Text as Data

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Measurement via repurposed discovery methods

1) Discovery categories, measure prevalence of categories
2) Once we fix interpretation, accuracy/precision/recall well defined

LDA Revisited

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\begin{aligned}
\boldsymbol{\theta}_k &\sim \text{Dirichlet}(\mathbf{1}) \\
\boldsymbol{\pi}_i|\boldsymbol{\alpha} &\sim \text{Dirichlet}(\boldsymbol{\alpha}) \\
\boldsymbol{\tau}_{im}|\boldsymbol{\pi}_i &\sim \text{Multinomial}(1, \boldsymbol{\pi}_i) \\
x_{im}|\boldsymbol{\theta}_k, \tau_{imk} = 1 &\sim \text{Multinomial}(1, \boldsymbol{\theta}_k)
\end{aligned}
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LDA Revisited

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\begin{aligned}
\textbf{Unigram Model}_k &\sim \text{Dirichlet}(\mathbf{1}) \\
\textbf{Doc. Prop}_i &\sim \text{Dirichlet}(\textbf{Pop. Proportion}) \\
\textbf{Word Topic}_{im} &\sim \text{Multinomial}(1, \textbf{Doc. Prop}_i) \\
\text{Word}_{im} &\sim \text{Multinomial}(1, \textbf{Unigram Model}_k)
\end{aligned}
$$

A General Hierarchical Structure

LDA:

Pop. Proportion

A General Hierarchical Structure

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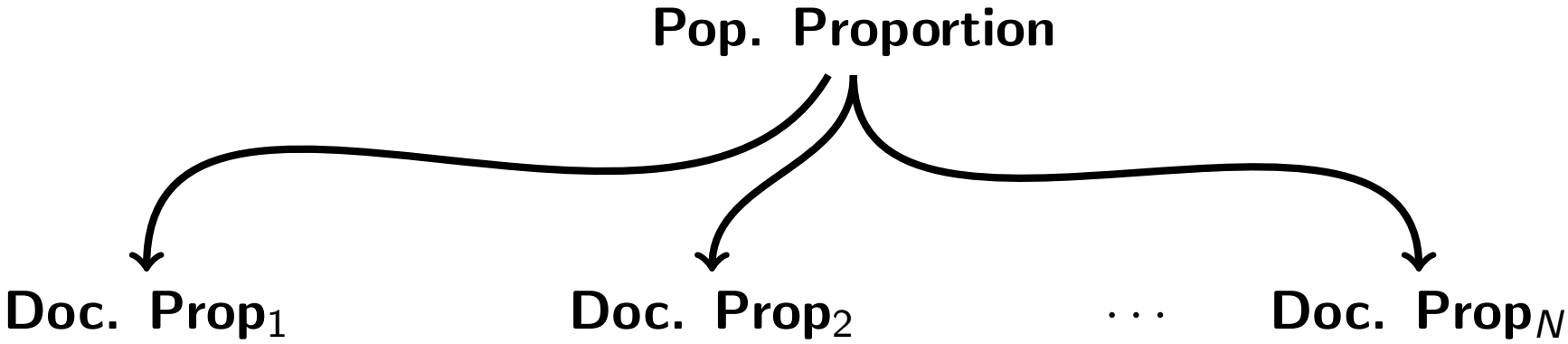

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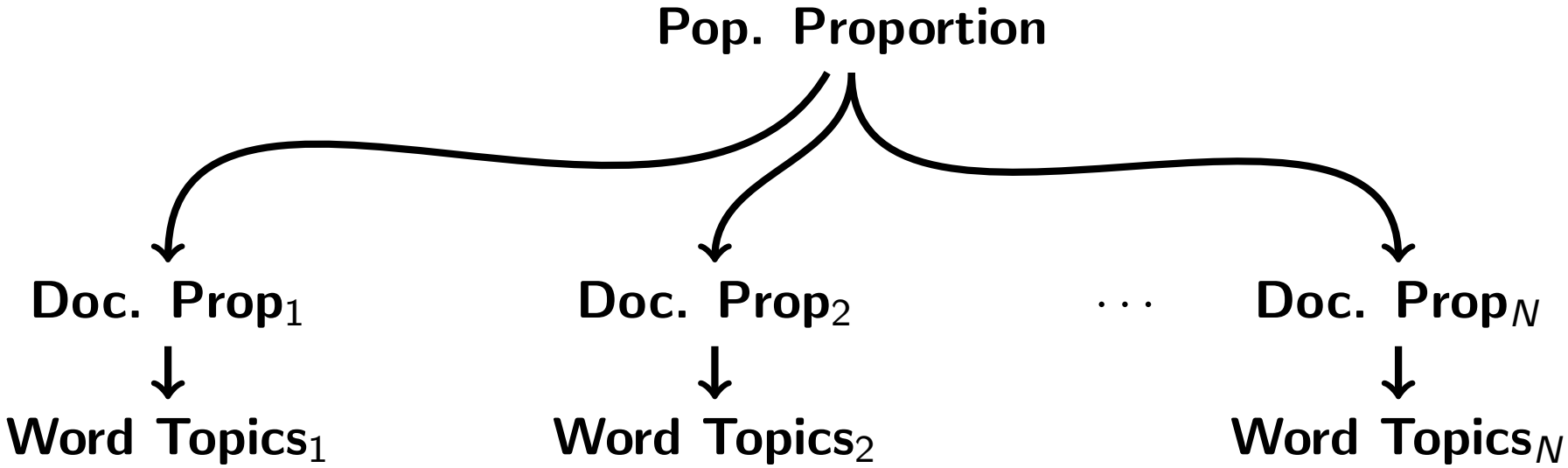

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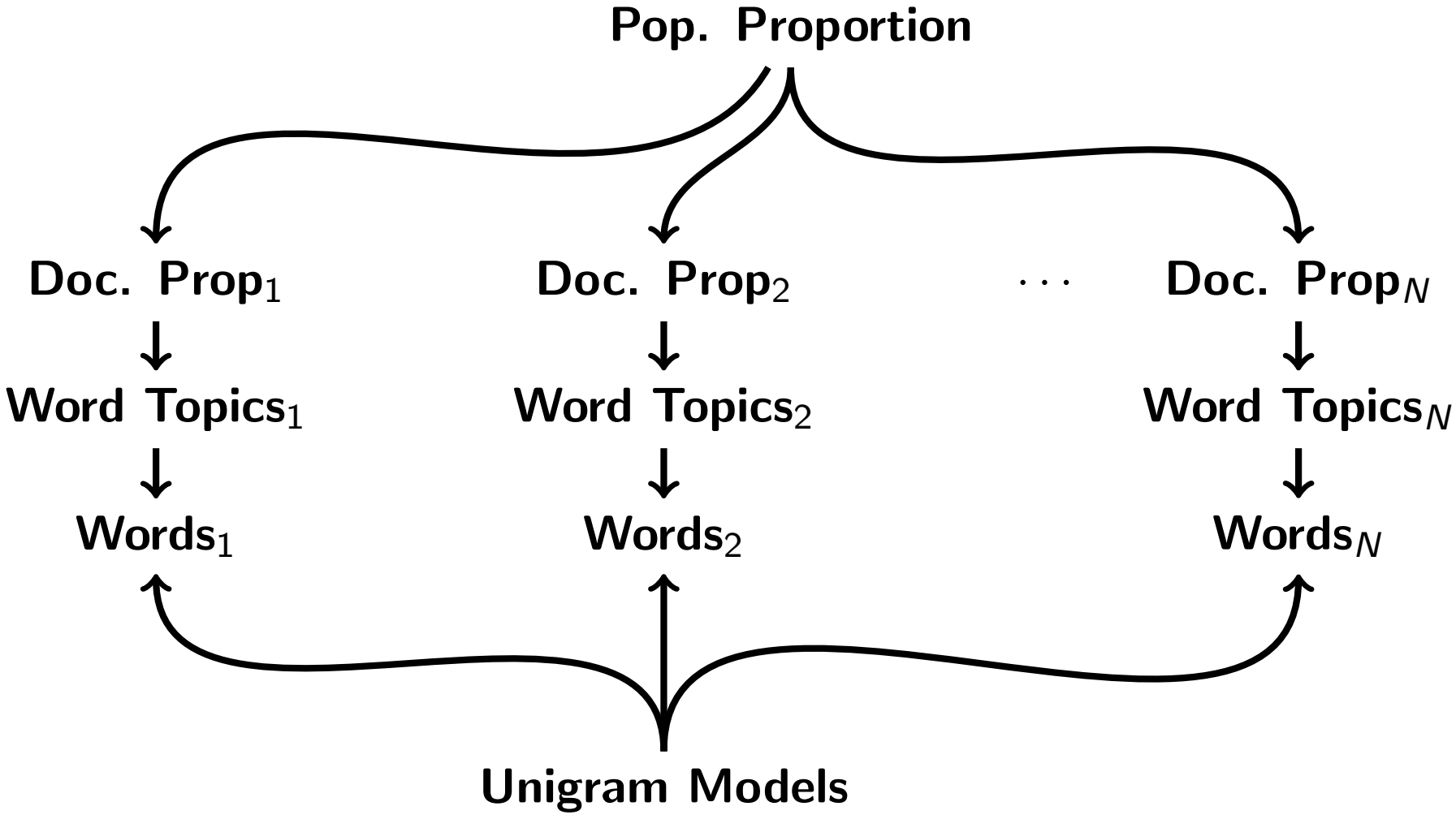

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Dynamic Topic Model (Quinn et al 2010)

Dynamic Prior Across Days

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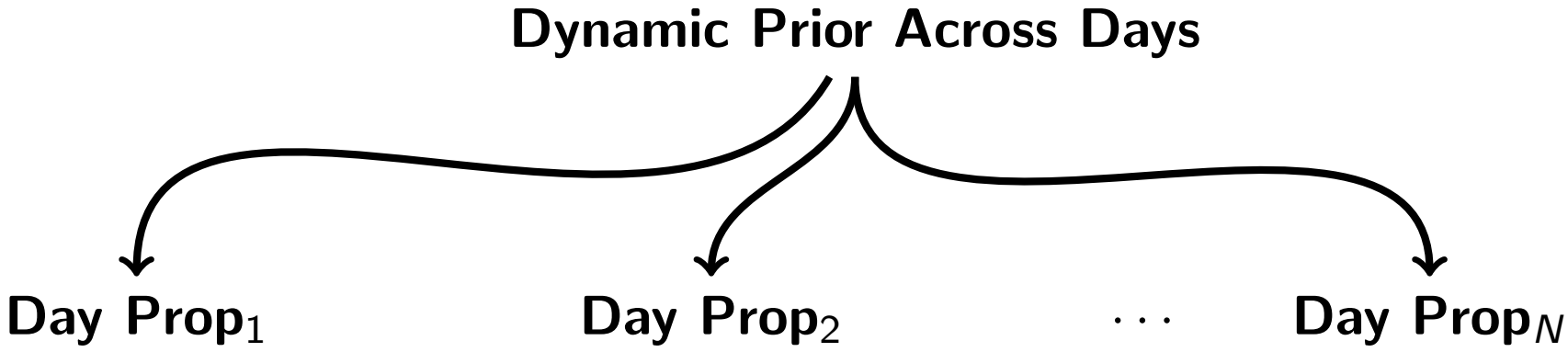

