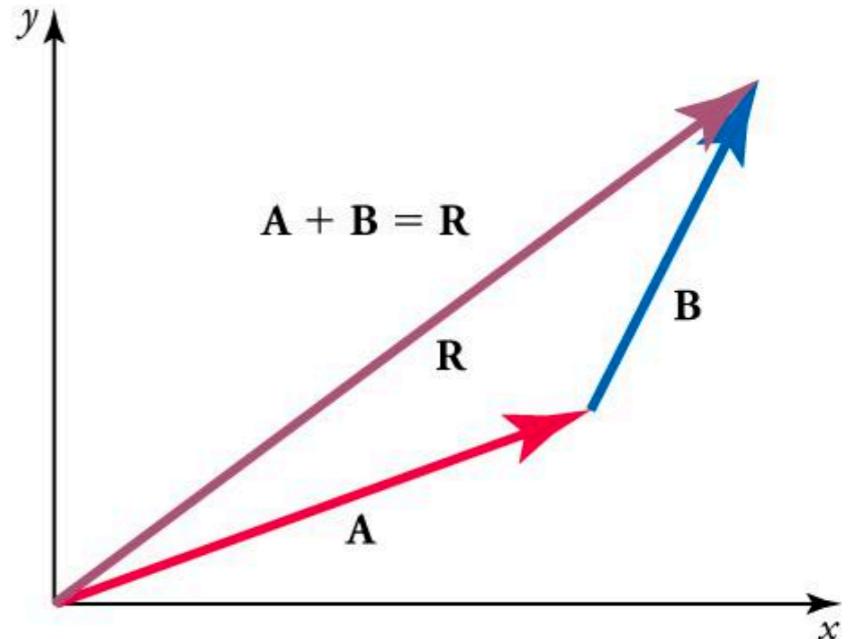
(Arora et al., 2017)

Sentence Embeddings

Simple

Add up the vectors of individual words

How to combine?
-Unweighted average



(Arora et al., 2017)

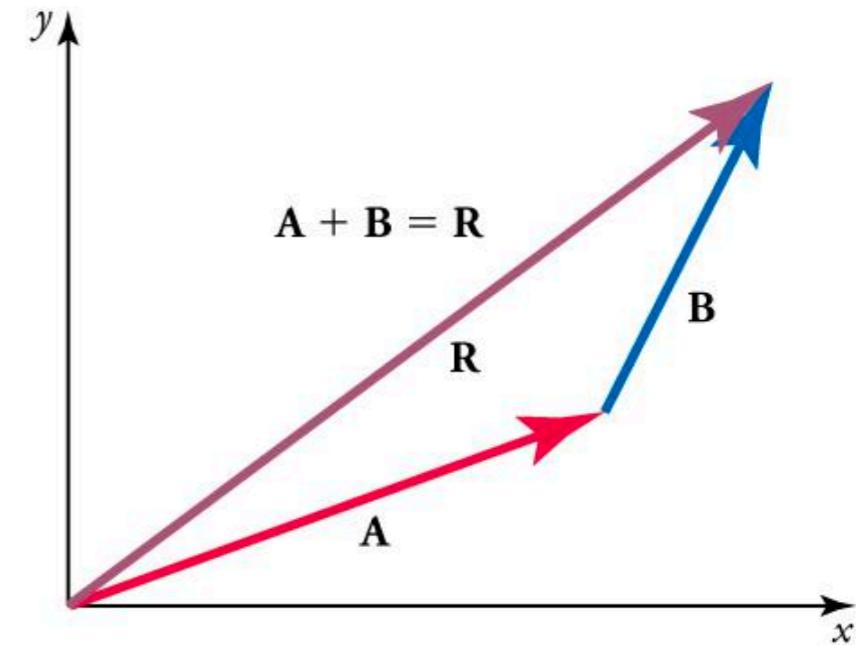
Sentence Embeddings

Simple

Add up the vectors of individual words

How to combine?
-Unweighted average

-Weight by inverse word frequency
contextual/universal frequency



(Arora et al., 2017)

Sentence Embeddings

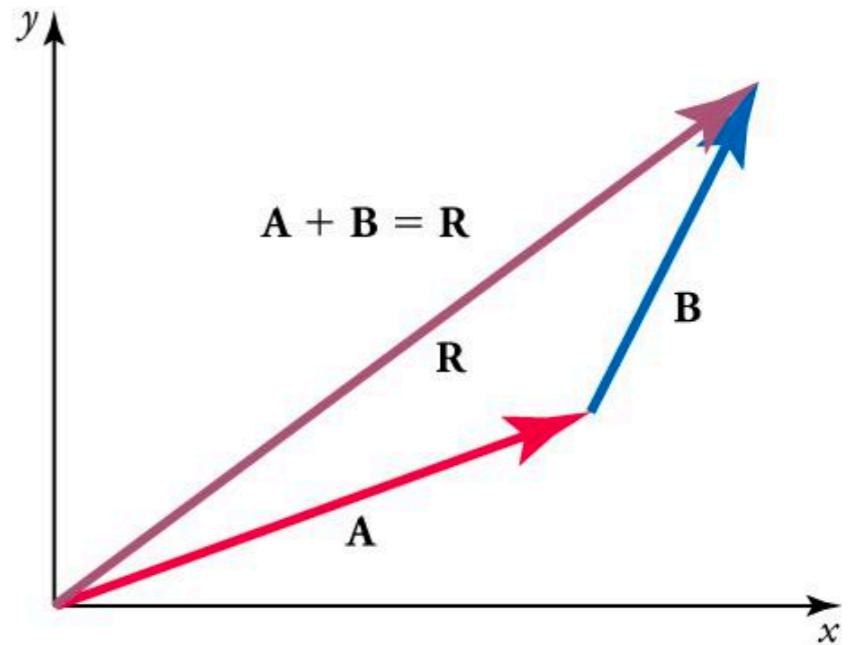
Simple

Add up the vectors of individual words

How to combine?
-Unweighted average

-Weight by inverse word frequency
contextual/universal frequency

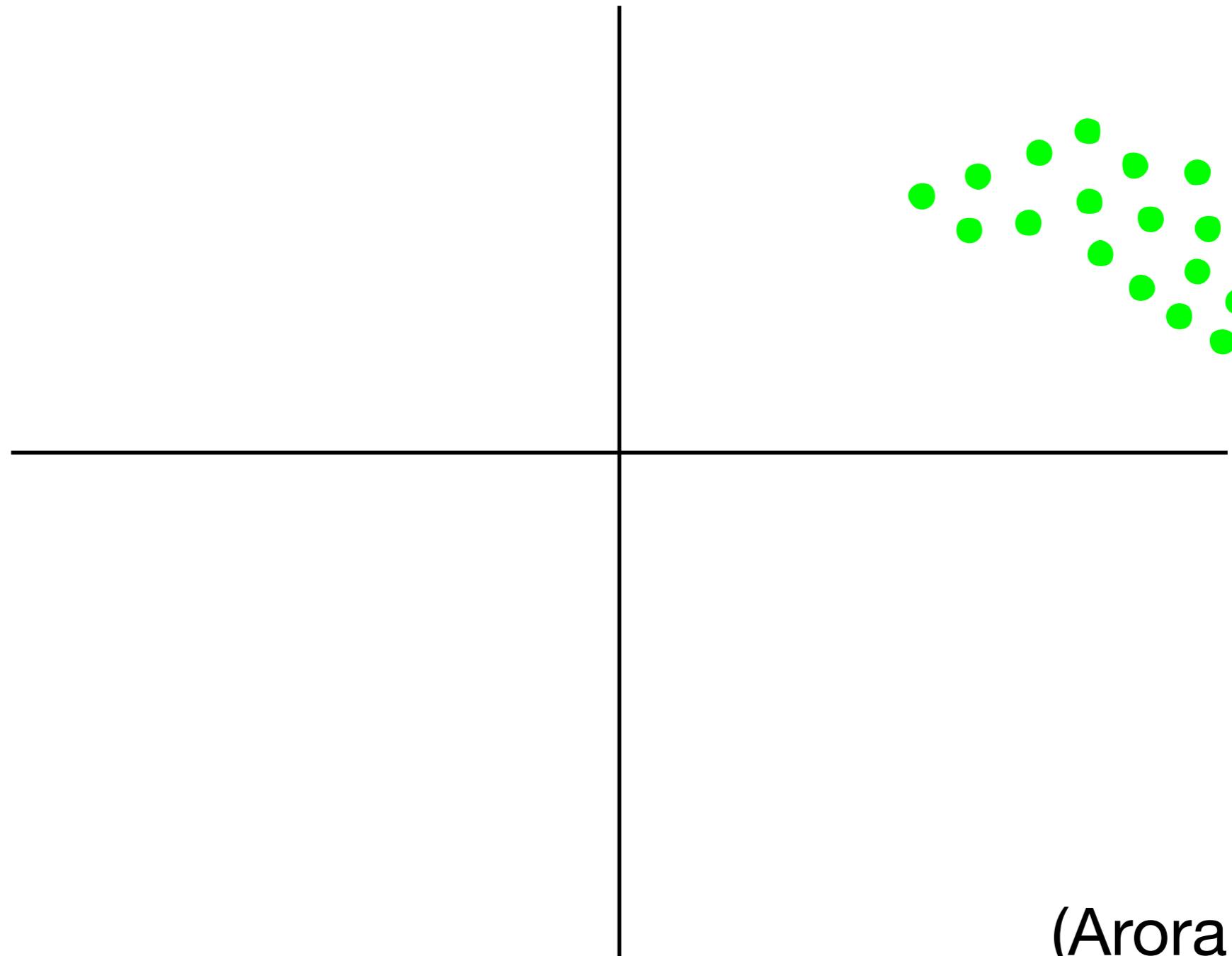
- Remove first principal component
(driven by in-context topics)



(Arora et al., 2017)

Sentence Embeddings

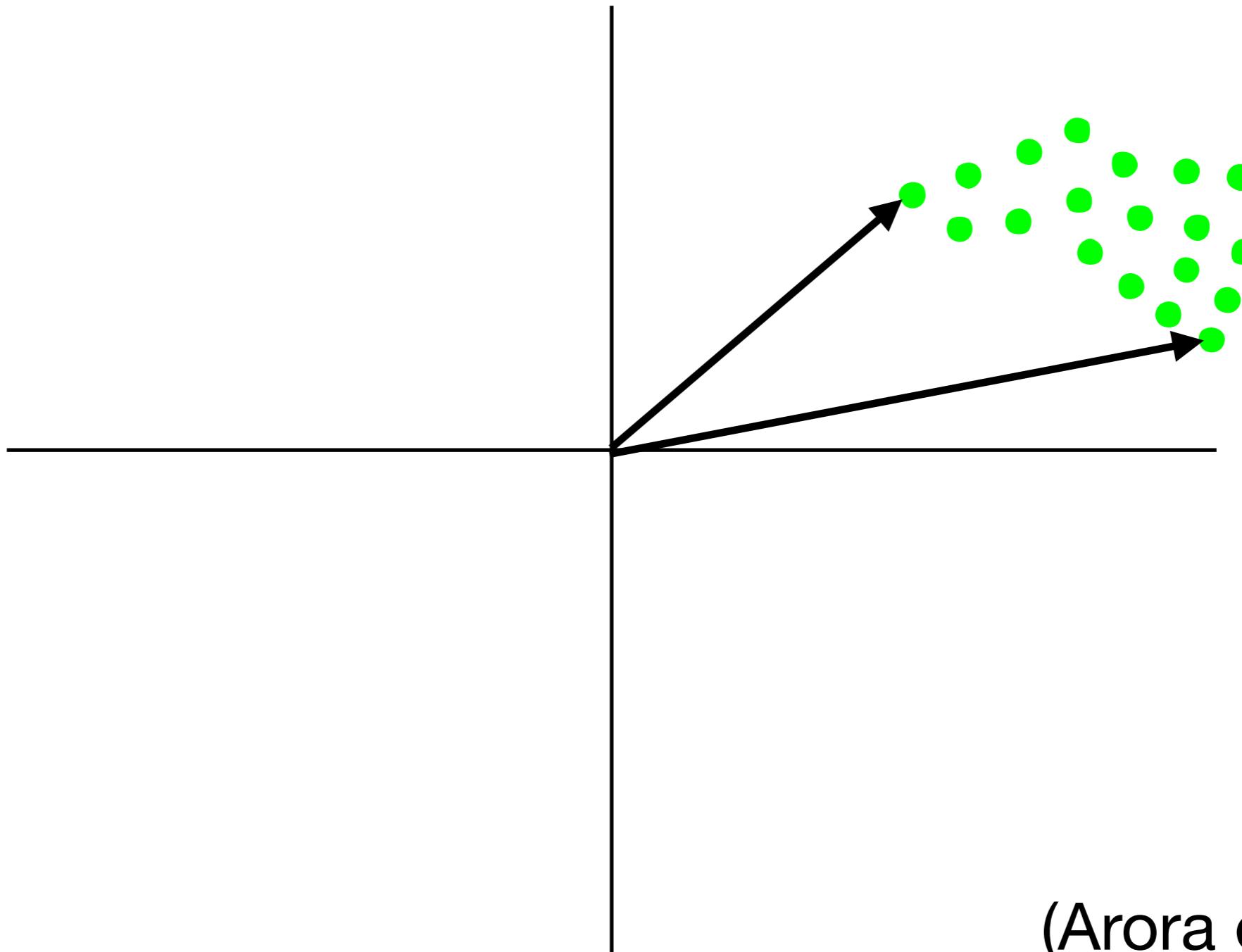
- Remove first principal component
(driven by in-context topics)



