

The New York Times

THE
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NATIONAL
REVIEW

THE WALL STREET JOURNAL.



Slate

THE ROOT

**words connected to news
coverage of Black Lives Matter,
terrorism, election etc
for different newspapers,
particularly, ones
reflecting bias in coverage**

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THE ROOT

Black Lives Matter Keeps Getting More Radical — Will the Media Care?



These Americans of good will have been had, with the media's help. Black Lives Matter is an instrument not of justice and reconciliation but rather of violence and revolution. It's shot through with its own form of racism — anti-Semitism — and with authoritarian demands that would not only strip Americans of their constitutional rights but bankrupt our nation and render it vulnerable to its enemies abroad. Doubt me? Read the organization's own words.

Black Lives Still Matter

In order to truly ensure that, we will have to confront the broader culture of violence that has long gripped this nation.

What Does Black Lives Matter Want? Now Its Demands Are Clearer Than Ever

After a year of planning, members of the movement have released a comprehensive platform.

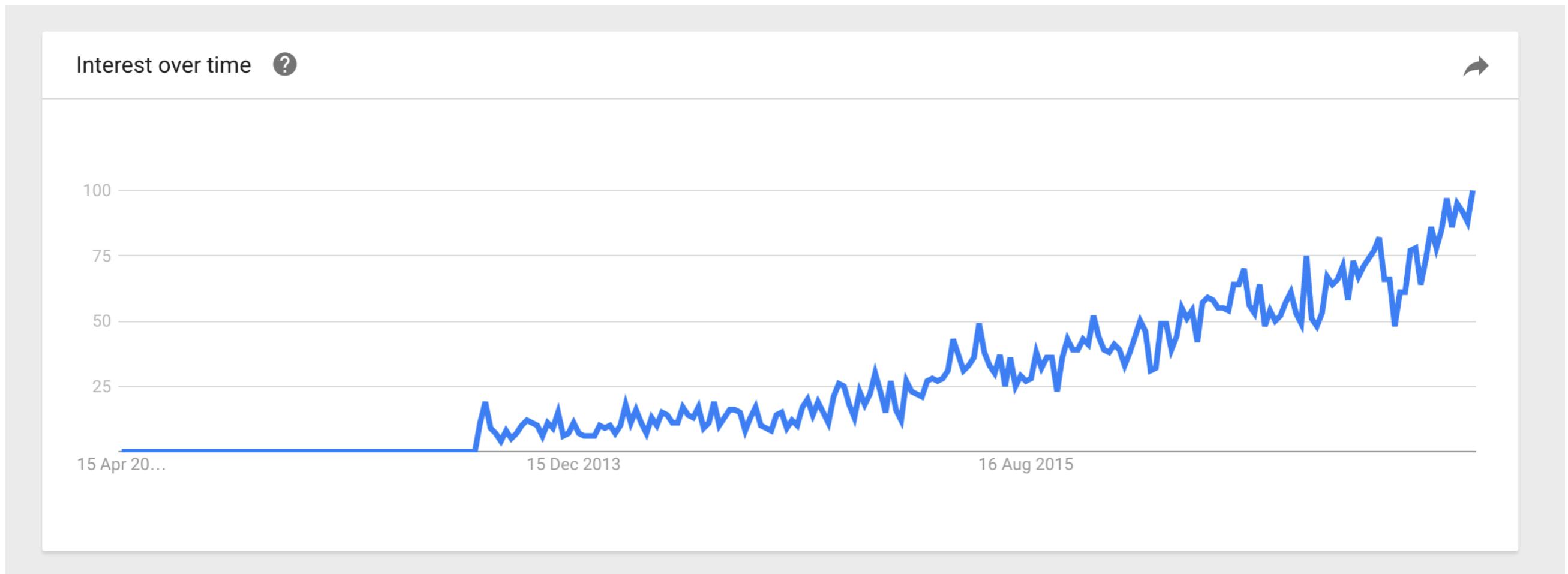
At both the Democratic and Republican conventions last month, there were plenty of indications that conversations strengthened and sustained by the current movement to end antiblack racism have made it to the national stage. The "Mothers of the Movement"—women whose children were killed by police or vigilantes or who died while in police custody—shared their stories at the Democratic National Convention, making the case that their fight for justice would be in good hands with a Clinton presidency. The previous

Black Lives Matter: Radicals Using Moderates to Help Tear America Apart



word2vec

A tool gaining a lot of interest in ML- based Natural Language Processing.

