FRIEDRICH-SCHILLER-
UNIVERSITÄT
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Jena University Language & Information Engineering Lab

Quantifying Word Meaning and Emotion in Historical Language

Sven Buechel

Jena University Language and Information Engineering (JULIE) Lab
Friedrich-Schiller-University Jena,
Jena, Germany

https://julielab.de

Short Bio

- Studied physics, sociology and German at University of Jena
- Pursuing PhD in computational linguistics since 2016 (Supervisor: Prof. Udo Hahn)
- 3-month research visit at the University of Pennsylvania in 2018 (Prof. Lyle Ungar)
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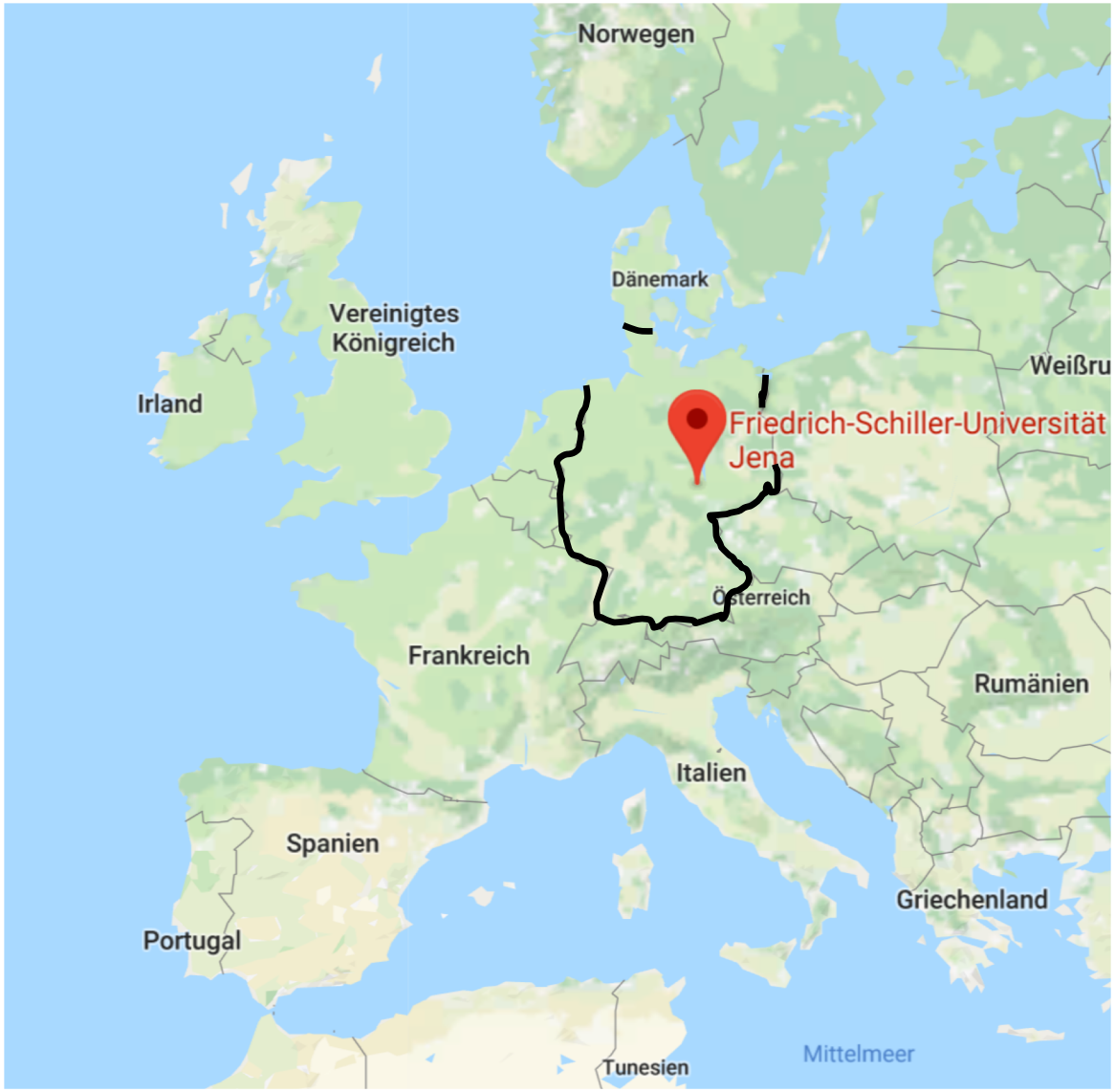
- Together with Johannes Hellrich (who was immensely helpful in preparing this talk): *Emotion in historical language*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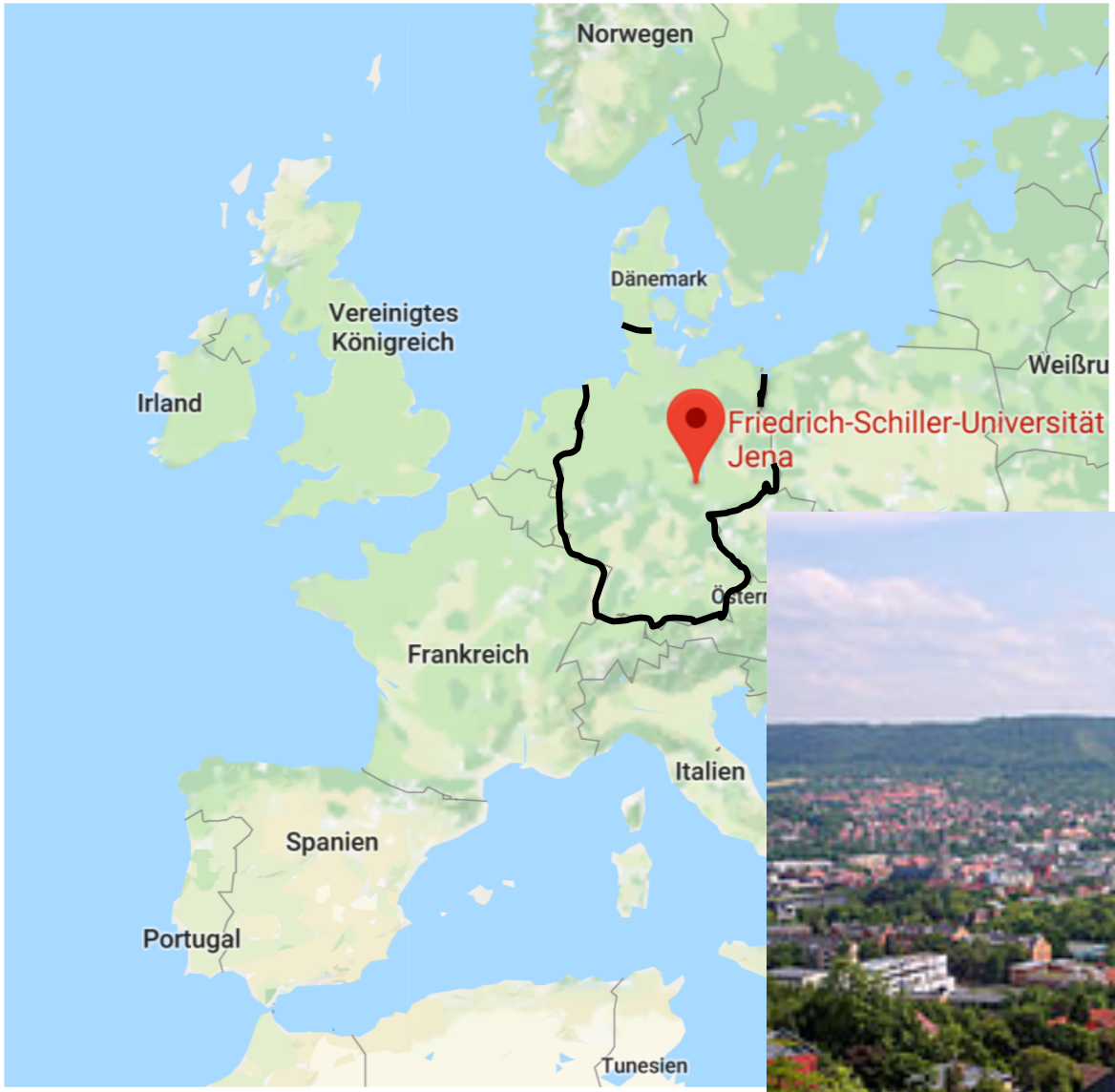
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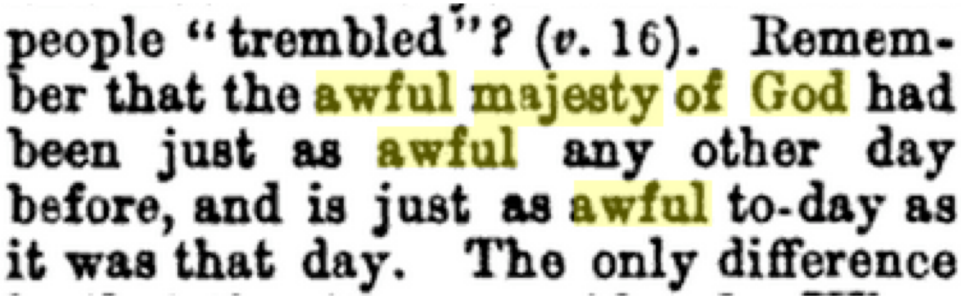
Content

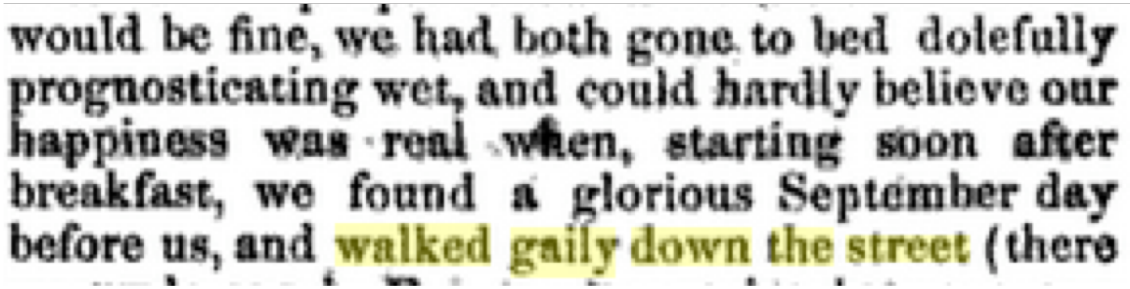
- Digital Approaches to Word Meaning Analysis
  - Computer-Assisted Manual Analysis
  - Statistical Computing
  - Semantic Computing
- Outlook: Emotion in Historical Language

Introduction

Evidence for Change of Word Meaning


people "trembled"? (*v.* 16). Remember that the awful majesty of God had been just as awful any other day before, and is just as awful to-day as it was that day. The only difference

(The Wesleyan Methodist Sunday School Magazine 1878, p. 196)


would be fine, we had both gone to bed dolefully prognosticating wet, and could hardly believe our happiness was real when, starting soon after breakfast, we found a glorious September day before us, and walked gaily down the street (there

(Eliakim Littell & Robert S. Littell. 1855. The Living Age ..., Vol. 45, p. 21)

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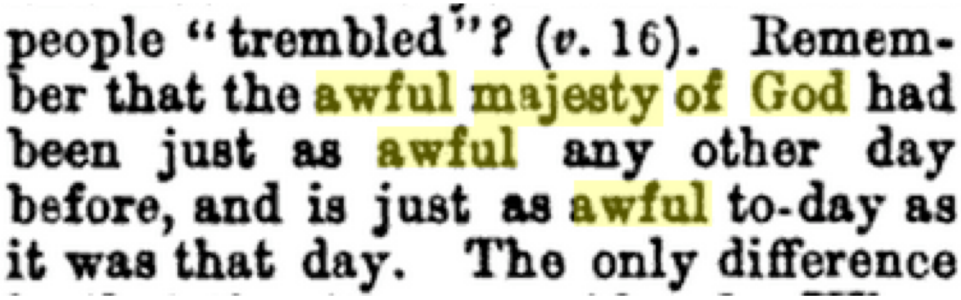
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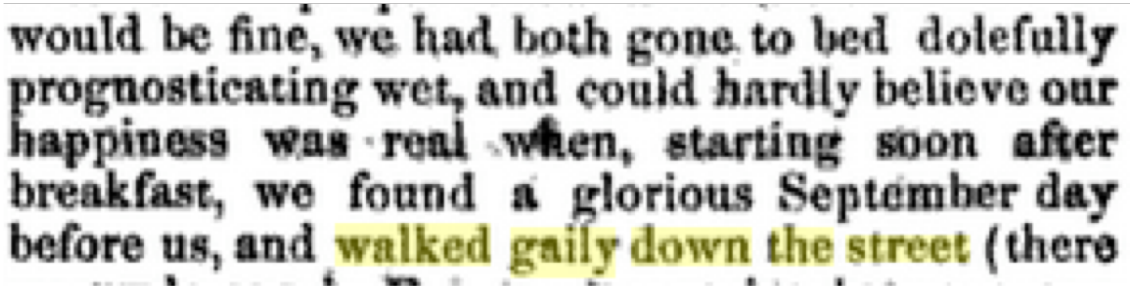
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- Obstacle for understanding and interpretation
- Object of research
- How can we find out what a word meant earlier?
- How can we trace meaning change over time?