(Arora et al., 2017)

Sentence Embeddings

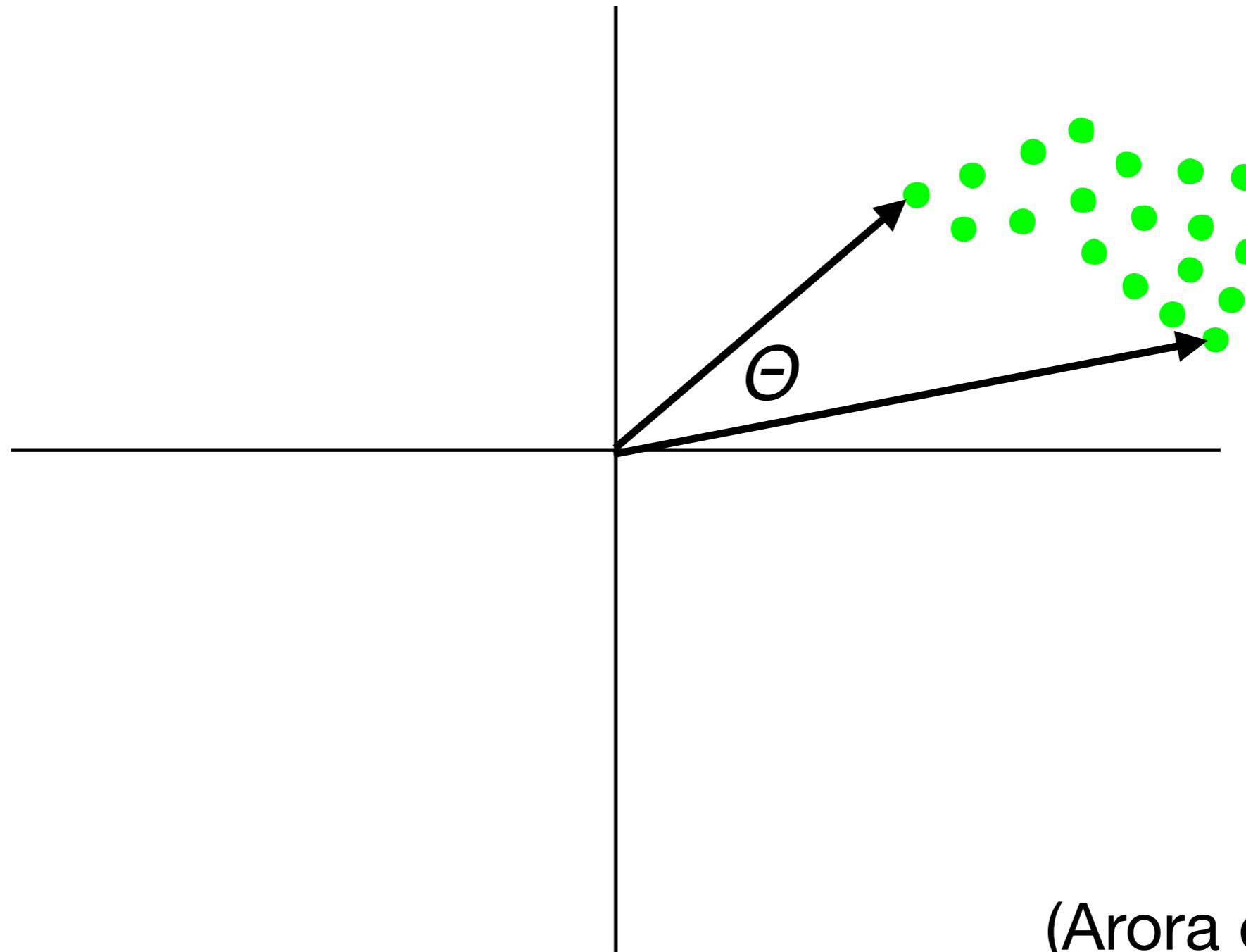
- Remove first principal component
(driven by in-context topics)



(Arora et al., 2017)

Sentence Embeddings

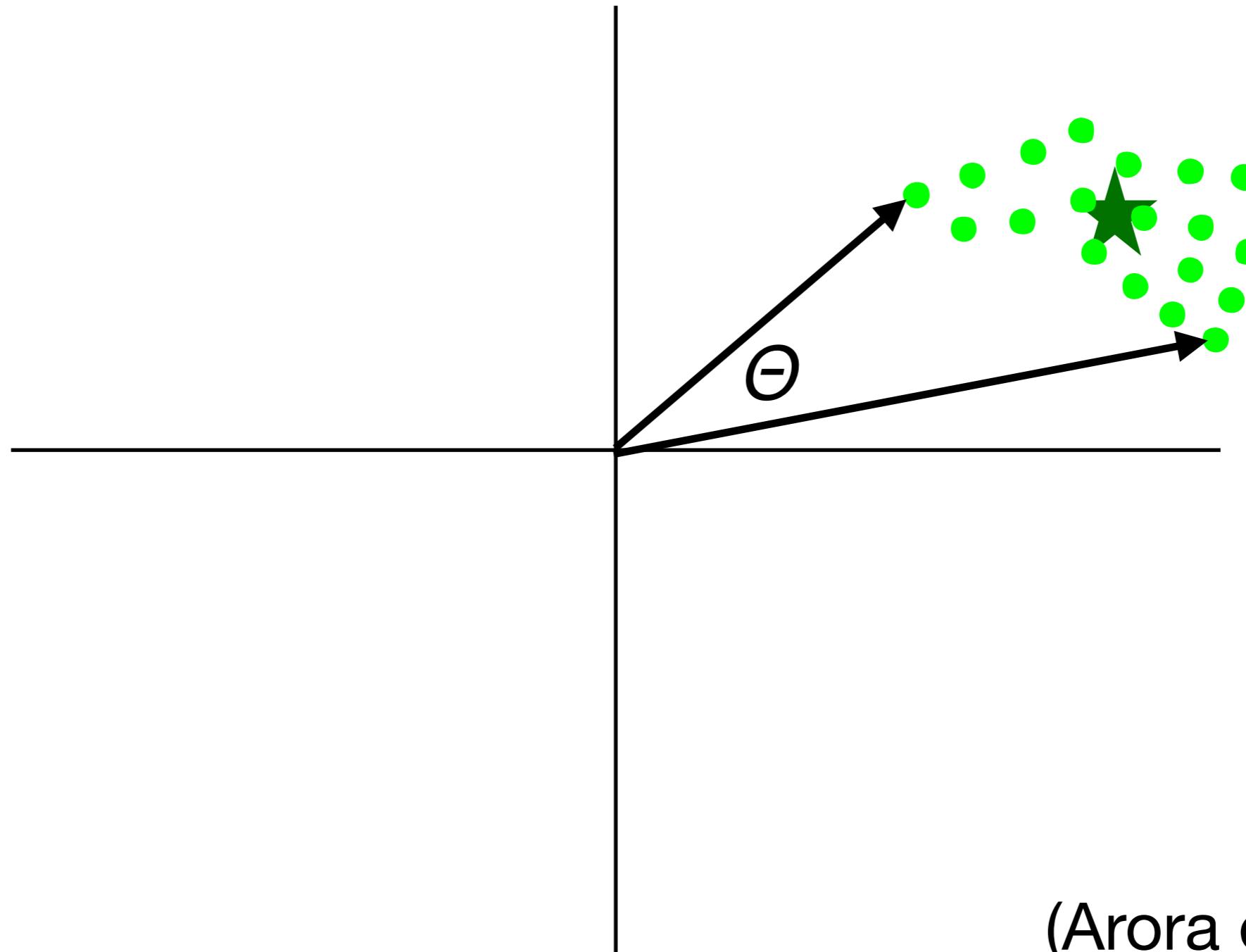
- Remove first principal component
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(Arora et al., 2017)

Sentence Embeddings

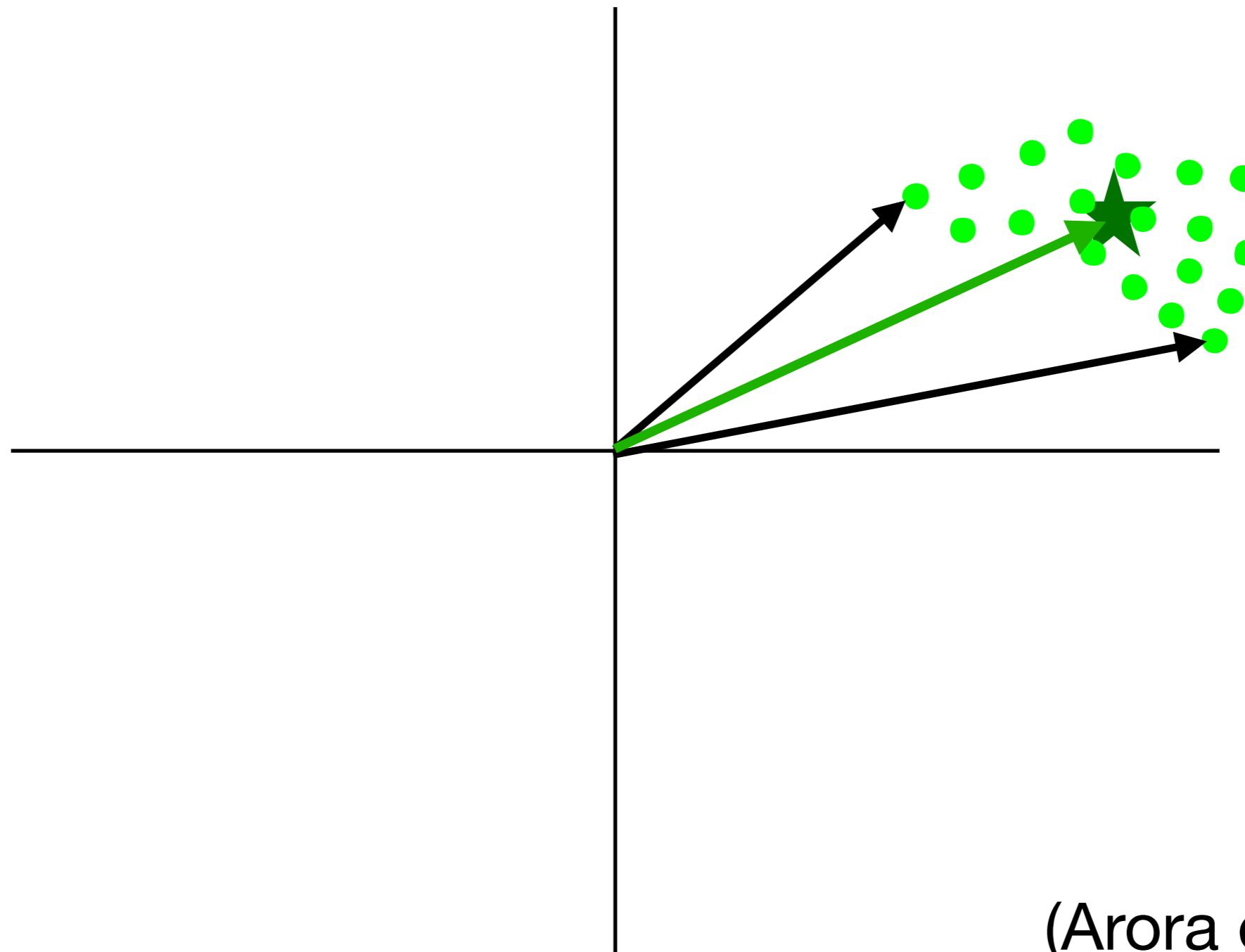
- Remove first principal component
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(Arora et al., 2017)