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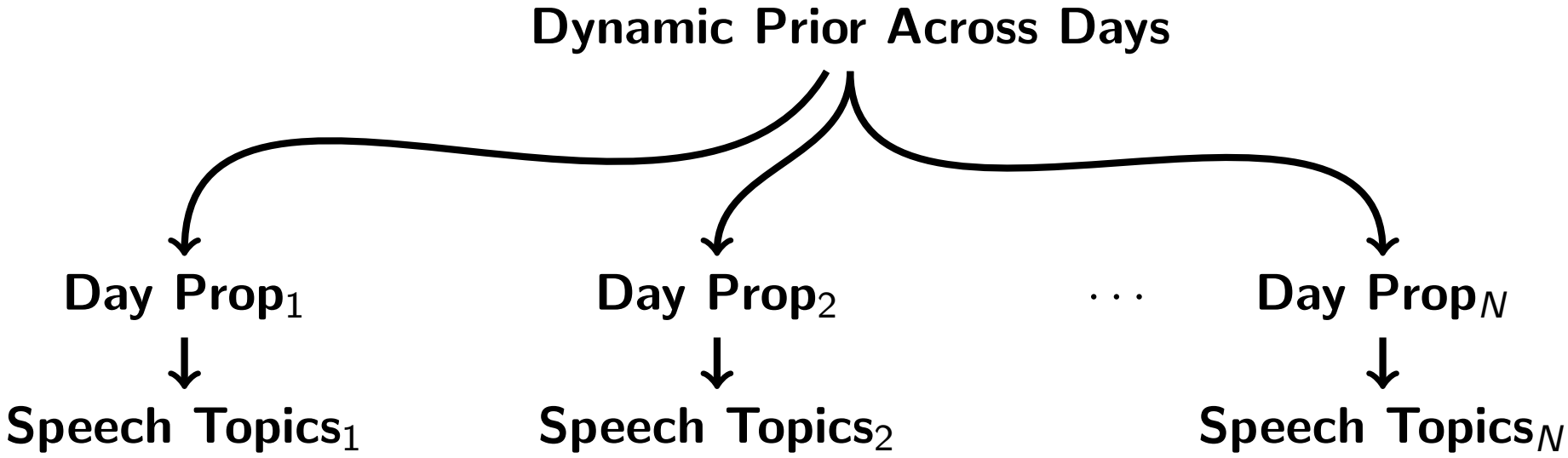

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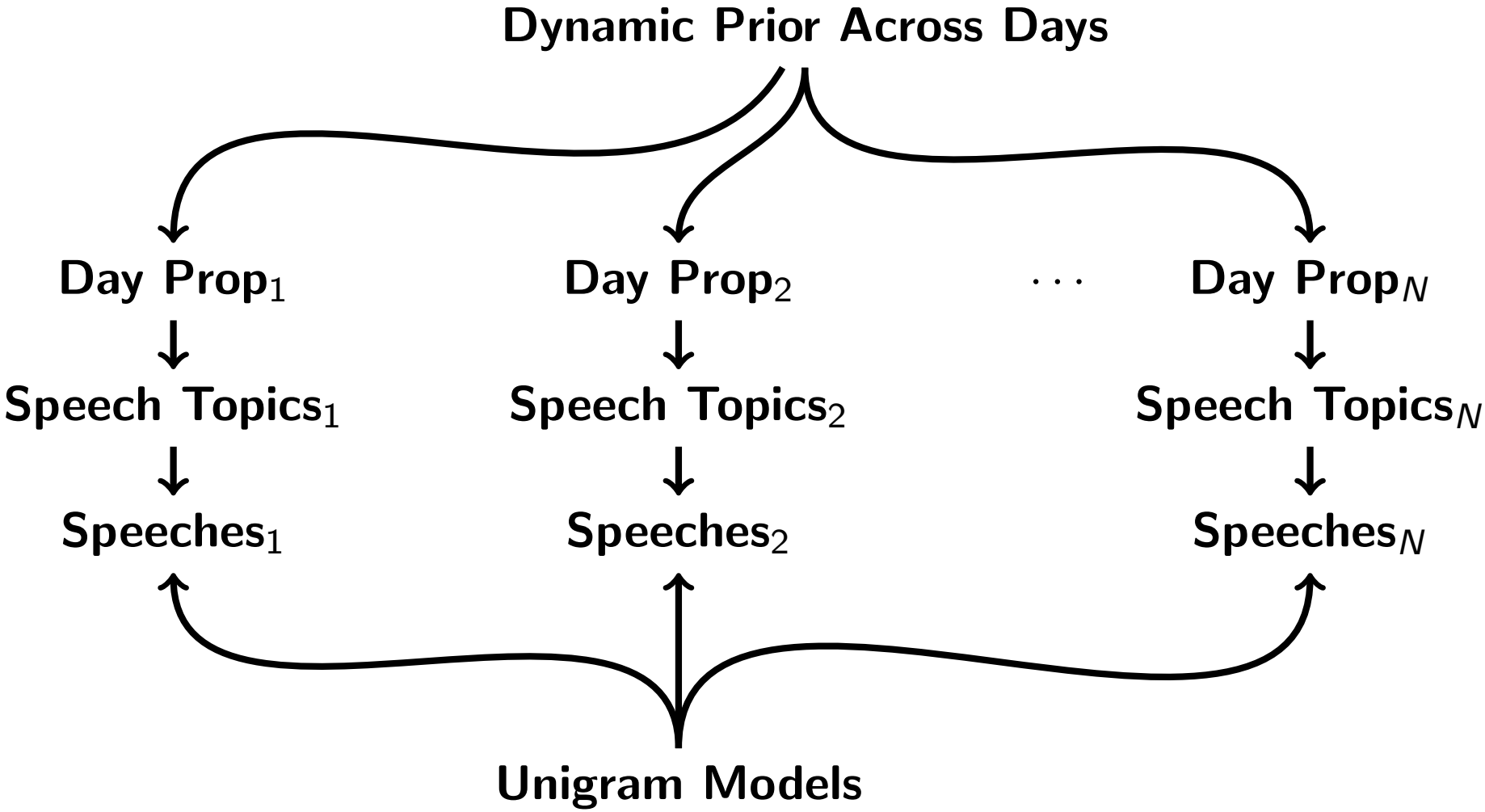

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Expressed Agenda Model (Grimmer 2010)

Average Attention Across Authors

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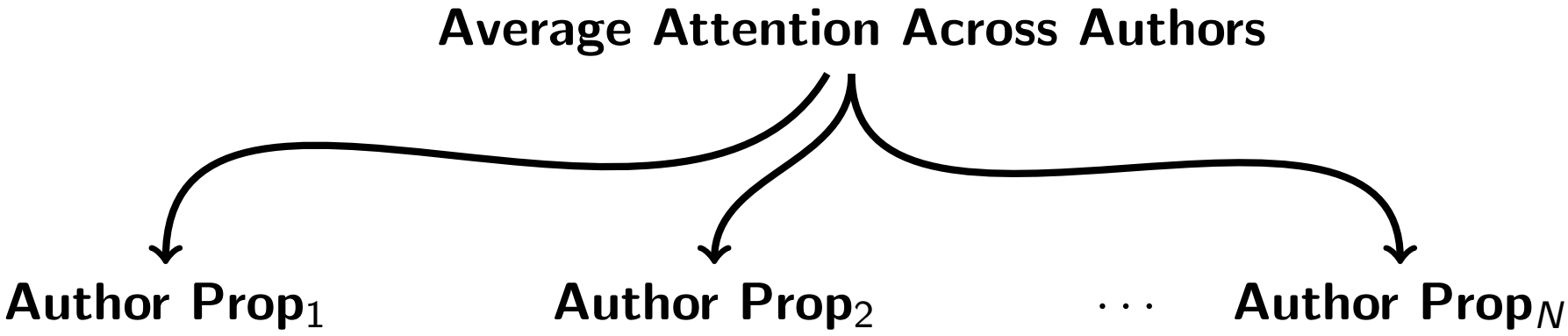

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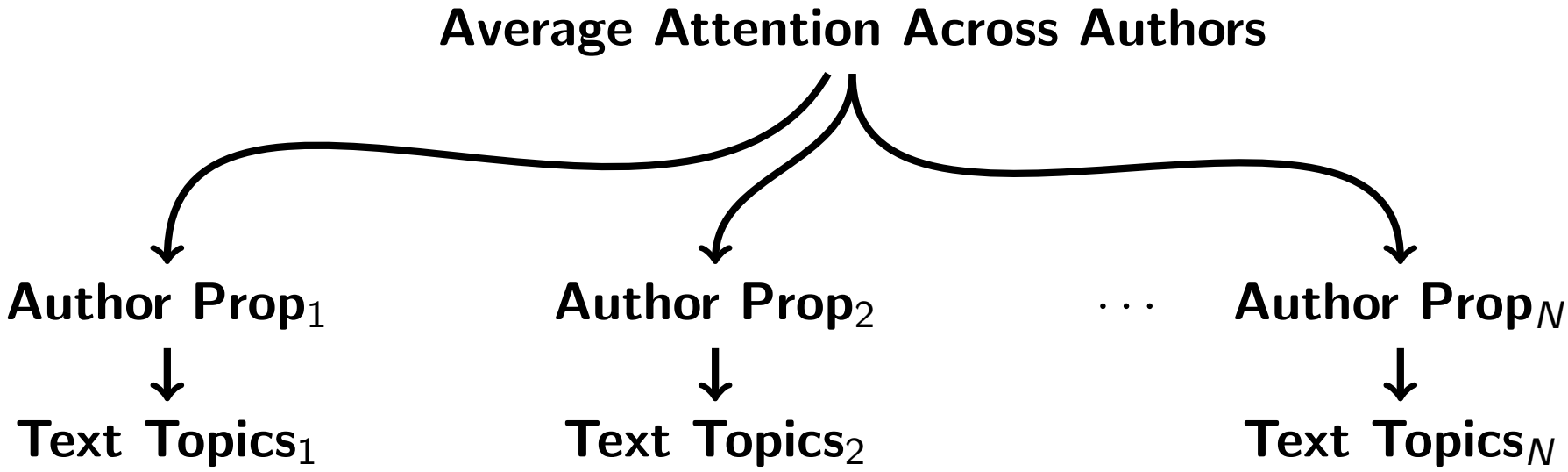