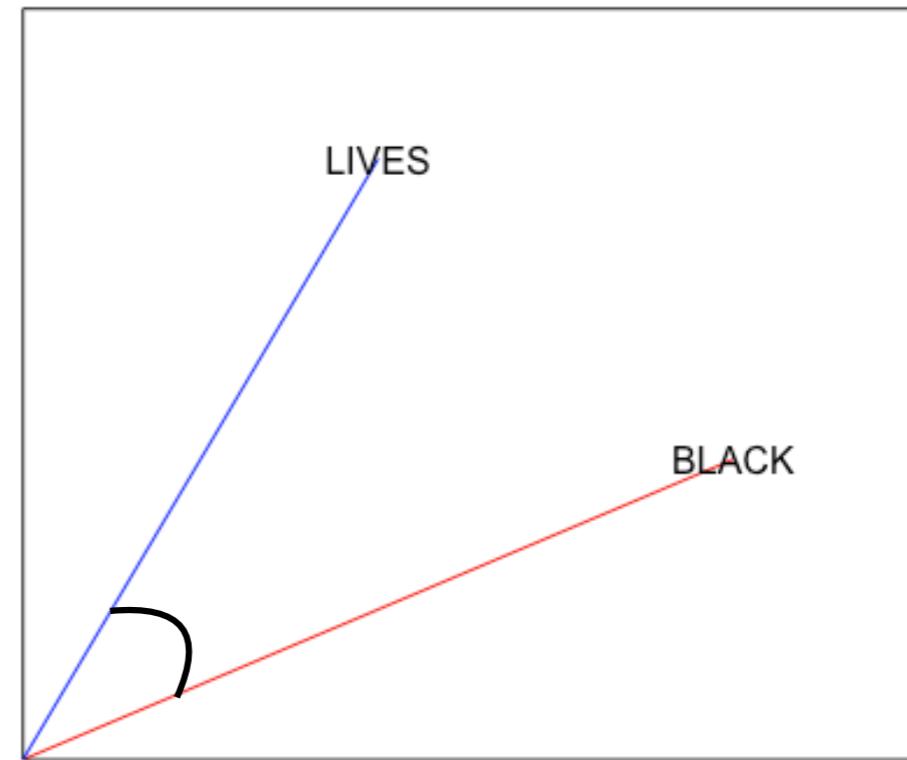


Word Embeddings

presents each word as a vector in some space

What is the cosine of the angle between
`vec("black")` and `vec("lives")`

word vector representation



Example of word embedding

Consider the following set of texts

I am speaking

I was eating

I was traveling

Example of word embedding

Consider the following set of texts

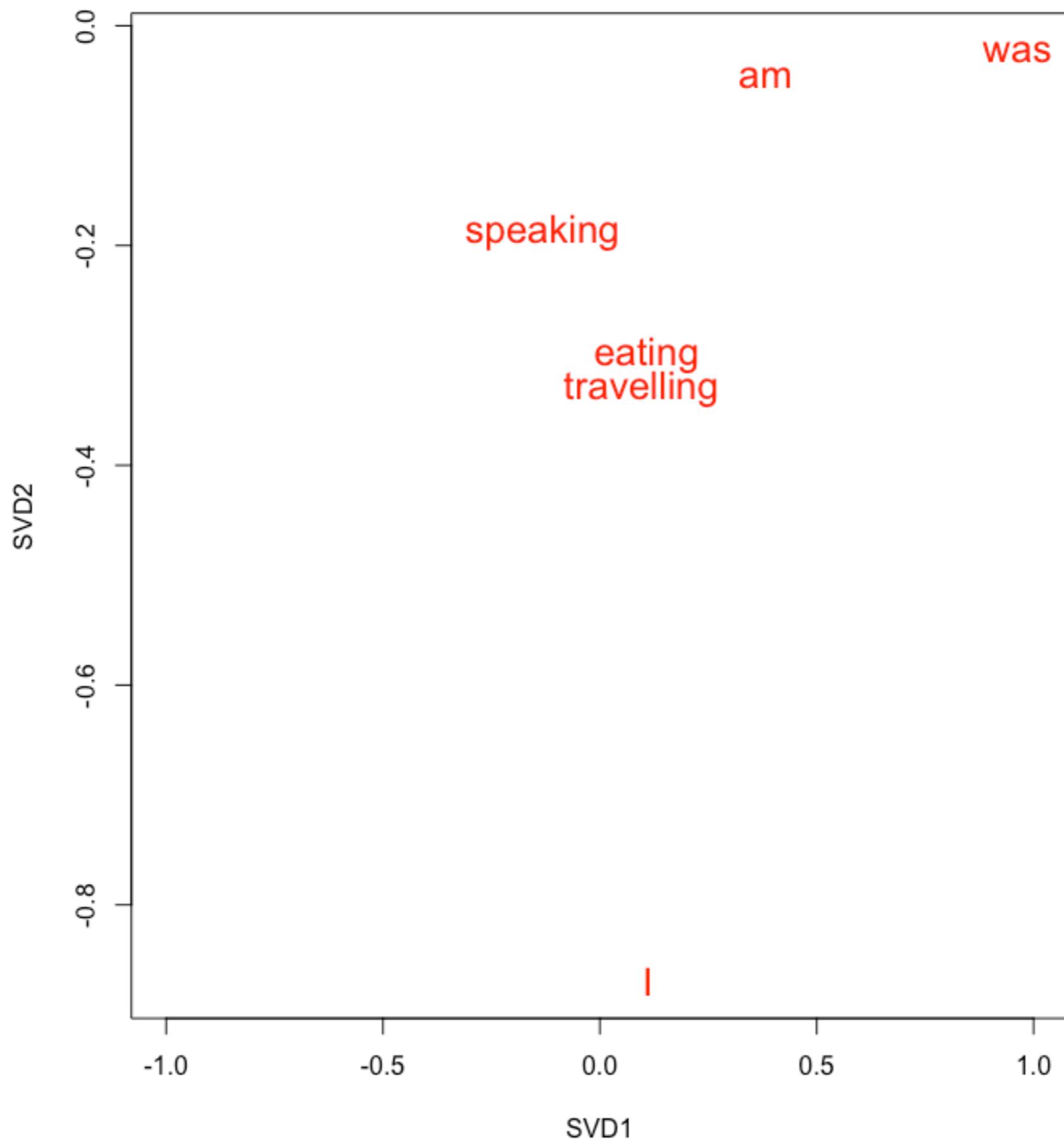
I am speaking

I was eating

I was traveling

Co-occurrence Matrix

	I	am	was	speaking	eating	travelling
I	0	1	2	0	0	0
am	1	0	0	1	0	0
was	2	0	0	0	1	1
speaking	0	1	0	0	0	0
eating	0	0	1	0	0	0
travelling	0	0	1	0	0	0



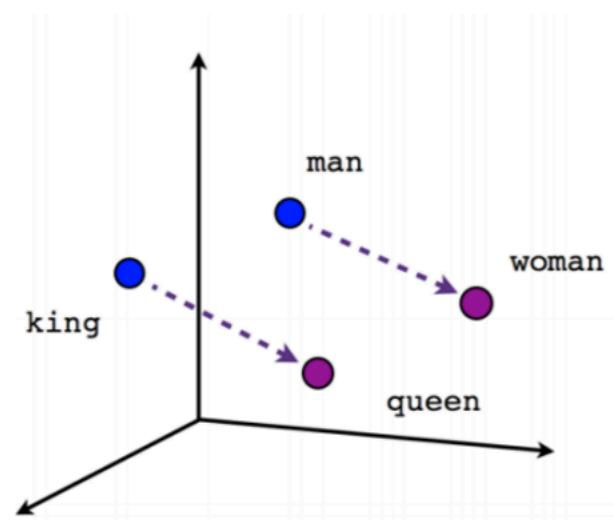
Why word2vec

word2vec usually projects on large dimensional vector space - 50 or 100 in general

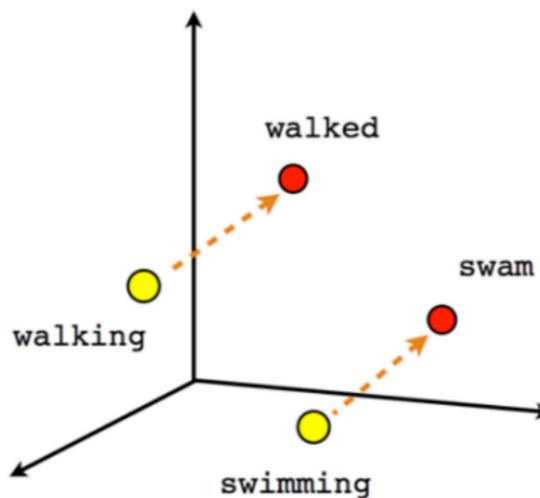
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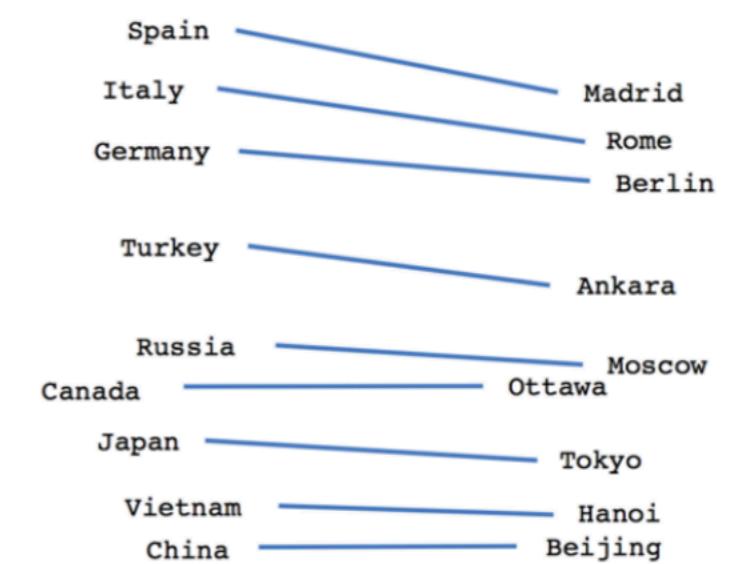
t-SNE projection of these high word2vec vectors



