



Measuring the meaning of words

Astrid van Aggelen
Information Access Group

SAY DIGITAL HUMANITIES

ONE MORE TIME

SAY DIGITAL HUMANITIES

TEXT MINING !

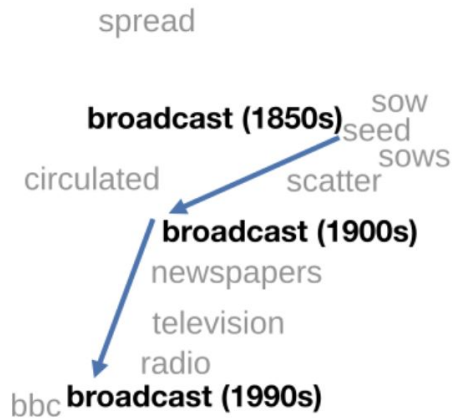
COMPUTATIONAL TEXT ANALYSIS !

NATURAL LANGUAGE PROCESSING !

ONE MORE TIME

Word meaning over time





This linguistic evolution is traceable in a large text corpus

Words occurring in similar (linguistic) contexts tend to be semantically similar (distributional hypothesis, Firth)

e.g. *broadcast* was once found in similar linguistic contexts as *sow* and *seed*

Distributional hypothesis:

John R. Firth. 1957. A synopsis of linguistic theory 1930–55. In *Studies in Linguistic Analysis (special volume of the Philological Society)*, pages 1–32, Oxford. The Philological Society.

Figure:

William L. Hamilton, Jure Leskovec, and Dan Jurafsky. ACL 2016. [Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change.](#)

Cosine similarity (distance) reflects semantic similarity (distance)

	get	see	use	hear	eat	kill
knife	0.027	-0.024	0.206	-0.022	-0.044	-0.042
cat	0.031	0.143	-0.243	-0.015	-0.009	0.131
dog	-0.026	0.021	-0.212	0.064	0.013	0.014
boat	-0.022	0.009	-0.044	-0.040	-0.074	-0.042
cup	-0.014	-0.173	-0.249	-0.099	-0.119	-0.042
pig	-0.069	0.094	-0.158	0.000	0.094	0.265
banana	0.047	-0.139	-0.104	-0.022	0.267	-0.042

Term = word, lemma, phrase, morpheme, ...

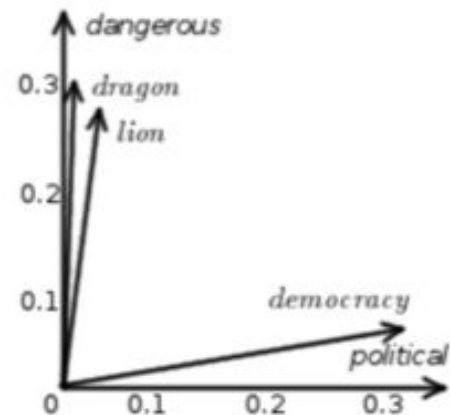


Figure left: Stefan Evert. Distributional Semantic Models
Tutorial at NAACL-HLT 2010, Los Angeles, CA.

Figure right: <http://aurelieherbelot.net/research/distributional-semantic-intro/>

$w1, t$



$w2, t$



$\text{sim}(w1, w2)$



$w1, t+1$



$w2, t+1$



$\text{sim}(w1, w2)$



time series of mutual cosine similarities
shows positive correlation with time

Word	Moving towards	Moving away	Shift start	Method	Corpus	% Correct	%Sig.
gay	homosexual, lesbian	happy, showy	ca 1950	PPMI	ENGALL	77.1	51.9
fatal	illness, lethal	fate, inevitable	<1800		COHA	85.7	52.4
awful	disgusting, mess	impressive, majestic	<1800	SVD	ENGALL	92.6	81.5
nice	pleasant, lovely	refined, dainty	ca 1890		COHA	95.8	62.5
broadcast	transmit, radio	scatter, seed	ca 1920	SGNS	ENGALL	100.0	88.9
monitor	display, screen	—	ca 1930		COHA	87.5	50.0
record	tape, album	—	ca 1920				
guy	fellow, man	—	ca 1850				
call	phone, message	—	ca 1890				