Digital Approaches to Word Meaning Analysis

Approach	Typical Methods	Role of Researcher	Role of the Machine
Computer-Assisted Manual Analysis			
Statistical Computing			
Semantic Computing			

Computer-Assisted Manual Analysis

Concordances

- List of all occurrences of a word in a particular corpus
- Very rarely done manually in pre-computer era
- Most commonly in KWIC (Key Word in Context) format
- Efficient inspection of word usage
- Allows to manually infer meaning from many examples

ong the former , one was of a most	monstrous	size . ... This came towards us ,
ON OF THE PSALMS . " Touching that	monstrous	bulk of the whale or ork we have r
ll over with a heathenish array of	monstrous	clubs and spears . Some were thick
d as you gazed , and wondered what	monstrous	cannibal and savage could ever hav
that has survived the flood ; most	monstrous	and most mountainous ! That Himmal
they might scout at Moby Dick as a	monstrous	fable , or still worse and more de
th of Radney .'" CHAPTER 55 Of the	monstrous	Pictures of Whales . I shall ere l
ing Scenes . In connexion with the	monstrous	pictures of whales , I am strongly
ere to enter upon those still more	monstrous	stories of them which are to be fo
ght have been rummaged out of this	monstrous	cabinet there is no telling . But
of Whale - Bones ; for Whales of a	monstrous	size are oftentimes cast up dead u

(From Herman Melville's "Moby Dick"; https://www.nltk.org/book/ch01.html)

Web-based Corpus Analysis

corpus.byu.edu

home corpora users related resources my account upgrade help

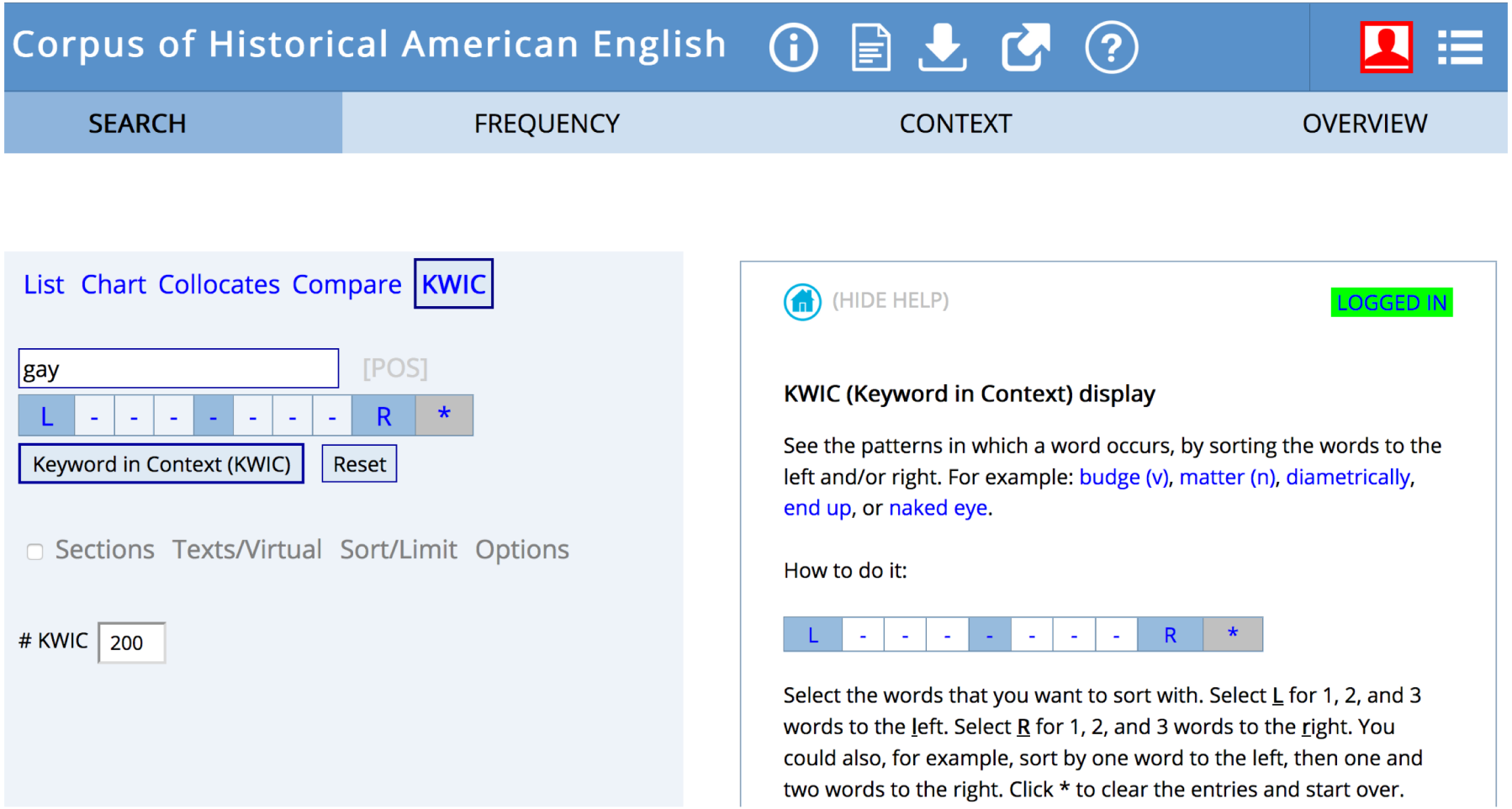
Created by Mark Davies, BYU (Google Scholar). **Overview**, search types, looking at variation, corpus-based resources.

The most widely used online corpora -- more than 130,000 distinct researchers, teachers, and students each month.

English	# words	language/dialect	time period	compare
iWeb: The Intelligent Web-based Corpus	14 **billion**	US/CA/UK/IE/AU/NZ	2017	**Info** (中文)
News on the Web (NOW)	7.3 **billion+**	20 countries / Web	2010-last month	
Global Web-Based English (GloWbE)	1.9 **billion**	20 countries / Web	2012-13	
Wikipedia Corpus	1.9 **billion**	English	2014	Info
Hansard Corpus	1.6 **billion**	British (parliament)	1803-2005	Info
Early English Books Online	755 million	British	1470s-1690s	
Corpus of Contemporary American English (COCA)	560 million	American	1990-2017	* * * * *
Corpus of Historical American English (COHA)	400 million	American	1810-2009	* *
The TV Corpus **NEW**	325 million	US/CA/UK/IE/AU/NZ	1950-2018	Info

https://corpus.byu.edu/

Corpus of Historical American English (COHA)



https://corpus.byu.edu/coha/

Gay — COHA 1900s

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Corpus of Historical American English

SEARCH | FREQUENCY | CONTEXT

FIND SAMPLE: 100 200 500
PAGE: << < 1 / 9 > >>

CLICK FOR MORE CONTEXT [?] SAVE LIST CHOOSE LIST ---------- CREATE NEW LIST [?]

1	1900	FIC	PhilipWinwood	A	B	C	perforce to banish dulness from the lives of their entertainers.' T was a **gay** town, indeed, for some folk, de
2	1900	FIC	PhilipWinwood	A	B	C	SO IN UNISON THAT MARGARET LAUGHED. " " Ay, and something of the **gay** life of the present, I'll warrant,
3	1900	FIC	PhilipWinwood	A	B	C	not show that, under all the feelings that held her to a life of **gay** coquetry, lay her love for Philip, not dead,
4	1900	FIC	PhilipWinwood	A	B	C	, gaze. " So then, " said she, as if to be **gay** at the expense of her husband's long absence, " now that three
5	1900	FIC	PhilipWinwood	A	B	C	himself to patience as with a long breath, and fell to humming softly a **gay** French air the while he stood le
6	1900	FIC	PhilipWinwood	A	B	C	. He was not as I had been before my maiden duel: blustering and **gay**, in a trance-like recklessness; assum
7	1900	FIC	PhilipWinwood	A	B	C	surprise, and, peering at our faces in the darkness, asked in his **gay**, good-natured way what fun was afoot
8	1900	NEWS	NYT-Ed	A	B	C	observing Paris during the celebration on July 14. the great fete day. Paris looked **gay** and delightful with C
9	1902	FIC	MrPatsLittleGirl	A	B	C	. None the less she had accepted courageously the reverses which at twenty brought her **gay** girlhood to a
10	1902	FIC	LittleGirlInOld	A	B	C	painted and whitewashed. Stores and shops spread out their attractions, booths were flying **gay** colors an

Gay — COHA 2000s

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Corpus of Historical American English

SEARCH | ERROR | CONTEXT

FIND SAMPLE: 100 200 500 1000
PAGE: << < 1 / 11 > >>

CLICK FOR MORE CONTEXT [?] SAVE LIST CHOOSE LIST ---------- CREATE NEW LIST [?]

1	2000	MAG	Time	A	B	C	366400 It used to be that gay men who wanted to meet other **gay** men had limited options. Among them: go
2	2000	MAG	Time	A	B	C	McCain, you can't always look at someone's face and know they're **gay**, " says Internet-privacy expert John Ar
3	2000	MAG	Time	A	B	C	According to estimates by Internet demographers, 20% of AOL's 21 million subscribers are **gay**, and at nearly
4	2000	MAG	Time	A	B	C	position. Frank Provasek of the local a.c.l.u. chapter conducted an informal investigation and said **gay** men's
5	2000	MAG	Time	A	B	C	policy. AOL issued a public apology, but complaints have persisted that AOL holds **gay** customers to different
6	2000	MAG	Time	A	B	C	of a love-hate affair. In 1998 an AOL employee let slip the identity of **gay** naval officer Timothy R. McVeigh to
7	2000	MAG	Time	A	B	C	XY magazine, a title aimed at young gay men. " If you ask **gay** men under 25 how they meet people, I think 99
8	2000	MAG	Time	A	B	C	says Peter Ian Cummings, publisher of XY magazine, a title aimed at young **gay** men. " If you ask gay men unc
9	2000	MAG	Time	A	B	C	# While the chat rooms are filling a void for millions of men, the **gay** community's relationship with AOL is mc
10	2000	MAG	Time	A	B	C	or learn to love solitude. Then came the Internet. Now, millions of **gay** men wait in line -- not to pay a cover cl

Digital Approaches to Word Meaning Analysis

Approach	Typical Methods	Role of Researcher	Role of the Machine
Computer-Assisted Manual Analysis	Concordances	• Compose research design • Interpret individual examples • Identify trends in usage patterns • Infer meaning from usage patterns • Quality assurance (biased data)	• Data storage • Search / retrieval • Data aggregation • Data Visualization • Automated sem. analysis
Statistical Computing			
Semantic Computing			

Statistical Computing

Statistical Methods: *N*-Grams

Call me Ishmael .
Some years ago
never mind how
long precisely ...

Tokenization: (automatically) splitting a text into individual „words“ (tokens)

n	Name	Examples
1	1-gram	Call | me | Ishmael | . | Some | years | ago | never | mind | ...
2	2-gram	Call me | me Ishmael | Ishmael . | . Some | Some years | ...
3	3-gram	Call me Ishmael | me Ishmael . | Ishmael . Some | . Some years | ...
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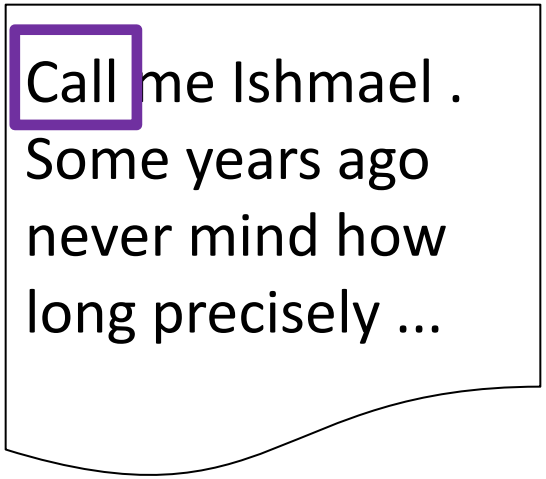

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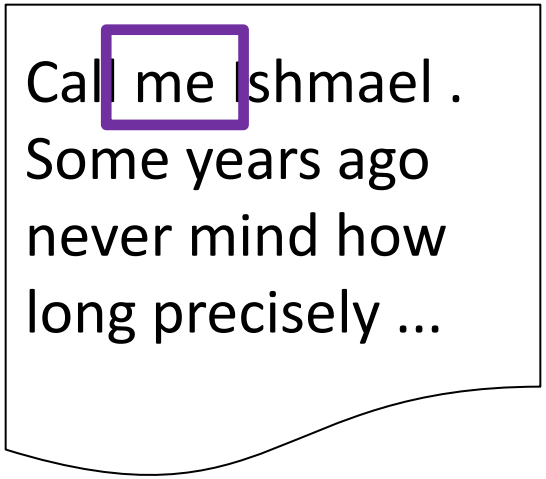

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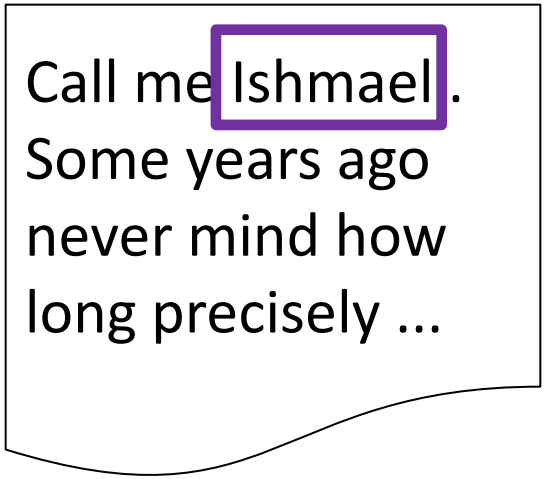

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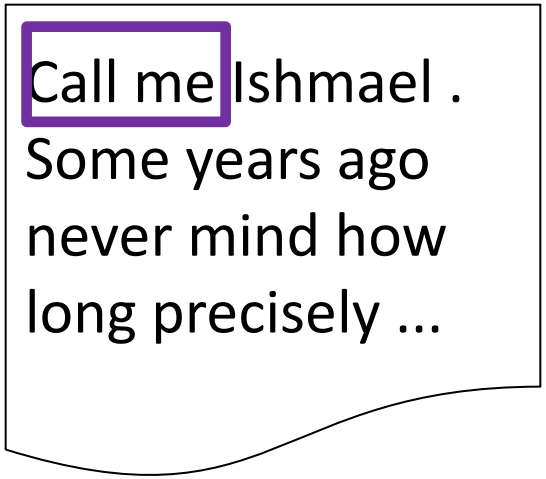

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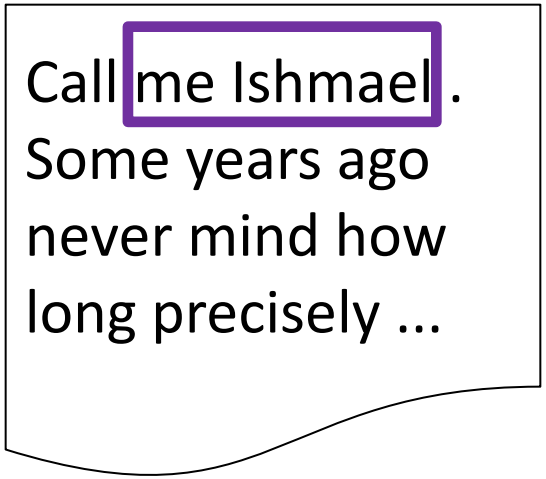

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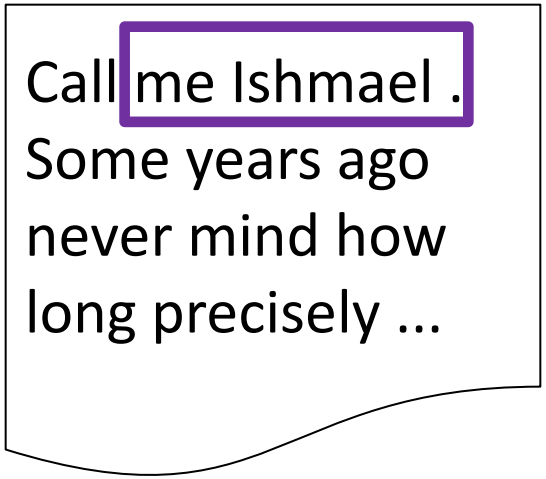

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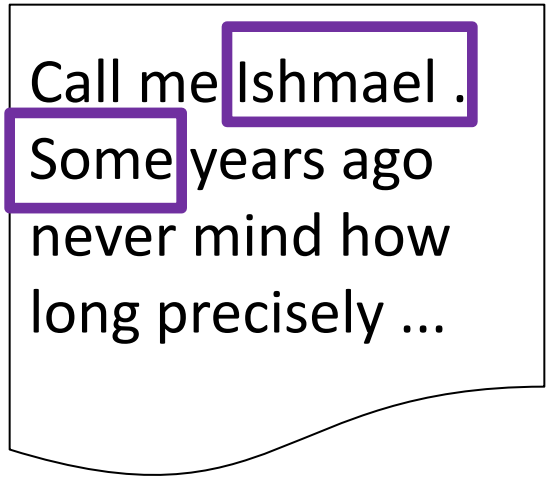