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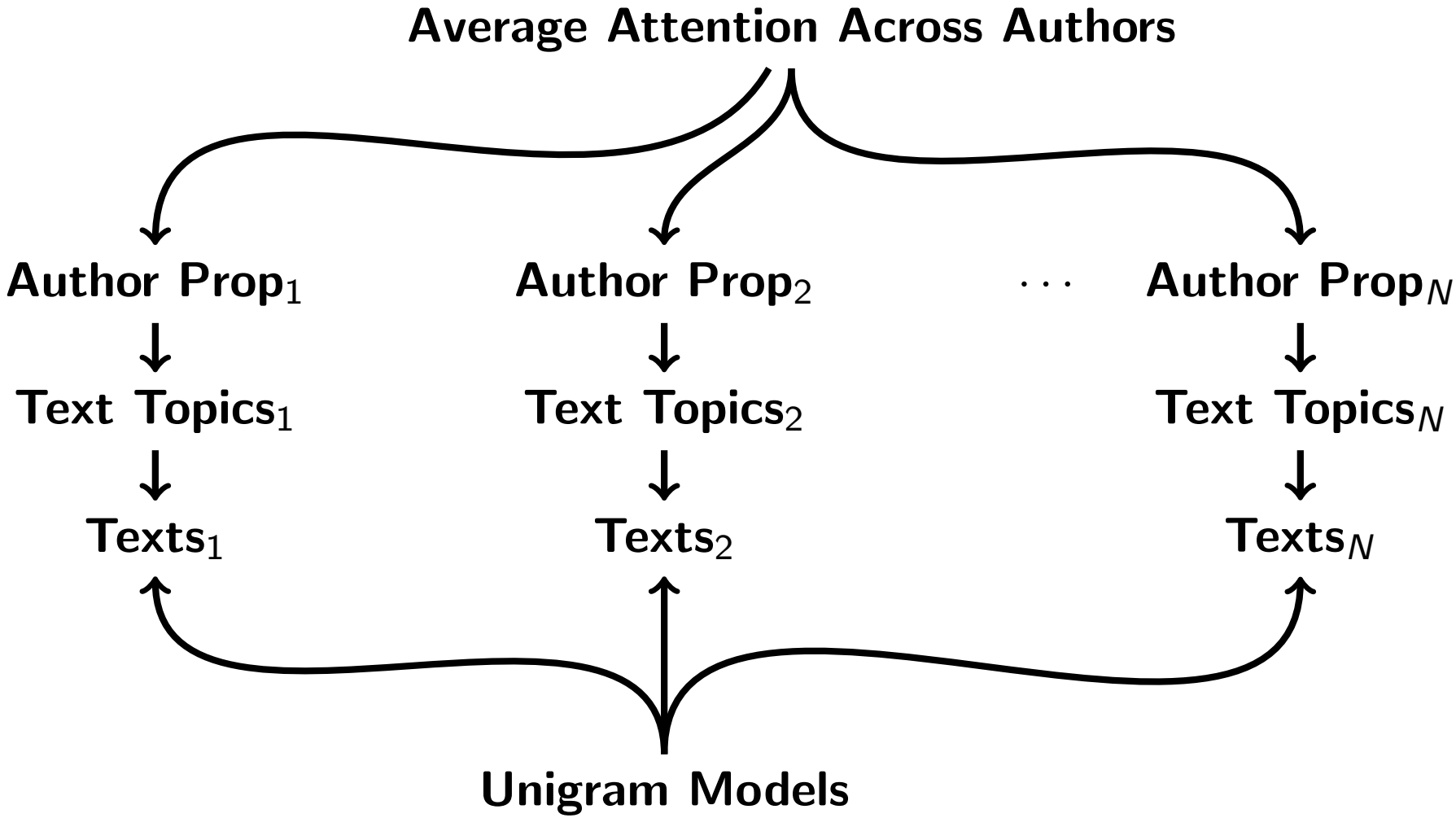

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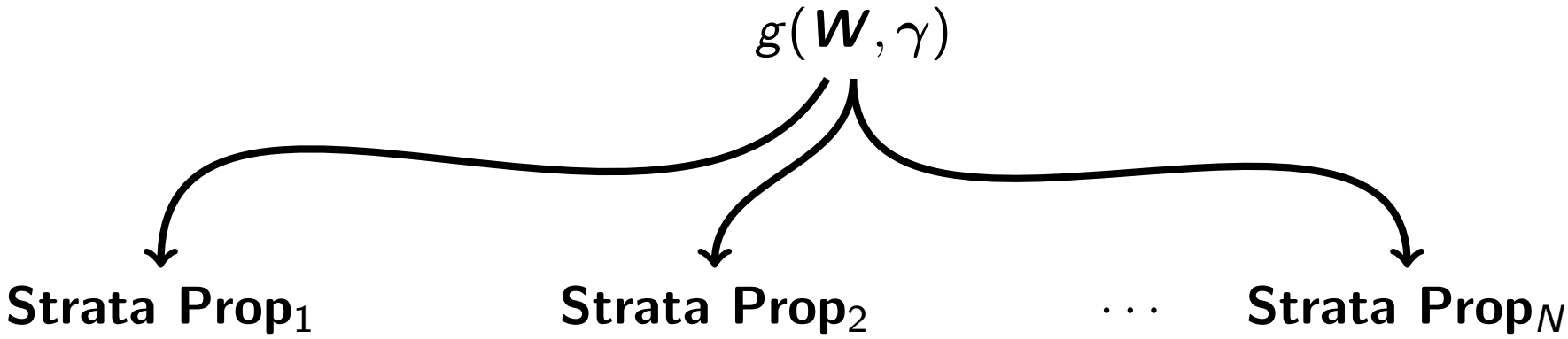

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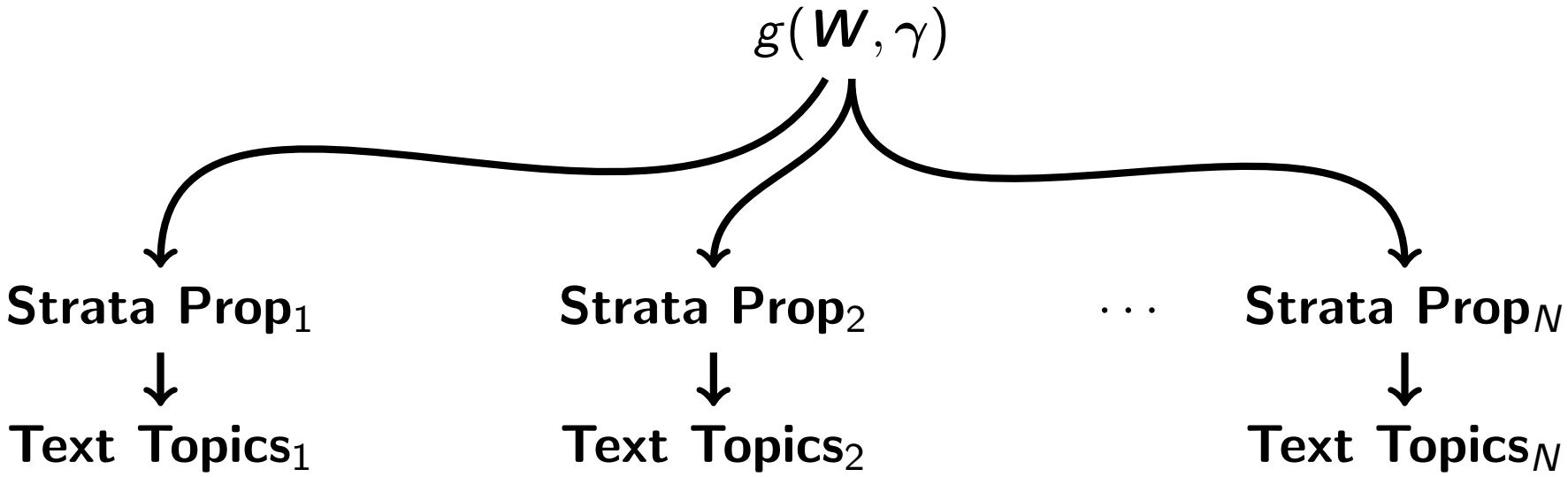

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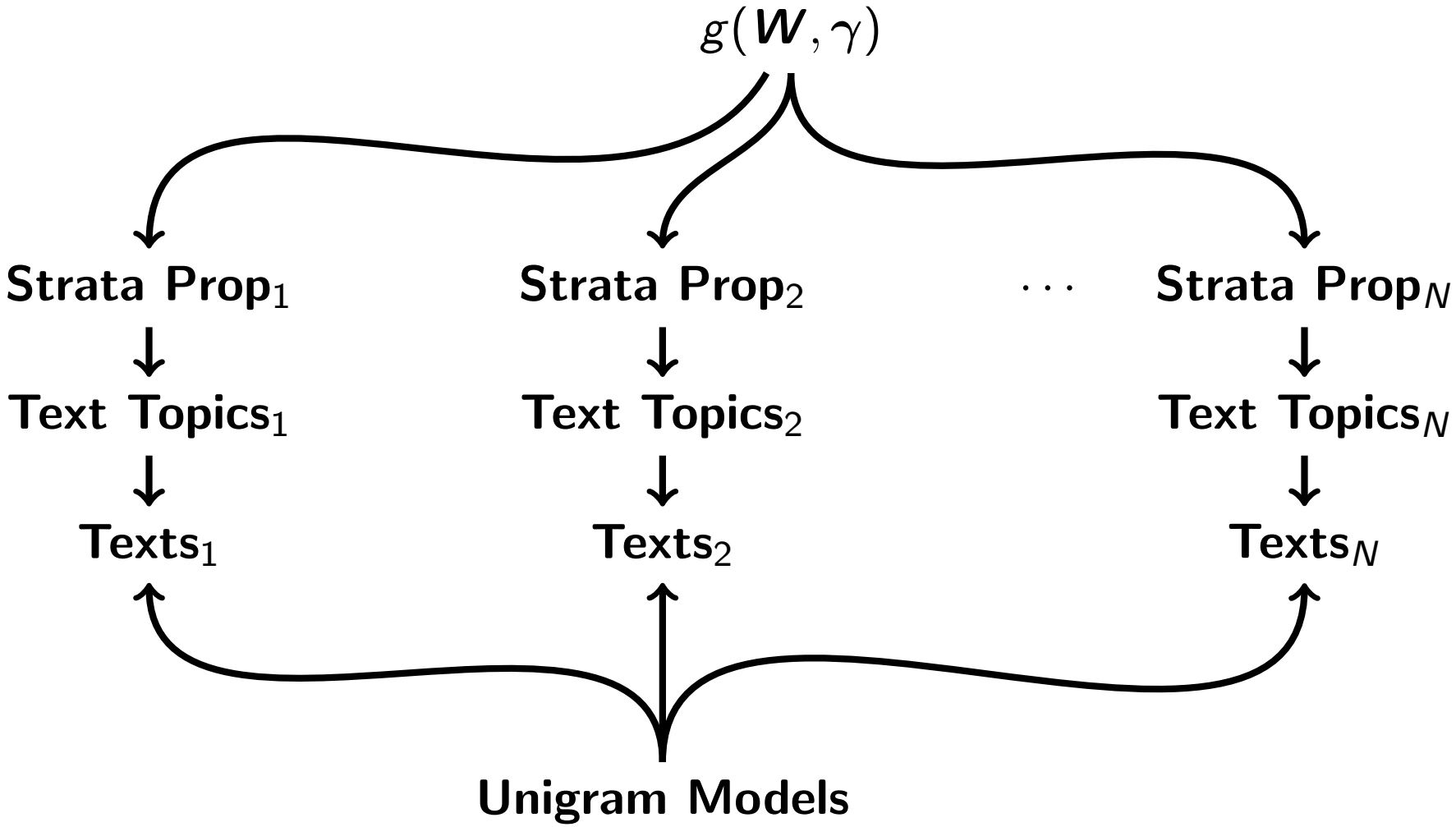