Sentence Embeddings

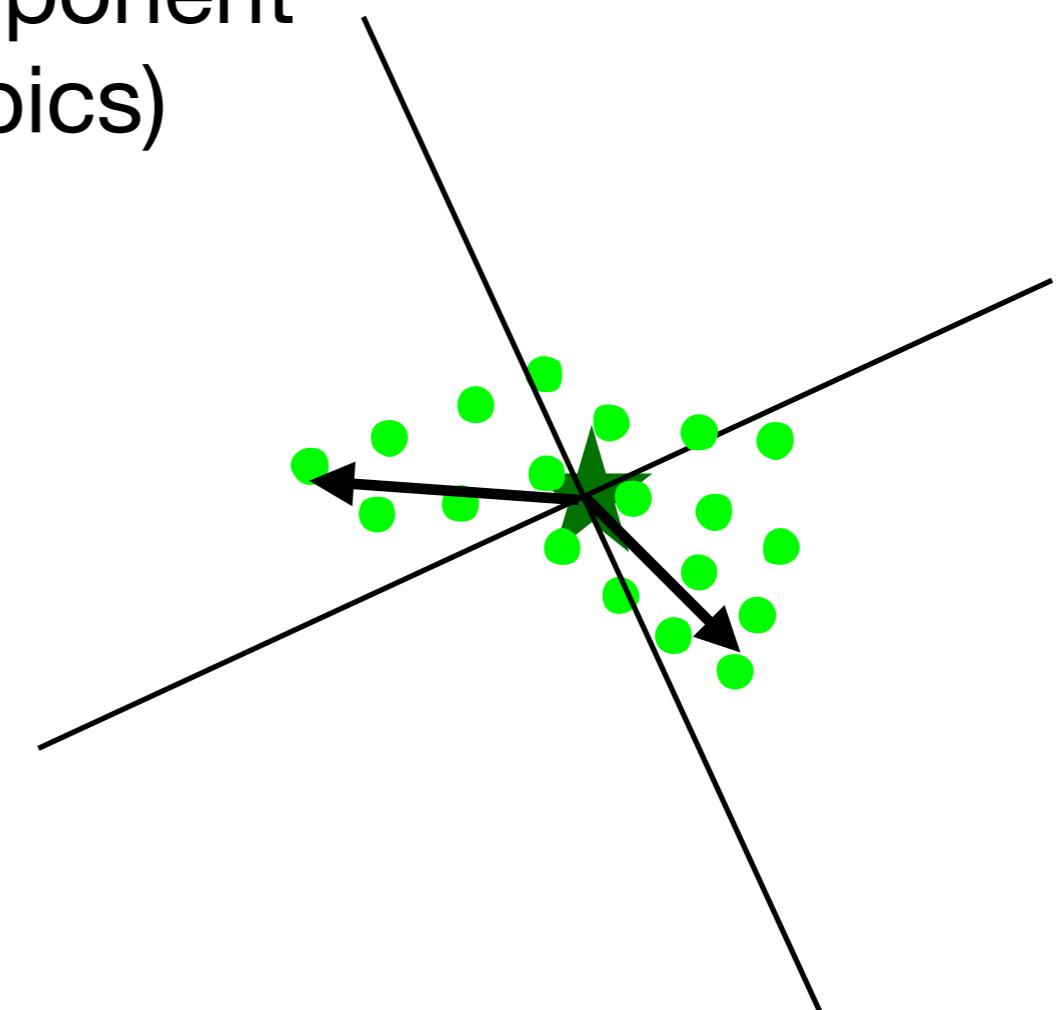
- Remove first principal component
(driven by in-context topics)



(Arora et al., 2017)

Sentence Embeddings

- Remove first principal component
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(Arora et al., 2017)

Sentence Embeddings

More complex

Train embeddings for whole sentences
(BERT, GPT-2, etc.)

Sentence Embeddings

More complex

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Many more layers, and attention to whole sentence

Sentence Embeddings

More complex

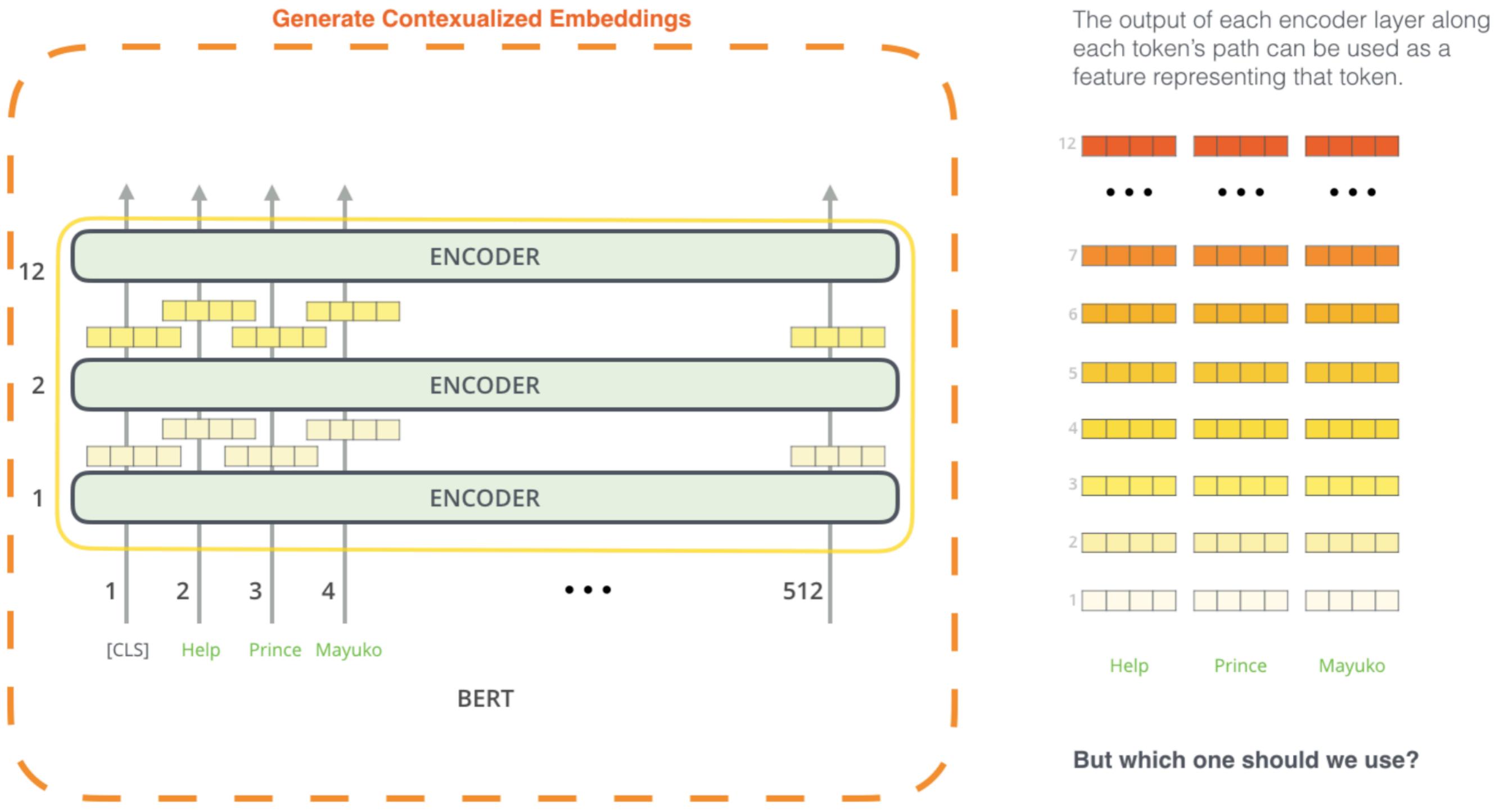
Train embeddings for whole sentences
(BERT, GPT-2, etc.)

Many more layers, and attention to whole sentence

Two objectives:

- Masked word prediction
- Two-sentence pairs: does one follow the other?

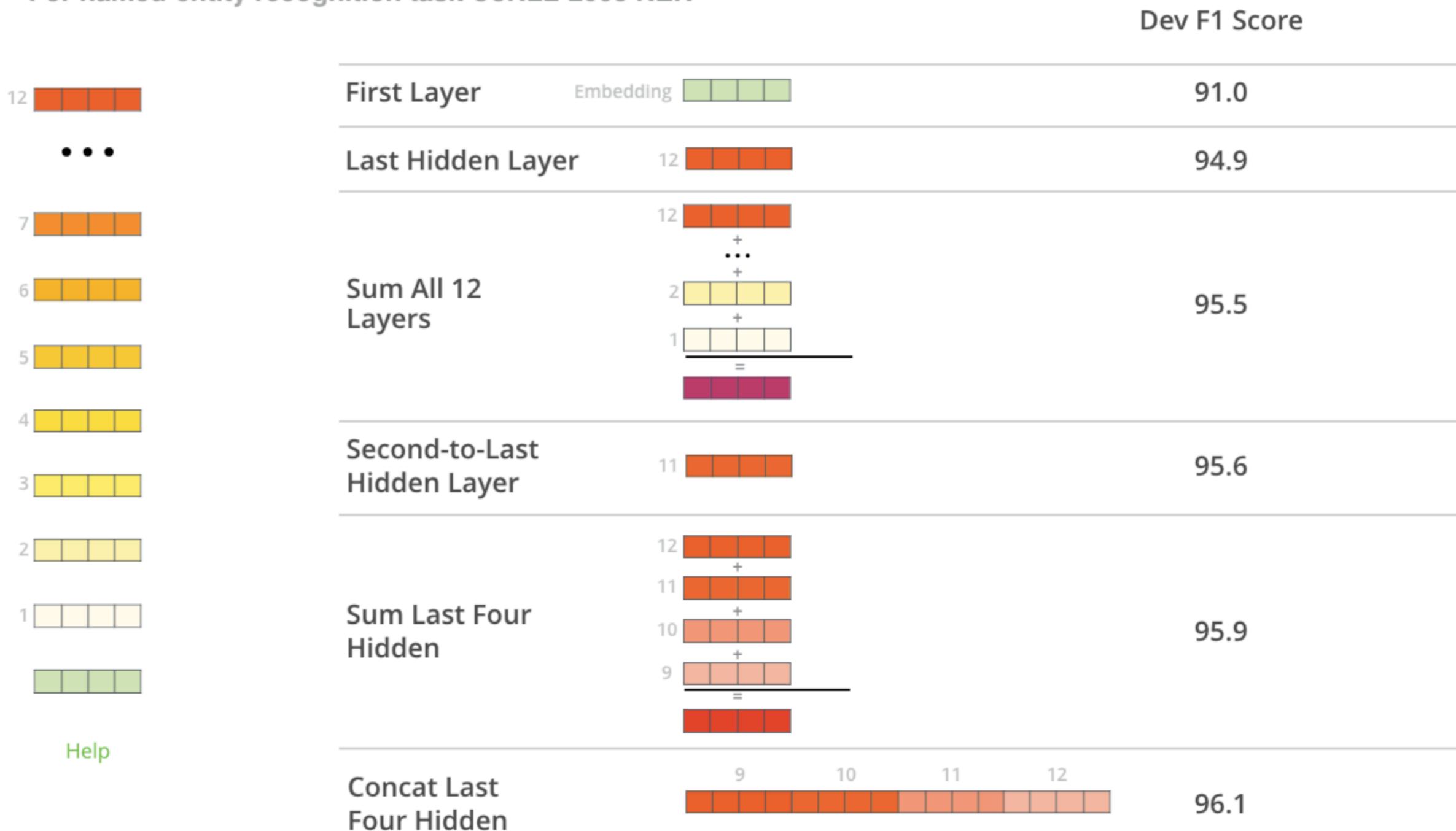
Sentence Embeddings



Sentence Embeddings

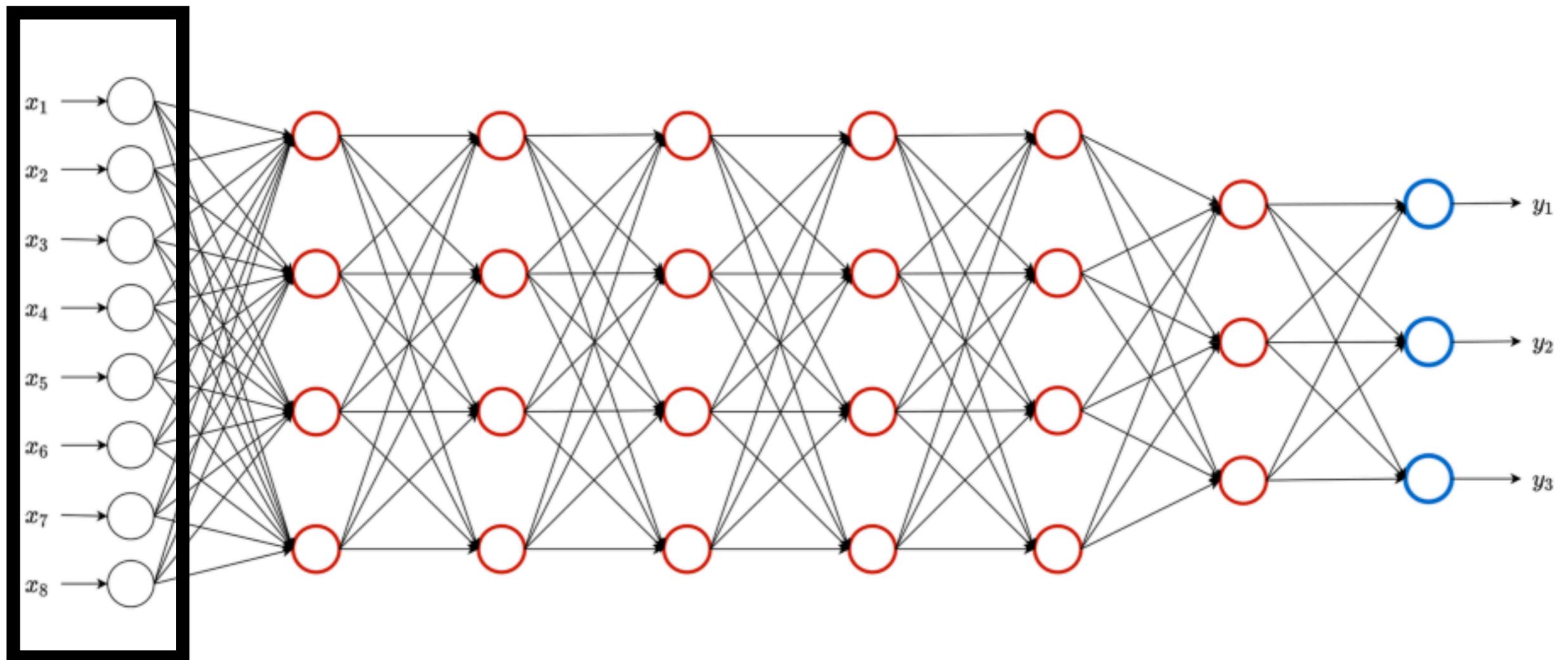
What is the best contextualized embedding for “**Help**” in that context?