Table 2: Set of attested historical shifts used to evaluate the methods. The examples are taken from previous works on semantic change and from the Oxford English Dictionary (OED), e.g. using ‘obsolete’ tags. The shift start points were estimated using attestation dates in the OED. The first six examples are words that shifted dramatically in meaning while the remaining four are words that acquired new meanings (while potentially also keeping their old ones).

William L. Hamilton, Jure Leskovec, and Dan Jurafsky. ACL 2016. [Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change.](#)

Word	Moving towards	Moving away	Shift start
gay	homosexual, lesbian	happy, showy	ca 1950
fatal	illness, lethal	fate, inevitable	<1800
awful	disgusting, mess	impressive, majestic	<1800
nice	pleasant, lovely	refined, dainty	ca 1890
broadcast	transmit, radio	scatter, seed	ca 1920
monitor	display, screen	—	ca 1930
record	tape, album	—	ca 1920
guy	fellow, man	—	ca 1850
call	phone, message	—	ca 1890

Method	Corpus	% Correct	%Sig.
PPMI	ENGALL	77.1	51.9
	COHA	85.7	52.4
SVD	ENGALL	92.6	81.5
	COHA	95.8	62.5
SGNS	ENGALL	100.0	88.9
	COHA	87.5	50.0

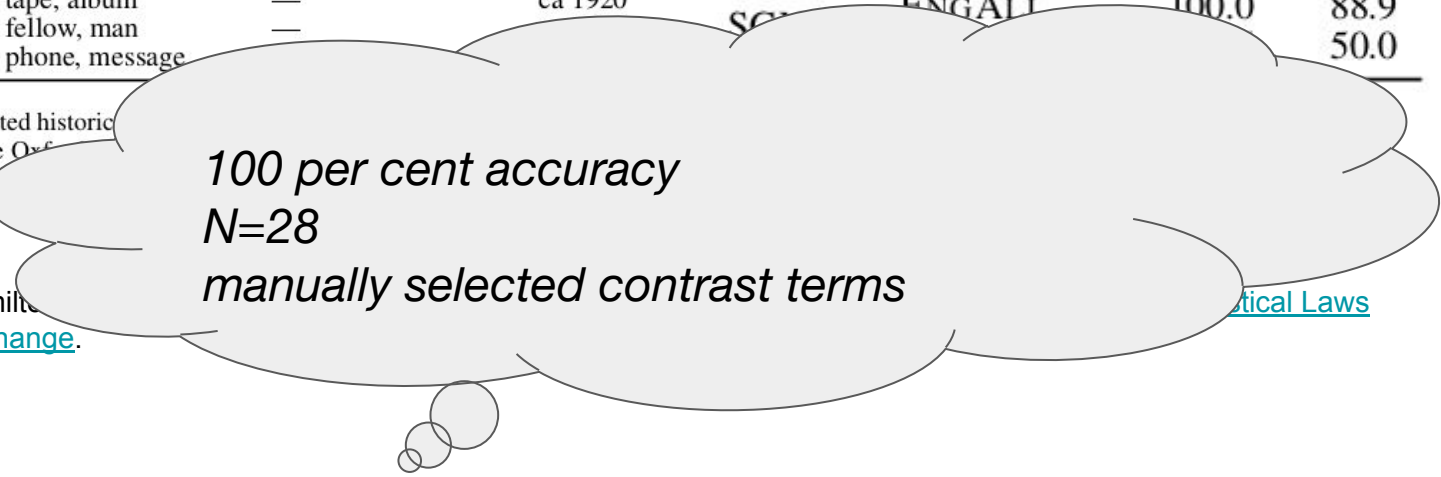
Table 2: Set of attested historical shifts used to evaluate the methods. The examples are taken from previous works on semantic change and from the Oxford English Dictionary (OED), e.g. using ‘obsolete’ tags. The shift start points were estimated using attestation dates in the OED. The first six examples are words that shifted dramatically in meaning while the remaining four are words that acquired new meanings (while potentially also keeping their old ones).