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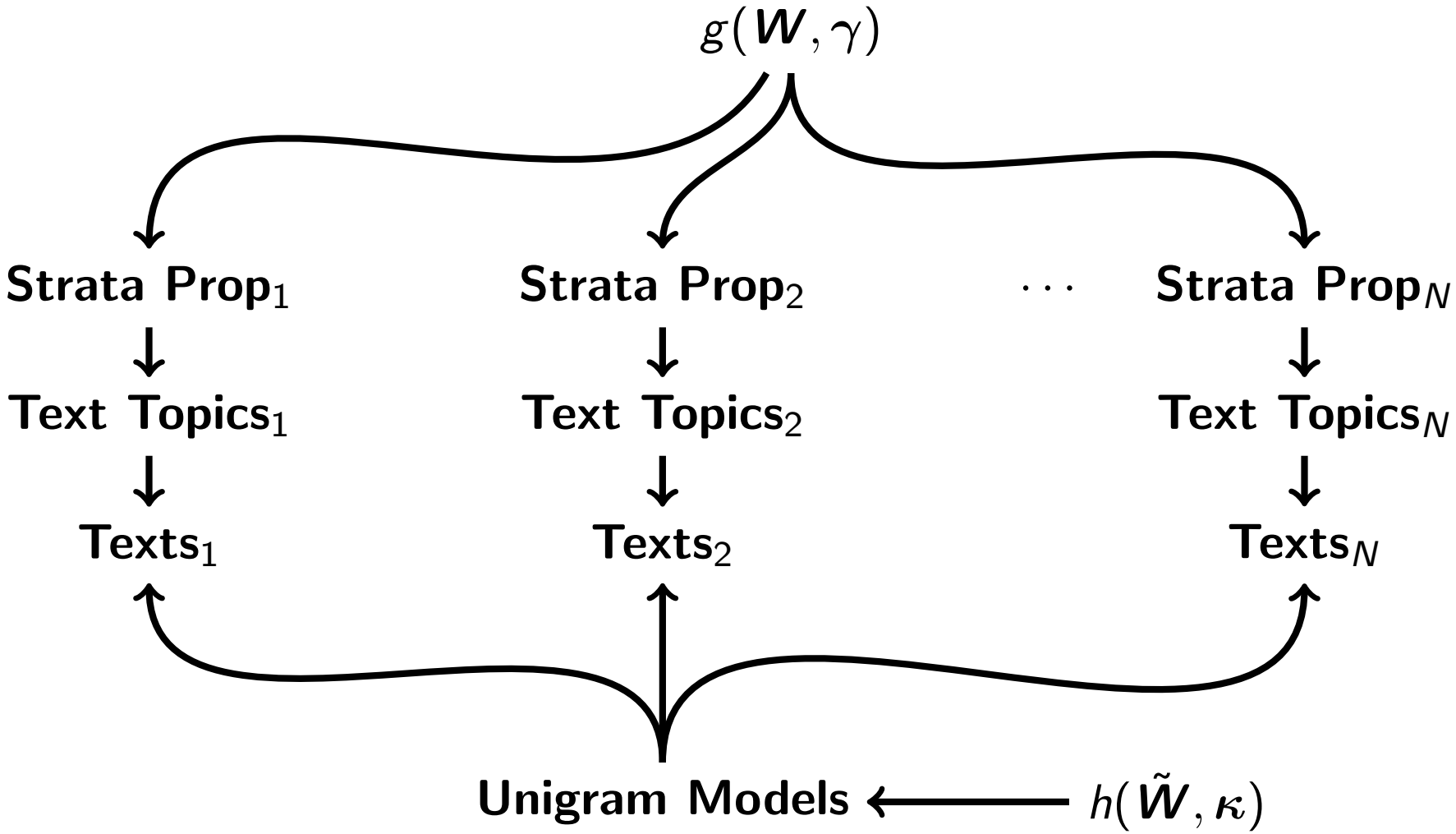

R Code

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Conditioning on Unknown Covariates$\rightsquigarrow$ levels of mixtures at proportions (Grimmer 2013; Wallach 2008)

Mixture of Top. Attn. Models

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Strata Indic. **Topic Attention Models**

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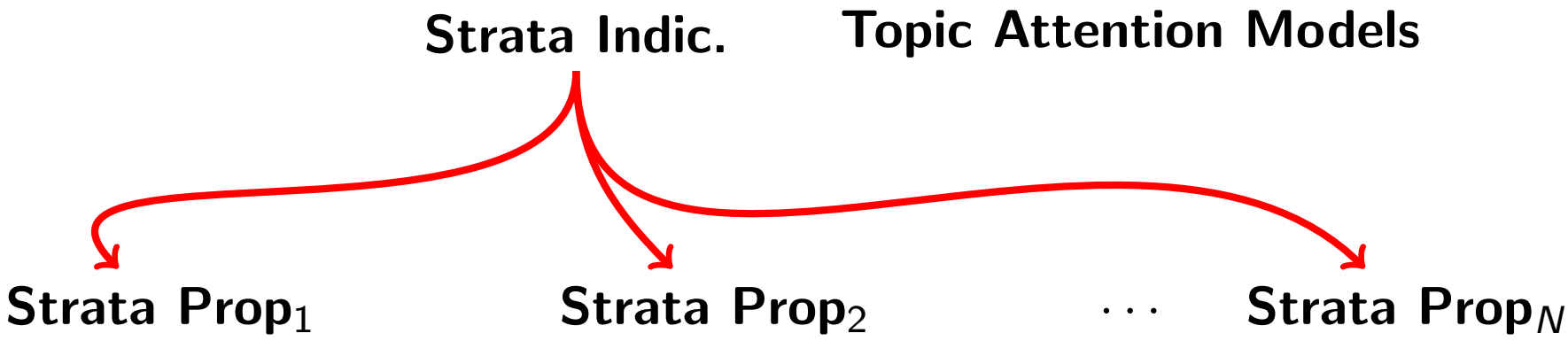

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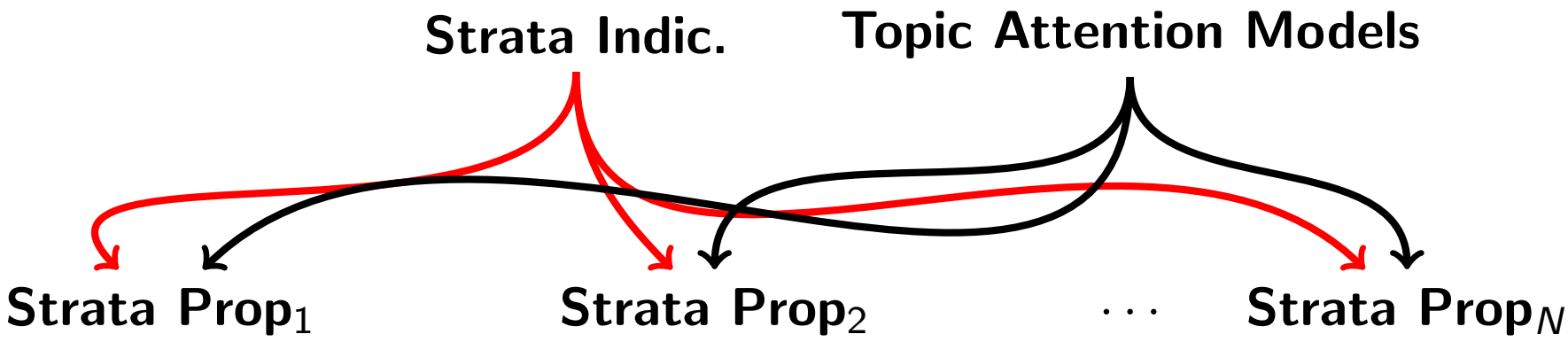

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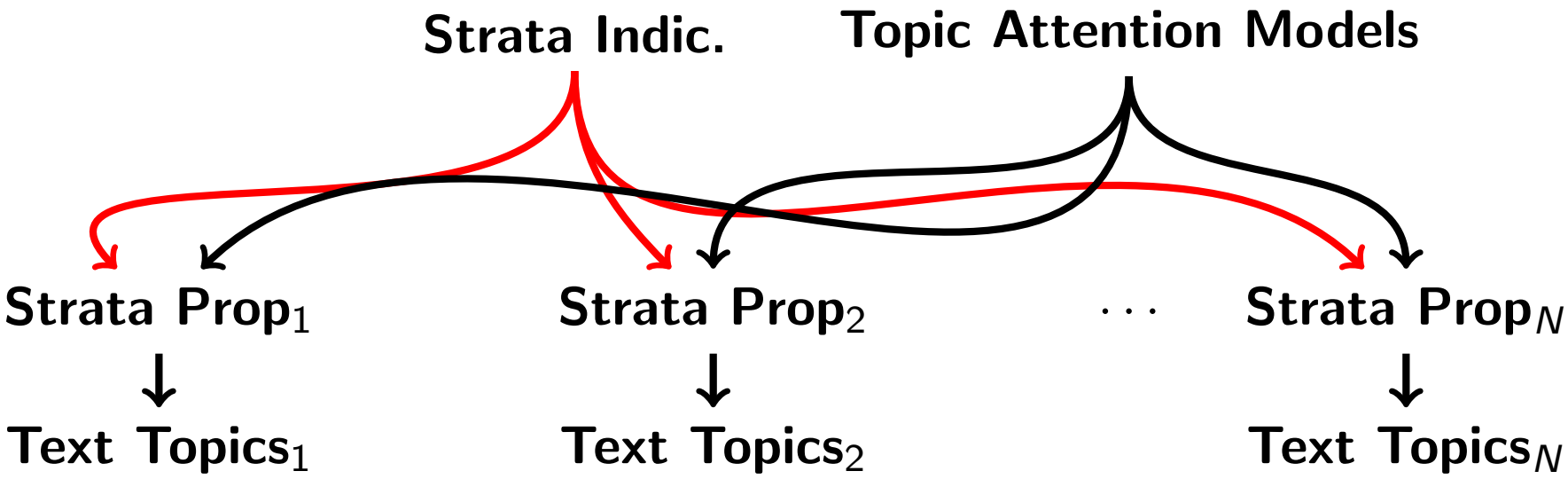

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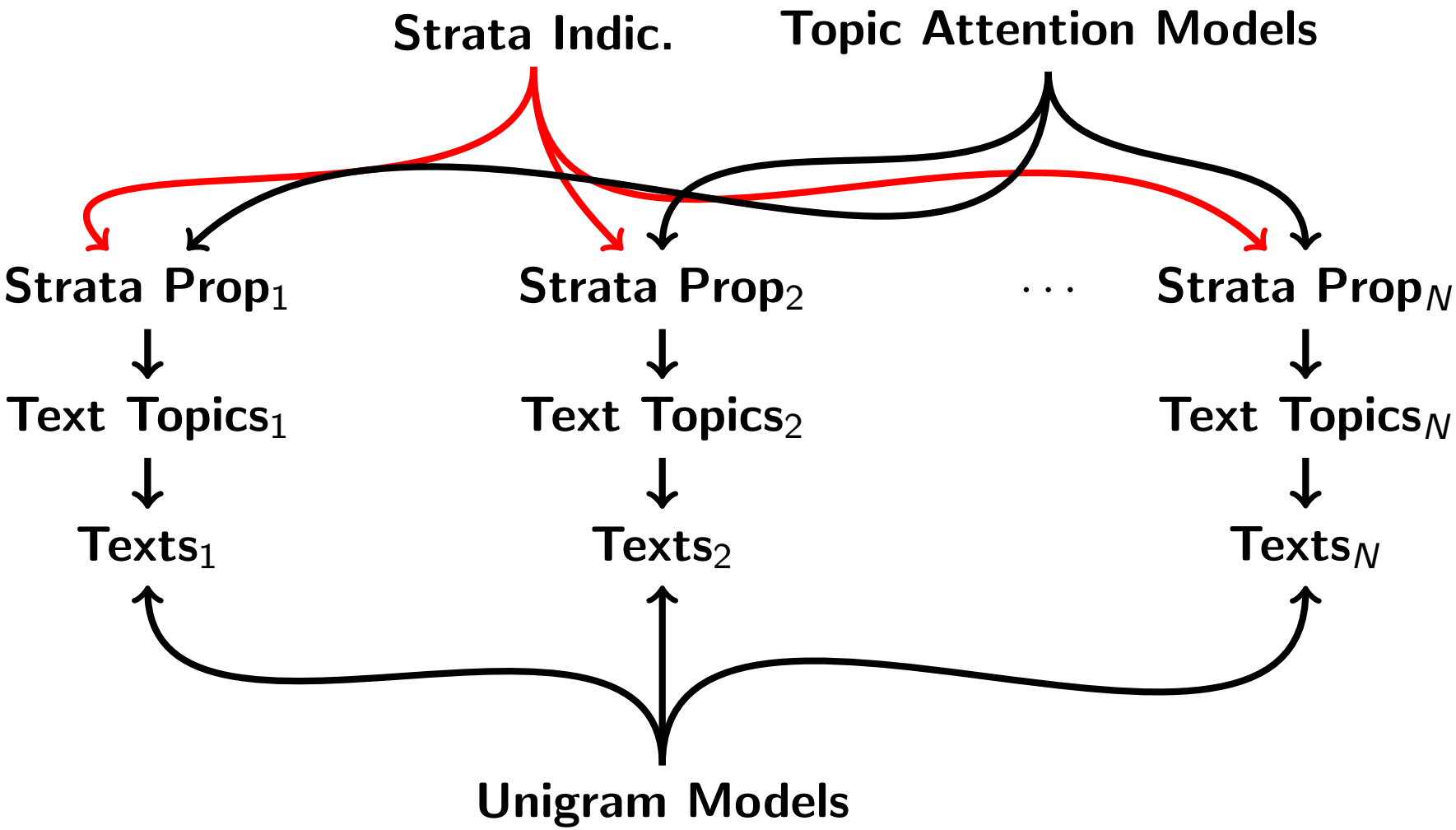