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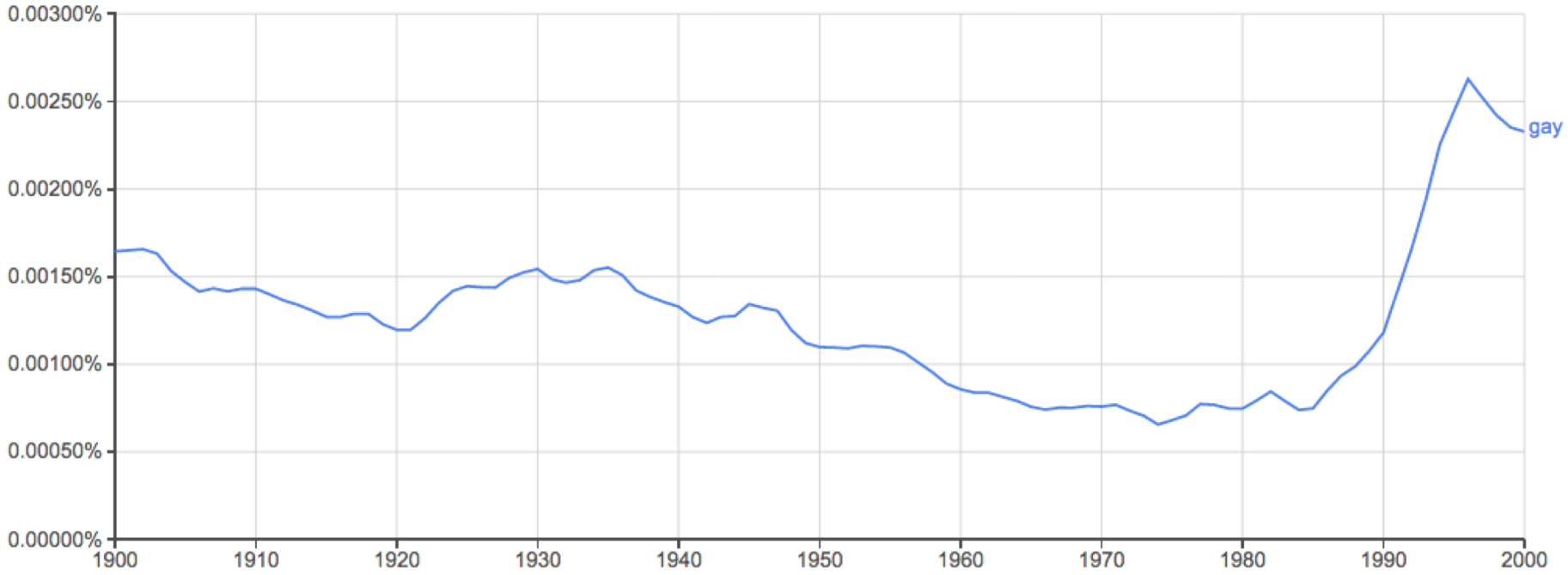
Gay — Google Books

Google Books Ngram Viewer

Graph these comma-separated phrases: gay case-insensitive

between 1900 and 2000 from the corpus English with smoothing of 1. Search lots of books



Based on Google Books corpus (≈ 4% of all books ever published)

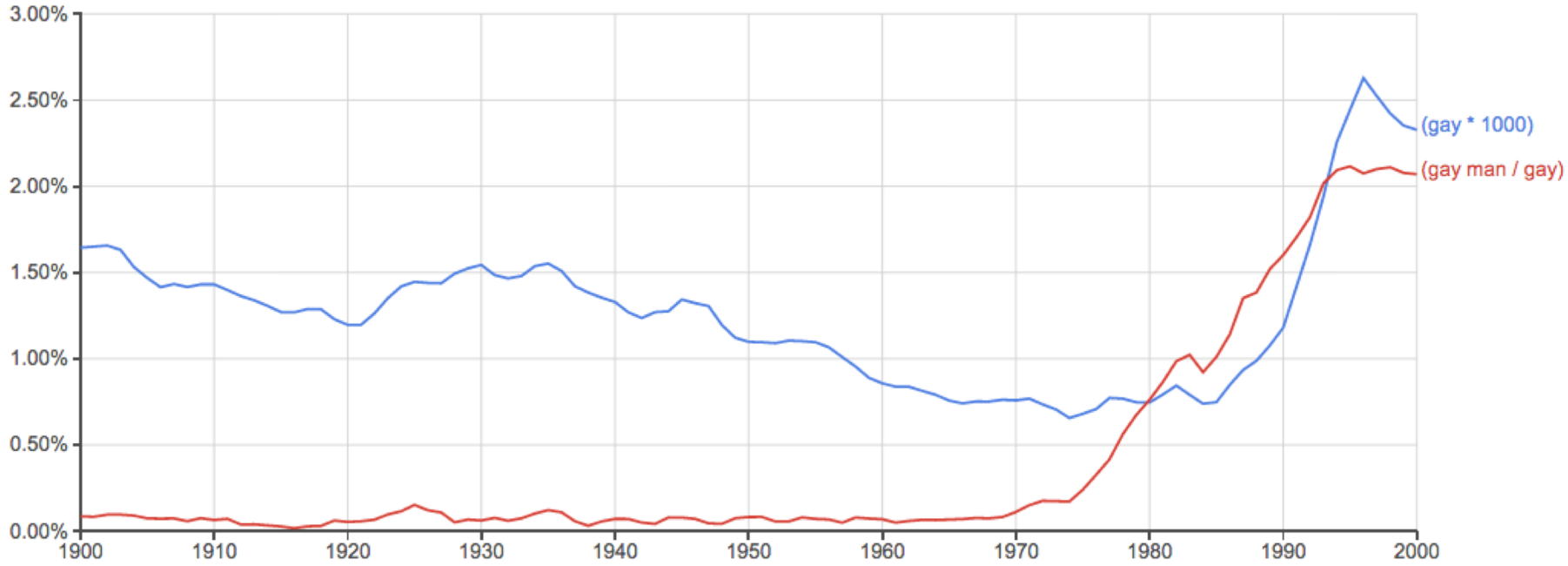
https://books.google.com/ngrams#

Gay — Google Books

Google Books Ngram Viewer

Graph these comma-separated phrases: (gay*1000),gay man / gay case-insensitive

between 1900 and 2000 from the corpus English with smoothing of 1. Search lots of books



Cell — Google Books

Google Books Ngram Viewer

Graph these comma-separated phrases: (cell*10000) case-insensitive

between 1800 and 2000 from the corpus English Fiction with smoothing of 2. Search lots of books

Cell — Google Books

Jena University Language & Information Engineering Lab

Google Books Ngram Viewer

Graph these comma-separated phrases: (cell*10000),cell phone / cell case-insensitive

between 1800 and 2000 from the corpus English Fiction with smoothing of 2. Search lots of books

Can You Guess the Word?

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Google Books Ngram Viewer

Graph these comma-separated phrases: [redacted] case-insensitive

between 1950 and 2008 from the corpus American English with smoothing of 0. Search lots of books

Can You Guess the Word?

Google Books Ngram Viewer

Graph these comma-separated phrases: Afghanistan case-insensitive

between 1950 and 2008 from the corpus American English with smoothing of 0. Search lots of books

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Google Books Ngram Viewer

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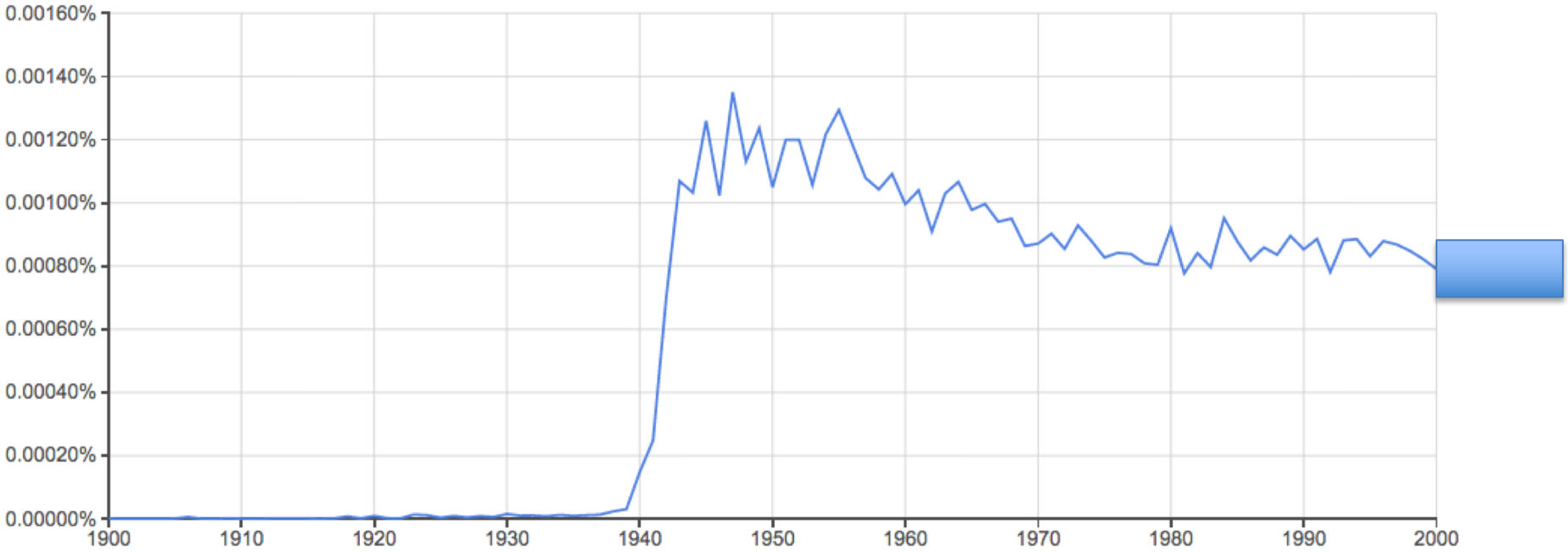


Can You Guess the Word?

Google Books Ngram Viewer

Graph these comma-separated phrases: World War I case-insensitive

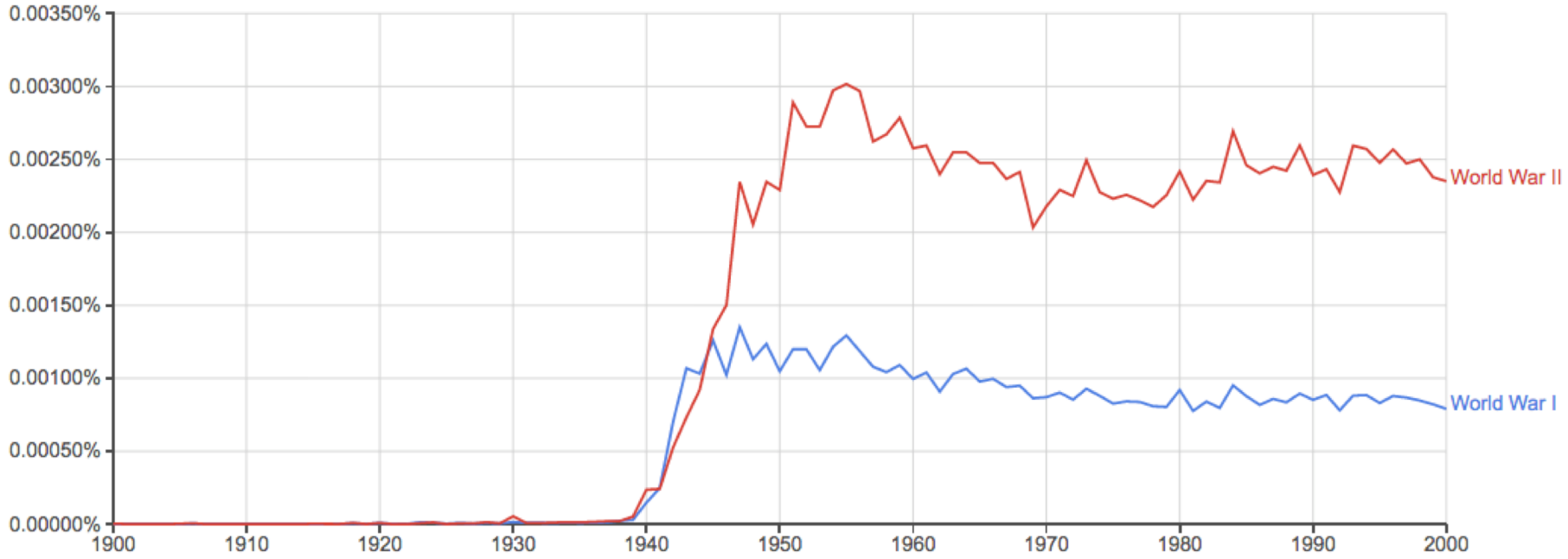
between 1900 and 2000 from the corpus American English with smoothing of 0 . Search lots of books

Can You Guess the Word?

Google Books Ngram Viewer

Graph these comma-separated phrases: World War I,World War II case-insensitive

between 1900 and 2000 from the corpus American English with smoothing of 0. Search lots of books



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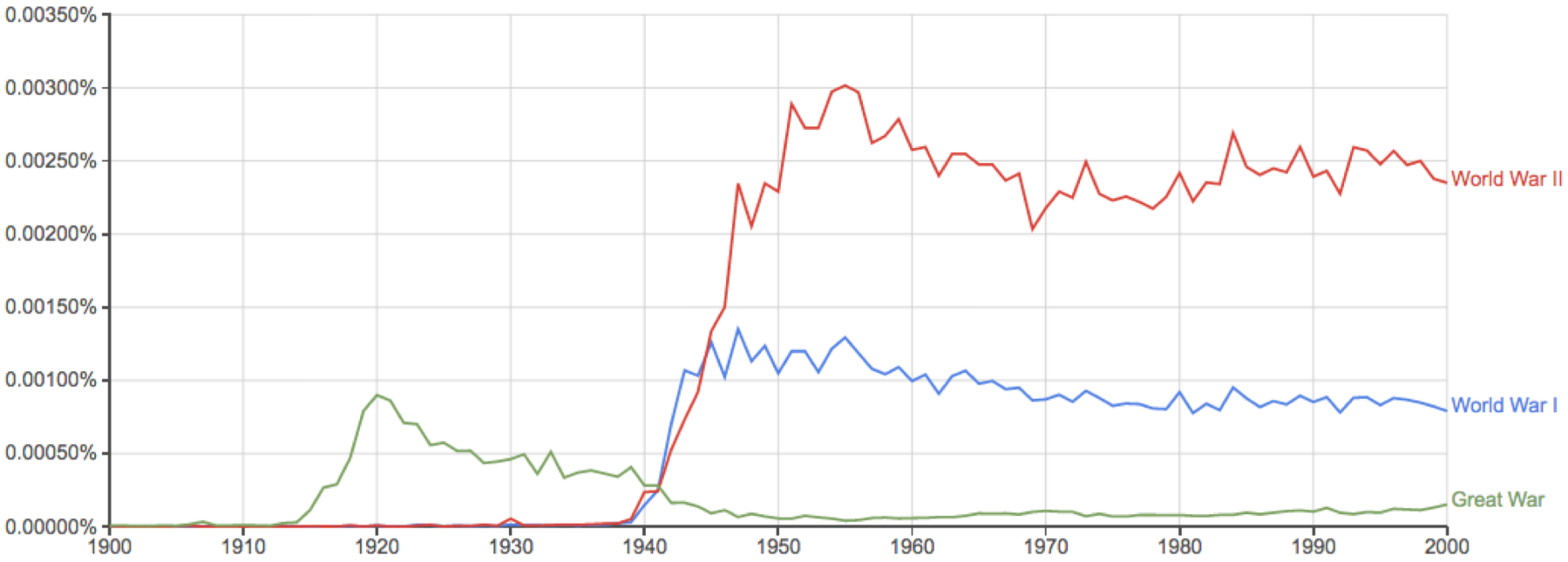
between 1900 and 2000 from the corpus American English with smoothing of 0 Search lots of books



Can You Guess the Word?