William L. Hamilton, Jure Leskovec, and Dan Jurafsky. ACL 2016. [Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change.](#)

Word	Moving towards	Moving away	Shift start
gay	homosexual, lesbian	happy, showy	ca 1950
fatal	illness, lethal	fate, inevitable	<1800
awful	disgusting, mess	impressive, majestic	<1800
nice	pleasant, lovely	refined, dainty	ca 1890
broadcast	transmit, radio	scatter, seed	ca 1920
monitor	display, screen	—	ca 1930
record	tape, album	—	ca 1920
guy	fellow, man	—	
call	phone, message		

Method	Corpus	% Correct	%Sig.
PPMI	ENGALL	77.1	51.9
	COHA	85.7	52.4
SVD	ENGALL	92.6	81.5
	COHA	95.8	62.5
SC	ENGALL	100.0	88.9
			50.0

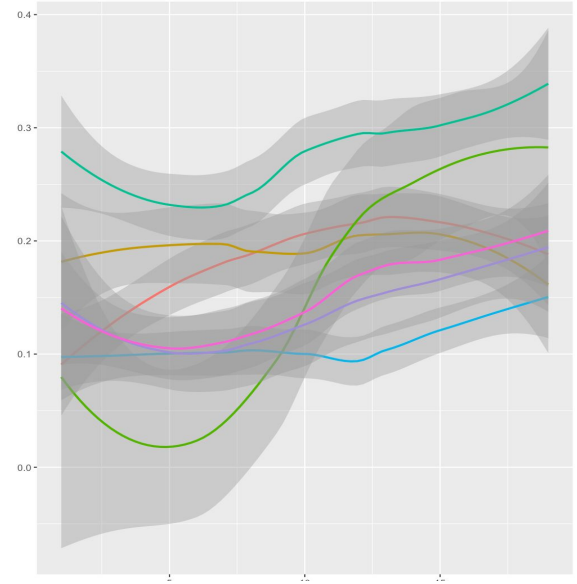
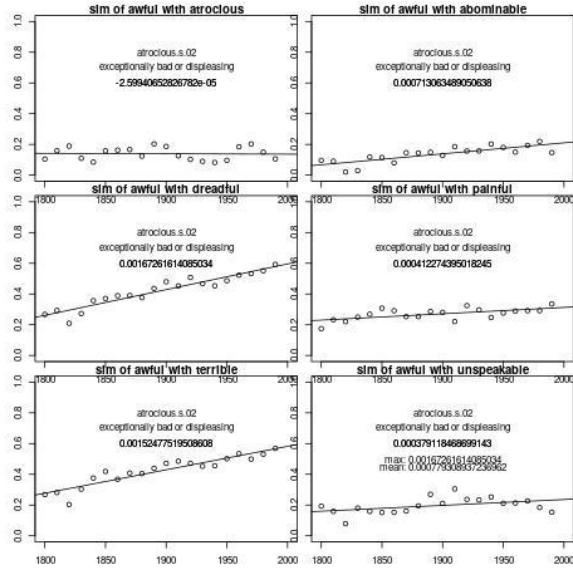
Table 2: Set of attested historic change and from the Oxford attestation dates in words that acquired



William L. Hamilton
[of Semantic Change.](#)

[Statistical Laws](#)

- New, larger dataset
- More contrast terms, automatically selected
- Aggregated findings per dictionary sense



Word-Shift-Eval	eng-all			
	HT+	wsct+	HW+	HW
setting 1				
correct(%)	51	79	80	100
sig(%)	42	55	62	89
<i>N</i>	1718	14	49	28
setting 2				
correct(%)	58	69	80	100
sig(%)	39	67	60	89
<i>N</i>	1459	13	44	27

