8. Unsupervised Techniques II: flipped

DS-GA 1015, Text as Data
Arthur Spirling

March 30, 2021

Housekeeping

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2. Will post some general advice on the final paper.

Political Speech: US Senate

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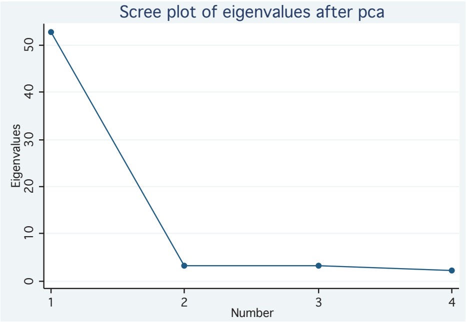
Fits several components, of which 1PC model looks very good. . .



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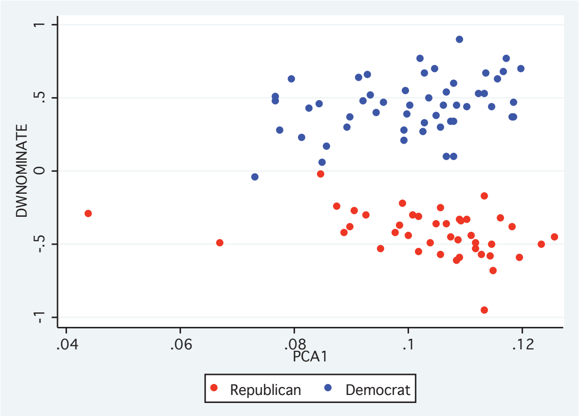

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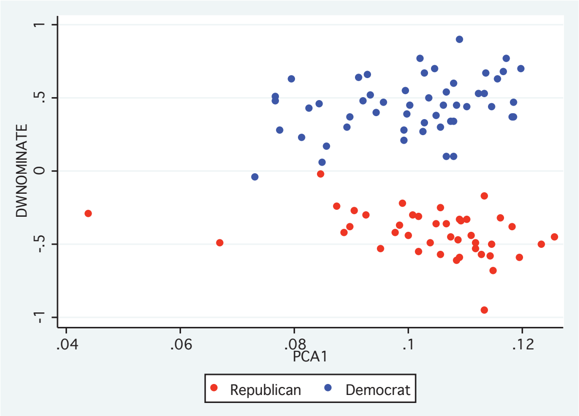

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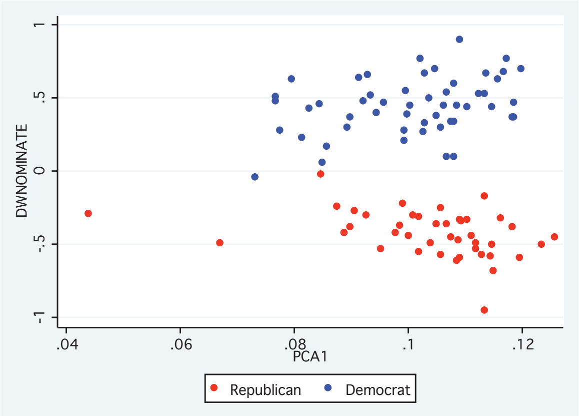

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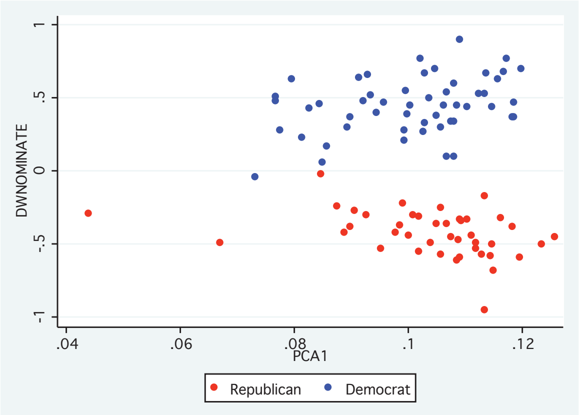

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Suppose you were modeling students organizing friendship groups based on who they know/see on a regular basis. Would you model this data using PCA or clustering? Why?

Item Response

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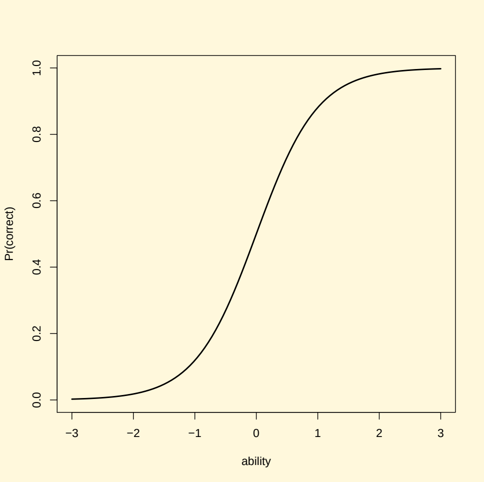