Male-Female



Verb tense



Country-Capital

Mikolov et al 2013

$$\text{vec}(\text{"king"}) - \text{vec}(\text{"man"}) + \text{vec}(\text{"woman"}) = \text{vec}(\text{"queen"})$$

Consider a word w_t

I

am

giving

a

talk

w_{t-2}

w_{t-1}

w_t

w_{t+1}

w_{t+2}

Consider a word w_t

I am giving a talk

w_{t-2} w_{t-1} w_t w_{t+1} w_{t+2}

We maximize the following objective function

$$J = \frac{1}{T} \sum_{t=1}^T \sum_{-n \leq j \leq n, j \neq 0} \log p(w_{t+j} | w_t)$$

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I **am** **giving** a talk

w_{t-2} w_{t-1} w_t w_{t+1} w_{t+2}

We maximize the following objective function

$$J = \frac{1}{T} \sum_{t=1}^T \sum_{-n \leq j \leq n, j \neq 0} \log p(w_{t+j} | w_t)$$

$$p(w_{t+j} | w_t) = \frac{\exp(v_{w_t}^T u_{w_{t+j}})}{\sum_{w_i \sim V} \exp(v_{w_t}^T u_{w_i})}$$

The parameters: $(v_w, u_w \forall w)$

If word2vec.....

why not gene2vec?

Gene2vec

neural word embeddings of genetic data



/// About

Gene2vec is an adaptation of the [Word2vec](#) model for use in nucleotide sequence data for the purposes of identifying previously unknown relationships among genes. Word2vec is an extension upon the continuous [Skip-gram](#) model that allows for precise representation of semantic and syntactic word relationships. Additionally, Word2vec representations exhibit additive composability such that vector arithmetic can be performed on words. Mikolov et al. illustrate this behavior by noting that the resulting vector space representation of ("Madrid" - "Spain" + "France") is closer to that of "Paris" than any other word.



is maintained by [davidcox143](#).

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is maintained by [davidcox143](#).

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RESEARCH ARTICLE

Continuous Distributed Representation of Biological Sequences for Deep Proteomics and Genomics

Ehsaneddin Asgari, Mohammad R. K. Mofrad

Published: November 10, 2015 • <https://doi.org/10.1371/journal.pone.0141287>

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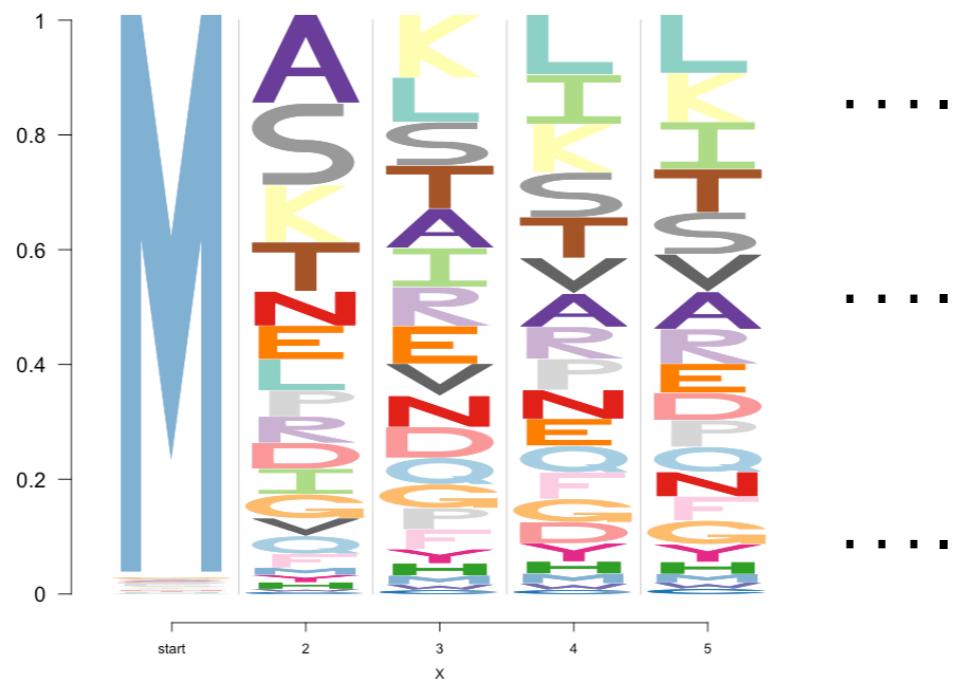
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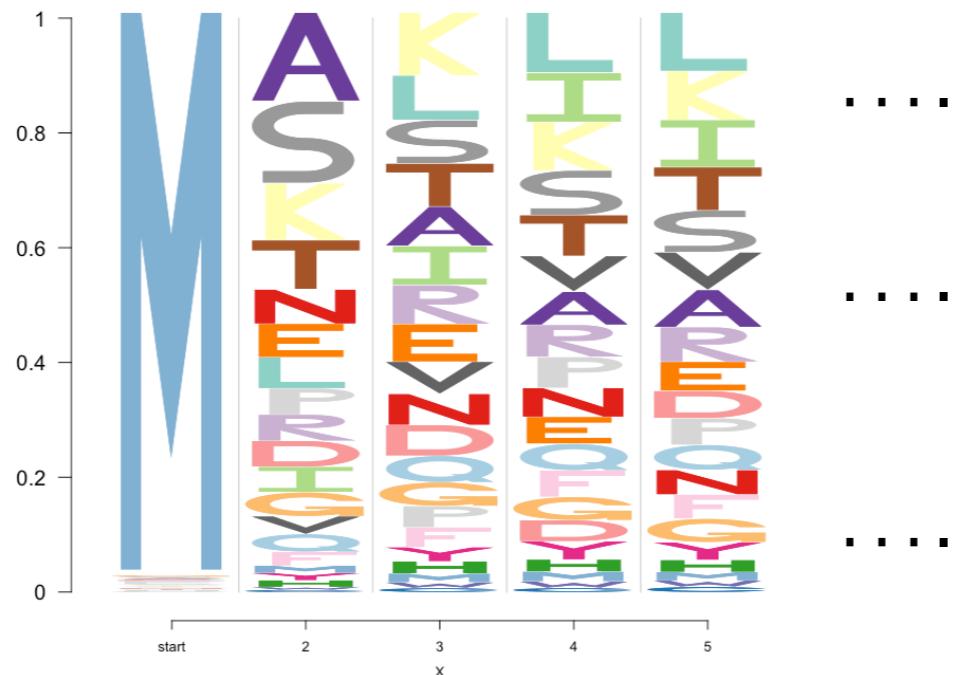
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The authors looked at 324,018 protein sequences obtained from Swiss Port coming from > 7000 protein families.



