SCALING

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Hertie School

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SCALING

We can think about document living in some kind of *space* with θ as the positione.g.

- → affect, a.k.a. sentiment analysis
- → unidimensional policy preferences
- → multidimensional ideological position

How to place documents in space?

- → Think of a row in the document term matrix as a vocabulary profile, e.g. by normalize the counts
- → This is a point in a (very high-dimensional) space
- → Which has distances to every other document in that space

But we can also collapse them down into a smaller space, e.g. one or two dimensions

- → Often we think they really live there
- → Sometimes it's just visualization

PLAN

- → Where does information about position live?
- → The model
- → Spatial talking
- → Special cases
- → Validation
- → Comparing positions

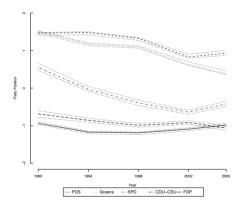
REMINDER

A matrix of document by word/topic counts is a *contingency table*

	neue	vor	Menschen	wie	nur	Arbeitsplätze	
FDP-2005	11	20	6	22	31	17	
FDP-2002	17	17	27	30	35	9	
PDS-2005	5	10	17	10	9	12	
PDS-2002	15	19	8	9	3	9	
GREENS-2005	42	21	47	46	19	17	
GREENS-2002	27	18	27	28	22	21	
SPD-2005	8	15	26	11	13	10	
SPD-2002	16	18	16	16	9	7	
CDU-2005	21	12	10	13	19	22	
CDU-2002	20	20	14	15	18	7	

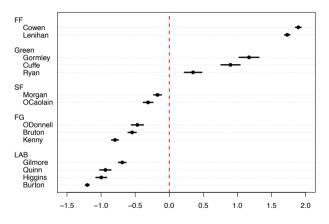
SCALING: PARTY POSITION DYNAMICS

Left–Right Positions in Germany, 1990–2005 including 95% confidence intervals



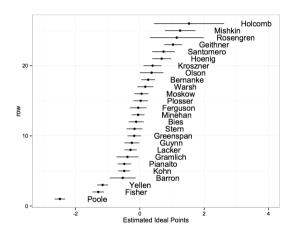
German party position on the economy (Slapin & Proksch, 2008)

SCALING: IRISH BUDGET DEBATES



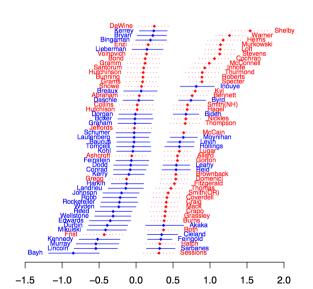
Estimated FOMC member ideal points from meeting transcripts (Lowe & Benoit, 2013)

SCALING: FOMC TRANSCRIPTS



Estimated FOMC member ideal points from meeting transcripts (Baerg & Lowe, 2020)

SCALING: SENATORS (MONROE & MAEDA)



		Word			
	Party	Wirtschaft	soziale	Förderung	
2002	FDP	14	4	15	
	CDU	11	8	20	
	SPD	15	9	10	
	PDS	7	16	9	
	Grüne	2	41	12	

Assumptions:

- → Position does not depend on *document length*
- → Position does not depend on word frequency

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Implication

→ table margins are uninformative

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That leaves only association structure.

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The CDU uses 'Wirtschaft' (business) 11/8 = 1.38 times more than 'soziale' (social).

)

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The FDP uses 'Wirtschaft' (business) 14/4 = 3.5 times more than 'soziale' (social).

Many (N-1)(V-1) small but relevant facts about relative proportional emphasis

- 1. FDP's emphasis on Wirtschaft over soziale is 3.5/1.375 = 2.55 times larger than that of the CDU.
- 2. CDU's emphasis on Wirtschaft over soziale is 0.82...
- 3. ...