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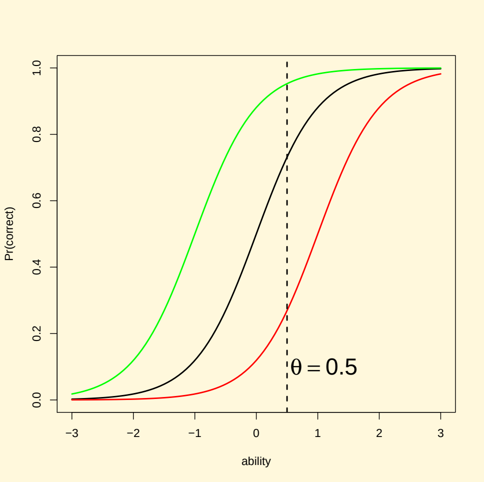
- easy items are ones where even those with low θ can get correct
- hard items are ones where only those with high θ can get correct
- can think about a particular individual with e.g. $\theta = 0.5$
- item difficulty can be given as θ for which $\Pr(\text{correct}) = 0.5$



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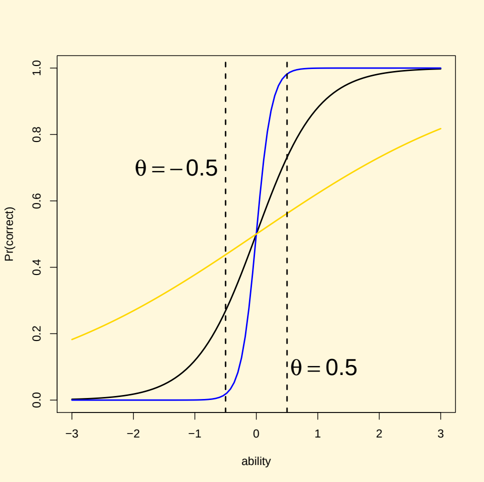
- contrast e.g. $\theta = 0.5$ student to $\theta = -0.5$ student



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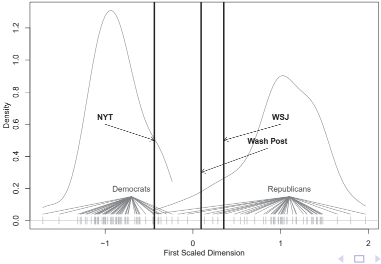
Incorporation of words allows one to place e.g. newspapers in same space as legislators:



Latent Semantic Analysis

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... which we multiply by the LWF to give:

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- we then have $1 + \left(\frac{1/6\log(1/6)+3/6\log(3/6)+2/6\log(2/6)}{\log(3)}\right) = 0.079$

. . . which we multiply by the LWF to give:

term	doc1	doc2	doc3
dog	0.055	0.110	0.087

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79 (not many for LSA!)

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Q1 What are these documents about? What do they have as their 'highest' (weighted) words?

Q2 How are terms related? What words are closely associated conceptually?

Q1

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	1942	1985	2002
original	war	freedom	america
	world	tax	security
	united	american	world
	people	time	american
	forces	growth	terror

Q1

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original	war	freedom	america
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	forces	growth	terror
transformed	1944	dollars	iraq
	japanese	tonight	iraqi
	war	we've	terrorists
	1942	million	qaida
	french	thats	terror
	germans	war	terrorist

Q2

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words	original	transformed

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communist, zarqawi	-0.08	-0.28

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How do you interpret these transformed correlations? What do they suggest about the relevant concepts?

Wordfish

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What is the expectation maximization algorithm for in this case?
What other (Bayesian) ways could we use to proceed here?

‘Eiffel Tower’ plot

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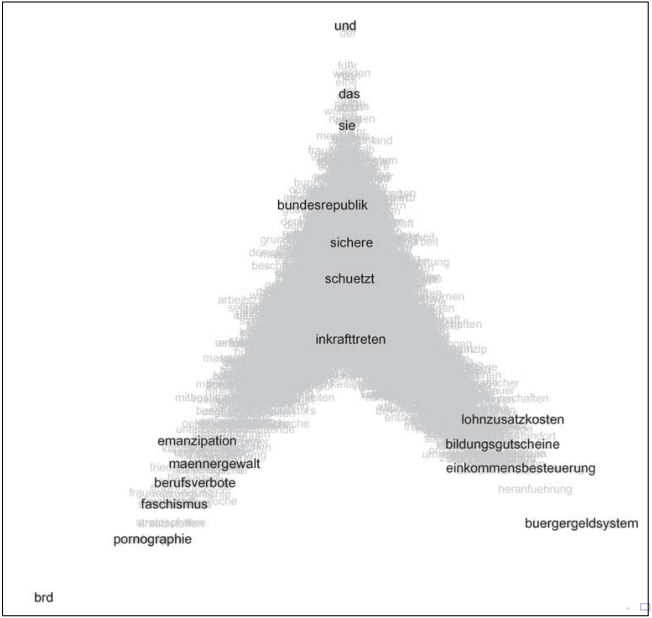

this plot shape in common: why?
What is x and y?

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- but then we find that the word "`defence`" co-occurs with '`military`' in the unlabeled documents (which we just classified)
- → use this to build more accurate classifier.

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