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Conditioning on Unknown Covariates for Topics$\rightsquigarrow$ hierarchy of topics (Li and McCallum 2006; Blaydes, Grimmer, and McQueen 2017)

Population attention

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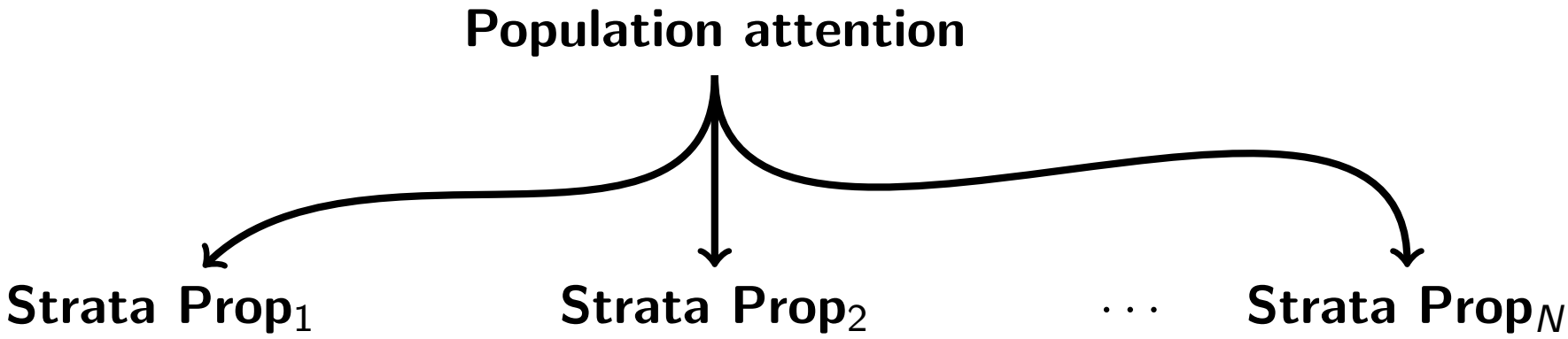

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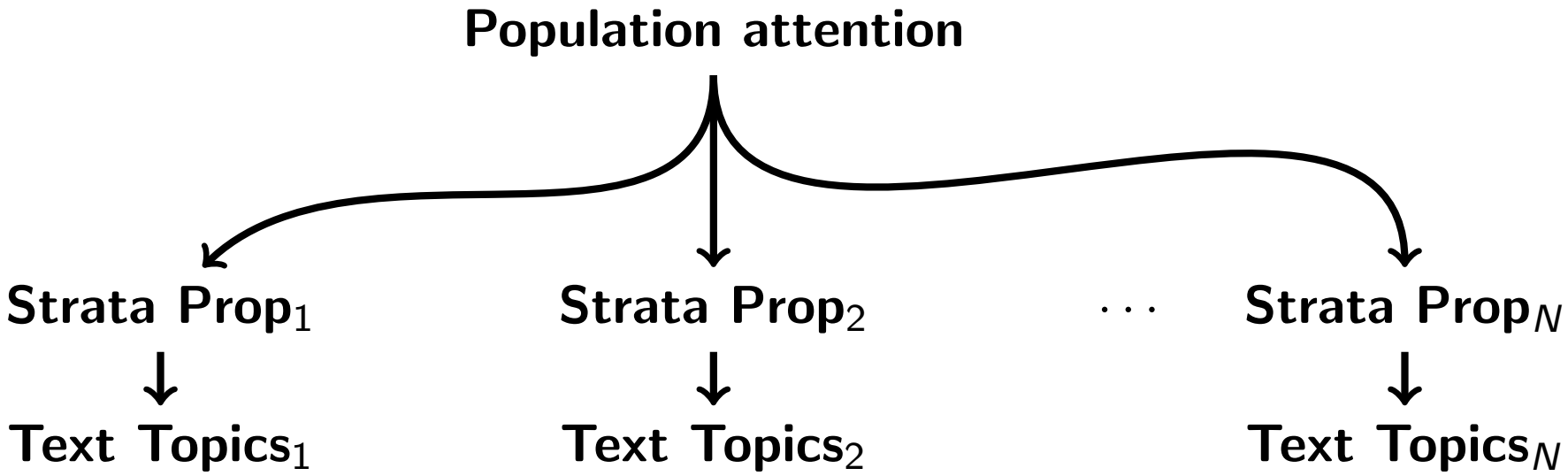

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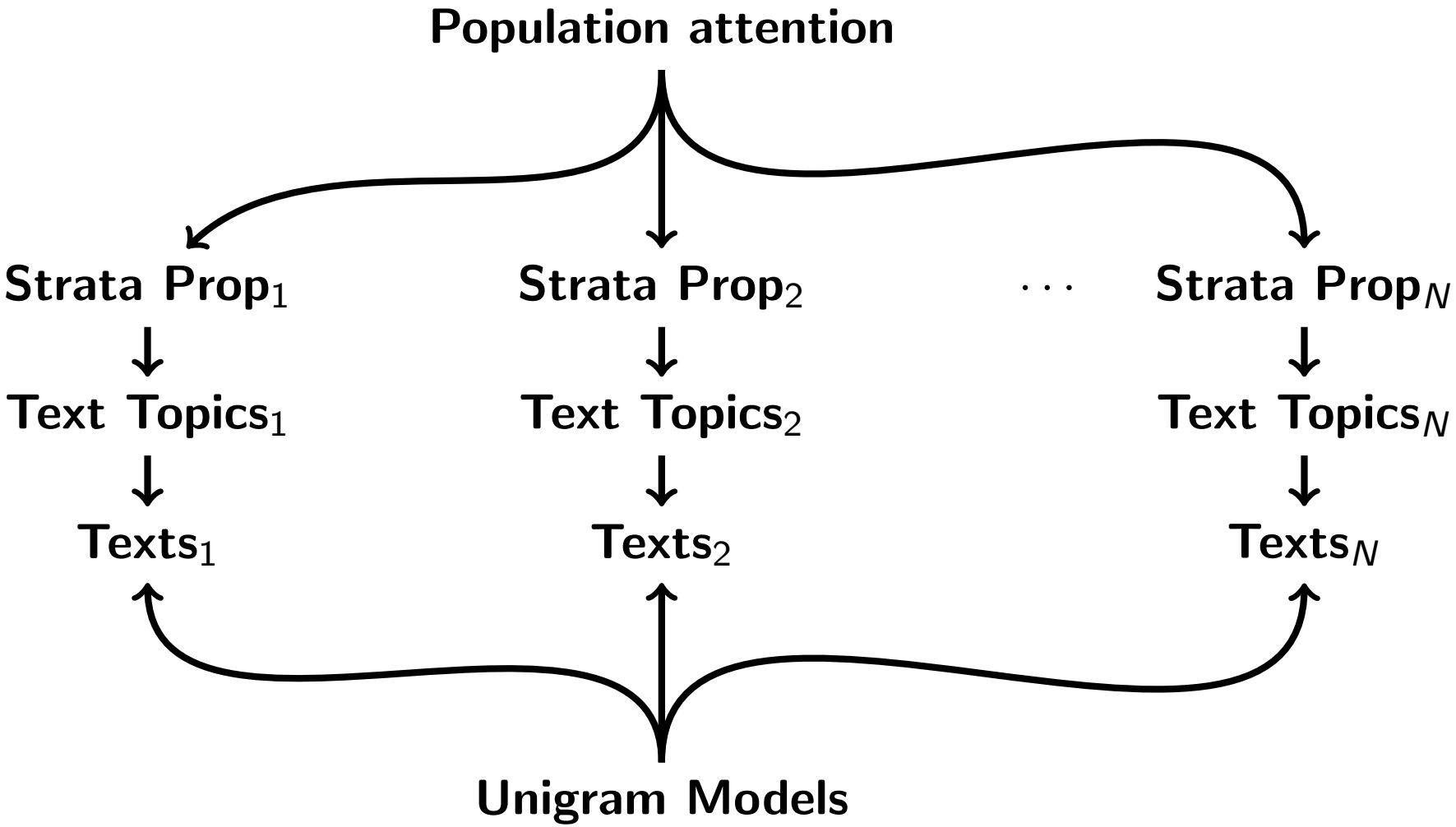

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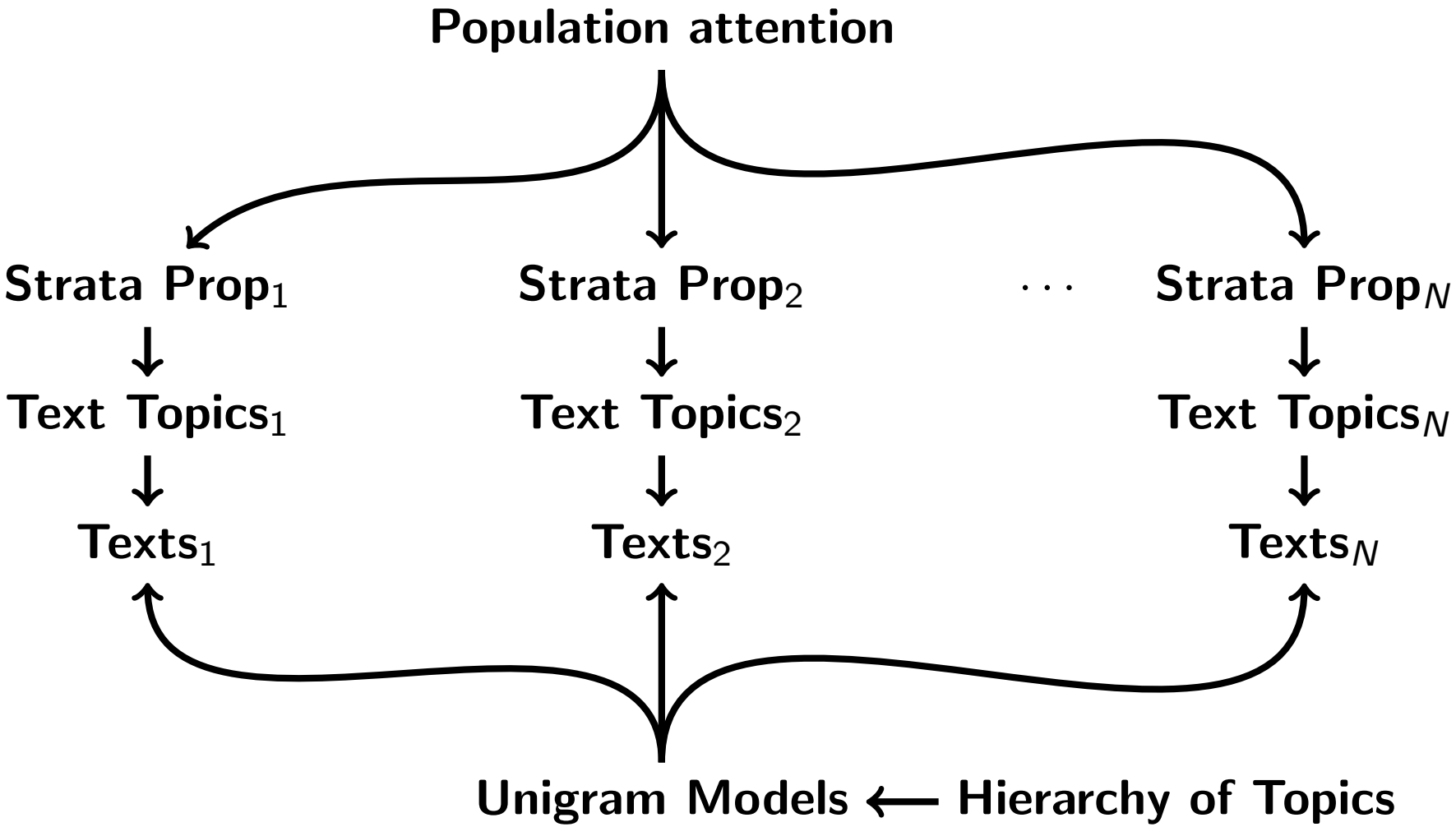