For named-entity recognition task CoNLL-2003 NER



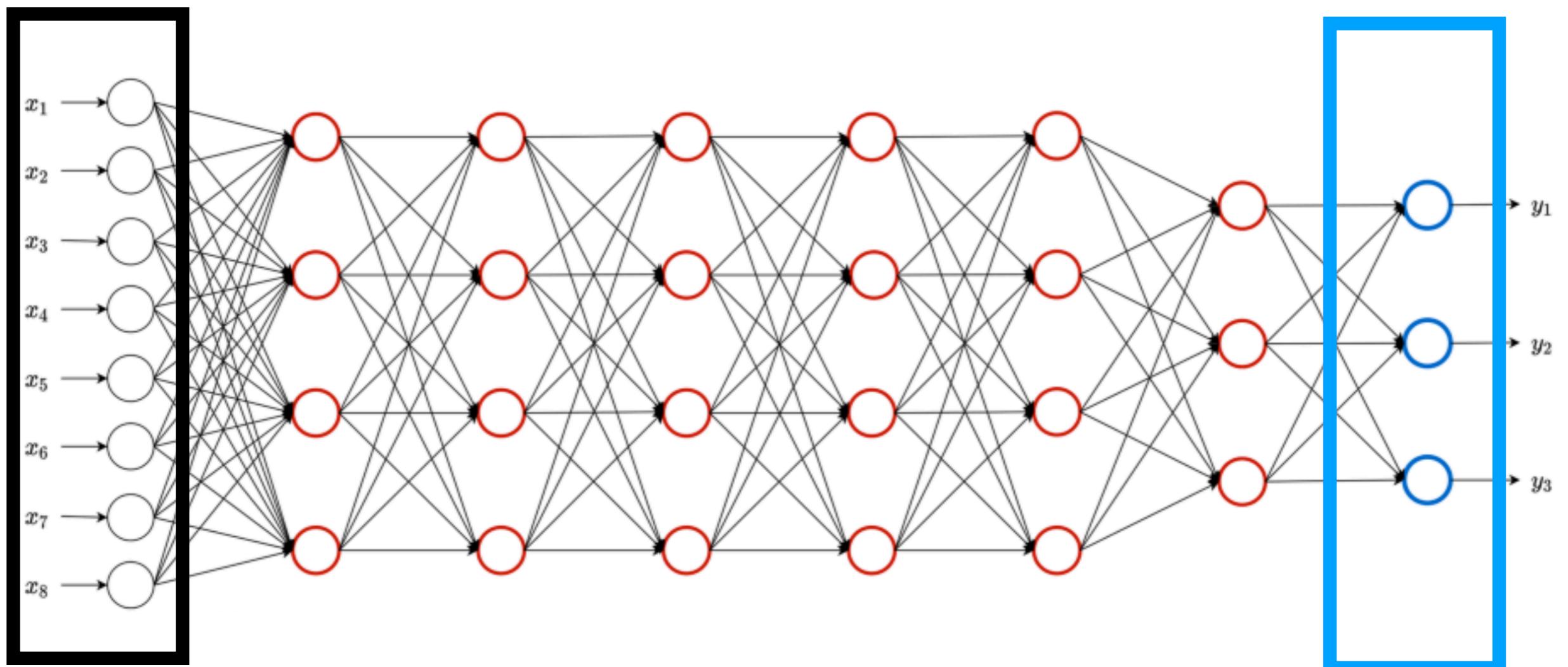
Pre-Trained Models

**Words in
documents**



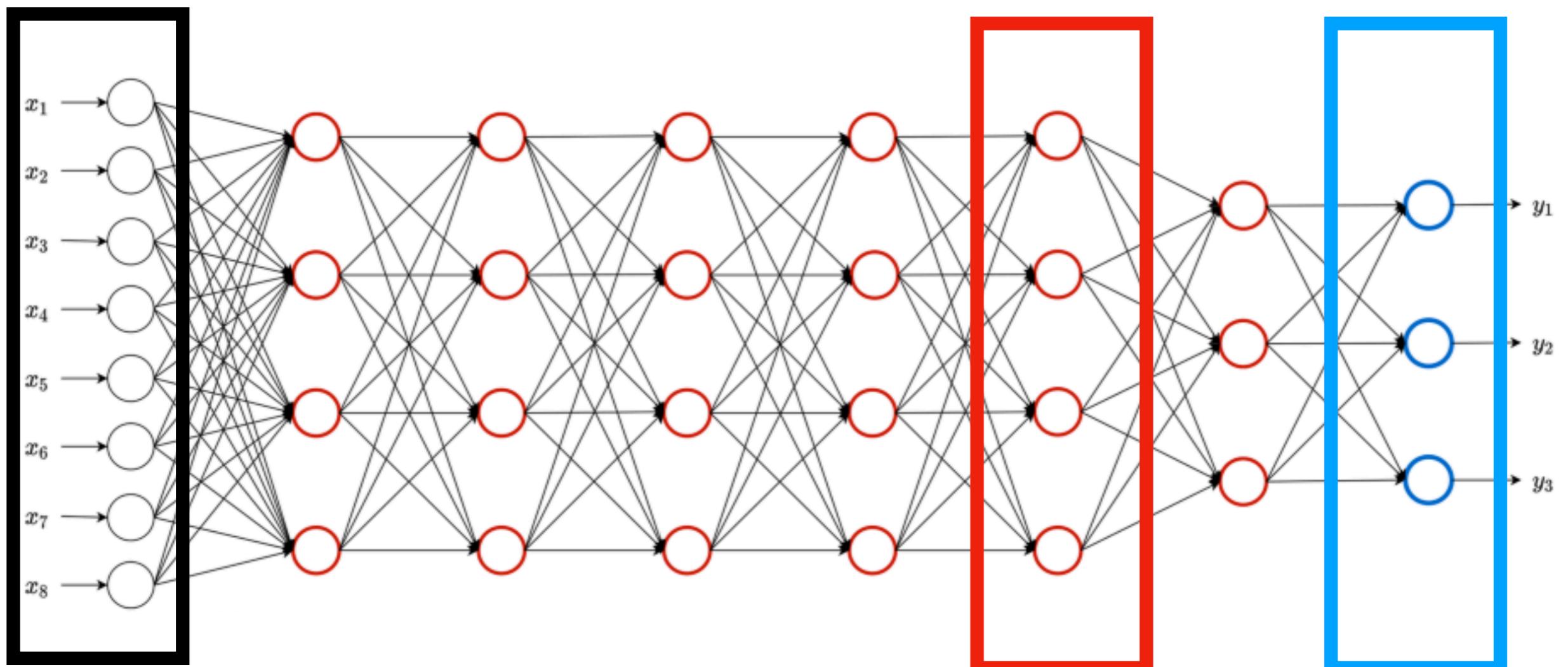
Pre-Trained Models

**Masked word
Prediction**



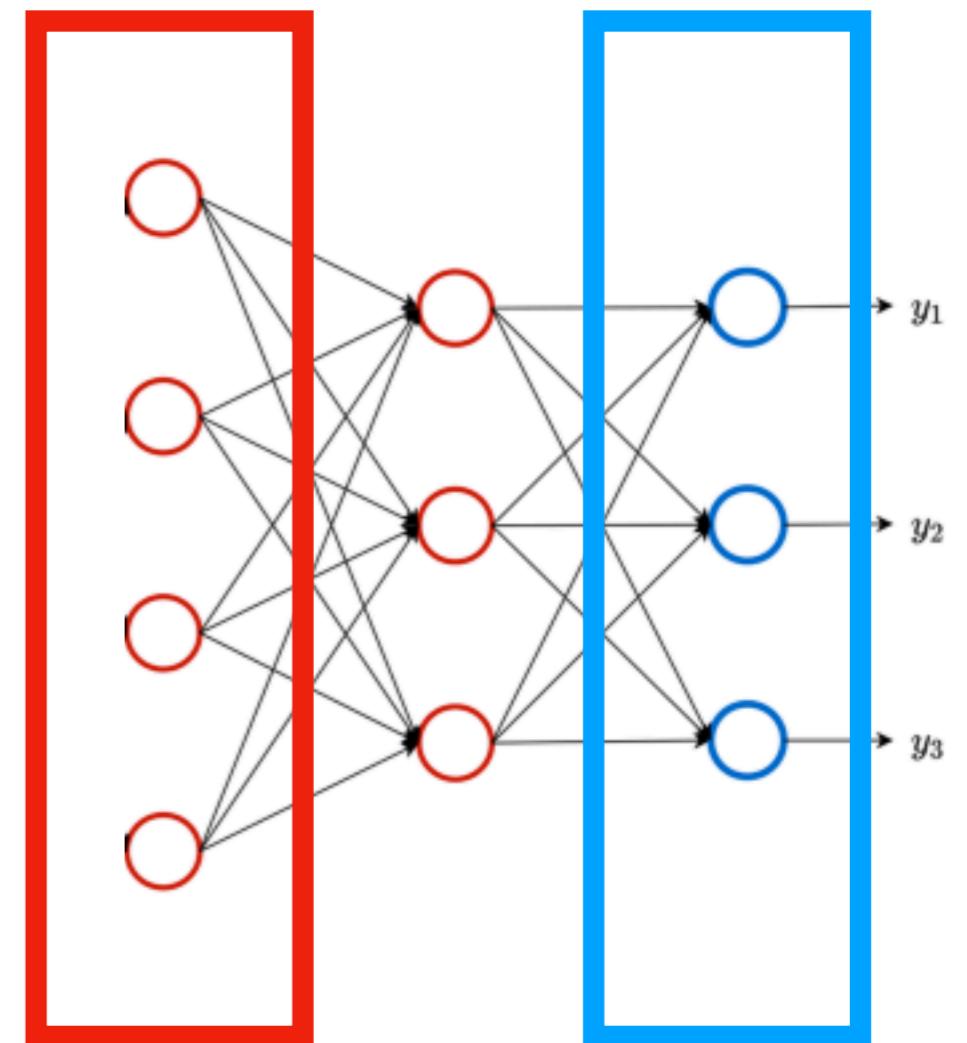
Pre-Trained Models

**The vector
representation**



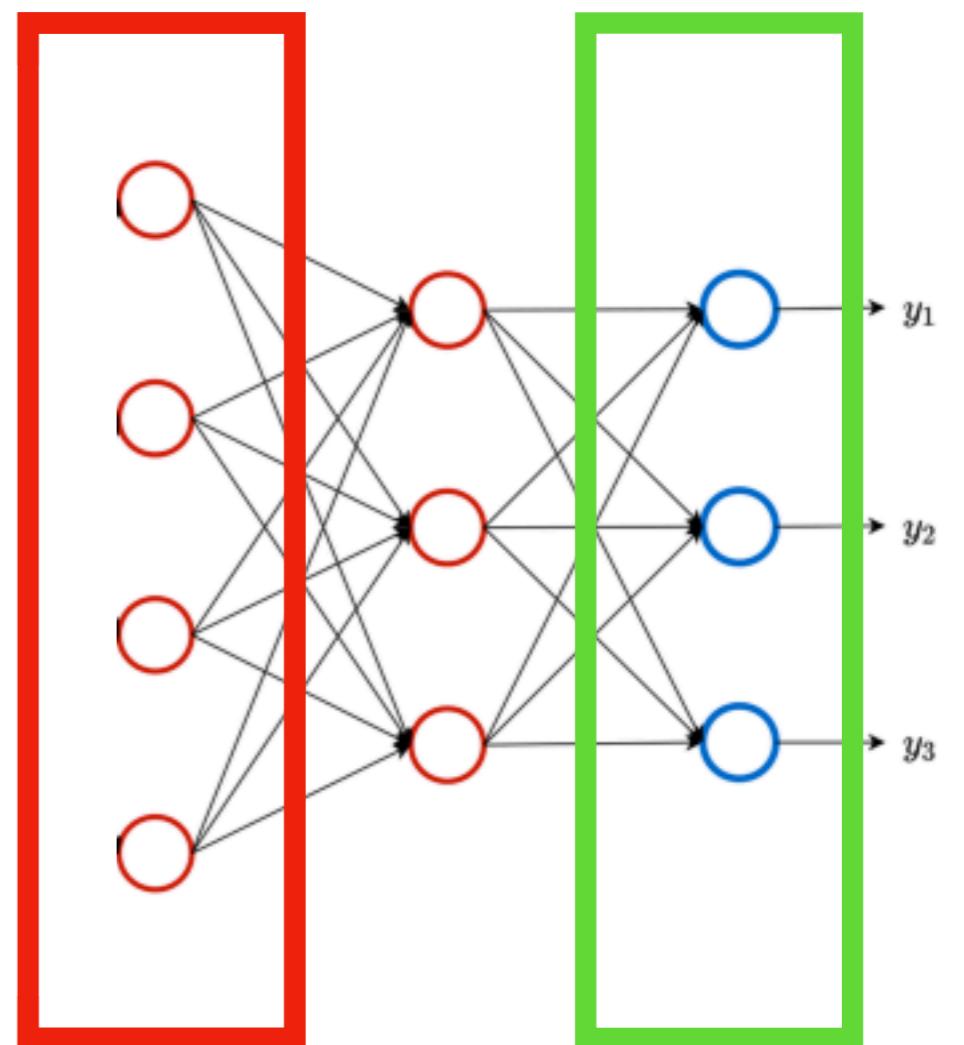
Pre-Trained Models

**The vector
representation**

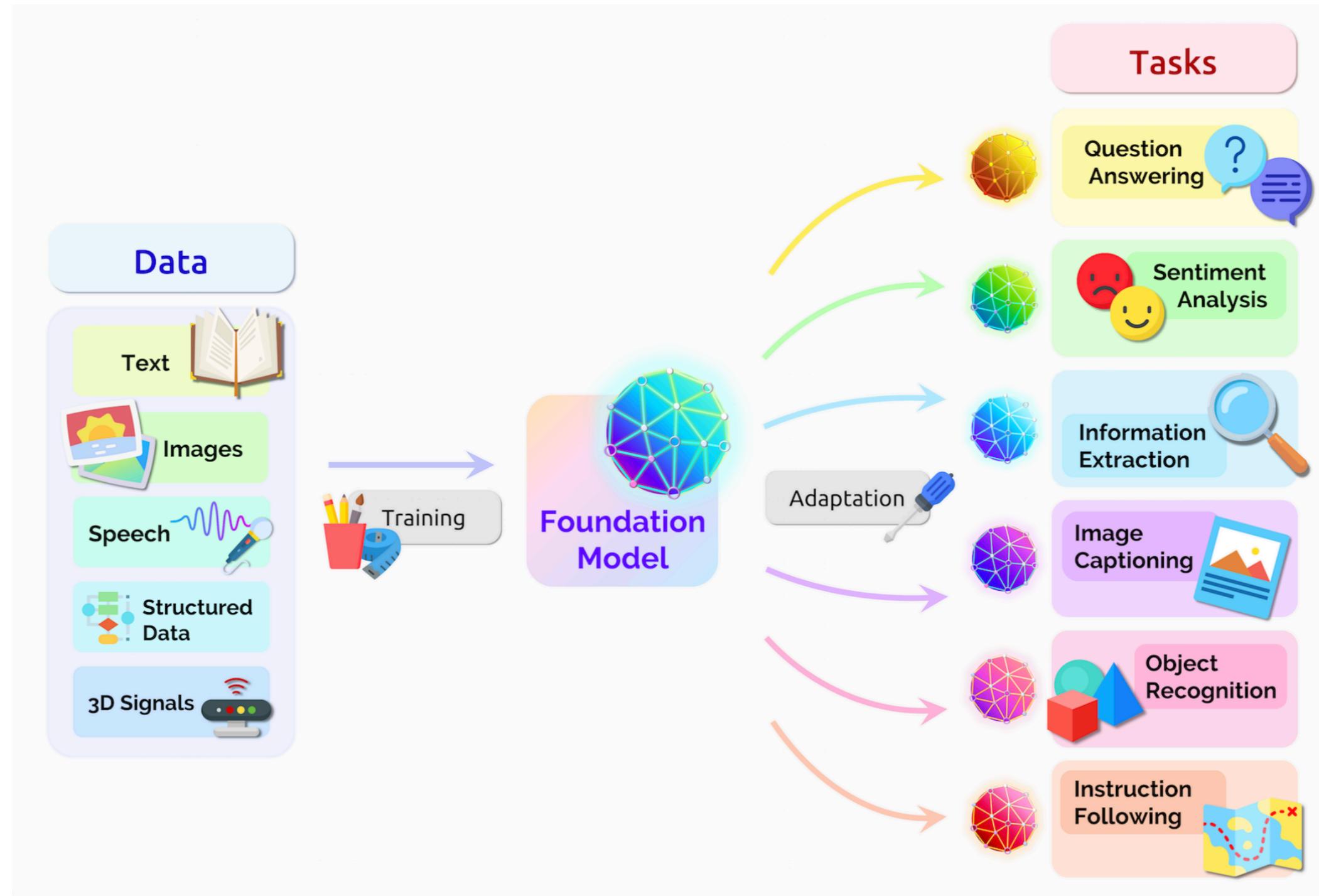


Pre-Trained Models

**New quantity
of interest**

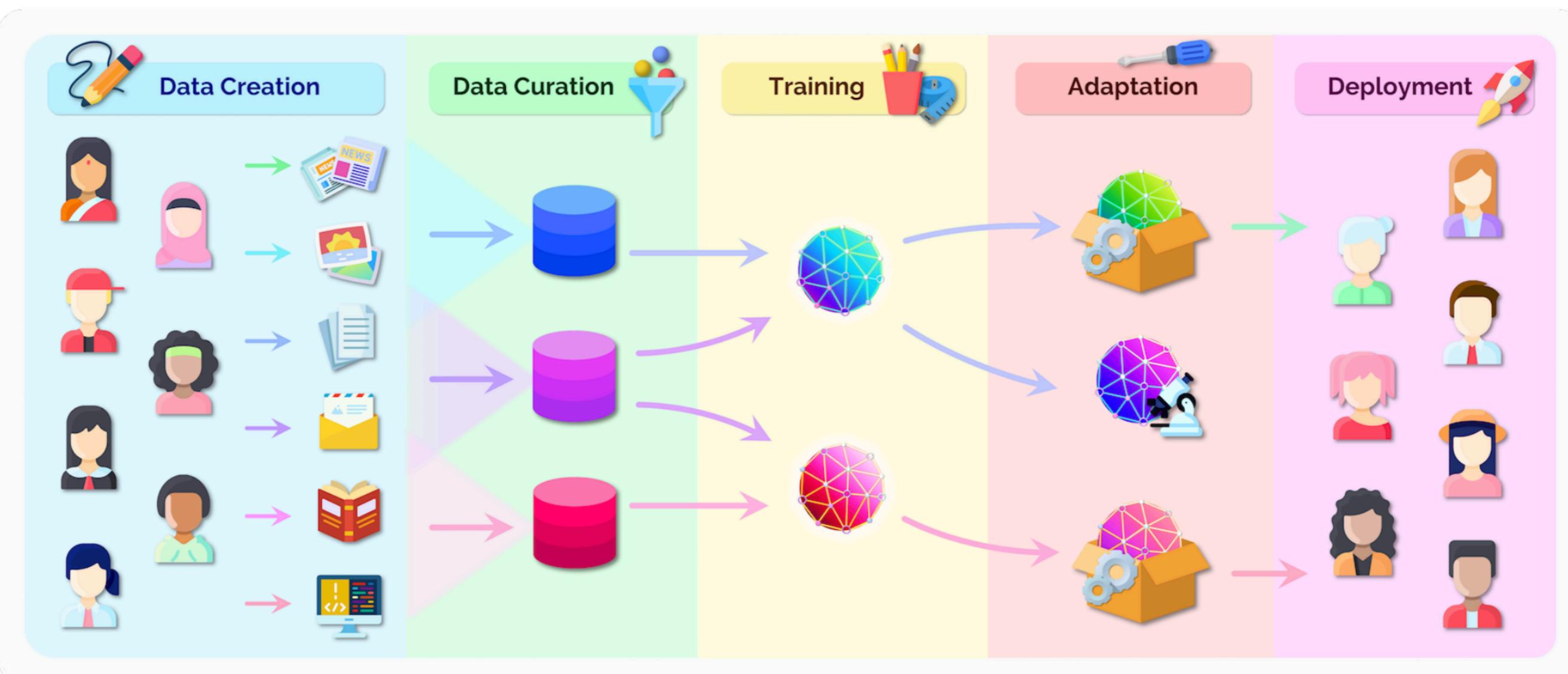