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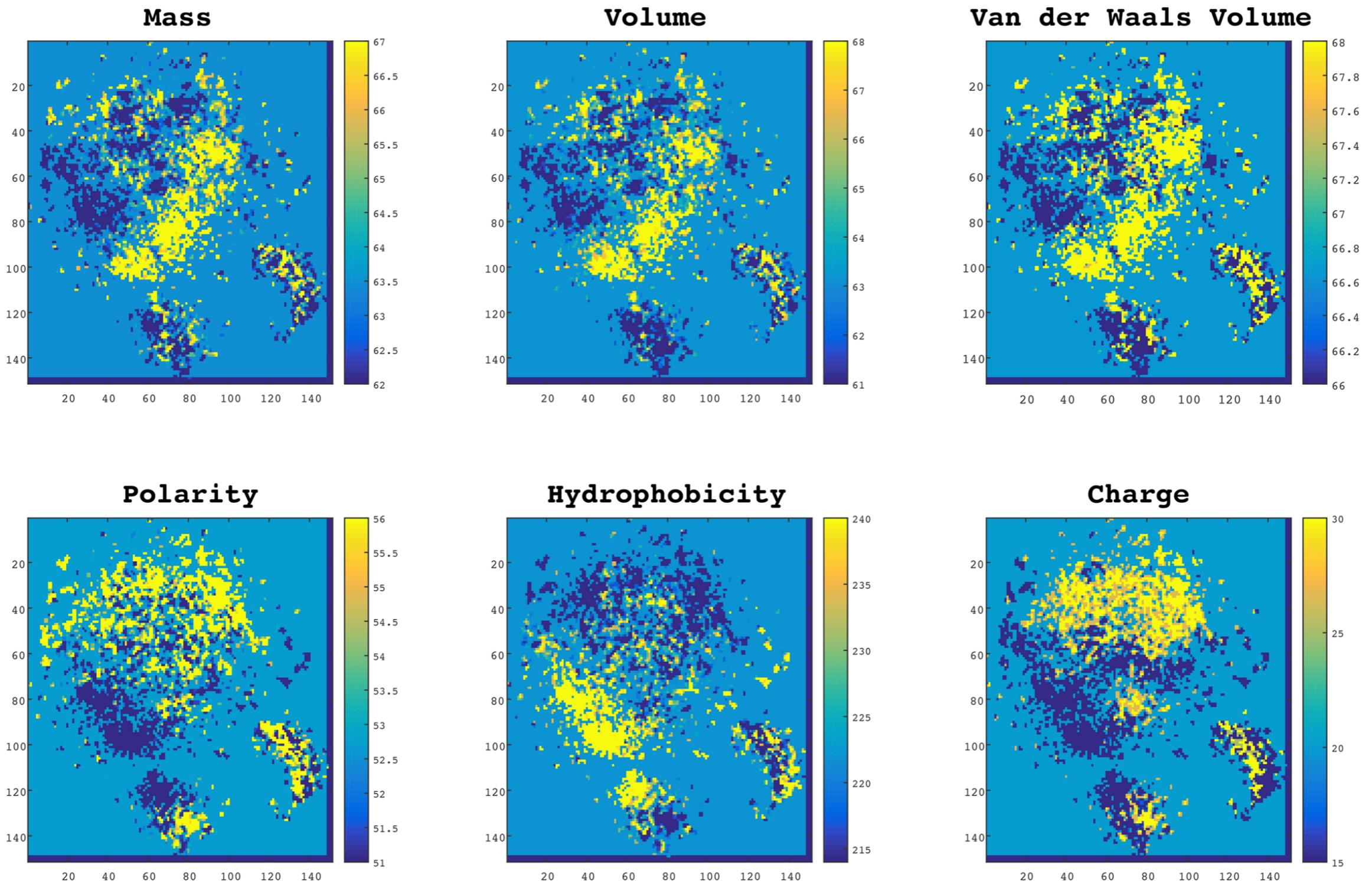


Original Sequence

(1) \vec{M} (2) \vec{A} (3) \vec{F} SAEDVLKEYDRRRRMEAL..

Splittings

- { 1) MAF, SAE, DVL, KEY, DRR, RRM, ..
- 2) AFS, AED, VLK, EYD, RRR, RME, ..
- 3) FSA ,EDV, LKE, YDR, RRR, MEA, ..



Back to word2vec

applying it on news paper data

7020 Articles scraped from the Nation
between Jan 14 and Mar 16.
Data was missing in August 2014 and 2015.

Keywords:

*black, lives, matter, police, brutality, racism, crime,
violence, laquan, mcdonald, trump, clinton, terrorism*

> nearest_to(model2, model2[["black"]], 20)	black	latino	white	unarmed
	2.220446e-16	3.238422e-01	3.296694e-01	3.950784e-01
subordination		blacks	vigilantes	lives
4.032799e-01		4.125458e-01	4.227586e-01	4.229431e-01
teenager		african	supremacy	latinos
4.289137e-01		4.309424e-01	4.324514e-01	4.381511e-01
young		men	racial	criminalization
4.412078e-01		4.485662e-01	4.556035e-01	4.559089e-01
dylann		jackets	ferguson	disproportionately
4.573308e-01		4.578751e-01	4.581132e-01	4.618305e-01

top words - **Clinton**

hillary	clinton's	sanders	candidacy	bernie	presumptive
0.9154660	0.8522816	0.7526696	0.6760095	0.6666568	0.6490119
hillary's	vt	sanders's	rodham	campaign's	spar
0.6068201	0.5969407	0.5957619	0.5955374	0.5931926	0.5875940
walters	thorny	democratic	dfa	candidate	woodruff
0.5790676	0.5735087	0.5717317	0.5544882	0.5514192	0.5449966
nomination	unbeatable				
0.5447019	0.5443936				

... the palestinian authority pa and hamas spar including health public works

.....*bernie sanders and hillary clinton spar over which one is more progressive.....*

.... from the public by having them spar mostly on weekends or holidays

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hillary	clinton's	sanders	candidacy	bernie	presumptive
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... the palestinian authority pa and hamas spar including health public works

.....*bernie sanders and hillary clinton spar over which one is more progressive.*.....

.... from the public by having them spar mostly on weekends or holidays

top words - matter

lives	black	question	devoid
0.6518010	0.5320571	0.5103602	0.4554311
domestically	matters	blacklivesmatter	longer
0.4390956	0.4380126	0.4345750	0.4343148
there's	exists	clear	coincidence
0.4306680	0.4301122	0.4292051	0.4144670
hashtags	makes	dismissively	surmised
0.4135828	0.4037018	0.3983225	0.3979131
racist	supremacy	exist	imaginable
0.3926556	0.3920765	0.3852060	0.3838286

three occurrences

.....*the genre of drone videos grows increasingly popular domestically weddings sporting events.*.....

.....*about the values that guide this country as it engages domestically and internationally.*.....

.....*religious rights seem to be a matter of rare consensus both domestically and internationally.*.....

CorShrink

on word2vec cosine similarities

We obtain the **word2vec** cosine similarity values between any two words of interest - say ***black*** and ***lives***. We treat cosine similarity as correlation.