SenseShift-Eval	eng-all		
	HT+	wsct+	HW+
setting 1			
average vec.	50	100	73
argmax(corr)	54	100	92
argmax(freq)	52	80	85
majority vote	44	100	77
argmin(p(corr))	54	100	92
<i>AVG</i>	51	96	84
<i>N</i>	504	5	13
setting 2			
average vec.	56	100	78
argmax(corr)	61	100	85
argmax(freq)	57	80	85
majority vote	51	100	77
argmin(p(corr))	62	100	85
<i>AVG</i>	57	96	82
<i>N</i>	449	5	13

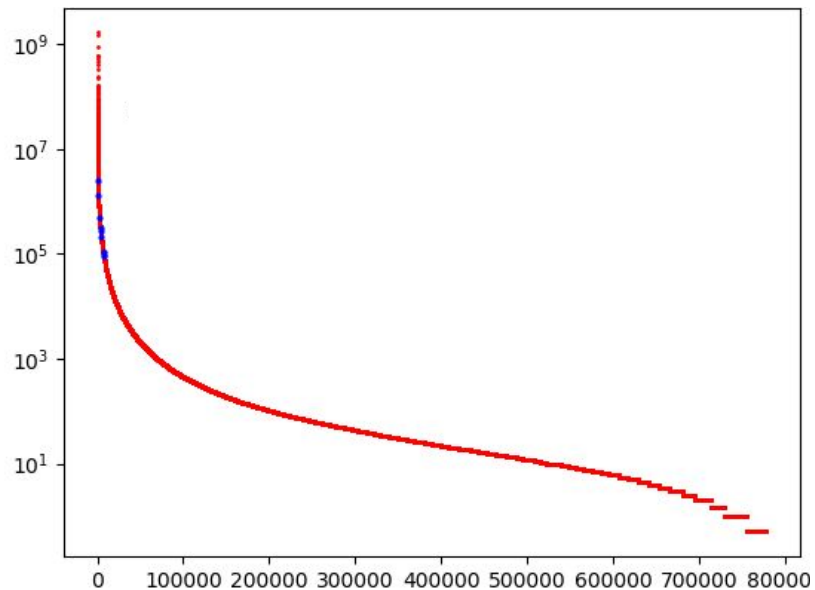
Word-Shift-Eval	eng-all			
	HT+	wsct+	HW+	HW
setting 1				
correct(%)	51	79	80	100
sig(%)	42	55	62	89
<i>N</i>	1718	14	49	28
setting 2				
correct(%)	58	69	80	100
sig(%)	39	67	60	89
<i>N</i>	1459	13	44	27

Note the differences in results between

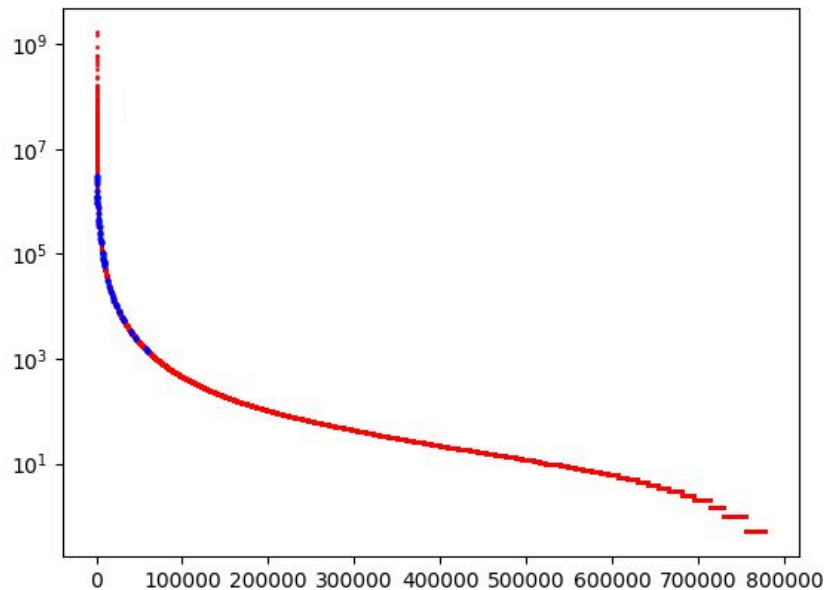
- *evaluation sets*
- *setting 1 and 2 (computational artefact)*