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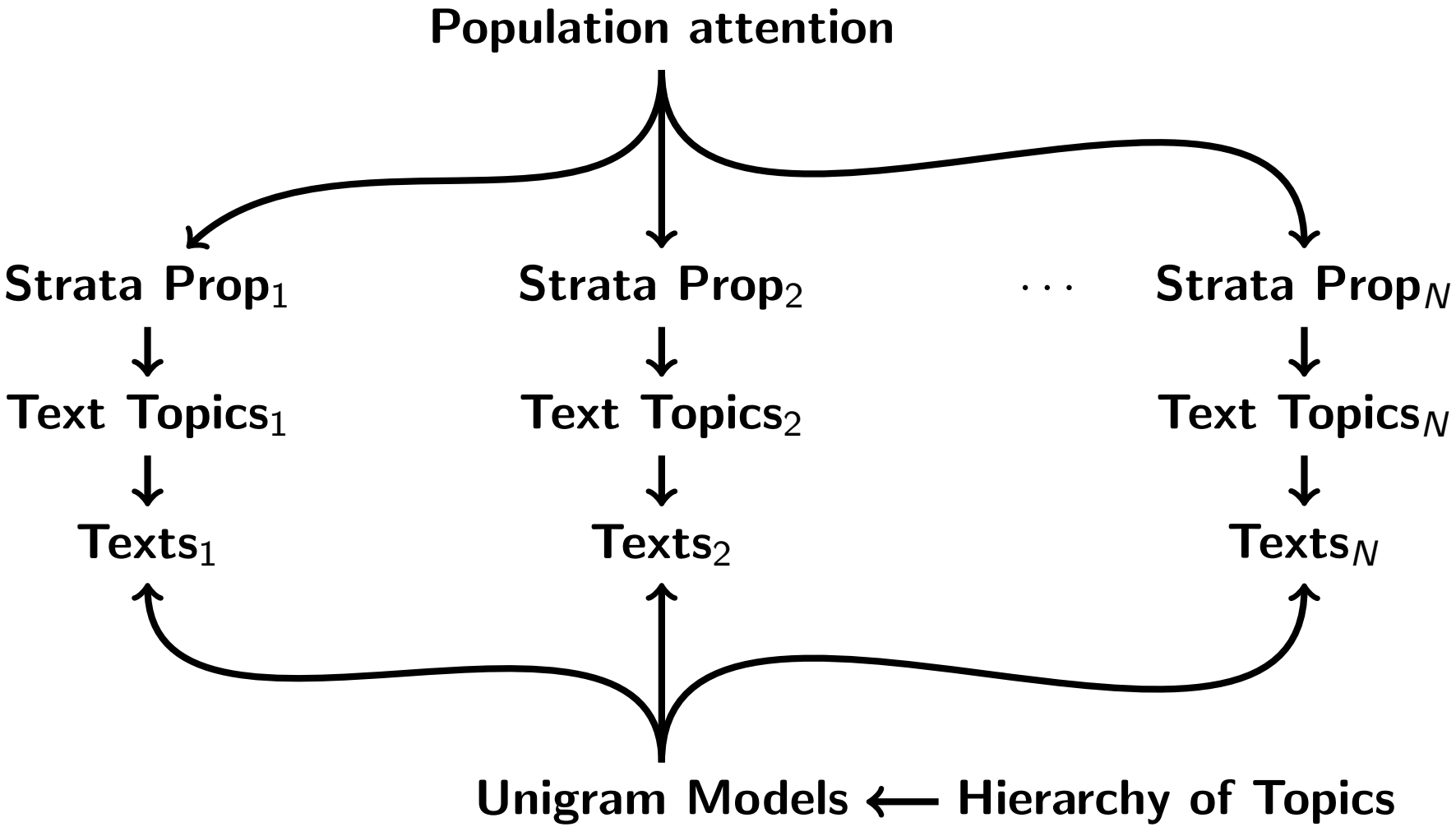

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  - Improved topics$\rightsquigarrow$ small word conditions, structure could help

Plan for the Class

1) Discuss model with unknown covariates for strata proportions$\rightsquigarrow$ presentational style
2) Discuss model with hierarchy of topics$\rightsquigarrow$ mirrors genre

Unknown Covariates for Issue Attention: Measuring Attention in Senate Press Releases

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- Characterize representation provided to constituents
- Divide attention over a set of topics
- Given attention to topics, write press releases

Presentational Styles$\rightsquigarrow$ Objective Function

- $\pi_{itk} \equiv$ Attention senator i allocates to issue k in year t
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- If $\tau_{ijtk} = 1$ then

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\boldsymbol{\theta}_k &\sim \text{Dirichlet}(\boldsymbol{\lambda}) \\
\alpha_{ks} &\sim \text{Gamma}(0.25, 1) \\
\boldsymbol{\sigma}_{it} &\sim \text{Multinomial}(1, \boldsymbol{\beta}) \\
\boldsymbol{\pi}_{it} | \sigma_{its} = 1, \boldsymbol{\alpha}_s &\sim \text{Dirichlet}(\boldsymbol{\alpha}_s) \\
\boldsymbol{\tau}_{ijt} | \boldsymbol{\pi}_{it} &\sim \text{Multinomial}(1, \boldsymbol{\pi}_{it}) \\
\boldsymbol{x}_{ijt} | \tau_{ijtk} = 1, \boldsymbol{\theta}_k &\sim \text{Multinomial}(n_{ijt}, \boldsymbol{\theta}_k)
\end{aligned}
$$

Presentational Styles$\rightsquigarrow$ Objective Function

$$
\begin{aligned}
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\alpha_{ks} &\sim \text{Gamma}(0.25, 1) \\
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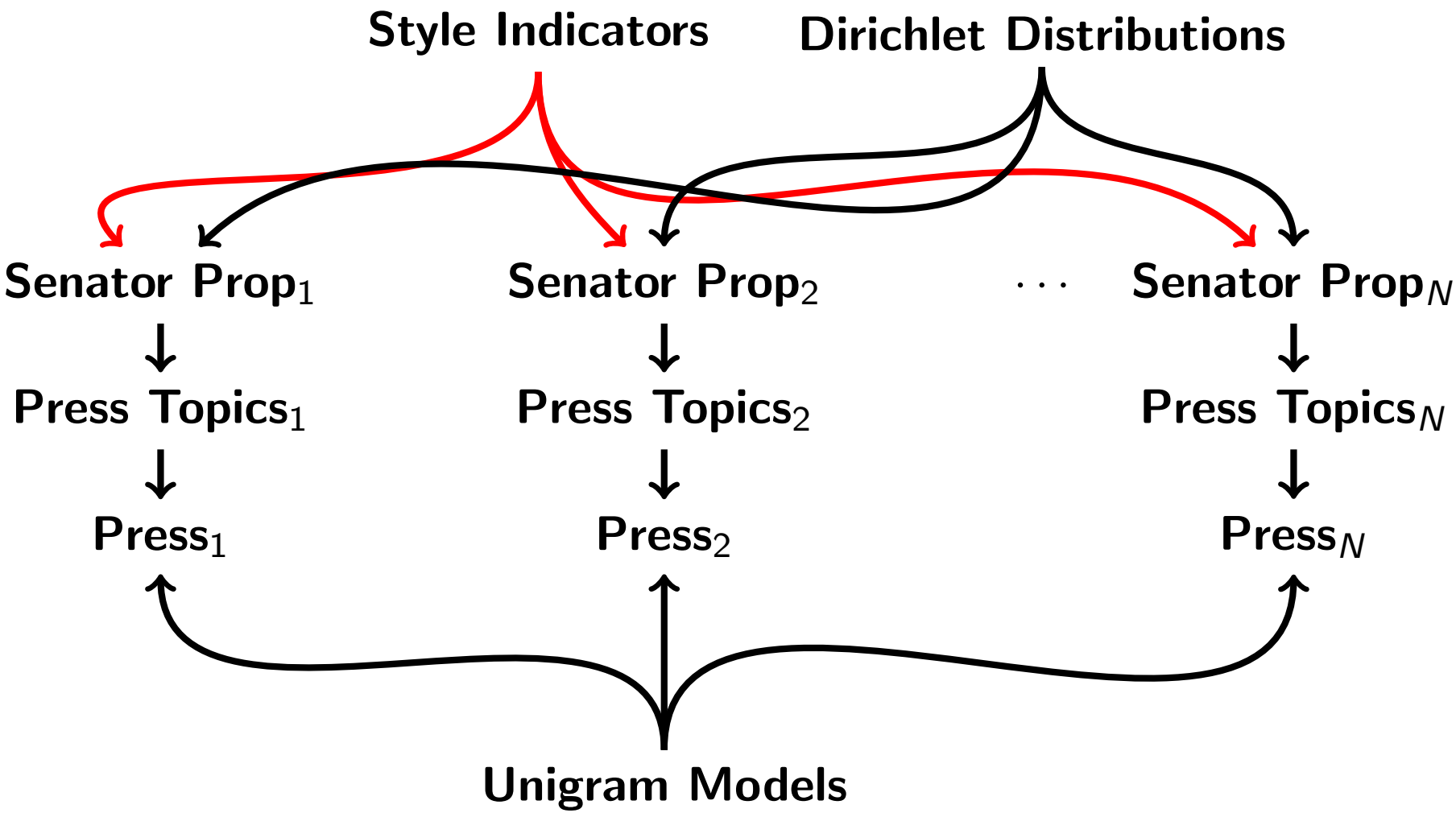
\boldsymbol{x}_{ijt} | \tau_{ijtk} = 1, \boldsymbol{\theta}_k &\sim \text{Multinomial}(n_{ijt}, \boldsymbol{\theta}_k)
\end{aligned}
$$

Mixture of Styles, Mixture of Topics



Posterior:

$$p(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\theta}, \boldsymbol{\sigma}, \boldsymbol{\pi}, \boldsymbol{\tau} | \boldsymbol{X}) \propto \prod_{k=1}^{K} \prod_{s=1}^{S} \frac{\exp(-\frac{\alpha_{ks}}{1/4})}{1/4} \times \frac{\Gamma(\sum_{w=1}^{W} \lambda_w)}{\prod_{w=1}^{W} \Gamma(\lambda_w)} \prod_{w=1}^{W} \theta_{k,w}^{\lambda_w - 1} \times$$

$$\prod_{i=1}^{N} \prod_{t=2005}^{2007} \prod_{s=1}^{S} \left[\beta_s \frac{\Gamma(\sum_{k=1}^{K} \alpha_{ks})}{\prod_{k=1}^{K} \Gamma(\alpha_{ks})} \prod_{k=1}^{K} \pi_{itk}^{\alpha_{ks} - 1} \prod_{j=1}^{D_{it}} \prod_{k=1}^{K} \left[\pi_{itk} \prod_{w=1}^{W} \theta_{kw}^{x_{ijtw}} \right]^{\tau_{ijtk}} \right]^{\sigma_{its}}$$

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1) Estimate with Variational Approximation