Pre-Trained Models



(Bommasani et al., 2021)

Pre-Trained Models



(Bommasani et al., 2021)

Next Steps in Meaning

Next Steps in Meaning

Benchmark Tasks

Next Steps in Meaning

Benchmark Tasks

Natural Language Inference

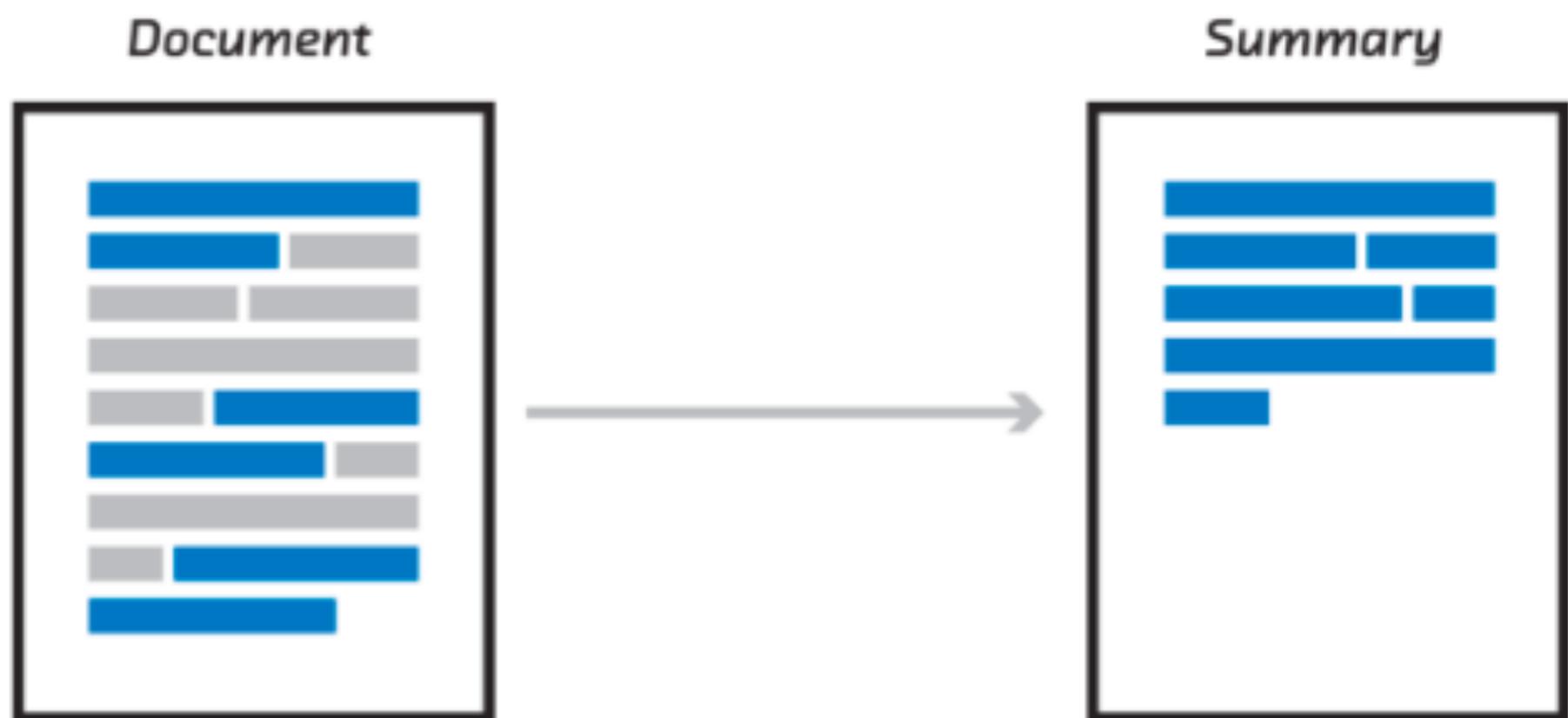
P^a	A senior is waiting at the window of a restaurant that serves sandwiches.	Relationship
	A person waits to be served his food.	Entailment
H^b	A man is looking to order a grilled cheese sandwich.	Neutral
	A man is waiting in line for the bus.	Contradiction
^a P, Premise.		
^b H, Hypothesis.		