You might recognize 2.55 and 0.82 and so on as odds ratios

$$\frac{P(\text{Wirtschaft} \mid \text{FDP})}{P(\text{soziale} \mid \text{FDP})} / \frac{P(\text{Wirtschaft} \mid \text{CDU})}{P(\text{soziale} \mid \text{CDU})} = \frac{14}{4} / \frac{11}{8}$$

which are delightfully indifferent to document lengths and word frequencies.¹

¹Add *k* the frequency of Wirtschaft, keeping the odds ratio the same, and notice that it just adds (some function of) *k* to both numerator and denominator, which cancel.

Actually this is where all substantively interesting information in document term matrices lives

→ where else is there?

Any kind of text model, e.g. a topic model

- → implies constraints on how these odds ratios can vary
- \rightarrow reduces the dimensionality of word distributions to a lower than V space

So let's think about building a model of them from first principles

First we'll assume that each C_{ij} is a Poisson distributed with some expected rate

$$C_{ij} \sim \text{Poisson}(\mu_{ij})$$

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There are two log-linear models of any contingency table

$$\log \mu_{ij} = \alpha_i + \psi_j$$
 (boring)
= $\alpha_i + \psi_j + \lambda_{ij}$ (pointless)

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There are two log-linear models of any contingency table

$$\log \mu_{ij} = \alpha_i + \psi_j \qquad \text{(independence)}$$
$$= \alpha_i + \psi_i + \lambda_{ii} \qquad \text{(saturated)}$$

All the *relative emphasis*, all the odds ratio information, and all the *position-taking* is in λ Reminder:

- \rightarrow In log linear model land, the matrix of λ values is just the same size as C
- \rightarrow but the influence of the row and column margins has been *removed* by the α and ψ parameters

INFER DIMENSIONAL STRUCTURE

Intuition: λ has an orthogonal decomposition

$$\lambda = \Theta \Sigma B^{T}$$

$$= \sum_{m}^{M} \theta_{(m)} \sigma_{(m)} \beta_{(m)}^{T}$$

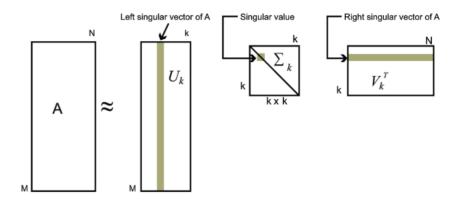
$$\approx \theta \sigma \beta^{T}$$
(SVD)
(Rank 1 approx.)

 θ are document positions

 β are word positions

 σ says how much relative emphasizing is happening in this dimension

SINGULAR VALUE DECOMPOSITION



where A is our λ , U is our θ and V is our β

Modeling Proportional Relative Emphasis

That small fact from earlier

→ FDP's emphasis on 'Wirtschaft' over 'soziale' is 3.5/1.375 = 2.55 times larger than that of the CDU.

According to the model:

$$\log\left(\frac{3.5}{1.375}\right) \approx (\theta_{\text{FDP}} - \theta_{\text{CDU}}) \sigma (\beta_{\text{Wirtschaft}} - \beta_{\text{soziale}})$$

This is a very good idea

Everybody has it...

→ Ecology, archaeology, psychology, political science

and has been having it since Hirschfeld (1935), as

- → the RC Association model (Goodman, 1981)
- → Wordfish (Slapin & Proksch, 2008)
- → Rhetorical Ideal Points (Monroe & Maeda, 2004)

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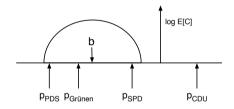
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That was just algebra – why is this a very good idea?

SPATIAL TALKING

How much will each party use word *b*?