Google Books Ngram Viewer

Graph these comma-separated phrases: [redacted] case-insensitive

between 1800 and 2000 from the corpus American English with smoothing of 0. Search lots of books

Can You Guess the Word?

Google Books Ngram Viewer

Graph these comma-separated phrases: 1900 case-insensitive

between 1800 and 2000 from the corpus American English with smoothing of 0. Search lots of books

Background

- Examples partly adopted from Michel et al. (Science 2011)
- Report on creation of Google Books Corpus
- „Culturomics“: Quantitative Analysis of Culture
- Targeted phenomena:
  - evolution of grammar
  - adoption of technology
  - personal fame
  - censorship
- Criticism: Severe change in genre distribution in 20th century (Pechenick et al., Plos One 2015)

Analyzing Frequency vs. Cooccurrence

- Changes in n-gram frequency can be a good indicator of meaning change but is not always
  - new infrequent senses
  - change in sense distribution
  - cultural phenomena
- Gives only indication THAT but does not tell HOW
  - We can use other n-grams to test our hypothesis (*gay man*)
  - But what if we don‘t have a hypothesis to start with?
  - Is there a more direct way to to identify HOW word meaning changes?

Counting Cooccurrences

- ***Cooccurrence***: tokens appearing together in a corpus within a window of pre-determined size

He reads a poem .
Susanne reads a novel .
The novel has 100 pages .
Her poem has 3 pages .
Susanne listens to an opera .
Peter listens to a song .
The song is in D-minor .
The opera is in D-minor .

Counting Cooccurrences

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Peter listens to a song .
The song is in D-minor .
The opera is in D-minor .

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Counting Cooccurrences

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The opera is in D-minor .

Cooccurrence Matrix — Raw Frequency

	read	pages	…	listen
novel	98	60	…	2
poem	67	10	…	8
…	…	…	…	…
opera	4	8	…	38

Cooccurrence Matrix — Raw Frequency

Adding marginal frequencies

	read	pages	…	listen	Σ
novel	98	60	…	2	172
poem	67	10	…	8	90
…	…	…	…	…	…
opera	4	8	…	38	166
Σ	199	229		199	**2461**

total number of cooccurrences

Cooccurrence Matrix — Relative Frequency

Divide every cell by total number of cooccurrences

	read	pages	…	listen	$P(w_1)$
novel	.049	.024	…	.001	.070
poem	.027	.004	…	.003	.037
…	…	…	…	…	…
opera	.002	.003	…	.015	.067
$P(w_2)$	.081	.093		.077	**1**

Relative frequency can be usede to estimate occurrence probability *P(w)*

Pointwise Mutual Information (PMI) Matrix

Compute PMI for each cell:

Statistical Association: How much more often than chance do 2 words cooccur?

PMI	read	pages	…	listen	$P(w_1)$
novel	0.94	0.57	…	-0.73	.070
poem	0.95	0.07	…	0.02	.037
…	…	…	…	…	…
opera	-0.43	-0.32	…	0.46	.067
$P(w_2)$	.081	.093	…	.077	1

$$PMI(w_1, w_2) := log \frac{P(w_1, w_2)}{P(w_1) \times P(w_2)}$$

PMI for Word Meaning Analysis: *Gay* — 1900s

SEC 1 (1900): 22,097,593 WORDS

	WORD/PHRASE	TOKENS 1	TOKENS 2	PM 1	PM 2	RATIO
1	FLOWERS	13	0	0.6	0.0	58.8
2	LAUGH	12	0	0.5	0.0	54.3
3	BRIGHT	12	0	0.5	0.0	54.3
4	GLAD	10	0	0.5	0.0	45.3
5	PARIS	9	0	0.4	0.0	40.7
6	SMILE	9	0	0.4	0.0	40.7
7	HAPPY	8	0	0.4	0.0	36.2
8	THRONG	8	0	0.4	0.0	36.2
9	GIRL	7	0	0.3	0.0	31.7
10	LAUGHTER	6	0	0.3	0.0	27.2

https://corpus.byu.edu/coha/

- compute PMI of target word with every other word
- rank cooccurring words in descending order of PMI
- manual inspection of most strongly associated words

PMI for Word Meaning Analysis: *Gay* — 2000s

SEC 2 (2000): 29,567,390 WORDS

	WORD/PHRASE	TOKENS 2	TOKENS 1	PM 2	PM 1	RATIO
1	MARRIAGE	81	0	2.7	0.0	274.0
2	RIGHTS	57	0	1.9	0.0	192.8
3	COMMUNITY	32	0	1.1	0.0	108.2
4	BECAUSE	19	0	0.6	0.0	64.3
5	ALSO	18	0	0.6	0.0	60.9
6	LESBIAN	78	1	2.6	0.0	58.3
7	LESBIANS	16	0	0.5	0.0	54.1
8	ABORTION	14	0	0.5	0.0	47.3
9	BISEXUAL	14	0	0.5	0.0	47.3
10	ISSUES	12	0	0.4	0.0	40.6

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- compute PMI of target word with every other word
- rank cooccurring words in descending order of PMI
- manual inspection of most strongly associated words

Awful — 1810s...1850s vs. 2000s

Corpus of Historical American English

SEARCH | FREQUENCY | CONTEXT | ACCOUNT

SEE CONTEXT: CLICK ON WORD (ALL SECTIONS) OR NUMBER (SPECIFIED SECTION) [HELP...]

SEC 1 (1820, 1830, 1840, 1850, 1810): 54,403,008 WORDS

	WORD/PHRASE	TOKENS 1	TOKENS 2	PM 1	PM 2	RATIO
1	UPON	64	0	1.2	0.0	117.6
2	STILLNESS	35	0	0.6	0.0	64.3
3	PRESENCE	29	0	0.5	0.0	53.3
4	SHALL	27	0	0.5	0.0	49.6
5	DOOM	25	0	0.5	0.0	46.0
6	SOLEMN	22	0	0.4	0.0	40.4
7	MAJESTY	21	0	0.4	0.0	38.6
8	MYSTERIOUS	21	0	0.4	0.0	38.6
9	WHOSE	21	0	0.4	0.0	38.6
10	SOUL	20	0	0.4	0.0	36.8

SEC 2 (2000): 29,567,390 WORDS

	WORD/PHRASE	TOKENS 2	TOKENS 1	PM 2	PM 1	RATIO
1	LOT	71	0	2.4	0.0	240.1
2	HAPPENED	10	0	0.3	0.0	33.8
3	GRANDMOTHER	9	0	0.3	0.0	30.4
4	SMELL	7	0	0.2	0.0	23.7
5	MEAN	6	0	0.2	0.0	20.3
6	PRETTY	6	0	0.2	0.0	20.3
7	'RE	11	1	0.4	0.0	20.2
8	HAPPEN	5	0	0.2	0.0	16.9
9	PROBABLY	5	0	0.2	0.0	16.9
10	TASTED	5	0	0.2	0.0	16.9

Cell — 1850s vs. 2000s

Corpus of Historical American English

SEARCH | **FREQUENCY** | CONTEXT | OVERVIEW

SEE CONTEXT: CLICK ON WORD (ALL SECTIONS) OR NUMBER (SPECIFIED SECTION) [HELP...]

SEC 1 (1850): 16,471,649 WORDS

	WORD/PHRASE	TOKENS 1	TOKENS 2	PM 1	PM 2	RATIO
1	QUEEN	9	0	0.5	0.0	54.6
2	CONDEMNED	7	0	0.4	0.0	42.5
3	THY	6	0	0.4	0.0	36.4
4	HONEY	6	0	0.4	0.0	36.4
5	BEES	6	0	0.4	0.0	36.4
6	YOUNG	6	0	0.4	0.0	36.4
7	ROYAL	5	0	0.3	0.0	30.4
8	HERMIT	5	0	0.3	0.0	30.4
9	GLOOMY	5	0	0.3	0.0	30.4
10	FELON	7	1	0.4	0.0	12.6

SEC 2 (2000): 29,567,390 WORDS

	WORD/PHRASE	TOKENS 2	TOKENS 1	PM 2	PM 1	RATIO
1	PHONE	917	0	31.0	0.0	3,101.4
2	PHONES	258	0	8.7	0.0	872.6
3	STEM	97	0	3.3	0.0	328.1
4	-	71	0	2.4	0.0	240.1
5	YOU	65	0	2.2	0.0	219.8
6	)	43	0	1.5	0.0	145.4
7	RESEARCH	43	0	1.5	0.0	145.4
8	N'T	42	0	1.4	0.0	142.0
9	TALKING	40	0	1.4	0.0	135.3
10	RANG	36	0	1.2	0.0	121.8

Cell — 1850s vs. 2000s

Corpus of Historical American English

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SEE CONTEXT: CLICK ON WORD (ALL SECTIONS) OR NUMBER (SPECIFIED SECTION) [HELP...]

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4	HONEY	6	0	0.4	0.0	36.4
5	BEES	6	0	0.4	0.0	36.4
6	YOUNG	6	0	0.4	0.0	36.4
7	ROYAL	5	0	0.3	0.0	30.4
8	HERMIT	5	0	0.3	0.0	30.4
9	GLOOMY	5	0	0.3	0.0	30.4
10	FELON	7	1	0.4	0.0	12.6

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10	RANG	36	0	1.2	0.0	121.8

Downside: statistical association does not necessarily entail a semantic relationship

Cell — 1850s

Jena University Language & Information Engineering Lab

Corpus of Historical American English

SEARCH | FREQUENCY | CONTEXT

SECTION: 1850 **(9)** (SHUFFLE)

CLICK FOR MORE CONTEXT [?] SAVE LIST CHOOSE LIST --------- CREATE NEW LIST [?]

1	1853	NF	LangstrothOnHive	A	B	C	proceed as follows: With a very sharp knife, carefully cut out a **queen** **cell**, on a piece of comb an inch or
2	1853	NF	MysteriesBee-keeping	A	B	C	ADVANTAGES OF THIS METHOD. It is very plain that a **queen** from such finished **cell** must be ready to d
3	1853	NF	MysteriesBee-keeping	A	B	C	then, until further evidence contradicts it, that the first perfect **queen** leaving her **cell**, makes it her busi
4	1853	NF	MysteriesBee-keeping	A	B	C	pieces by the time the bee gets out. The covering to the **queen**'s **cell** is like the drone's, but larger in dia
5	1853	NF	MysteriesBee-keeping	A	B	C	of growth, as well as the eggs. Fig. 1 represents a **queen**'s **cell** just commenced. They are usually started
6	1853	NF	MysteriesBee-keeping	A	B	C	and removed by the workers. It will be perceived that each finished **queen**'s **cell** contains as much wax a
7	1853	NF	MysteriesBee-keeping	A	B	C	foregoing conditions of the stock may require their use). STATE OF **QUEEN**'S **CELL** WHEN USED. They ar
8	1853	NF	MysteriesBee-keeping	A	B	C	one of these methods could be relied upon. Instead of constructing a **queen**'s **cell**, and then removing t
9	1853	NF	MysteriesBee-keeping	A	B	C	the fact, that a few times I have found a quantity remaining in the **cell** after the **queen** had left. The con

Digital Approaches to Word Meaning Analysis

Approach	Typical Methods	Role of Researcher	Role of the Machine
Computer-Assisted Manual Analysis	Concordances	• Compose research design • Interpret individual examples • Identify trends in usage patterns • Infer meaning from usage patterns • Quality assurance (biased data)	• Data storage • Search / retrieval • Data aggregation • Data Visualization • Automated sem. analysis
Statistical Computing	N-gram freq., PMI	• Compose research design • Interpret individual examples • Identify trends in usage patterns • Infer meaning from usage patterns • Quality assurance (biased data)	• Data storage • Search / retrieval • Data aggregation • Data visualization • Automated sem. analysis
Semantic Computing			

Semantic Computing

PMI Matrix

PMI	read	pages	…	listen	$P(w_1)$
novel	0.94	0.57	…	-0.73	.070
poem	0.95	0.07	…	0.02	.037
…	…	…	…	…	…
opera	-0.43	-0.32	…	0.46	.067
$P(w_2)$	.081	.093	…	.077	1

$$PMI(w_1, w_2) := log \frac{P(w_1, w_2)}{P(w_1) \times P(w_2)}$$

PMI Matrix

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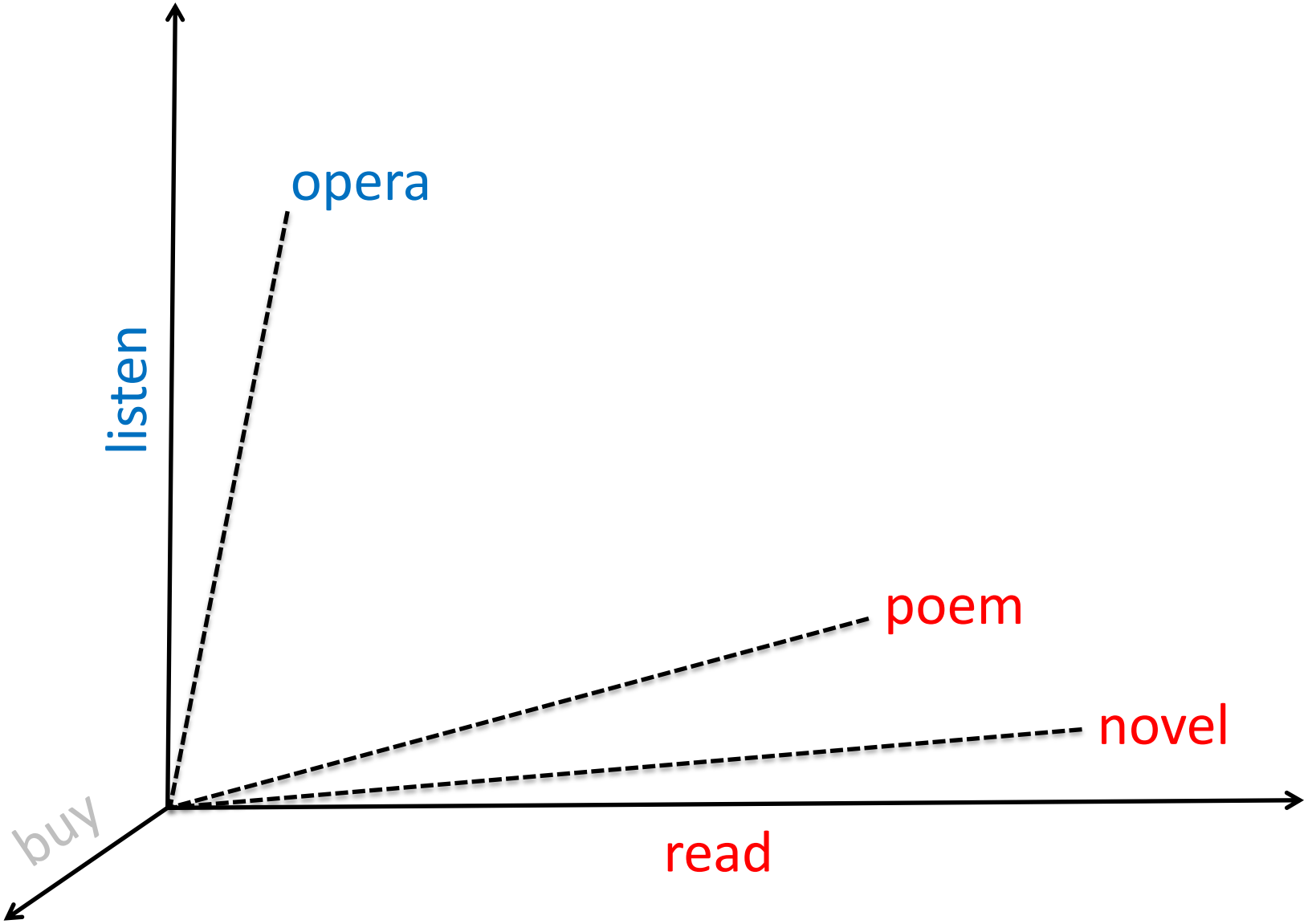
novel	0.94	0.57	…	-0.73
poem	0.95	0.07	…	0.02
…	…	…	…	…
opera	-0.43	-0.32	…	0.46