Next Steps in Meaning

Benchmark Tasks

Natural Language Inference

Text Summarization



Next Steps in Meaning

Benchmark Tasks

Natural Language Inference

Text Summarization

Co-reference Resolution

1 A horse walks into a bar. 0 The shocked bartender points a finger 0 his way in alarm and yells , “ Hey ! ”

1 The horse says , “ 0 You read 1 my mind , buddy . ”

Next Steps in Meaning

Benchmark Tasks

Natural Language Inference

Text Summarization

Co-reference Resolution

Question Answering

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called “showers”.

What causes precipitation to fall?
gravity

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?
graupel

Where do water droplets collide with ice crystals to form precipitation?
within a cloud

Next Steps in Meaning

Benchmark Tasks

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	Average -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
BERT _{BASE}	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
BERT _{LARGE}	86.7/85.9	72.1	92.7	94.9	60.5	86.5	89.3	70.1	82.1

Table 1: GLUE Test results, scored by the evaluation server (<https://gluebenchmark.com/leaderboard>). The number below each task denotes the number of training examples. The “Average” column is slightly different than the official GLUE score, since we exclude the problematic WNLI set.⁸ BERT and OpenAI GPT are single-model, single task. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. We exclude entries that use BERT as one of their components.

Next Steps in Meaning

Benchmark Tasks

	PP	DAN	RNN	LSTM (no)	LSTM (o.g.)	skip-thought	Ours
similarity (SICK)	84.9	85.96	73.13	85.45	83.41	85.8	86.03
entailment (SICK)	83.1	84.5	76.4	83.2	82.0	-	84.6
sentiment (SST)	79.4	83.4	86.5	86.6	89.2	-	82.2

Table 2: Results on similarity, entailment, and sentiment tasks. The sentence embeddings are computed unsupervisedly, and then used as features in downstream supervised tasks. The row for similarity (SICK) shows Pearson’s $r \times 100$ and the last two rows show accuracy. The highest score in each row is in boldface. Results in Column 2 to 6 are collected from (Wieting et al., 2016), and those in Column 7 for skip-thought are from (Lei Ba et al., 2016).

Embeddings Applications

Embeddings Applications

Supervised Learning

Embeddings as extracted features

Embeddings Applications

Supervised Learning

Embeddings as extracted features

$$\hat{y} = a_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + e$$

x = projections into pre-trained embedding space

Embeddings Applications

Supervised Learning

Embeddings as extracted features

Similarity

As an extracted feature

- imitation, novelty, topic switching

Accommodation

Accommodation

accommodation, mimicry, reciprocity, entrainment, mirroring...



Dimension	Canonical study
Posture	Condon and Ogston, 1967
Pause length	Jaffe and Feldstein, 1970
Utterance length	Matarazzo and Wiens, 1973
Self-disclosure	Derlenga et al., 1973
Head nodding	Hale and Burgoon, 1984
Backchannels	White, 1989
Linguistic style	Niederhoffer and Pennebaker, 2002

(review in Danescu-Niculescu-Mizil et al., 2012)

Accommodation



(Palagi et al., 2020)

Accommodation



(Palagi et al., 2020)

Accommodation

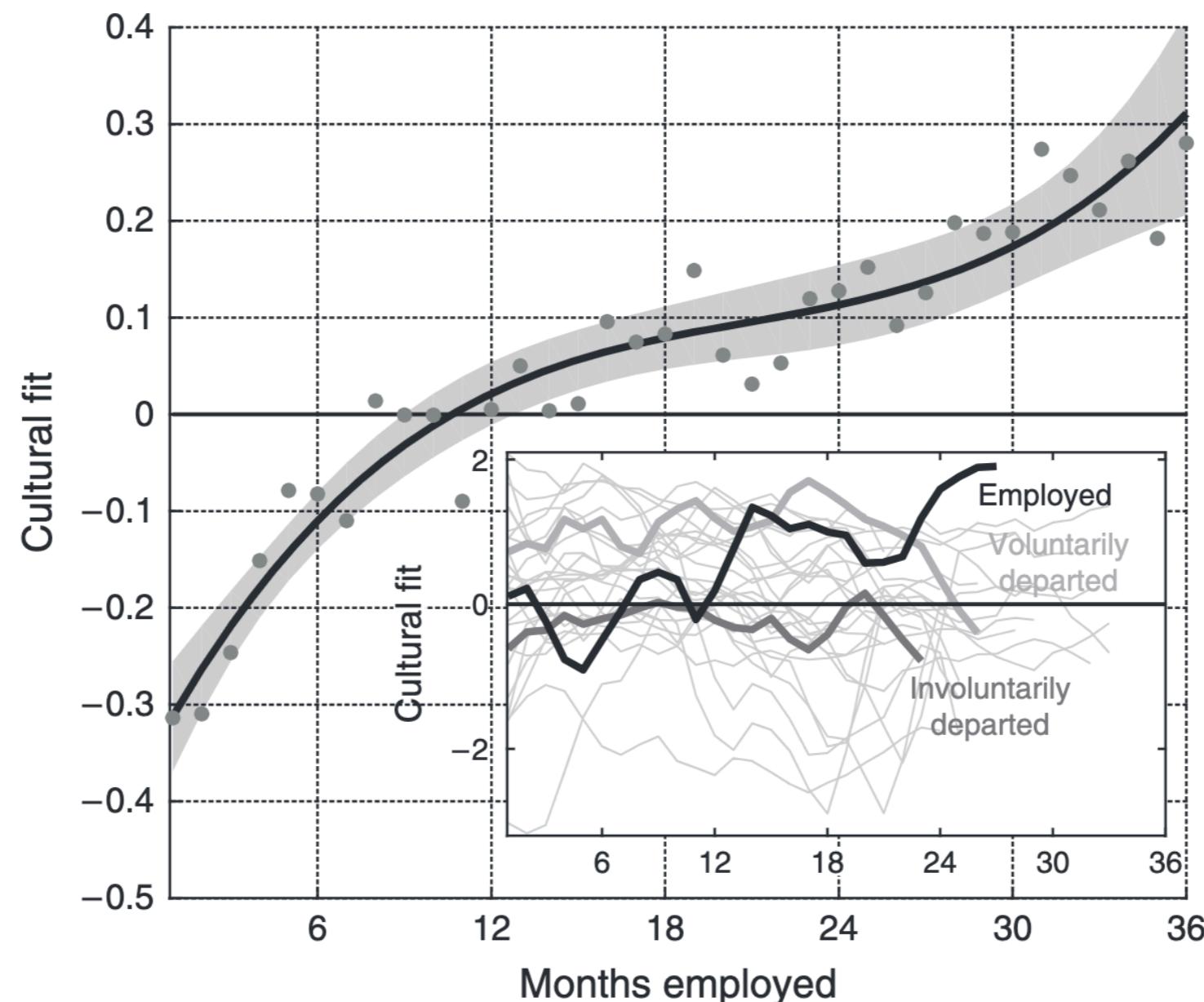


(Palagi et al., 2020)