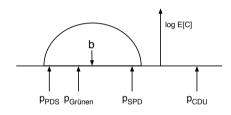
As a model

$$\log \mu_{ij} = r_i + c_j + \frac{(p_i - b_j)^2}{v}$$

where ν describes how fast the tendency to say b declines with distance

SPATIAL TALKING

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As a model

$$\log \mu_{ij} = r_i + c_j + \frac{(p_i - b_j)^2}{v}$$

where ν describes how fast the tendency to say b declines with distance

That we've seen before

$$r_{i} + c_{j} + \frac{(p_{i} - b_{j})^{2}}{k}$$

$$r_{i} + c_{j} + \frac{(p_{i}^{2} - 2p_{i}b_{j} + b_{j}^{2})}{v}$$

$$\underbrace{(r_{i} + p_{i}^{2}/v)}_{\alpha_{i}} + \underbrace{(c_{j} + b_{j}^{2}/v)}_{\psi_{j}} + \underbrace{p_{i}}_{\theta_{i}} \underbrace{(1/v)}_{\sigma} \underbrace{(-2b_{j})}_{\beta_{j}}$$

For the microeconomists, think

- \rightarrow stochastic utility decision model with V choices
- \rightarrow and very simple underlying preference structure
- → i.e. a huge structured IIA violation...

FOR THE POLITICAL SCIENTISTS

otherwise. Legislators are assumed to have quadratic utility functions over the policy space, $U_i(\zeta_j) = -\|x_i - \zeta_j\|^2 + \eta_{ij}$, and $U_i(\psi_j) = -\|x_i - \psi_j\|^2 + \nu_{ij}$, where $x_i \in \mathbb{R}^d$ is the *ideal point* of legislator i, η_{ij} and ν_{ij} are the errors or stochastic elements of utility, and $\|\cdot\|$ is the Euclidean norm. Utility maximization implies that $y_{ij} = 1$ if $U_i(\zeta_j) > U_i(\psi_j)$ and $y_{ij} = 0$ otherwise. The specification is completed by assigning a distribution to the errors. We assume that the errors η_{ij} and ν_{ij} have a joint normal distribution with $E(\eta_{ij}) = E(\nu_{ij})$, $\operatorname{var}(\eta_{ij} - \nu_{ij}) = \sigma_j^2$ and the errors are independent across both legislators and roll calls. It follows that

$$P(y_{ij} = 1) = P(U_i(\zeta_j) > U_i(\psi_j))$$

$$= P(v_{ij} - \eta_{ij} < \|\mathbf{x}_i - \psi_j\|^2 - \|\mathbf{x}_i - \zeta_j\|^2),$$

$$= P(v_{ij} - \eta_{ij} < 2(\zeta_j - \psi_j)'\mathbf{x}_i + \psi_j'\psi_j - \zeta_j'\zeta_j)$$

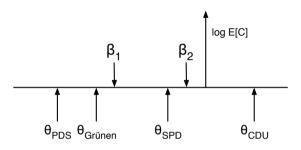
$$= \Phi(\beta_j'\mathbf{x}_i - \alpha_j), \qquad (1)$$

where $\beta_j = 2(\zeta_j - \psi_j)/\sigma_j$, $\alpha_j = (\zeta_j'\zeta_j - \psi_j'\psi_j)/\sigma_j$, and

← from Clinton et al. (2004)

Condition on document length to get a spatial 'voting' model (via the 'Multinomial-Poisson' transform', Baker, 1994; Lang, 2004)

FOR THE POLITICAL SCIENTISTS



Decision time: Should I say word 1 or word 2?

- → Depends on my distance to each of them
- → If I can say the word exactly once before being presented with another pair then this is the roll-call voting context and this is a logistic regression (embedded in an IRT model)

SPECIAL CASES: RILE

According to the folk at the WZB (Budge et al., 1987; Volkens et al., 2020), parties signal their ideology by making just such a sequence of choices, over topics

- \rightarrow Manually identify 'Right' topics R and 'Left' topics L, from a 56 topic codebook
- → For each party manifesto, sum up the Right topic proportions and subtract the sum of the Left topic proportions
- → That's Right-Left position, a.k.a. RILE

$$\hat{\theta}_i = \sum_{j \in R} \frac{C_{ij}}{C_{i.}} - \sum_{k \in L} \frac{C_{ik}}{C_{j.}}$$
 RILE

where

$$C_{i.} = \sum_{j} C_{ij}$$

is the document length

Consequences: Validation

Open questions:

- → Are these the correct category choices?
- → How could we get policy-specific scales? (Benoit et al., 2012; Lowe et al., 2011)
- → What about new categories where do they fall, ideologically speaking?