PMI Matrix

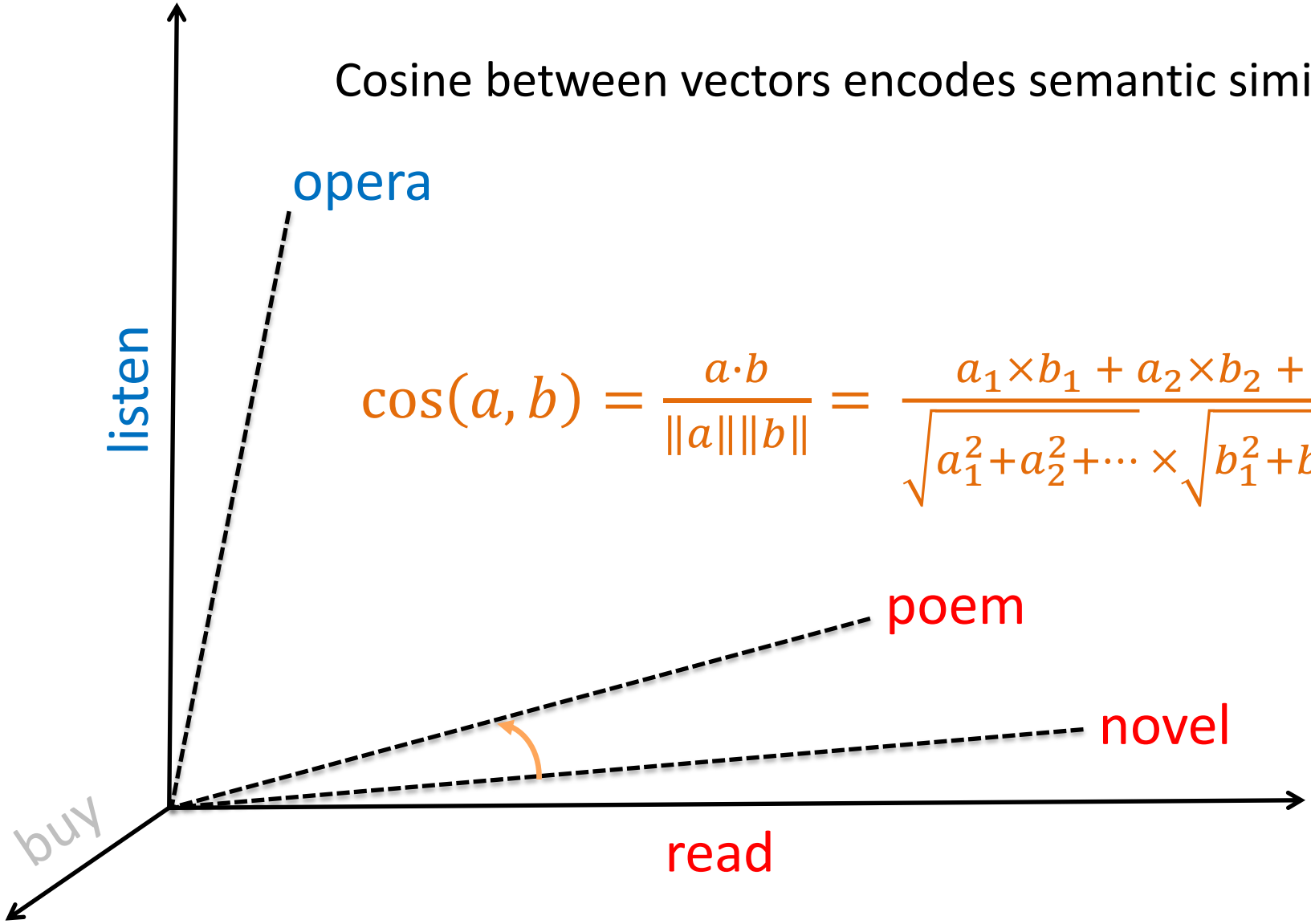
PMI	read	pages	…	listen
novel	0.94	0.57	…	-0.73
poem	0.95	0.07	…	0.02
…	…	…	…	…
opera	-0.43	-0.32	…	0.46

Vector Space Interpretation of PMI Matrix



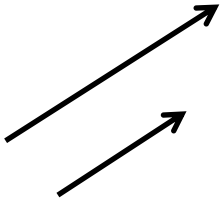
Vector Space Interpretation of PMI Matrix

Cosine between vectors encodes semantic similarity

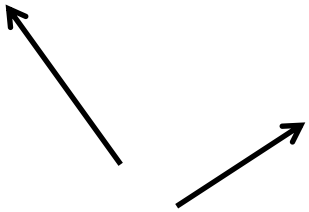


$$\cos(a,b) = \frac{a \cdot b}{\|a\|\|b\|} = \frac{a_1 \times b_1 + a_2 \times b_2 + \ldots}{\sqrt{a_1^2 + a_2^2 + \cdots} \times \sqrt{b_1^2 + b_2^2 + \ldots}}$$

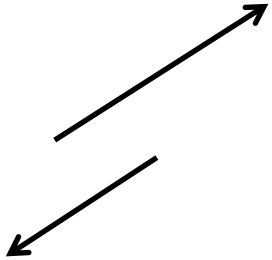
Illustration of Cosine Similarity



cos(a,b) = 1



cos(a,b) = 0



cos(a,b) = -1

PMI	read	pages	listen
novel	0.94	0.57	-0.73
poem	0.95	0.07	0.02

$$\cos(novel, poem) = \frac{.94\times.95 + .57\times.07 - .73\times.02}{\sqrt{.94^2 + .57^2 + .73^2} \times \sqrt{.95^2 + .07^2 + .02^2}} = \mathbf{.73}$$

Statistical Association vs. Semantic Similarity

- „Shallow“ text feature vs. „deep“ text feature
- Syntagmatic vs. paradigmatic
- Examples:
  - associated: *mashed* *potatoes*
  - similar: *potatoes* *fries*
  - associated and similar: *potato* *salad*
  - neither: *potato* *transcendent*

Empirically Validation: Word Similarity Lists

Word 1	Word 2	Similarity
Love	Sex	6.77
Tiger	Cat	7.35
Tiger	Tiger	10.00
Book	Paper	7.46

Example entries WordSim353 (Finkelstein et al., 2002)

- Ask 20 people how similar two words are on 1-to-10 scale
- Average responses for each word ("ground truth")
- Compute similarity of word pairs with cosine
- PMI vectors agree more with ground truth than two human raters with each other (Levy et al., TACL 2015)

Curse of Dimensionality

	read	pages	buy	eat	listen	
novel	98	60	3	0	2	
poem	67	10	1	0	8	…
opera	4	8	0	0	38	
⋮						

Typically 100,000 x 100,000 words
= 10 billion combinations!

Compressing the PMI Matrix

Singular Value Decomposition: Mathematical procedure allowing to reduce the number of columns of PMI matrix

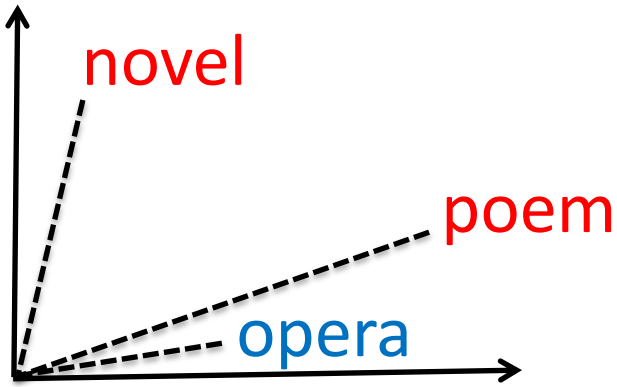
	Opaque Dimension 1	Opaque Dimension 2	Opaque Dimension 3	
novel	0.5	0.1	0.2	…
poem	0.3	0.0	0.3	
opera	0.1	-0.1	0.5	
⋮				

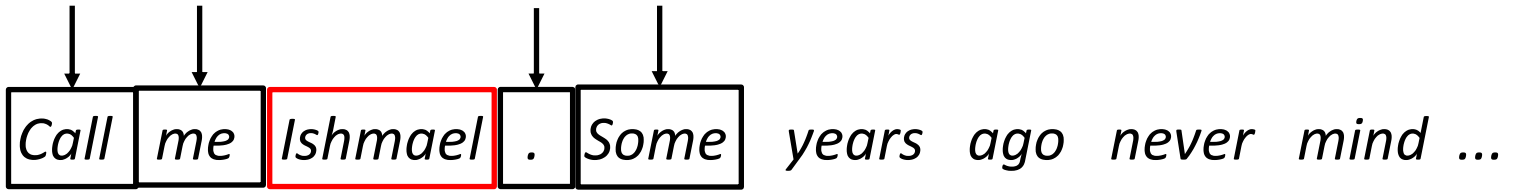
Typically 100,000 words x 300 dimensions
= 30 million combinations!

- ***Word Embeddings***: Dense (no or few zeros), low dimensional (50-1000) vector represenations of words

Word2Vec

(Mikolov et al., NIPS 2013)





- Start with random vectors of chosen dimensionality
- Predict surrounding words based on similarity of current vectors
- Iteratively update vectors to reduce error (machine learning)

Word2Vec

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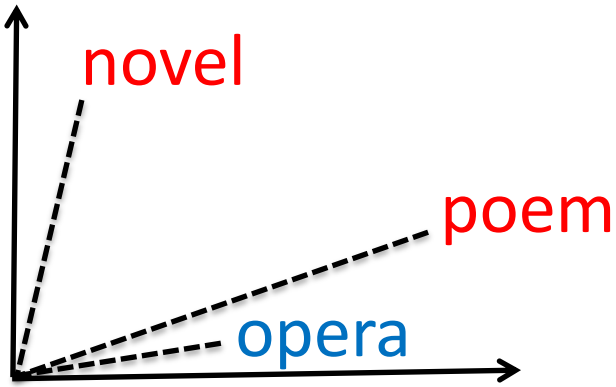

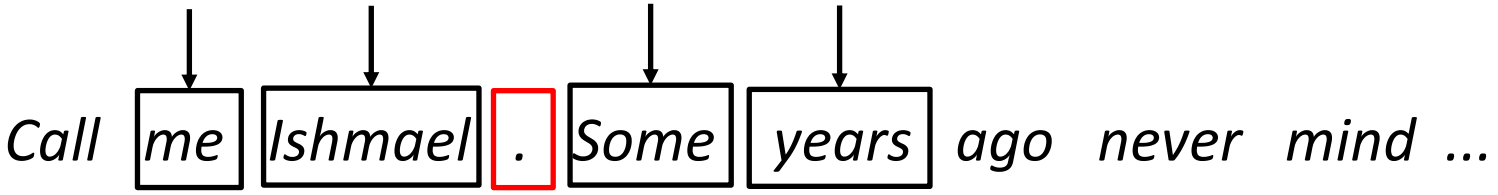

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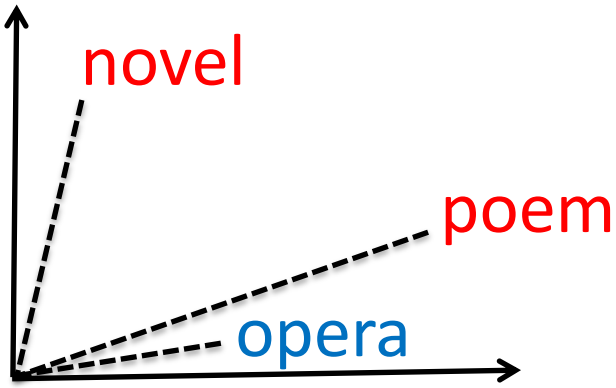

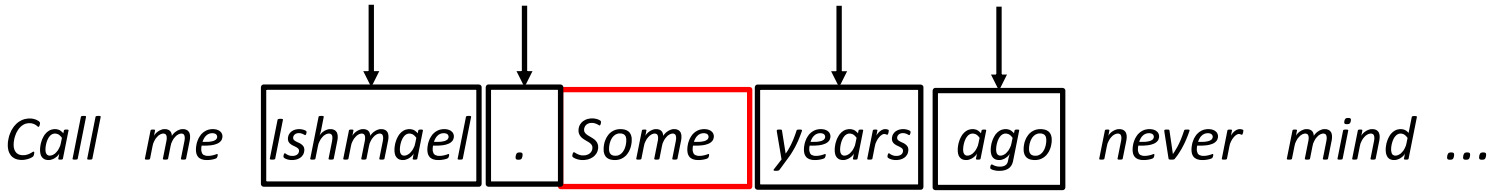

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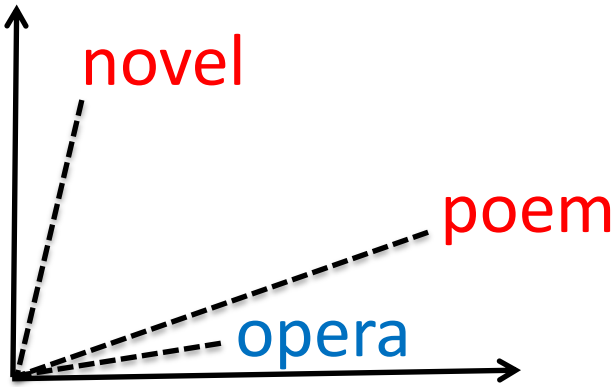