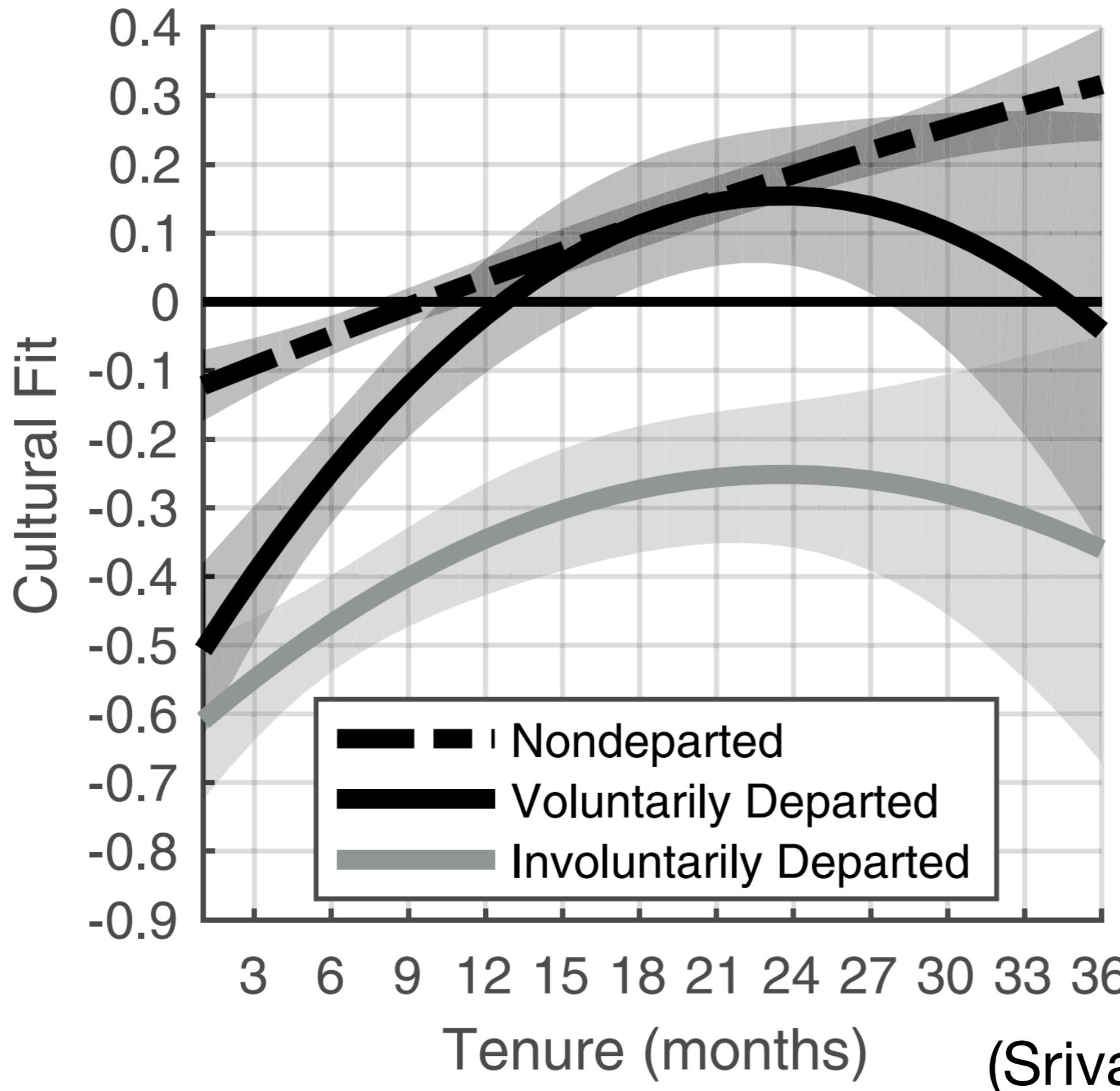
Accommodation

Figure 3. Cultural Fit (Standardized) as a Function of Number of Months Employed



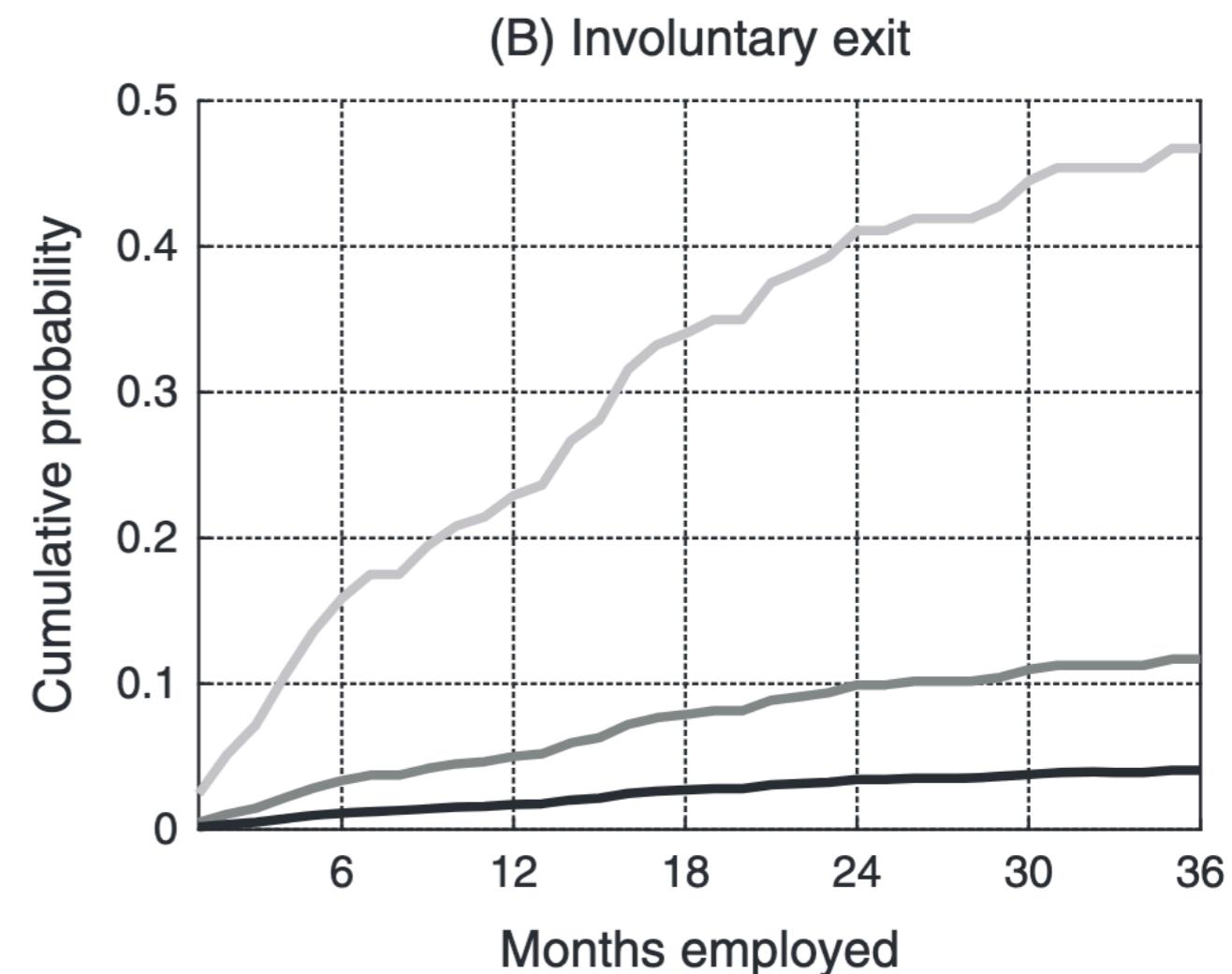
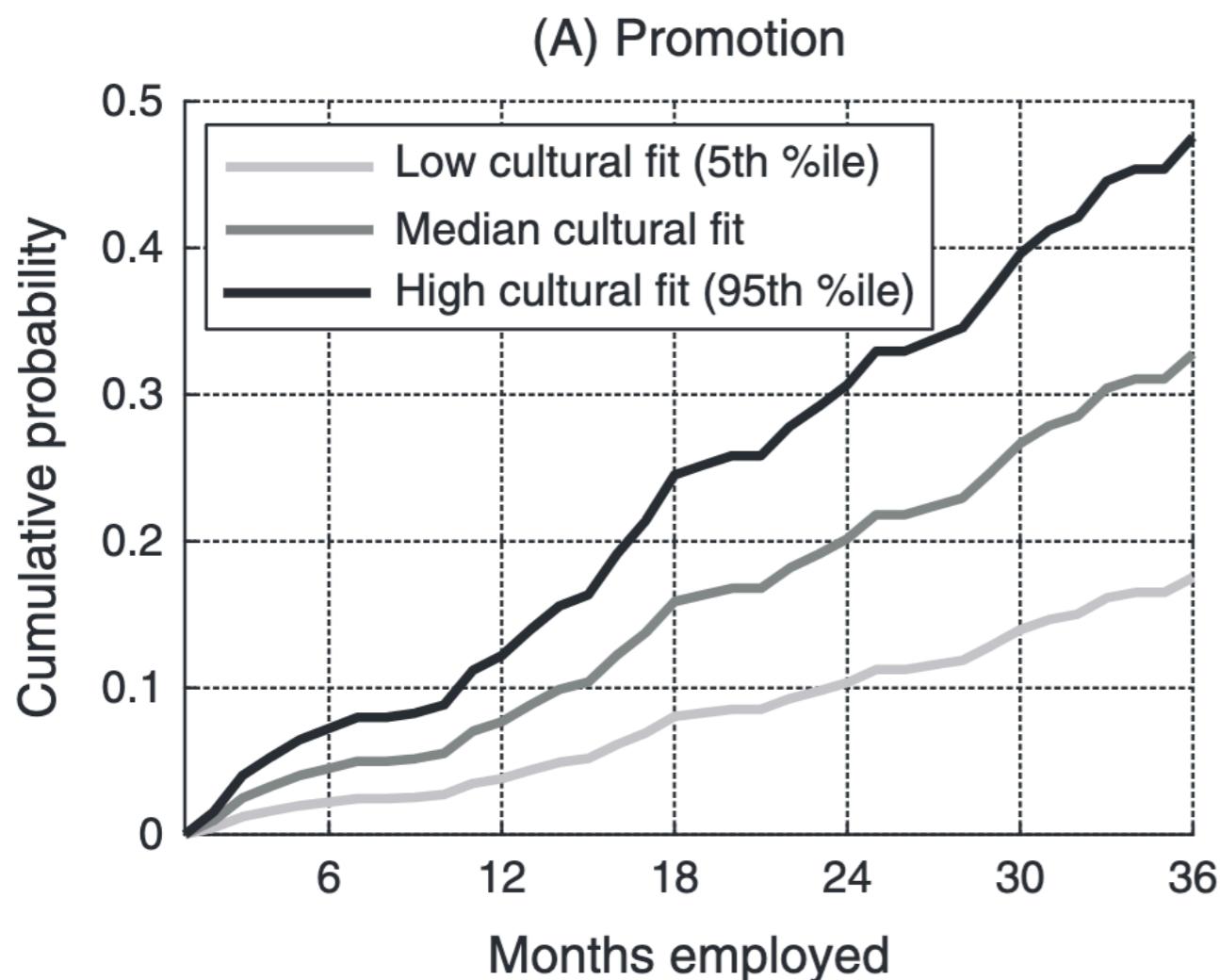
(Srivastava et al., 2018)

Accommodation



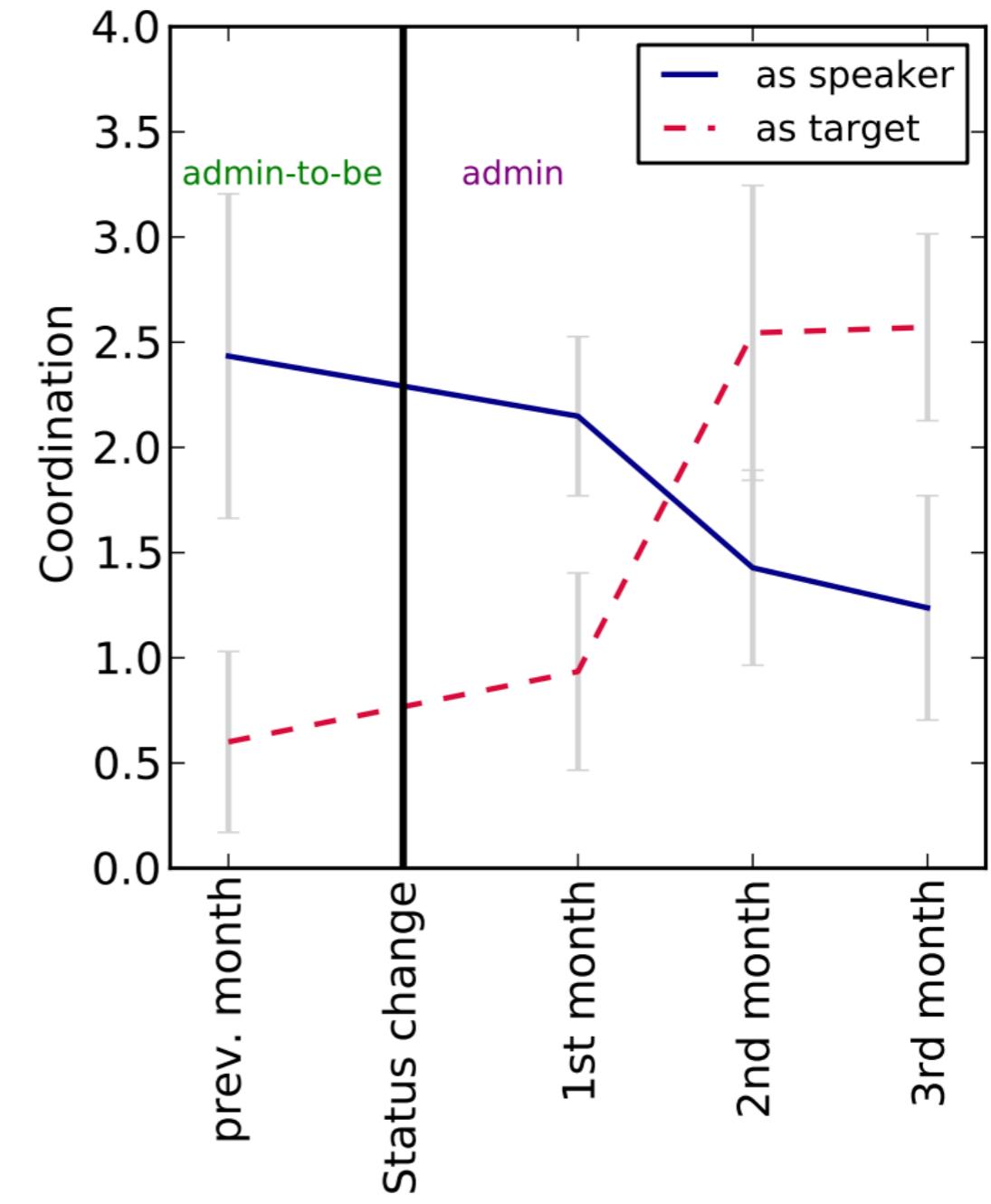
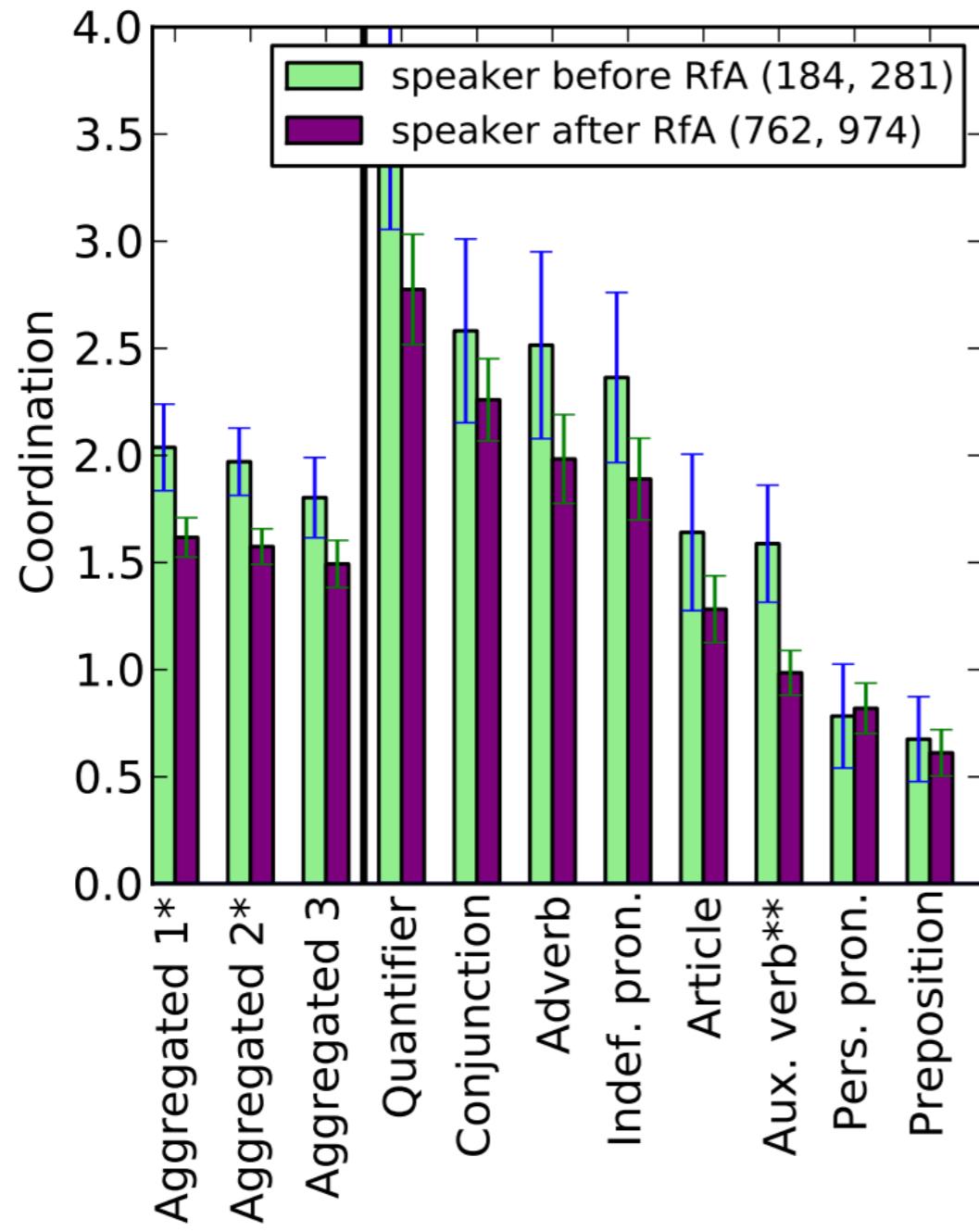
(Srivastava et al., 2018)

Accommodation



(Srivastava et al., 2018)

Accommodation



(Danescu-Niculescu-Mizil et al., 2012)

Accommodation

Tools

Accommodation

Tools

Linguistic Style Matching

Total counts across convos (too simple)

Accommodation

Tools

Linguistic Style Matching

Total counts across convos (too simple)

Latent Semantic Similarity

Similarity using principal components of unigrams (LSA)

Accommodation

Tools

Linguistic Style Matching

Total counts across convos (too simple)

Latent Semantic Similarity

Similarity using principal components of unigrams (LSA)

DNM Approach

- One feature at a time, and aggregated
- Separate into turns (“adjacency pairs”)
- Adjust for baseline usage

Accommodation

Tools

Linguistic Style Matching

Total counts across convos (too simple)

Latent Semantic Similarity

Similarity using principal components of unigrams (LSA)

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WHAM

Many texts per person/topic

Accommodation

Tools

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Total counts across convos (too simple)

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Is accommodation purely stylistic/unconscious? Maybe not

Accommodation

Tools

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Total counts across convos (too simple)

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Similarity using principal components of unigrams (LSA)

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WHAM

Many texts per person/topic

Is accommodation purely stylistic/unconscious? Maybe not

Is accommodation causal? Not always

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Supervised Learning

Embeddings as extracted features

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As an extracted feature

- imitation, novelty, topic switching

Data exploration

- which document is most like this one?