Some intermediate answers (Lowe et al., 2011)

→ Probably, but the functional form is not a difference of proportions

$$\hat{\theta}_i = \log \frac{\sum_{j \in R} C_{ij}}{\sum_{k \in L} C_{ik}}$$
 logit scores

- → By careful manual choice of categories
- **→** \$\$

Consequences: Validation

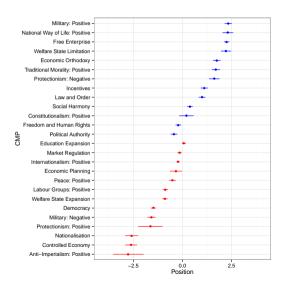
Better answer: Let's check

→ We know already that logit scores are a special case of the model with two 'words'

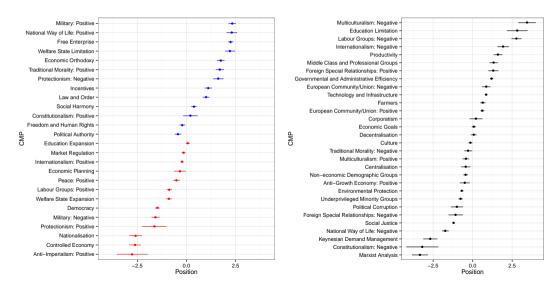
Plan:

- → Fit the scaling model here to post-1989 Germany
- \rightarrow See if the θ s agree with *RILE*
- \rightarrow See if the β s fall into two homogenously position groups
- \rightarrow Get scores for topics not in *L* and *R*

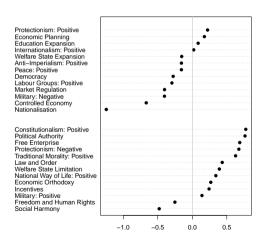
RILE AND OTHER CATEGORIES



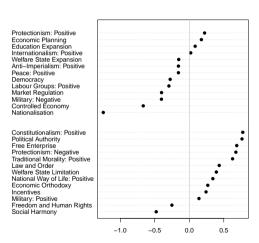
RILE AND OTHER CATEGORIES

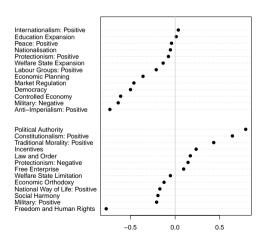


Brits...



Brits...





THEORETICAL QUESTIONS

- \rightarrow How can we know what θ represents?
- → How can we get policy-specific scores?
- → How comparable are these document and word position estimates?
- → (When) does it make sense to project different documents into a space
- → What would a multi-dimensional version of this model look like

IMPLEMENTATIONS

ASSOCIATION MODEL

- → What quanteda calls 'wordfish'
- → limited to scaling in one dimension
- → Provides uncertainty estimates for document positions (too small, Lowe and Benoit, 2013)
- → Fit by alternating maximum likelihood, so rather slow

CORRESPONDENCE ANALYSIS

- → The least squares version of the association model, so tends to agree with it
- → Very fast to fit just one SVD
- → Multiple dimensions possible at no extra cost
- $\rightarrow \theta$ called 'row coordinates' and β called 'column coordinates'
- → Uncertainty estimates harder to get (bootstrap is possible)
- → Very useful general purpose contingency table visualization tool

NEXT WEEK

- → Interpretation
- → Multidimensional models
- → Comparisons
- → Connections to other methods

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