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$$\rho = \frac{1}{2} \log\left(\frac{1+r}{1-r}\right)$$

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Obtain **bootstrap** standard error for the Fisher z-scores by sampling texts with replacement, pooling them, and running **word2vec** on those models. We chose bootstrap size **100**.

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For each word, say **black**, we record the Fisher z-scores for the top **1000** words and their Bootstrap standard errors, and apply **ash** on them.

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For each word, say **black**, we record the Fisher z-scores for the top **1000** words and their Bootstrap standard errors, and apply **ash** on them.

Inverse transform the posterior mean of the Fisher z-transform from ash output to get a vector of **shrunk correlations**

We generate **rankings** based on the **shrunk cosine similarities**.

top words - **Clinton** (before *CorShrink* adjustment)

hillary	clinton's	sanders	candidacy	bernie	presumptive
0.9154660	0.8522816	0.7526696	0.6760095	0.6666568	0.6490119
hillary's	vt	sanders's	rodham	campaign's	spar
0.6068201	0.5969407	0.5957619	0.5955374	0.5931926	0.5875940
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0.5790676	0.5735087	0.5717317	0.5544882	0.5514192	0.5449966
nomination	unbeatable				
0.5447019	0.5443936				

top words - **Clinton** (after *CorShrink* adjustment)

hillary	clinton's	sanders	bernie	candidacy	presumptive
0.9054996	0.8522804	0.7381915	0.6333450	0.6296040	0.5796187
campaign's	sanders's	hillary's	democratic	vt	candidate
0.5780555	0.5727214	0.5657258	0.5581314	0.5469533	0.5305830
walters	campaign	nomination	woodruff	vermont	rodham
0.5274639	0.5128978	0.5107737	0.5080026	0.5028814	0.4974063
insurgent	she				
0.4938642	0.4894352				

spar ranks **66th** after *CorShrink* is applied

top words - **matter** (before *CorShrink* adjustment)

lives 0.6518010	black 0.5320571	question 0.5103602	devoid 0.4554311
domestically 0.4390956	matters 0.4380126	blacklivesmatter 0.4345750	longer 0.4343148
there's 0.4306680	exists 0.4301122	clear 0.4292051	coincidence 0.4144670
hashtags 0.4135828	makes 0.4037018	dismissively 0.3983225	surmised 0.3979131
racist 0.3926556	supremacy 0.3920765	exist 0.3852060	imaginable 0.3838286

top words - **matter** (after *CorShrink* adjustment)

lives 0.6046905	question 0.4454659	black 0.4233648	clear 0.3447135
longer 0.3429932	exists 0.3402007	blacklivesmatter 0.3374417	there's 0.3371693
makes 0.3321932	matters 0.3290786	racist 0.3265337	movement 0.3264511
coincidence 0.3255307	no 0.3239187	devoid 0.3230350	imaginable 0.3229040
supremacy 0.3223244	mobilization 0.3205559	surmised 0.3200350	exist 0.3195980