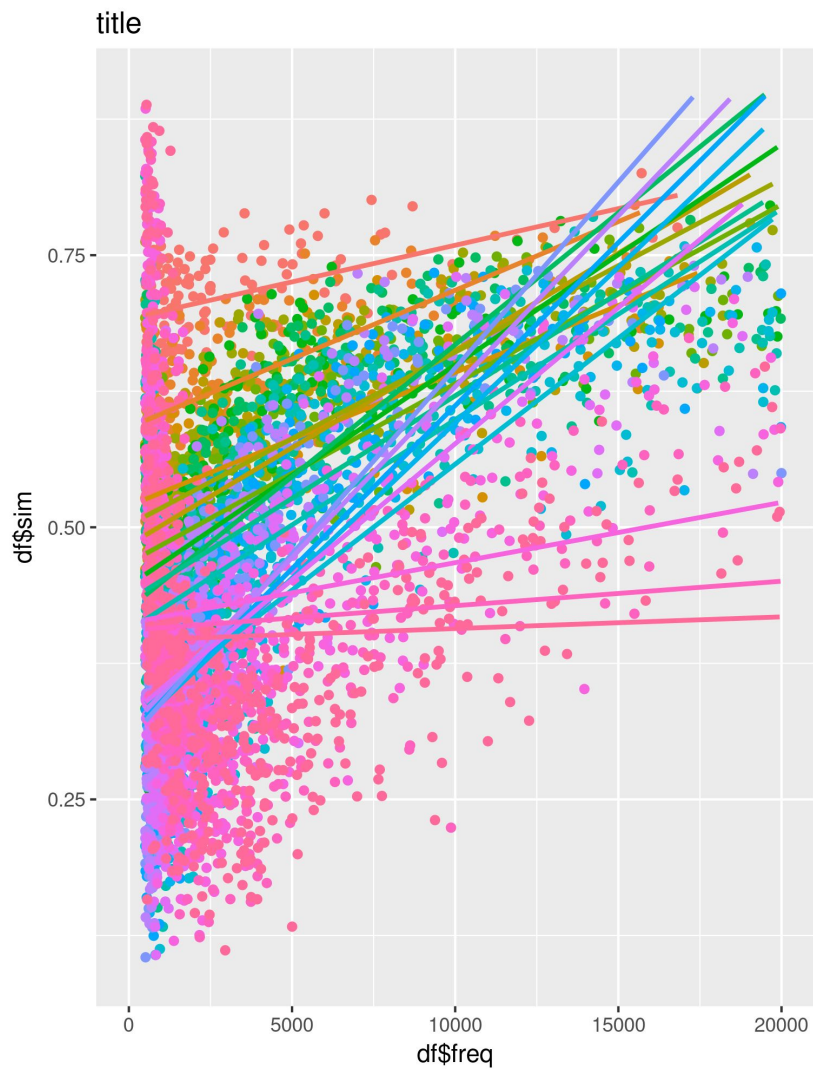
SenseShift-Eval	eng-all		
	HT+	wsct+	HW+
setting 1			
average vec.	50	100	73
argmax(corr)	54	100	92
argmax(freq)	52	80	85
majority vote	44	100	77
argmin(p(corr))	54	100	92
<i>AVG</i>	51	96	84
<i>N</i>	504	5	13
setting 2			
average vec.	56	100	78
argmax(corr)	61	100	85
argmax(freq)	57	80	85
majority vote	51	100	77
argmin(p(corr))	62	100	85
<i>AVG</i>	57	96	82
<i>N</i>	449	5	13