Posterior:

$$p(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\theta}, \boldsymbol{\sigma}, \boldsymbol{\pi}, \boldsymbol{\tau} | \boldsymbol{X}) \propto \prod_{k=1}^{K} \prod_{s=1}^{S} \frac{\exp(-\frac{\alpha_{ks}}{1/4})}{1/4} \times \frac{\Gamma(\sum_{w=1}^{W} \lambda_w)}{\prod_{w=1}^{W} \Gamma(\lambda_w)} \prod_{w=1}^{W} \theta_{k,w}^{\lambda_w - 1} \times$$
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1) Estimate with Variational Approximation
2) Determining number of clusters at top? (Grimmer, Shorey, Wallach, and Zlotnick, In Progress)

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1) Estimate with Variational Approximation
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$$p(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\theta}, \boldsymbol{\sigma}, \boldsymbol{\pi}, \boldsymbol{\tau} | \boldsymbol{X}) \propto \prod_{k=1}^{K} \prod_{s=1}^{S} \frac{\exp(-\frac{\alpha_{ks}}{1/4})}{1/4} \times \frac{\Gamma(\sum_{w=1}^{W} \lambda_w)}{\prod_{w=1}^{W} \Gamma(\lambda_w)} \prod_{w=1}^{W} \theta_{k,w}^{\lambda_w - 1} \times$$
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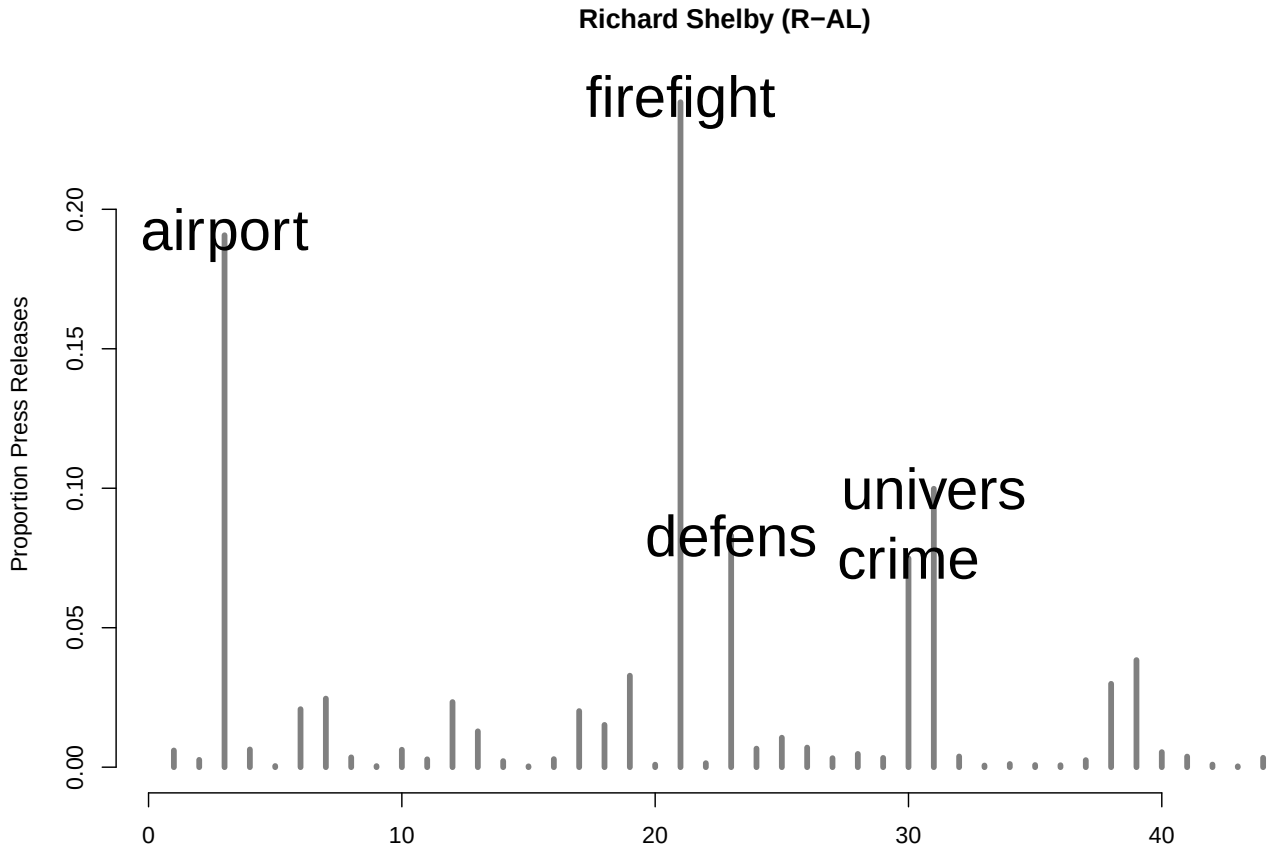
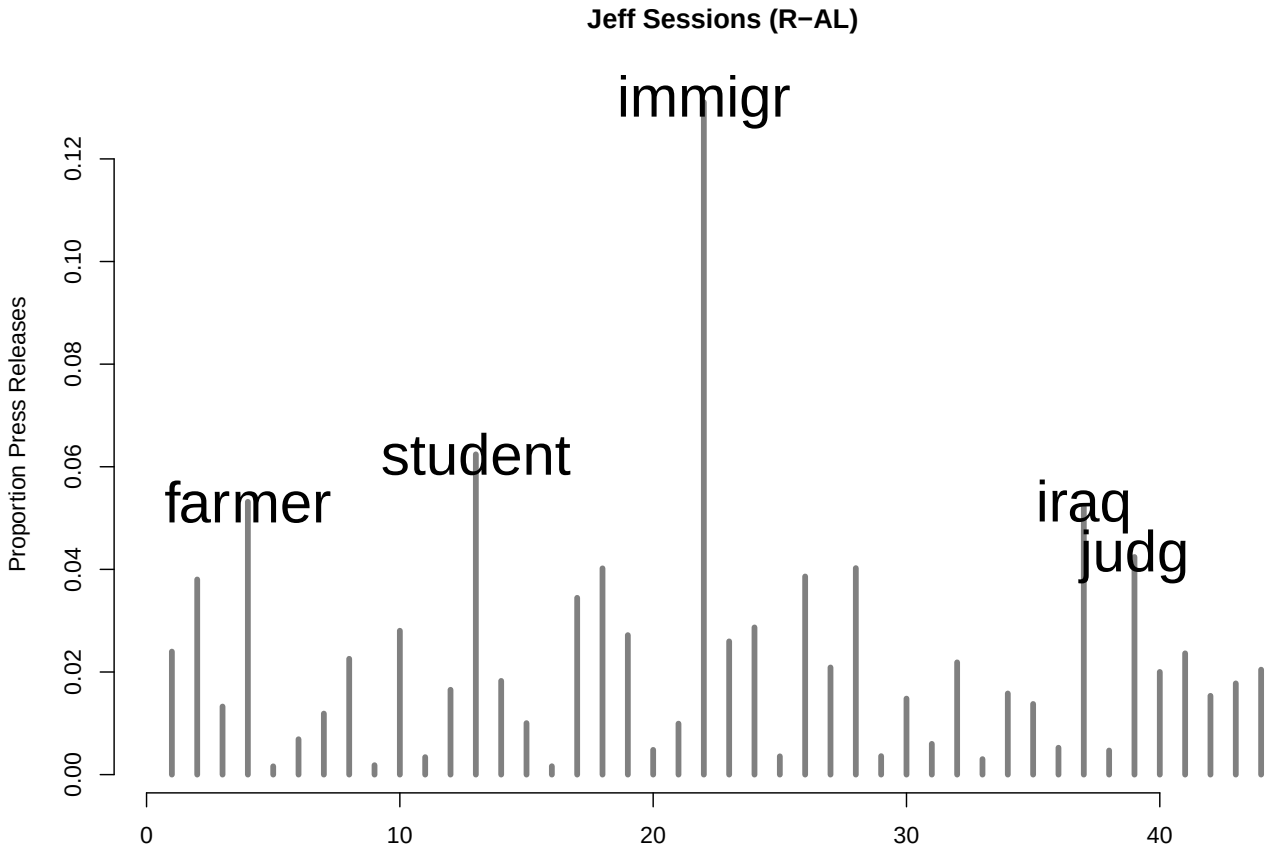
1) Estimate with Variational Approximation
2) Determining number of clusters at top? (Grimmer, Shorey, Wallach, and Zlotnick, In Progress)
   - Non-parametric model$\rightsquigarrow$ statistical selection
   - Experiments/Coding Exercises to assess


Richard Shelby (R−AL)
firefight
airport
univers
defens
crime
Proportion Press Releases
0.00
0.05
0.10
0.15
0.20
0
10
20
30
40


Jeff Sessions (R−AL)
immigr
student
farmer
iraq
judg
Proportion Press Releases
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0
10
20
30
40

Notions of validity: From Quinn, Monroe, et al (2010)

- Semantic Validity: All categories are coherent and meaningful
- Convergent Construct Validity: Measures concur with existing measures in critical details.
- Discriminant Construct Validity: Measures differ from existing measures in productive ways.
- Predictive Measure: Measures from the model corresponds to external events in expected ways.
- Hypothesis Validity: Measures generated from the model can be used to test substantive hypotheses.

To establish utility of new measures, demonstrate variety of validations
None of these validations are performed using a canned statistic
All: require substantive knowledge on areas (and what we expect!) [

Home Style Measures, Semantic Validity

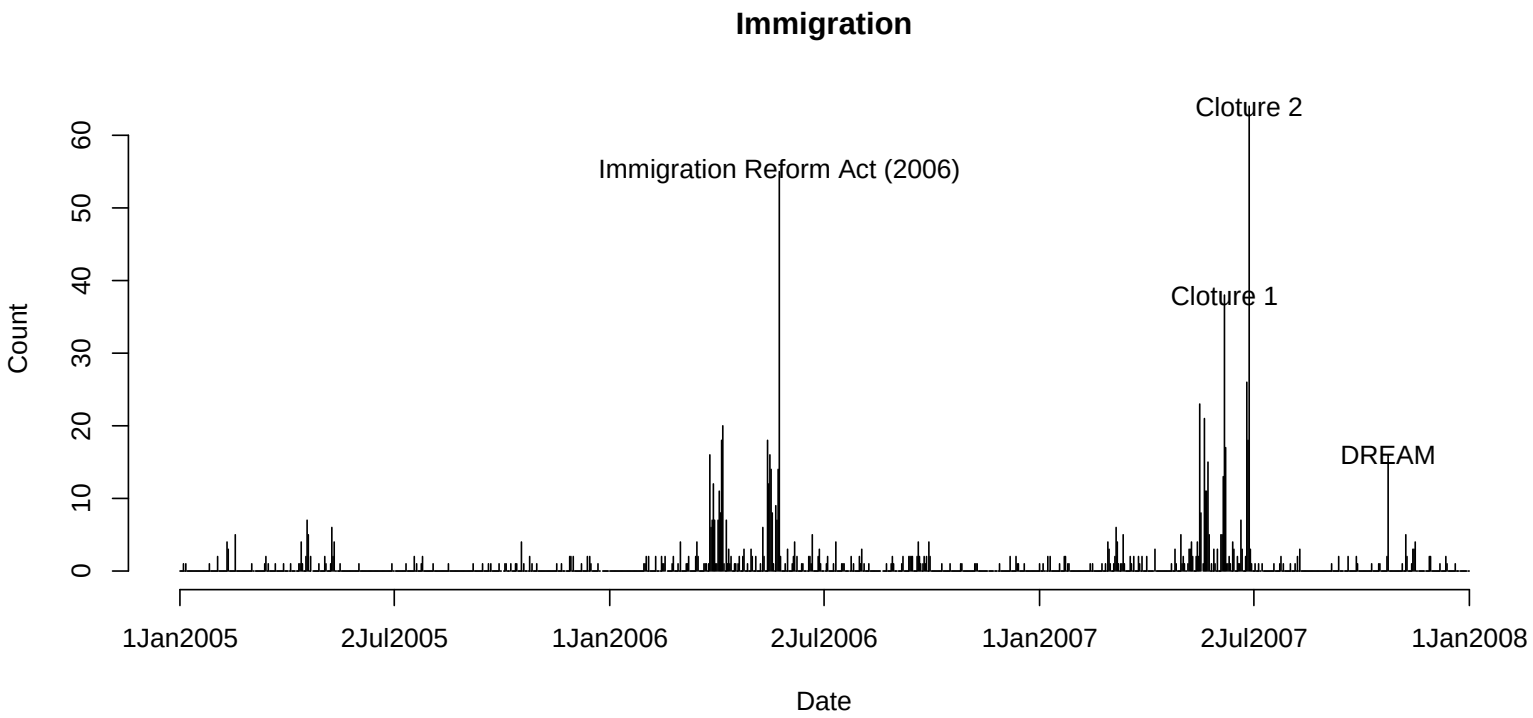
Must: Demonstrate to reader that topics are coherent and semantically meaningful