Embeddings Applications

Supervised Learning

Embeddings as extracted features

Similarity

As an extracted feature

- imitation, novelty, topic switching

Data exploration

- which document is most like this one?

Distributed dictionaries

- which document is most similar to these words?

Distributed Dictionaries

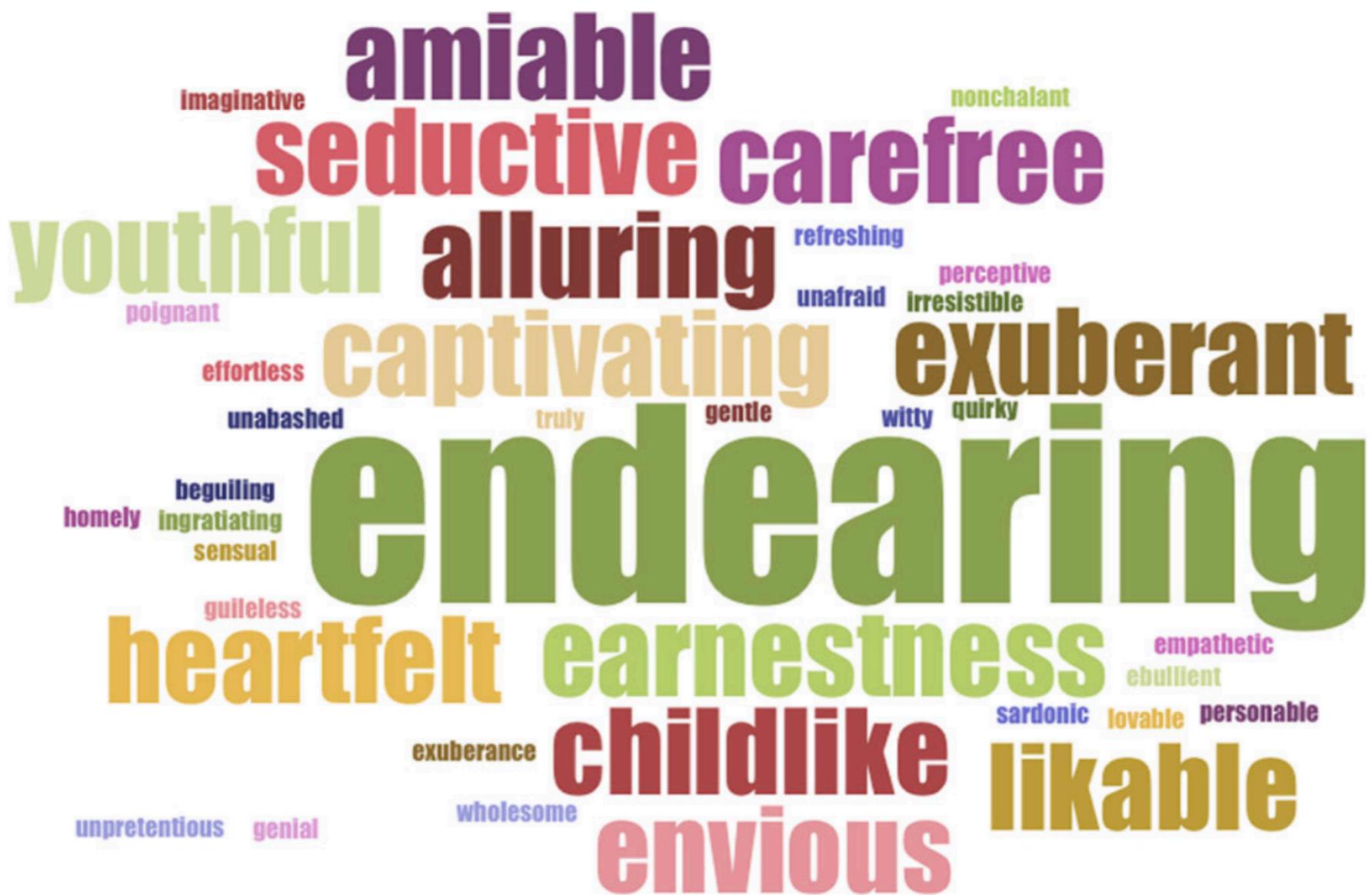


Fig. 4 Nearest neighbors of the LIWC positive emotions dictionary

(Garten et al., 2018)

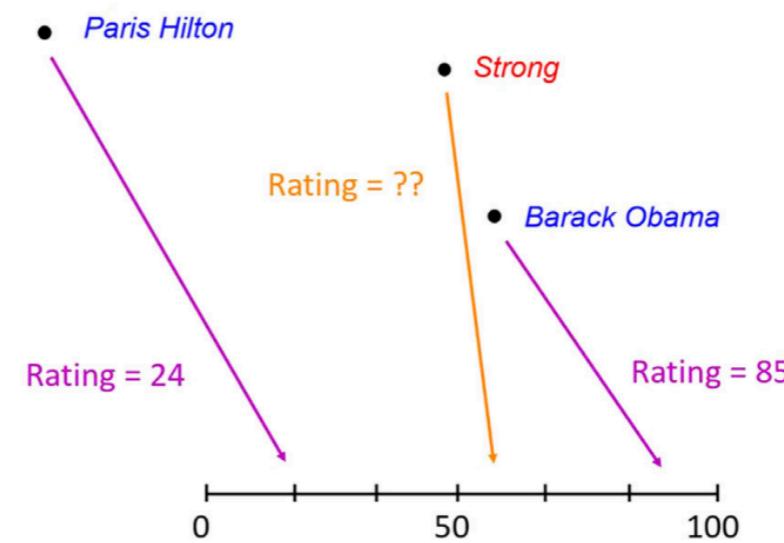
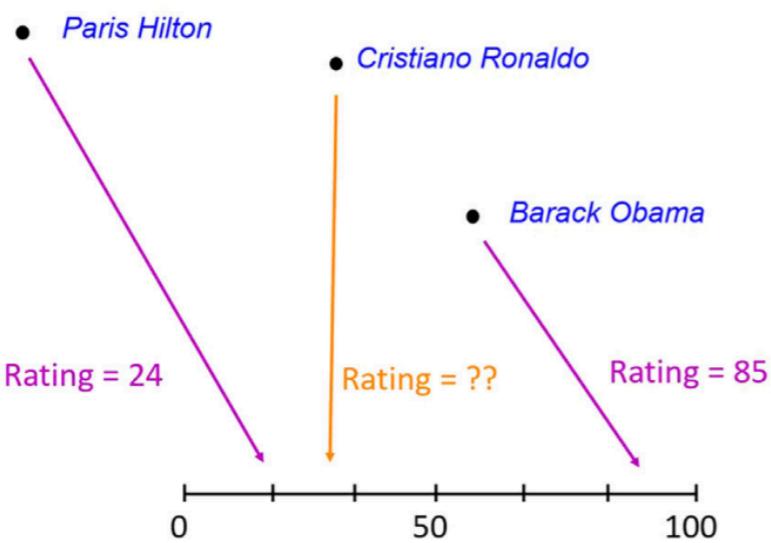
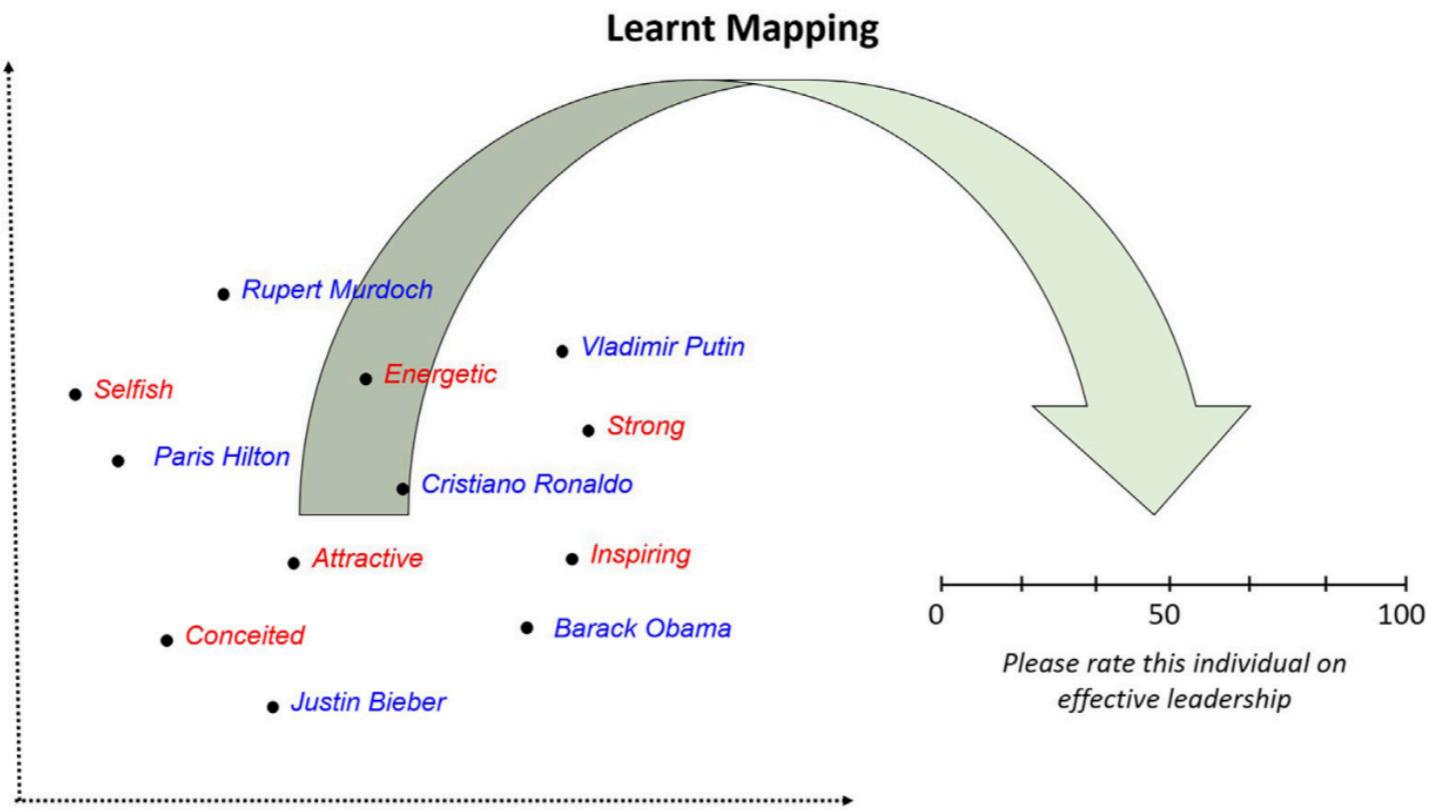
Distributed Dictionaries



Fig. 3 Nearest neighbors of the word “respect”

(Garten et al., 2018)

Distributed Dictionaries



(Bhatia et al., 2021)

Embedding Models

Advantages

Captures common synonymy

Embedding Models

Advantages

Captures common synonymy

Excellent for estimation

Embedding Models

Advantages

Captures common synonymy

Excellent for estimation

Natural for similarity-based tasks

Embedding Models

Advantages

Captures common synonymy

Excellent for estimation

Natural for similarity-based tasks

Limitations

Hard to interpret results

Computationally intensive