The baseline terms were among the top-10k most frequent words in the corpus



The terms in our datasets weren't

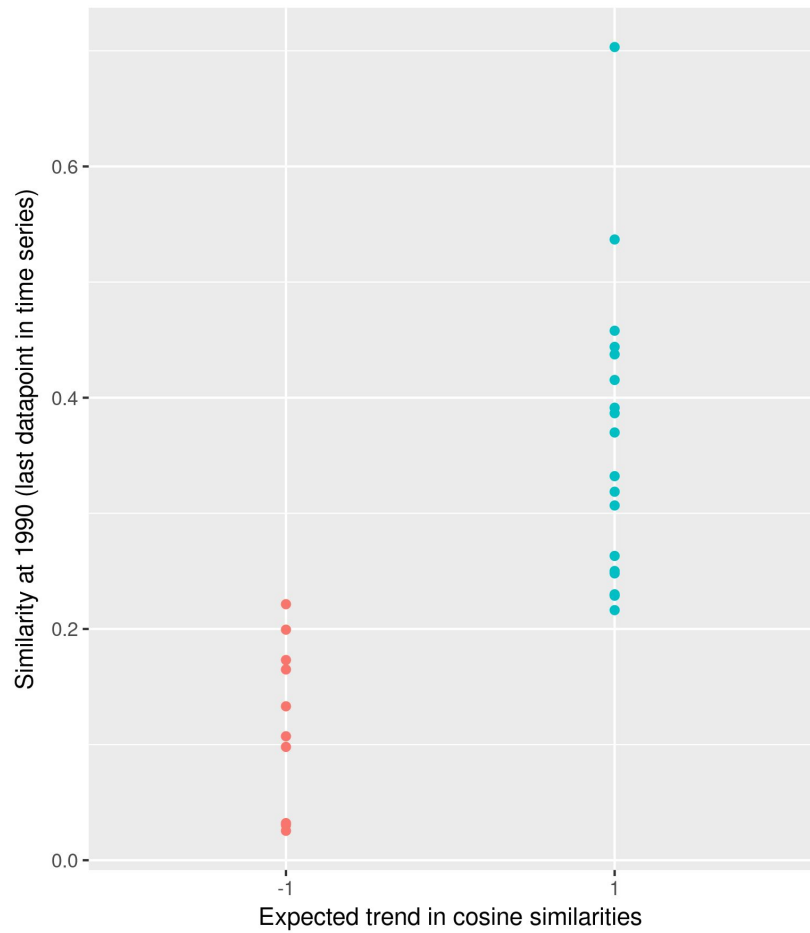




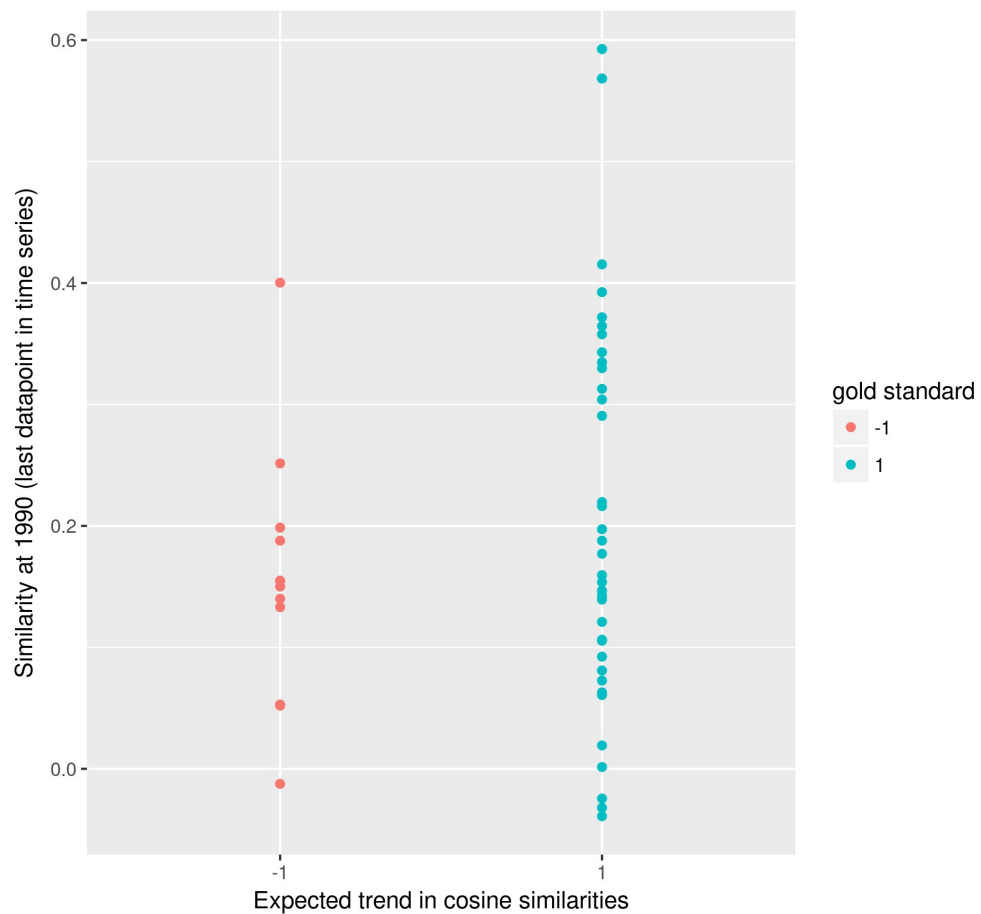
Self-similarity of terms
between t and $t+1$ and
term frequency

*The more frequent the
term,
the more stable (less
noisy) its distributional
representation*