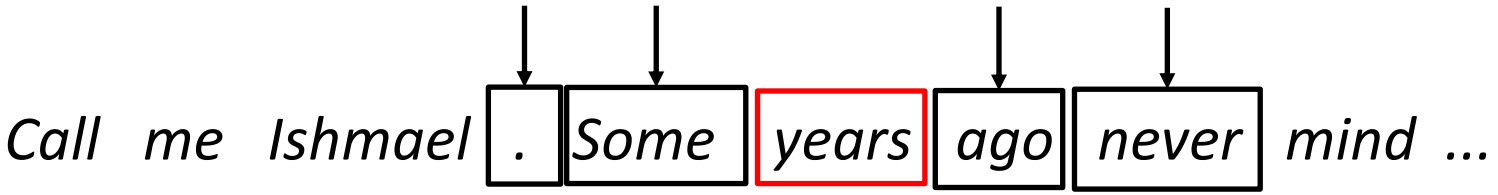

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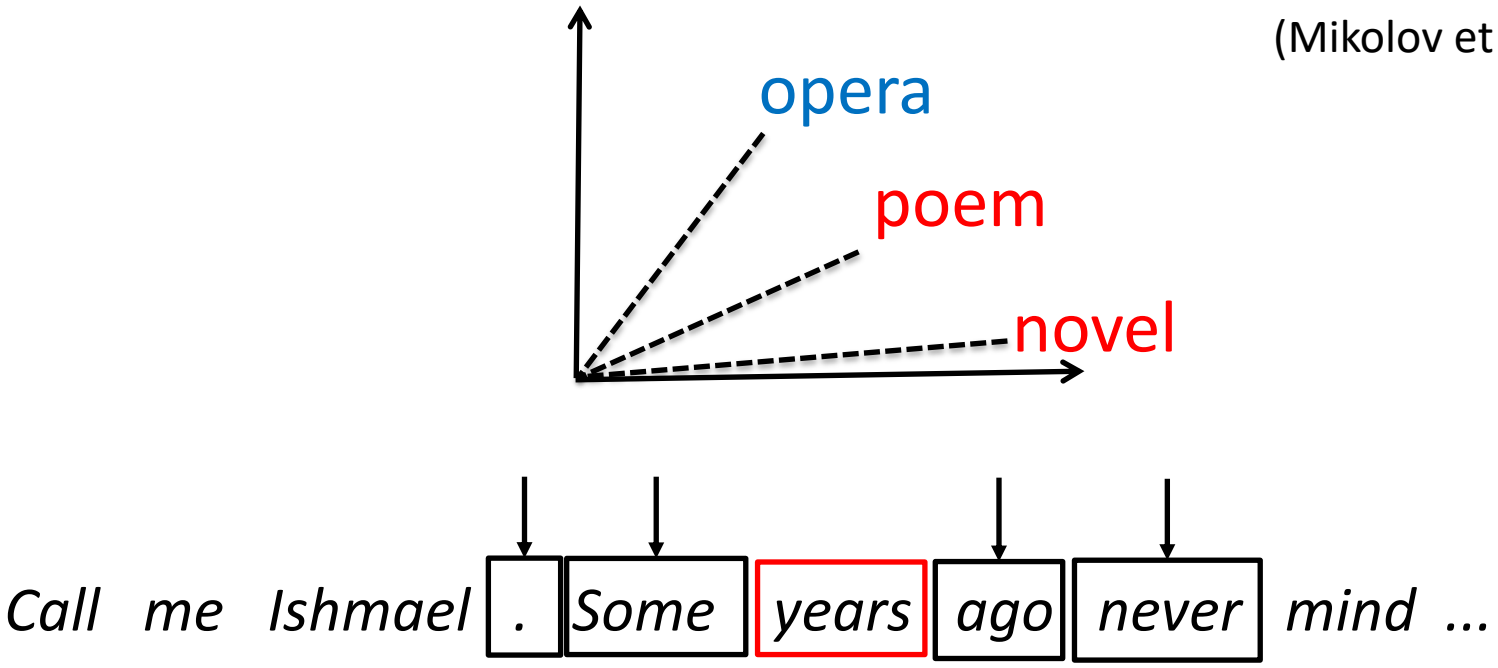
Word2Vec

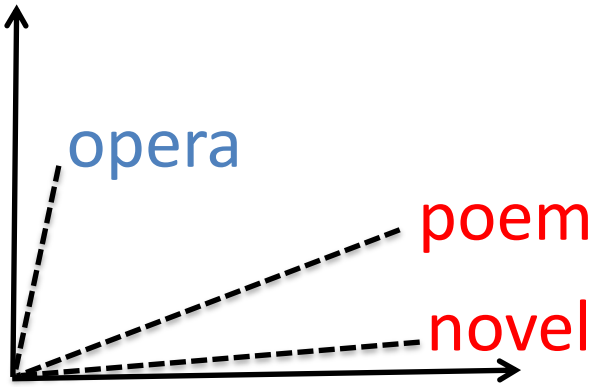
(Mikolov et al., NIPS 2013)

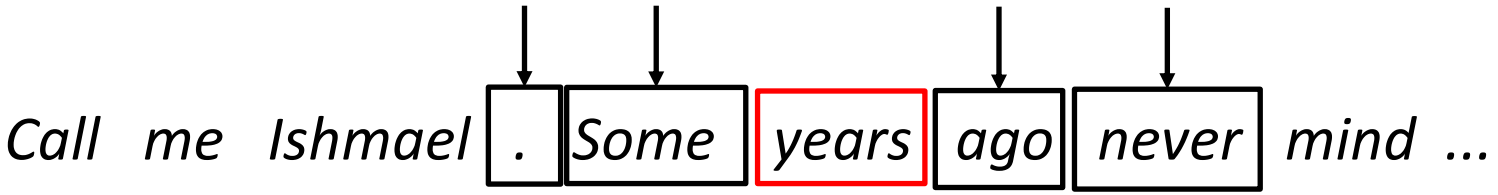


- Start with random vectors of chosen dimensionality
- Predict surrounding words based on similarity of current vectors
- Iteratively update vectors to reduce error (machine learning)

Word2Vec

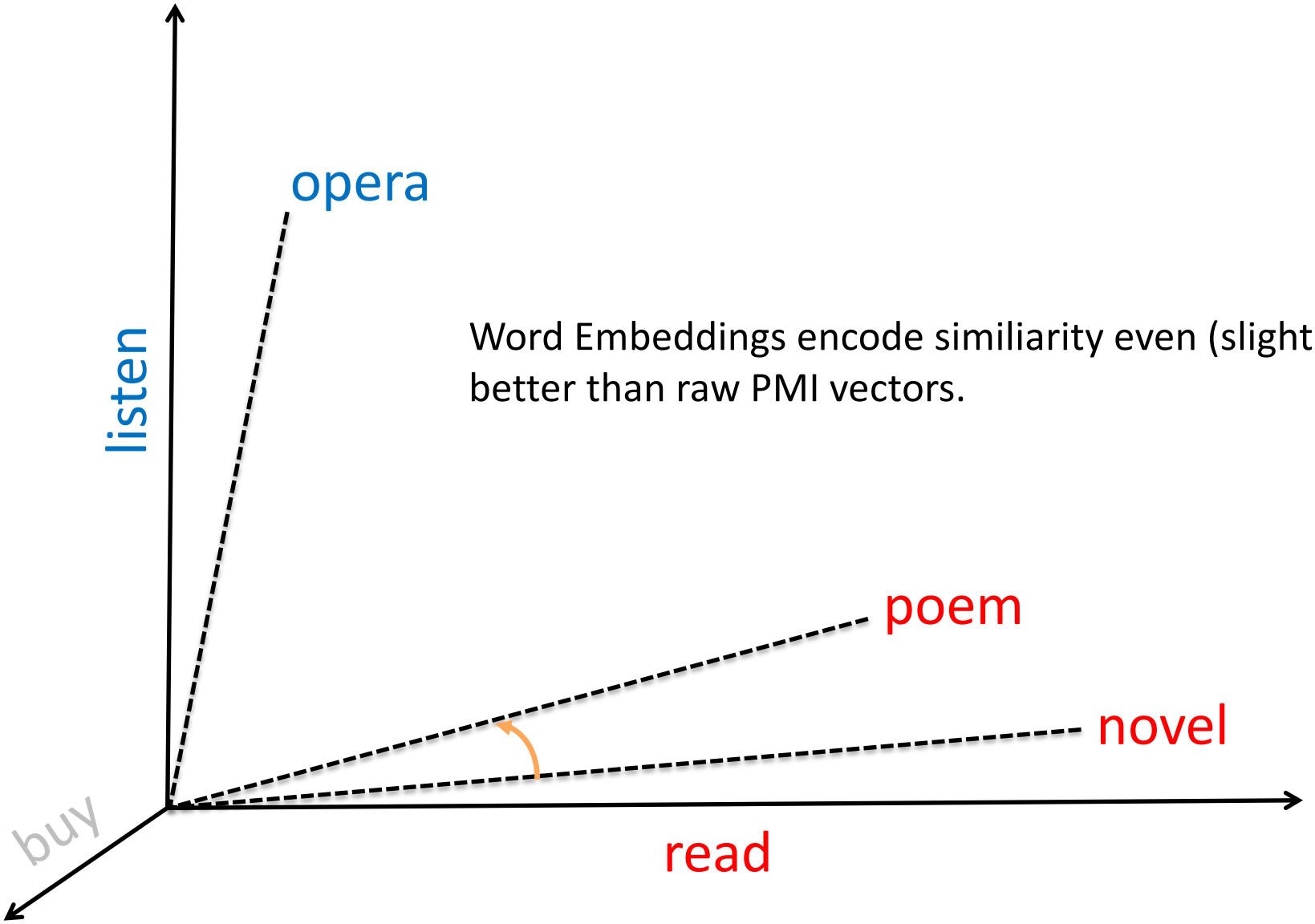
(Mikolov et al., NIPS 2013)





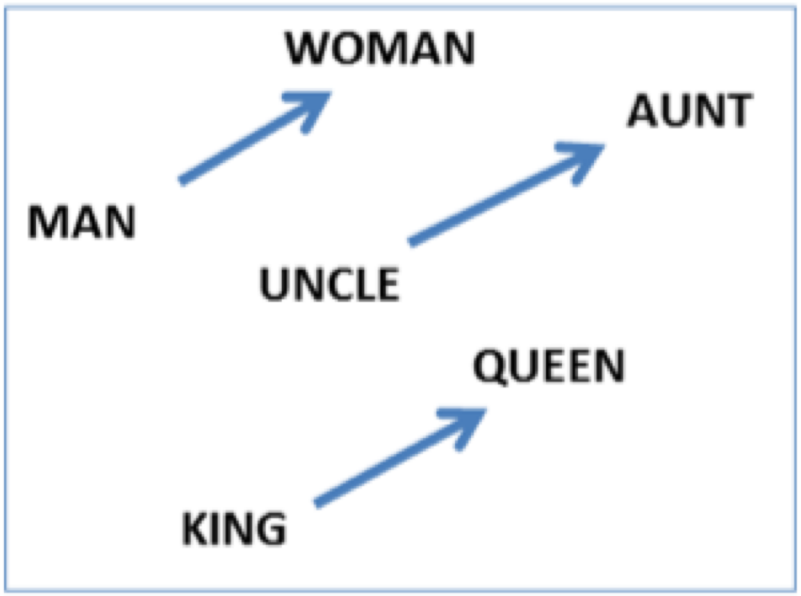
- Start with random vectors of chosen dimensionality
- Predict surrounding words based on similarity of current vectors
- Iteratively update vectors to reduce error (machine learning)

Computing Similarity



Word Embeddings encode similiarity even (slightly) better than raw PMI vectors.

Computing Word Analogies



(Mikolov et al., NAACL 2013)

- Semantic relationships are encoded by vectors, too
- Questions like „What is to *king* as *woman* is to *man*?“ can be answered with vector arithmetic

Surprising „Content“ of Word Embeddings

- Morphological relationships: sg.-pl., comparatives
  (Mikolov et al., NAACL 2013)
- Emotion: *terrorism* vs. *sunshine*
  (Buechel & Hahn, NAACL 2018)
- Abstractness: *freedom* vs. *laptop*
  (Köper & Schulte im Walde, LREC 2016)
- Geolocation, GDP, fertility rate and many other referential attributes of country names (*France, Italy, Spain,...)*
  (Gupta et al., EMNLP 2015)

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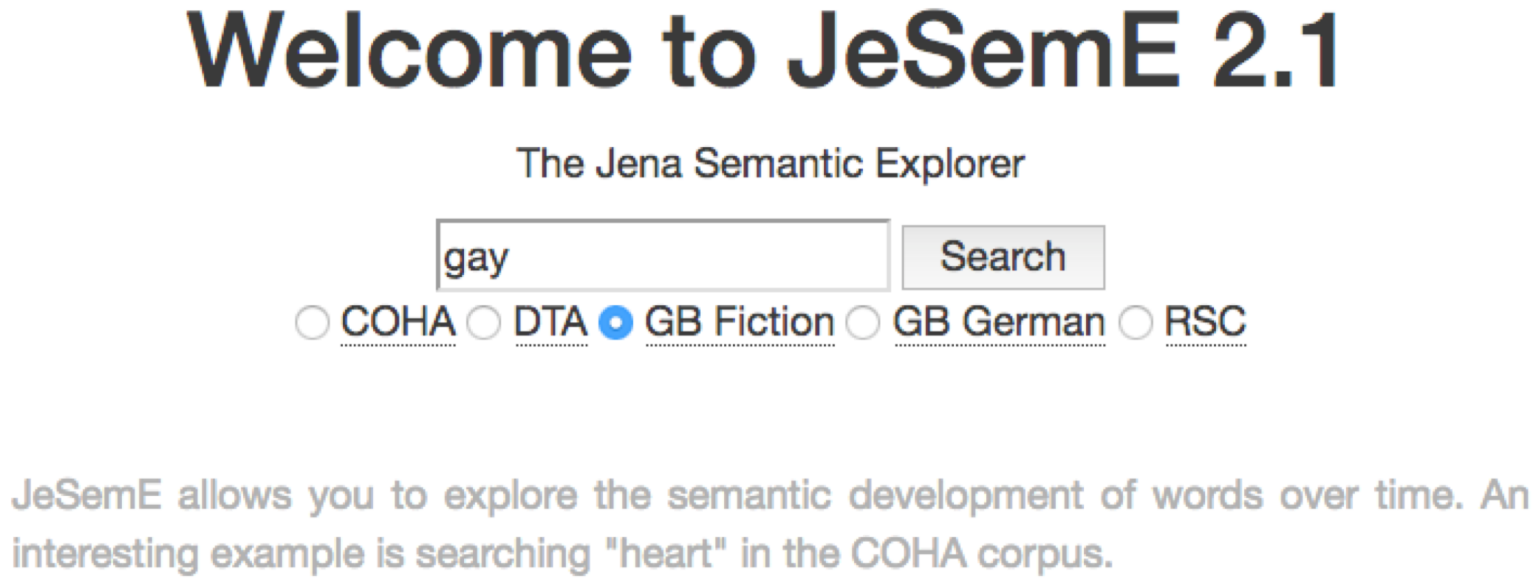
- **Problem**: Word Embeddings require technical skill and computational resources to work with