domestically ranks **180th** after *CorShrink* is applied

CorShrink -

**generalizing to correlation
matrix shrinkage**

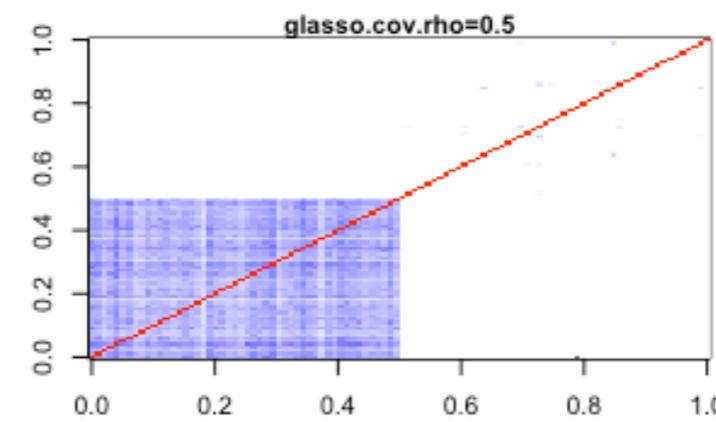
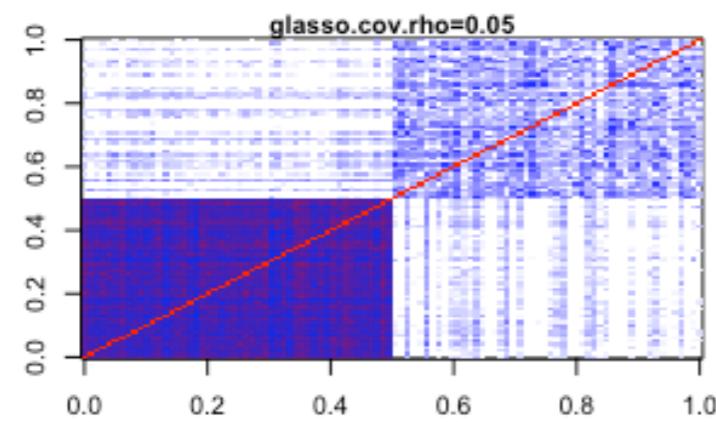
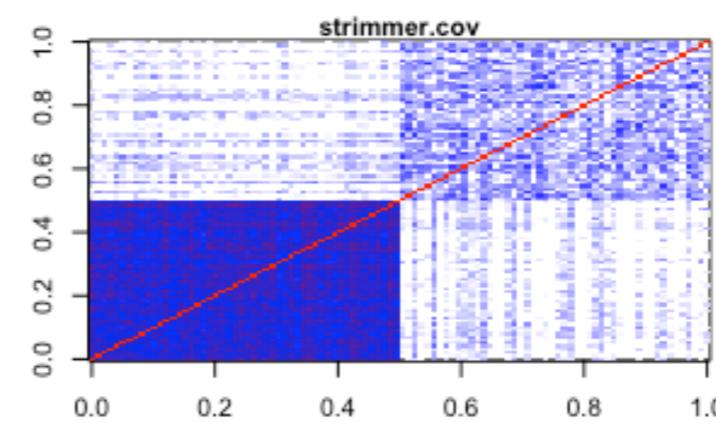
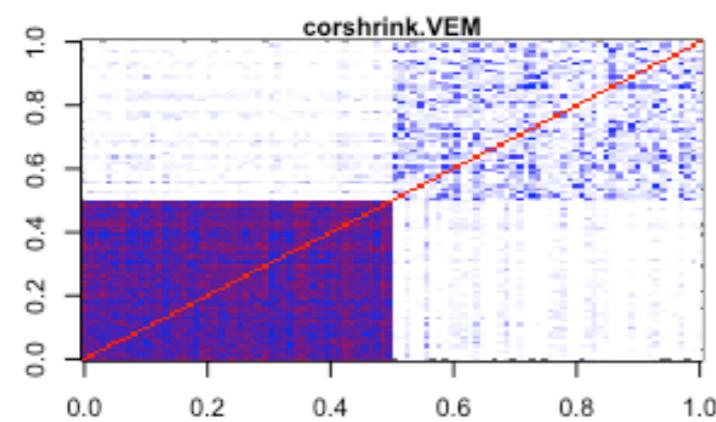
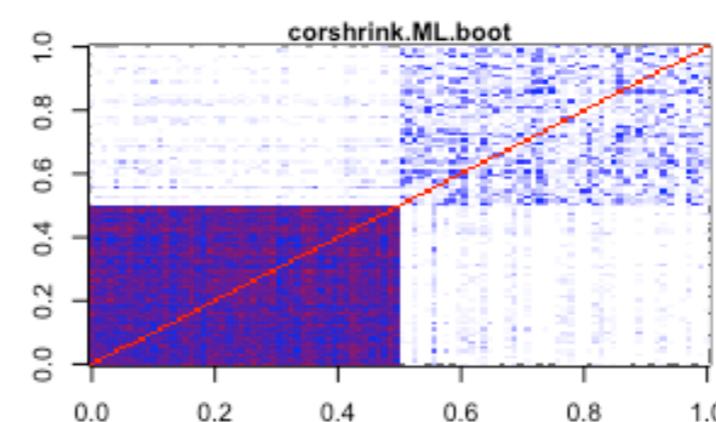
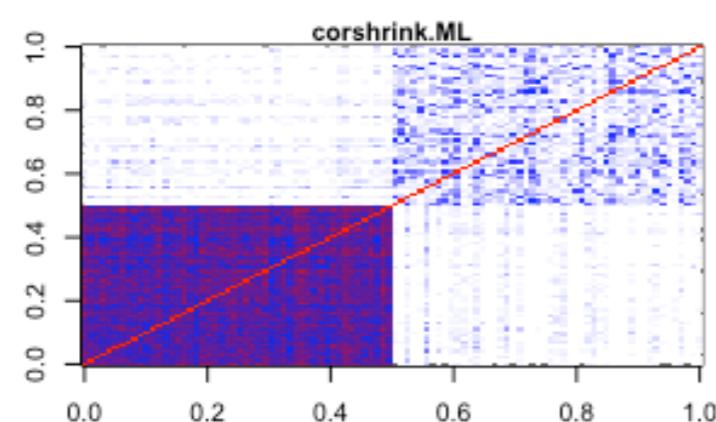
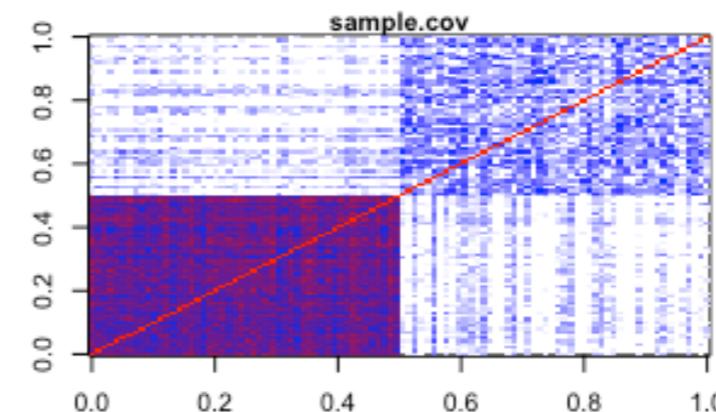
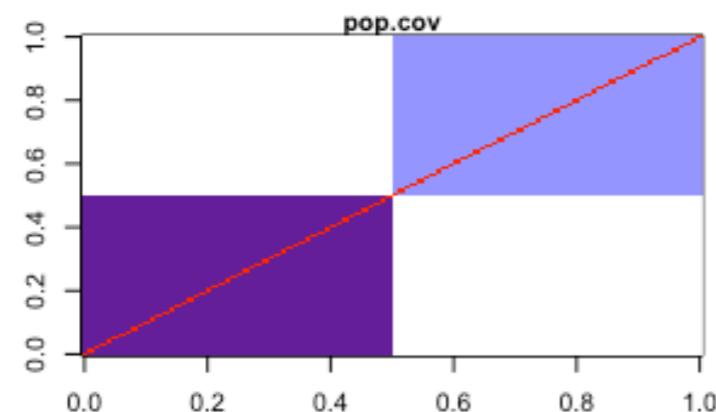
Same idea as in word2vec application, but here we may not always have the standard errors for correlation or may not want to use Bootstrap, in which case we take an ad-hoc standard error of Fisher z-scores as