Similarity at 1990 and gold standard, baseline

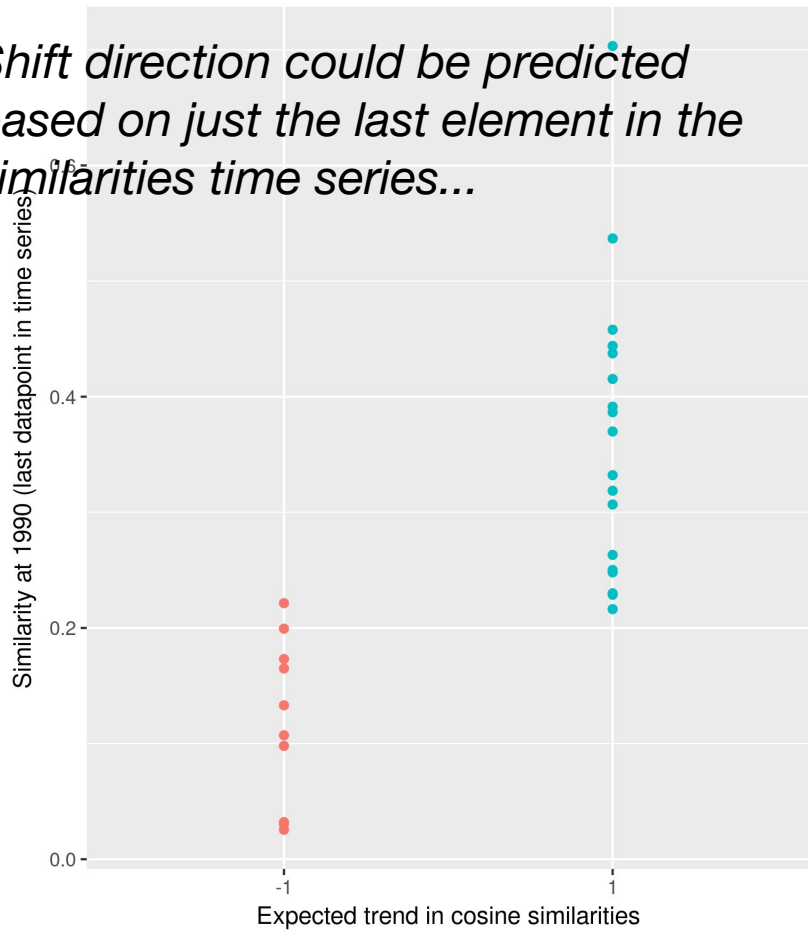


Similarity at 1990 and gold standard, HW-WN



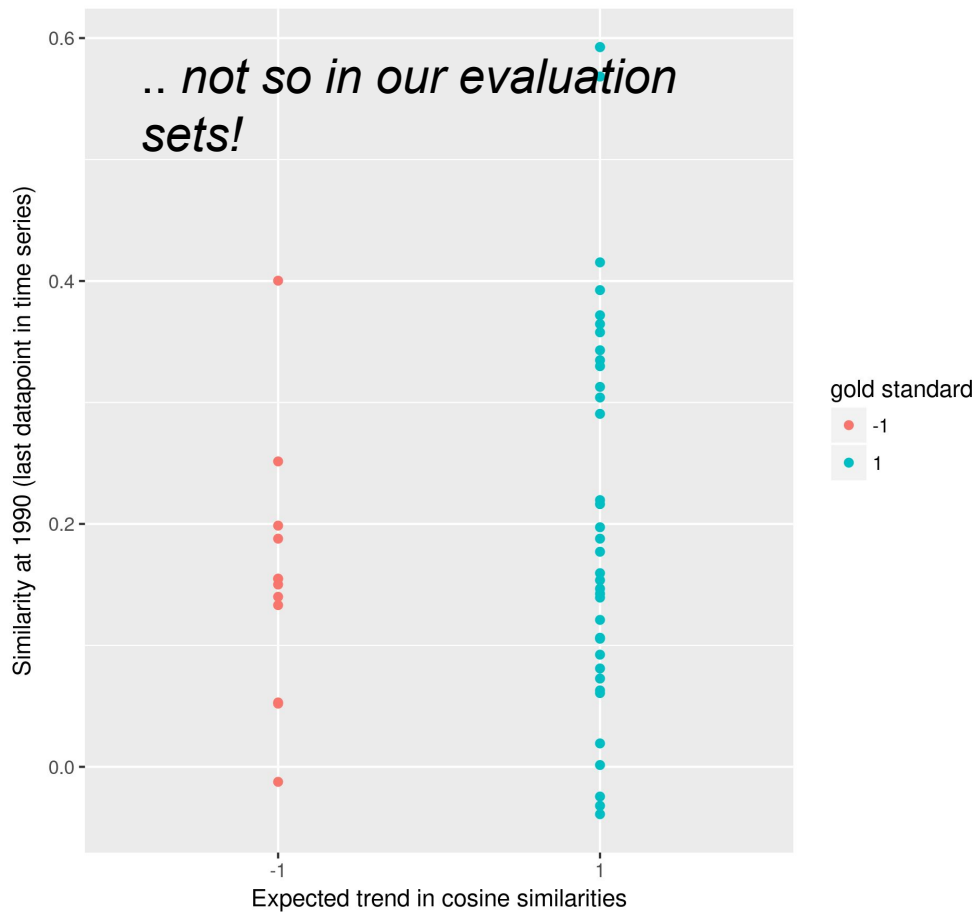
Similarity at 1990 and gold standard, baseline

Shift direction could be predicted based on just the last element in the similarities time series...



Similarity at 1990 and gold standard, HW-WN

.. not so in our evaluation sets!



Conclusions:

- Existing baseline based on "privileged" examples
- Findings vary very strongly for different datasets and ways of handling missing data
- We really haven't mastered this task yet
- New baseline for (necessary) future work
- Crucial to examine and report characteristics of evaluation set
- Crucial to make implementation "details" explicit



Next project: Implicit bias in portrayal of men and women as experts in the media