-0.13102 -0.054447 -0.051866 -0.10289 -0.072061 0.16523 -0.17298 0.21865 0.041183 -0.010858 0.074741 0.35226 0.42662 -0.071747 0.25112 0.12082 -0.33192 -0.4728 -0.0090568 0.0030266 0.032861 0.074323 -0.38017 0.091399 -0.16034 -0.050232 -0.094194 0.16656 0.40901 0.069625 0.059306 0.01991 -0.35846 -0.14549 0.24894 0.50184 -0.0073098 -0.4589 -0.10073 -0.099315 0.30583 -0.40577 0.16586 0.055741 0.26776 -0.13515 0.28127 0.069221 -0.20907 0.092053 0.39419 -0.2412 0.01173 -0.16856 -0.0053851 0.14282 0.17513 0.34775 0.178 0.35883 -0.17684 0.53104 0.04751 -0.30134 -0.53297 -0.22041 0.097703 0.052288 0.10849 0.12409 -0.11369 0.19042 0.19554 -0.14949 -0.29675 -0.14285 0.22217 0.21503 -0.2309 0.4381 0.22739 -0.052386 -0.20003 0.19725 -0.032432 -0.14307 0.021958 0.36876 -0.10084 -0.18536 0.27691 -0.43856 0.087418 -0.33836 0.083161 -0.40672 0.14497 -0.41334 0.0012195 -0.32266 0.067225 0.18359 0.010442 -0.15499 -0.82943 -0.069867 -0.26416 0.42656 0.26765 -0.12262 -0.116 -0.076926 -0.16992 0.055428 -0.20699 -0.090381 0.082171 -0.31509 -0.12135 0.055464 0.9075 0.18585 -0.20836 0.019945 0.17853 -0.31707 0.054172 0.40715 0.32685 -0.20493 0.099457 0.15329 -0.28035 0.36088 0.31671 -0.2216 -0.094332 0.33993 -0.23604 0.44507 -0.025739 0.2082 -0.28423 0.18867 -0.30867 -0.015983 0.13985 0.035387 0.25648 -0.18241 0.50119 -0.31602 -0.19771 -0.3002 0.048059 0.14868 -0.45165 0.11831 0.045376 0.31328 -0.052771 0.08615 -0.18376 0.071614 0.30406 0.26742 -0.22895 0.17671 0.33062 0.17738 0.042157 -0.29211 -0.10786 -0.064557 -0.10006 0.39087 -0.21173 -0.085387 -0.040239 -0.1044 -0.019623 -0.32887 0.15656 0.039189 -0.30531 0.235 -0.025831 0.041146 0.30737 -0.16955 -0.18446 -0.11642 0.038028 0.094888 -0.25135 -0.011466 0.18069 0.44957 -0.28939 -0.46813 0.035372 0.045633 0.1507 -0.098108 -0.31644 -0.19265 -0.3108 0.32345 0.57775 0.042428 0.2334 -0.093899 -0.50785 -0.68498 0.088108 -0.25361 -0.018187 -0.50159 -0.19892 -0.12127 -0.21447 0.22551 0.021314 0.078556 -0.0828 -0.27046 -0.19486 0.13457 0.44123 0.13542 -0.37831 0.36109 -0.04392 0.21795 -0.092712 -0.12707 -0.1428 -0.021229 -0.13407 -0.12783 -0.099737 -0.055585 0.042925 -0.41051 -0.044614 -0.2326 -0.033486 -0.1761 -0.042099 -0.20191 -0.042496 -0.08971 0.062699 -0.39227 0.2632 0.13261 -0.45002 -0.2213 0.31223 0.43488 -0.05547 0.22954 0.70868 -0.37327 0.2844 -0.24495 -0.28255 0.21883 -0.053093 -0.3006 -0.34203 -0.11602 0.36381 0.11346 0.1853 -0.014843 0.21921 0.047219 -0.0054492 0.2878 0.51144 0.17271 -0.026182 0.00051472 0.033597 -0.061401 0.25367 -0.13141 -0.056602 -0.0025169 0.44398 -0.26233 0.21532 0.34318 -0.081855 -0.030759 -0.022955 -0.1757 0.44088 -0.062219

-0.13102 -0.054447 -0.051866 -0.10289 -0.072061 0.16523 -0.17298 0.21865 0.041183 -0.010858 0.074741 0.35226 0.42662 -0.071747 0.25112 0.12082 -0.33192 -0.4728 -0.0090568 0.0030266 0.032861 0.074323 -0.38017 0.091399 -0.16034 -0.050232 -0.094194 0.16656 0.40901 0.069625 0.059306 0.01991 -0.35846 -0.14549 0.24894 0.50184 -0.0073098 -0.4589 -0.10073 -0.099315 0.30583 -0.40577 0.16586 0.055741 0.26776 -0.13515 0.28127 0.069221 -0.20907 0.092053 0.39419 -0.2412 0.01173 -0.16856 -0.0053851 0.14282 0.17513 0.34775 0.178 0.35883 -0.17684 0.53104 0.04751 -0.30134 -0.53297 -0.22041 0.097703 0.052288 0.10849 0.12409 -0.11369 0.19042 0.19554 -0.14949 -0.29675 -0.14285 0.22217 0.21503 -0.2309 0.4381 0.22739 -0.052386 -0.20003 0.19725 -0.032432 -0.14307 0.021958 0.36876 -0.10084 -0.18536 0.27691 -0.43856 0.087418 -0.33836 0.083161 -0.40672 0.14497 -0.41334 0.0012195 -0.32266 0.067225 0.18359 0.010442 -0.15499 -0.82943 -0.069867 -0.26416 0.42656 0.26765 -0.12262 -0.116 -0.076926 -0.16992 0.055428 -0.20699 -0.090381 0.082171 -0.31509 -0.12135 0.055464 0.9075 0.18585 -0.20836 0.019945 0.17853 -0.31707 0.054172 0.40715 0.32685 -0.20493 0.099457 0.15329 -0.28035 0.36088 0.31671 -0.2216 -0.094332 0.33993 -0.23604 0.44507 -0.025739 0.2082 -0.28423 0.18867 -0.30867 -0.015983 0.13985 0.035387 0.25648 -0.18241 0.50119 -0.31602 -0.19771 -0.3002 0.048059 0.14868 -0.45165 0.11831 0.045376 0.31328 -0.052771 0.08615 -0.18376 0.071614 0.30406 0.26742 -0.22895 0.17671 0.33062 0.17738 0.042157 -0.29211 -0.10786 -0.064557 -0.10006 0.39087 -0.21173 -0.085387 -0.040239 -0.1044 -0.019623 -0.32887 0.15656 0.039189 -0.30531 0.235 -0.025831 0.041146 0.30737 -0.16955 -0.18446 -0.11642 0.038028 0.094888 -0.25135 -0.011466 0.18069 0.44957 -0.28939 -0.46813 0.035372 0.045633 0.1507 -0.098108 -0.31644 -0.19265 -0.3108 0.32345 0.57775 0.042428 0.2334 -0.093899 -0.50785 -0.68498 0.088108 -0.25361 -0.018187 -0.50159 -0.19892 -0.12127 -0.21447 0.22551 0.021314 0.078556 -0.0828 -0.27046 -0.19486 0.13457 0.44123 0.13542 -0.37831 0.36109 -0.04392 0.21795 -0.092712 -0.12707 -0.1428 -0.021229 -0.13407 -0.12783 -0.099737 -0.055585 0.042925 -0.41051 -0.044614 -0.2326 -0.033486 -0.1761 -0.042099 -0.20191 -0.042496 -0.08971 0.062699 -0.39227 0.2632 0.13261 -0.45002 -0.2213 0.31223 0.43488 -0.05547 0.22954 0.70868 -0.37327 0.2844 -0.24495 -0.28255 0.21883 -0.053093 -0.3006 -0.34203 -0.11602 0.36381 0.11346 0.1853 -0.014843 0.21921 0.047219 -0.0054492 0.2878 0.51144 0.17271 -0.026182 0.00051472 0.033597 -0.061401 0.25367 -0.13141 -0.056602 -0.0025169 0.44398 -0.26233 0.21532 0.34318 -0.081855 -0.030759 -0.022955 -0.1757 0.44088 -0.062219

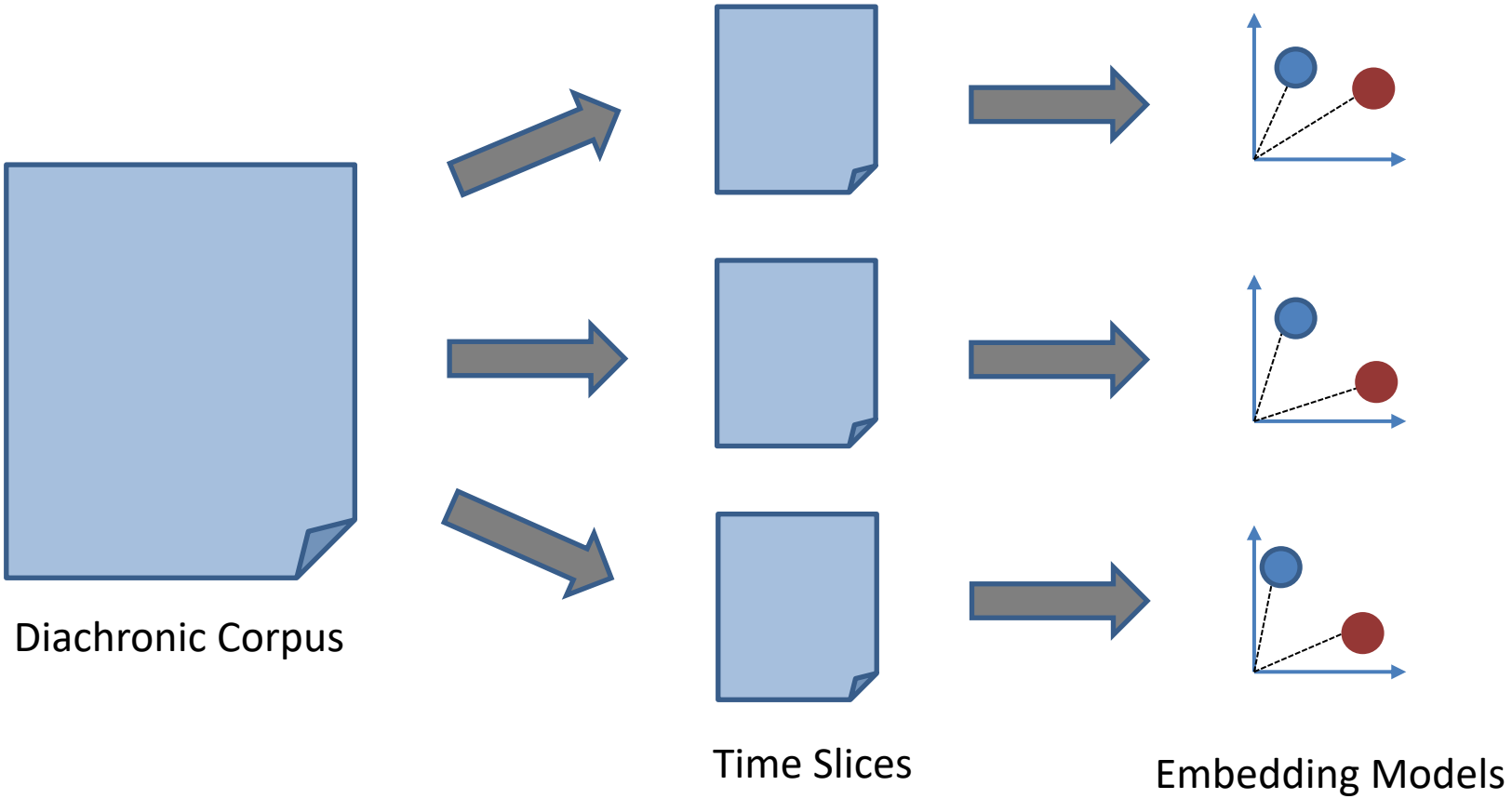
(*sunshine*)

JeSemE: Word Embedding Exploration for DH

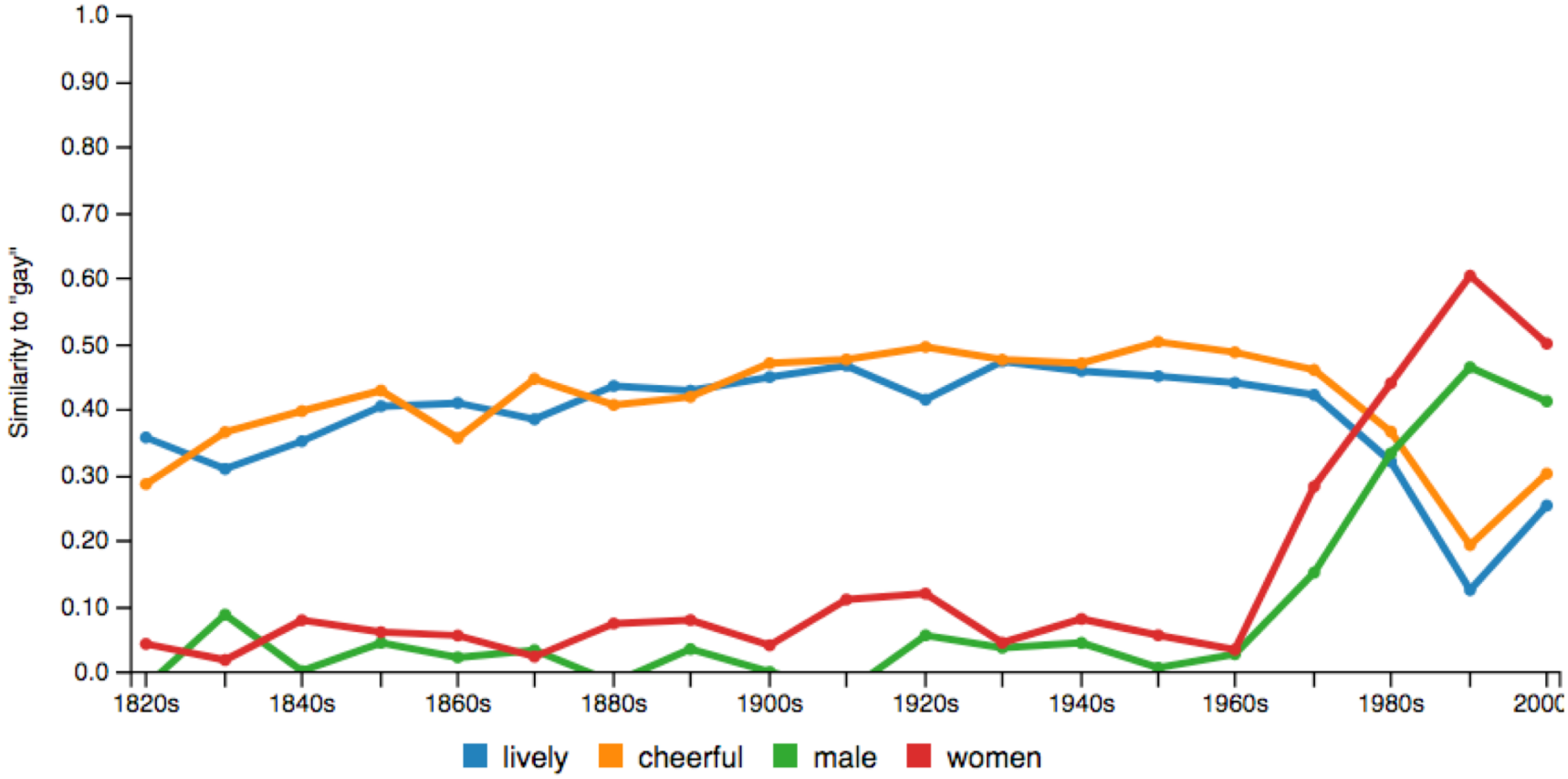


http://jeseme.org/
(Hellrich, Buechel & Hahn, COLING 2018)