$$\sqrt{\frac{1}{n - 3}}$$

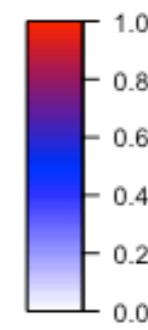
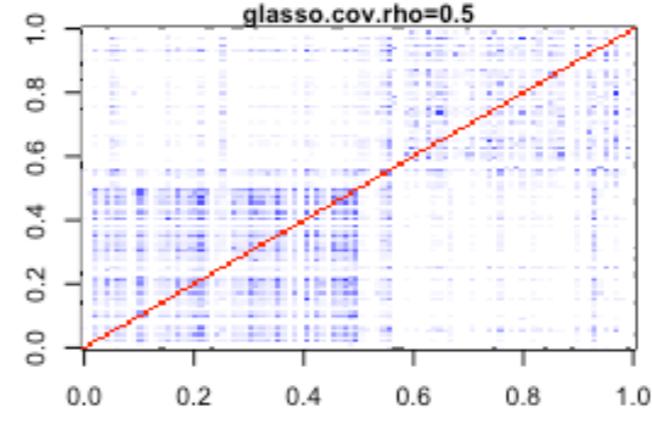
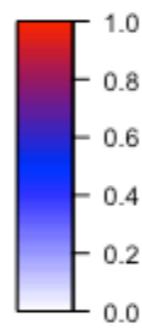
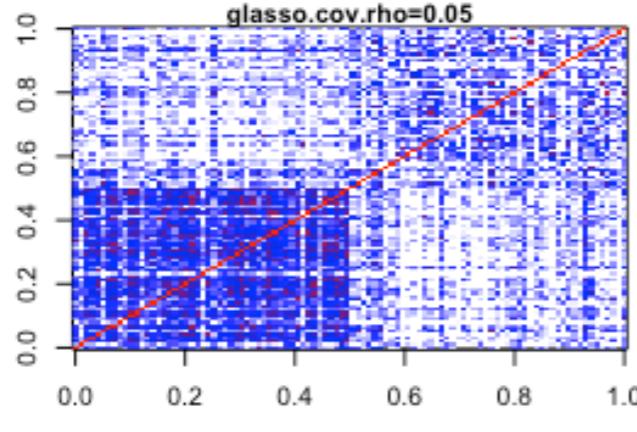
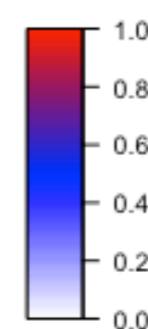
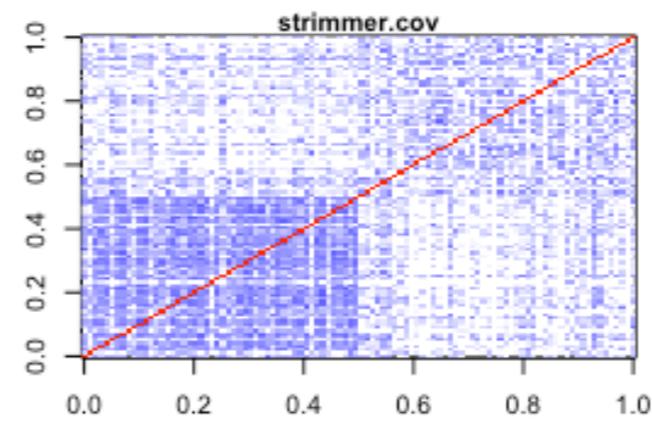
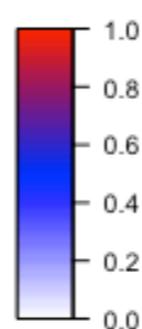
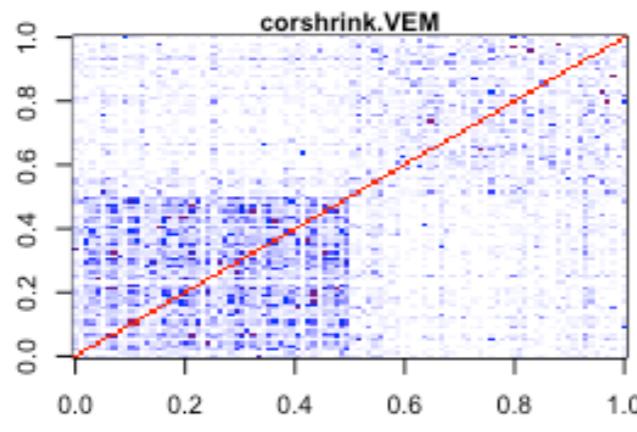
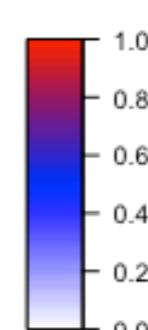
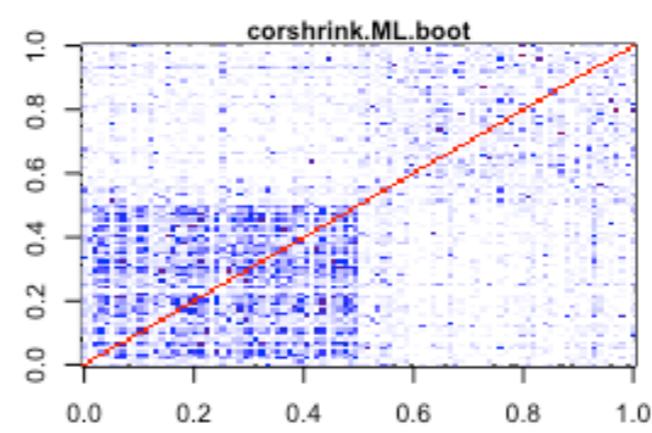
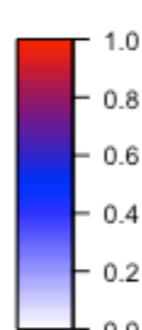
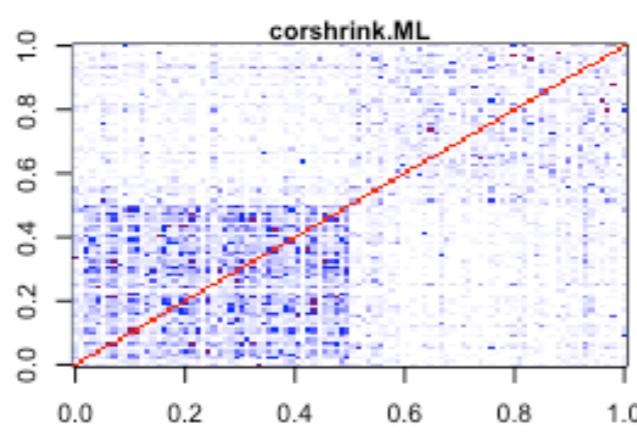
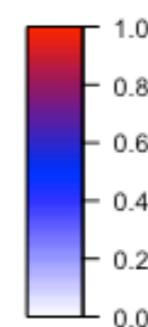
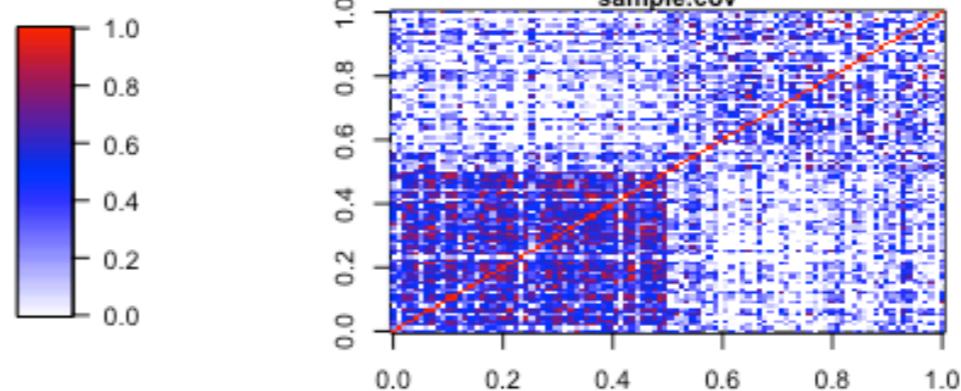
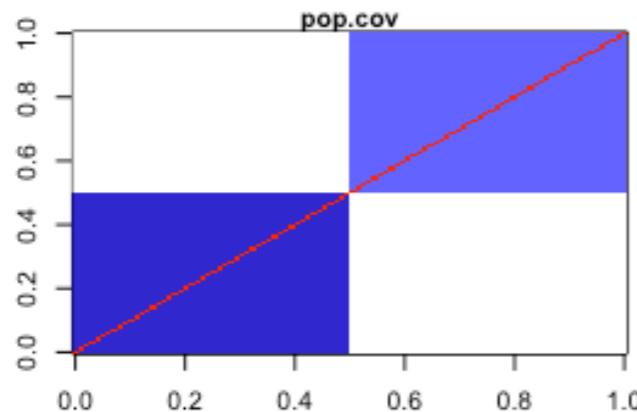
Literature Review

- Schafer and Strimmer (2005) :
- GLASSO
- Lancewiki and Aladjem (2014) :
- CorShrink :

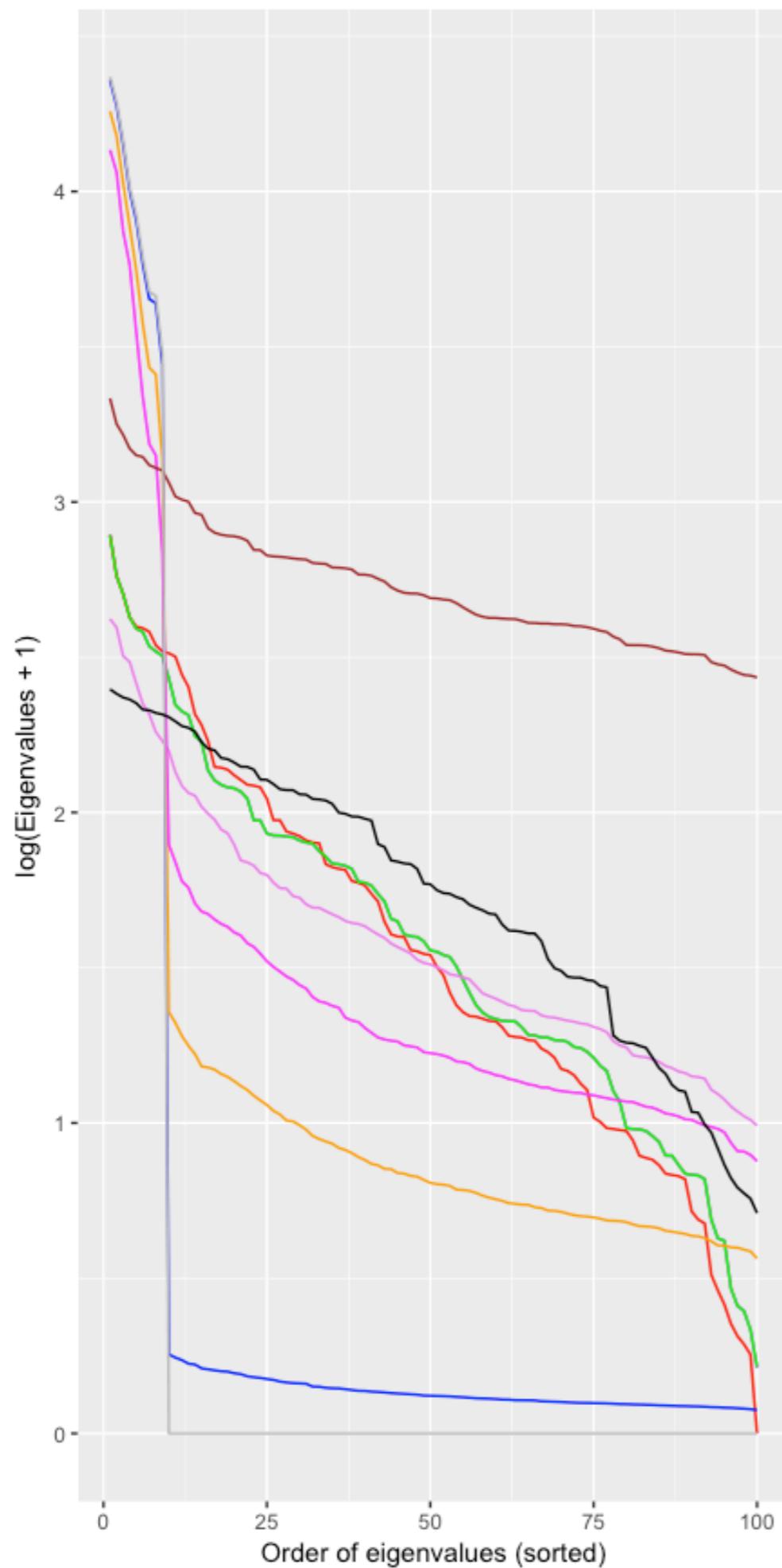
n=50, p = 100



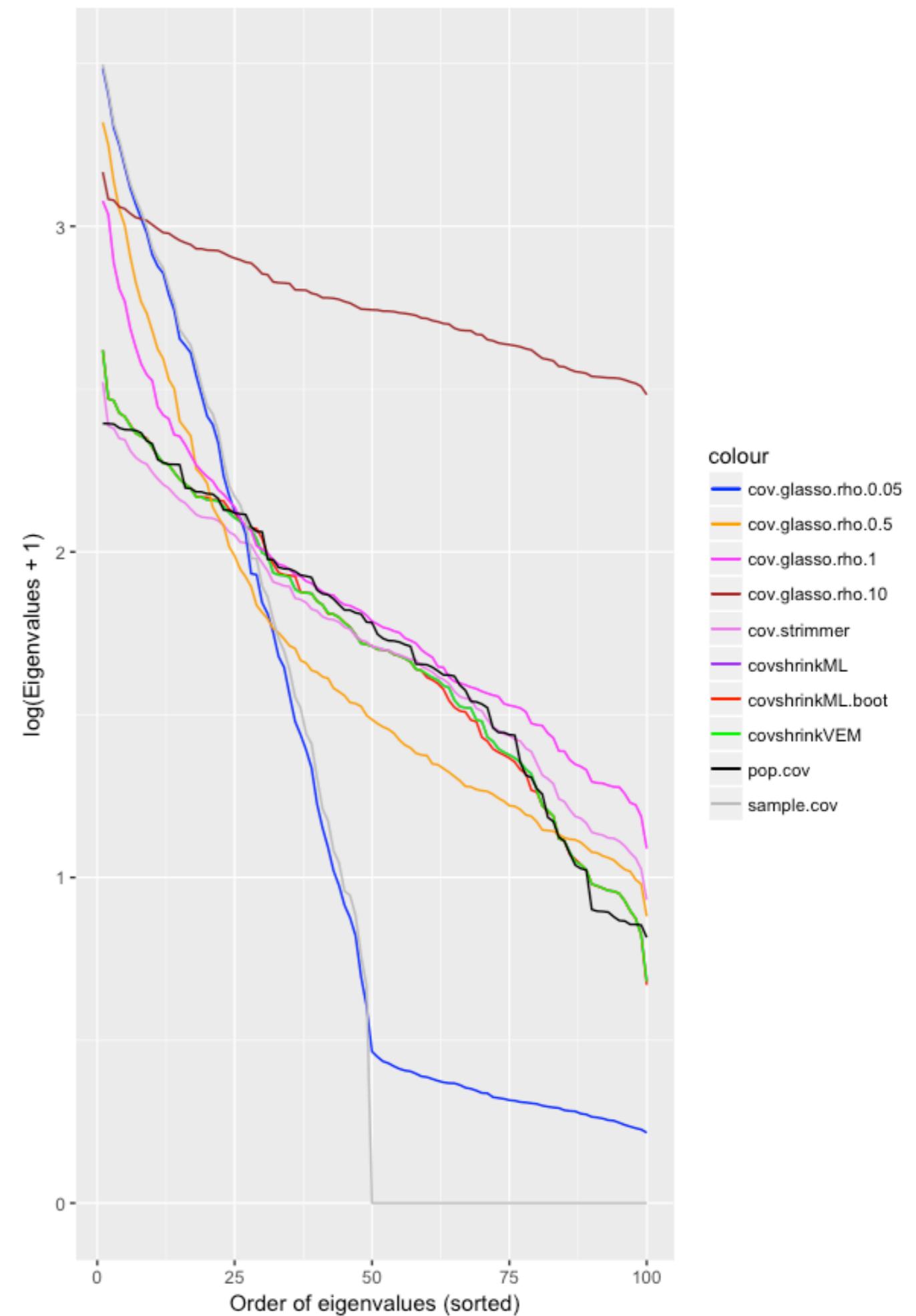
n=10, p = 100



$n/p=0.1$



$n/p=0.5$



Deng et al