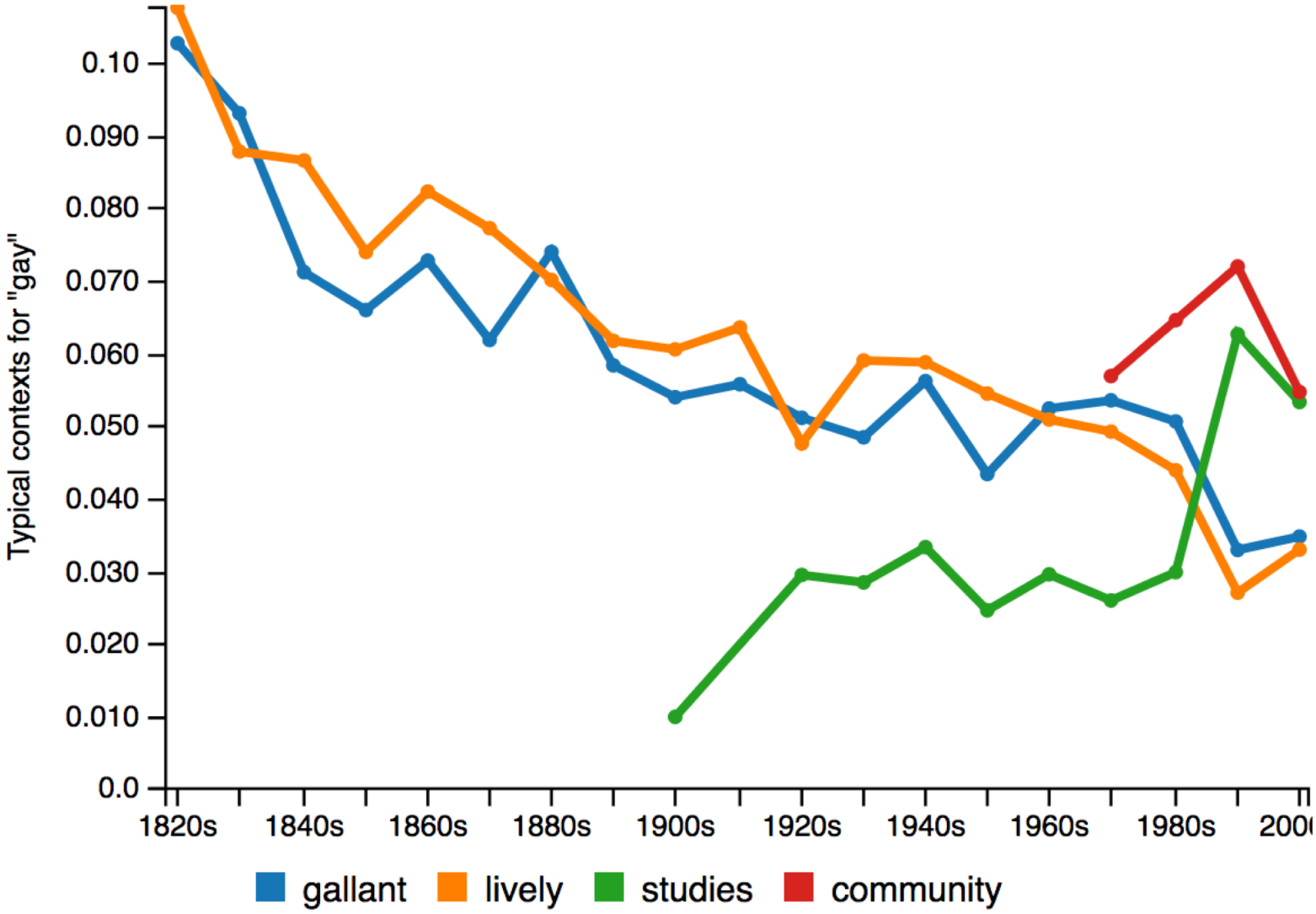
Underlying Data



Gay — Meaning in Google Books Fiction

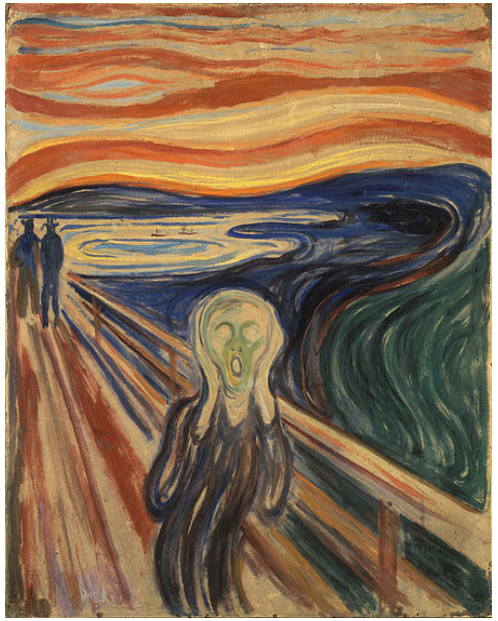


Gay — Association in Google Books Fiction



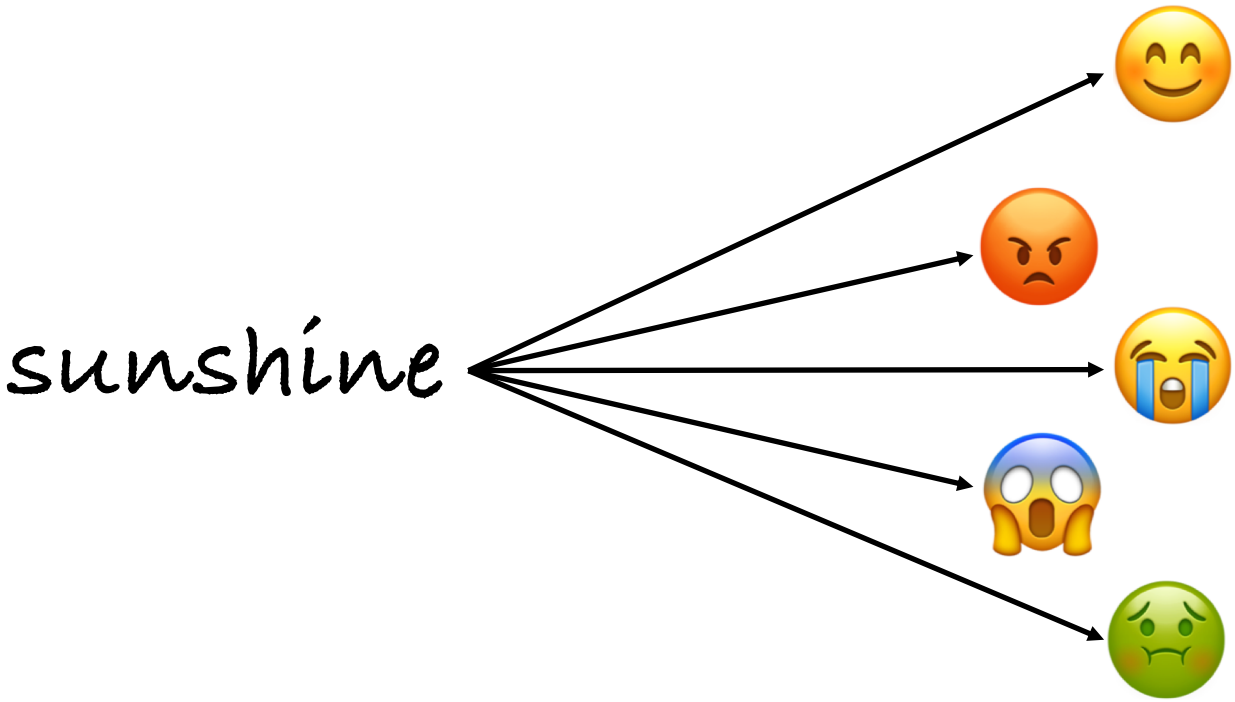
Semantic Computing: Historical Word Emotion

Motivation: Emotion in the Humanities



https://de.wikipedia.org/wiki/Laokoon-Gruppe
https://de.wikipedia.org/wiki/Der_Schrei
http://www.br.de/telekolleg/faecher/deutsch/literatur/goethe-weimarer-klassik-100.html

Word Emotion Induction



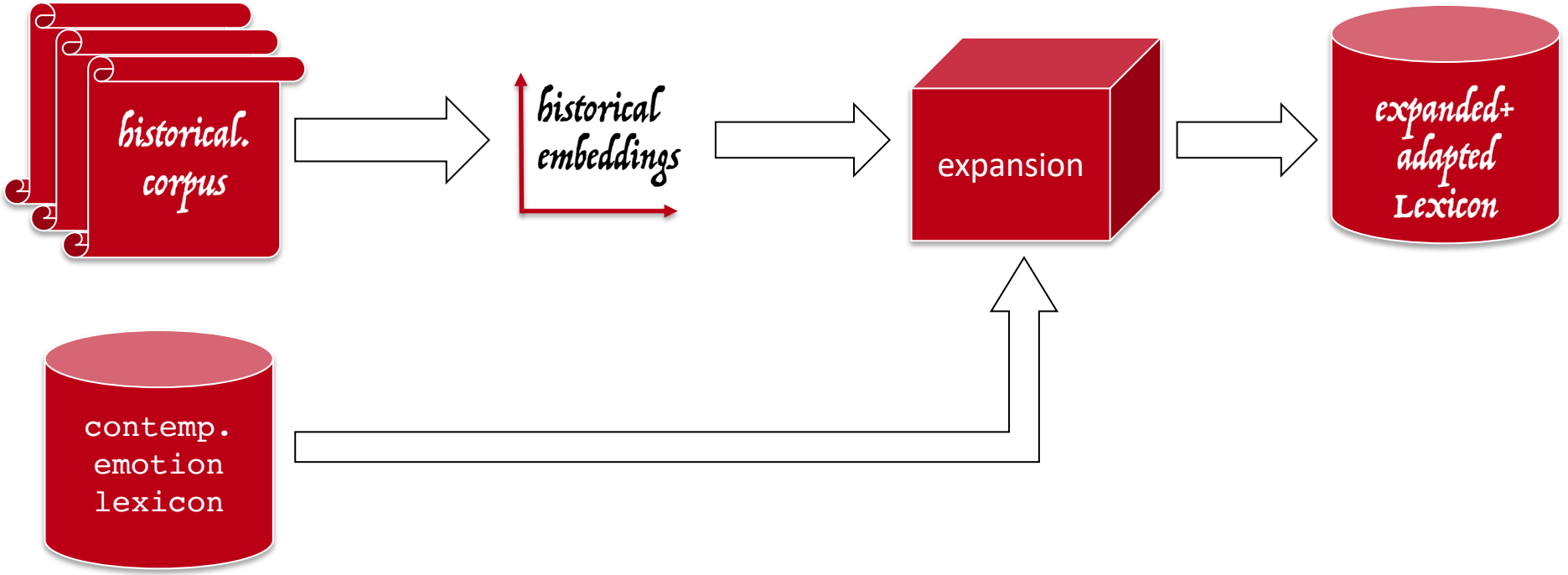
- Task: computational estimation of emotion of words
- Part of *Sentiment Analysis*, area of computational linguistics which addresses opinions, interpersonal relations and feelings

Emotion Lexicons

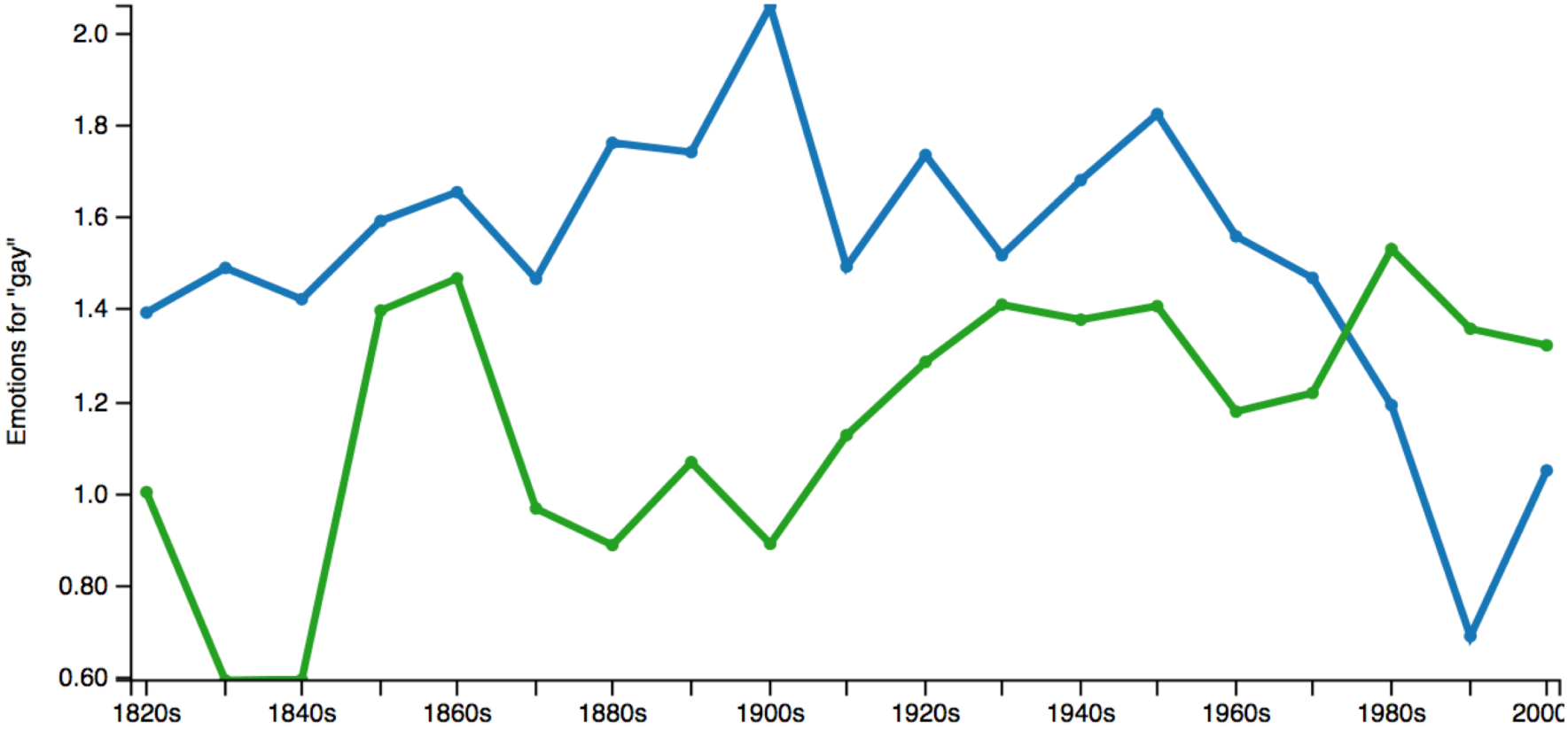
sunshine	
terrorism	
earthquake	

- Store emotion associated with individual words
- Created like word similarity lists

Temporal Adaptation and Expansion



Gay — Word Emotion



valence:	pleasant vs. unpleasant
arousal:	calm vs. excited

http://jeseme.org/

Digital Approaches to Word Meaning Analysis

Approach	Typical Methods	Role of Researcher	Role of the Machine
Computer-Assisted Manual Analysis	Concordances	• Compose research design • Interpret individual examples • Identify trends in usage patterns • Infer meaning from usage patterns • Quality assurance (biased data)	• Data storage • Search / retrieval • Data aggregation • Data Visualization • Automated sem. analysis
Statistical Computing	N-gram freq., PMI	• Compose research design • Interpret individual examples • Identify trends in usage patterns • Infer meaning from usage patterns • Quality assurance (biased data)	• Data storage • Search / retrieval • Data aggregation • Data visualization • Automated sem. analysis
Semantic Computing	Word embeddings, sentiment analysis	• Compose research design • Interpret individual examples • Identify trends in usage patterns • Infer meaning from usage patterns • Quality assurance (biased data)	• Data storage • Search / retrieval • Data aggregation • Data visualization • Automated sem. analysis

Conclusion

- Presented three approaches to word meaning analysis in historical corpora
- Varying degree of automation / technical sophistication:
  - Machine takes over more tasks
  - Role of researcher shifts towards study design & quality assurance
- Reflect methodological choices in other DH areas

➢ Different ”flavors” of DH:

Digital Humanities or *Computational Humanities* ?

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FRIEDRICH-SCHILLER-
UNIVERSITÄT
JENA

Jena University Language & Information Engineering Lab

Quantifying Word Meaning and Emotion in Historical Language

Sven Buechel

Jena University Language and Information Engineering (JULIE) Lab
Friedrich-Schiller-University Jena,
Jena, Germany

https://julielab.de