Description	Stems	%
Honorary	honor,prayer,rememb,fund,tribut	5.0
Transp. Grants	airport,transport,announc,urban,hud	4.8
Iraq	iraq,iraqi,troop,war,sectarian	4.7
DHS Policy	homeland,port,terrorist,dh,fema	4.1
Judicial Nom.	judg,court,suprem,nomin,nomine	3.8
Fire Dept. Grant	firefight,homeland,afgp,award,equip	3.7

How: examples in text are also useful.

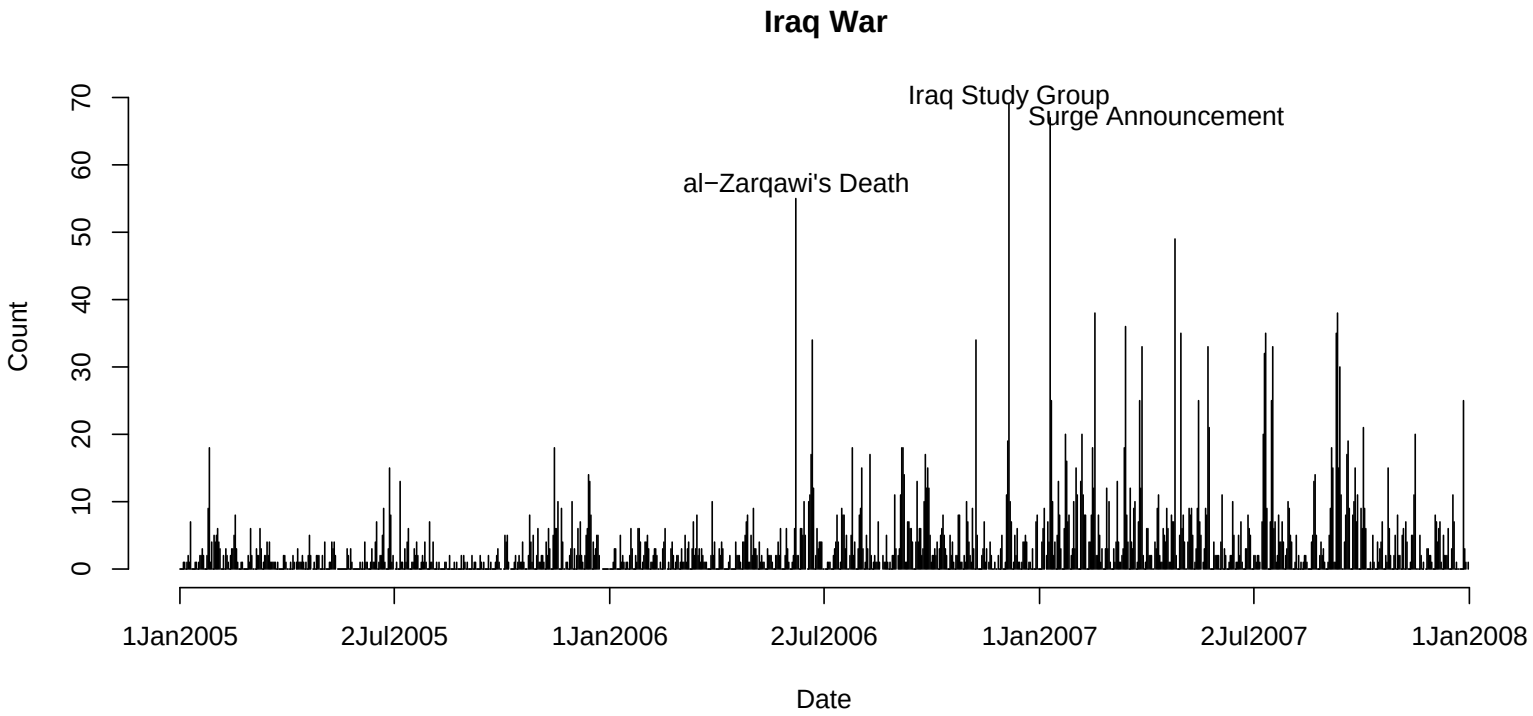
Home Style Measures, Convergent Validity

Over time variation



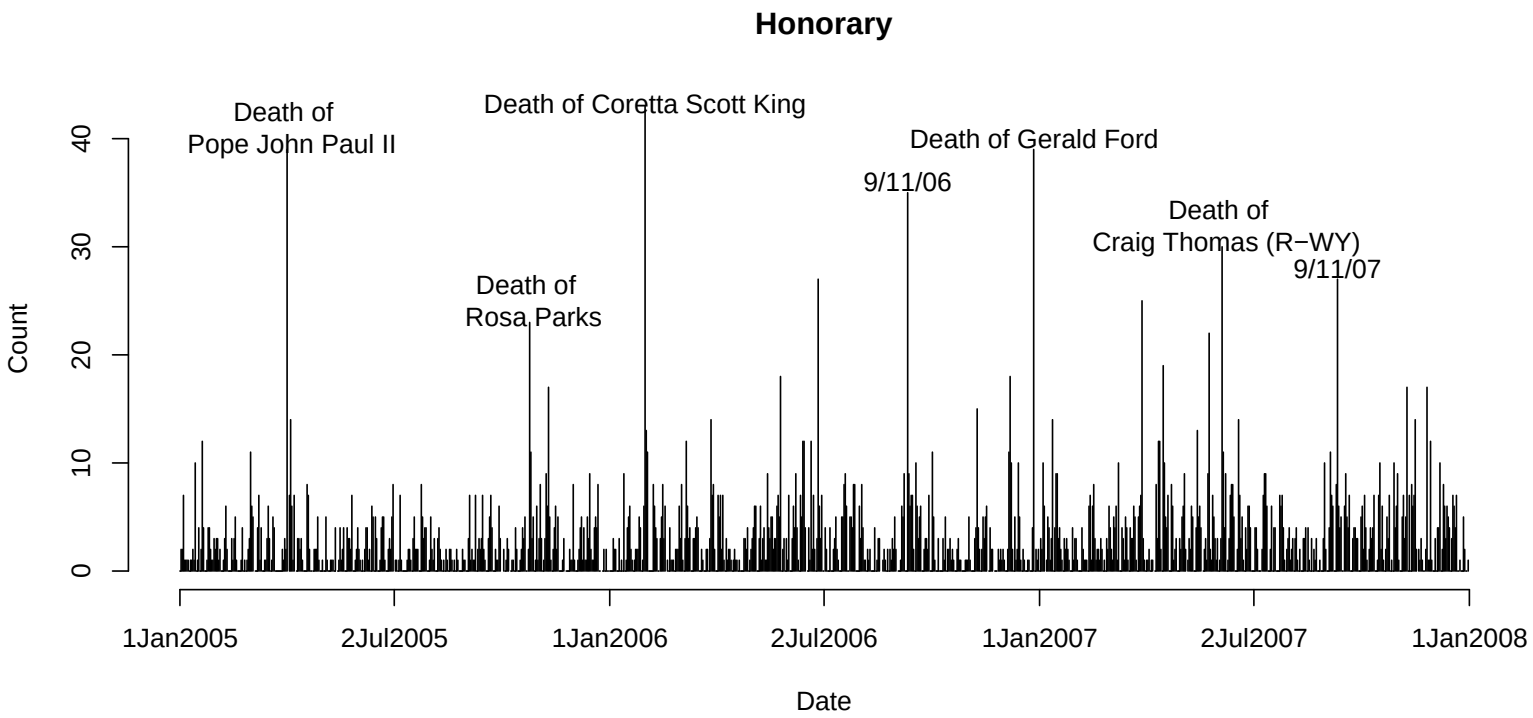
Home Style Measures, Convergent Validity

Over time variation



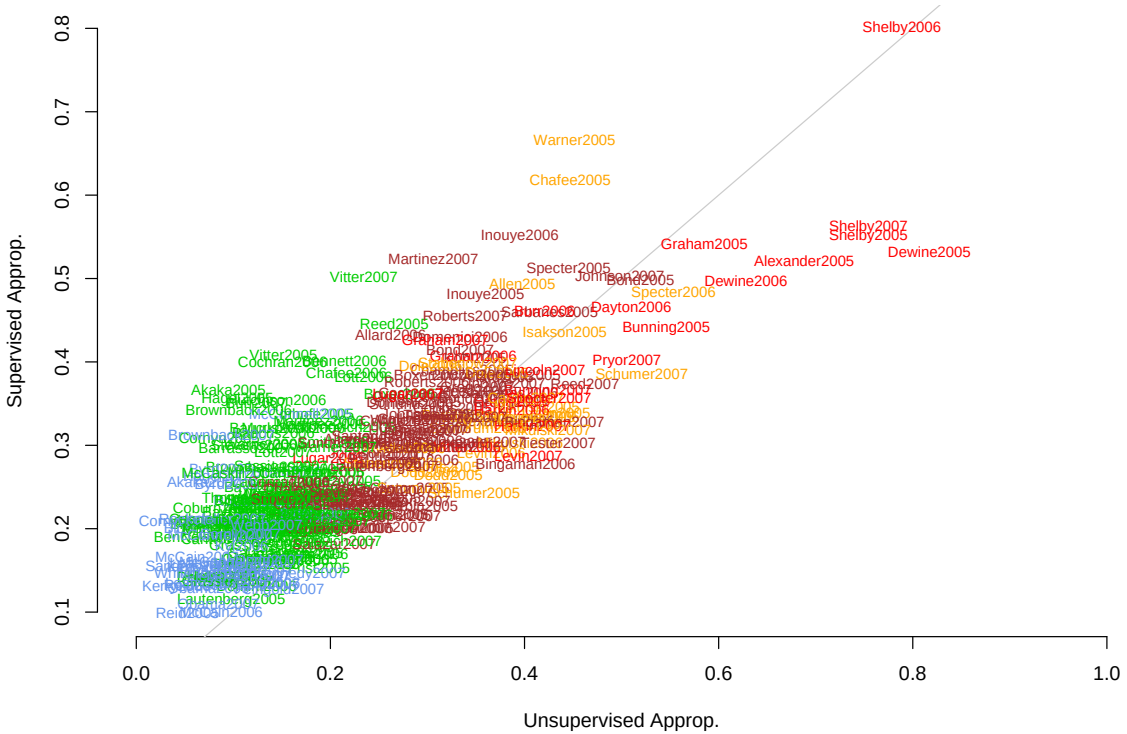
Home Style Measures, Convergent Validity

Over time variation

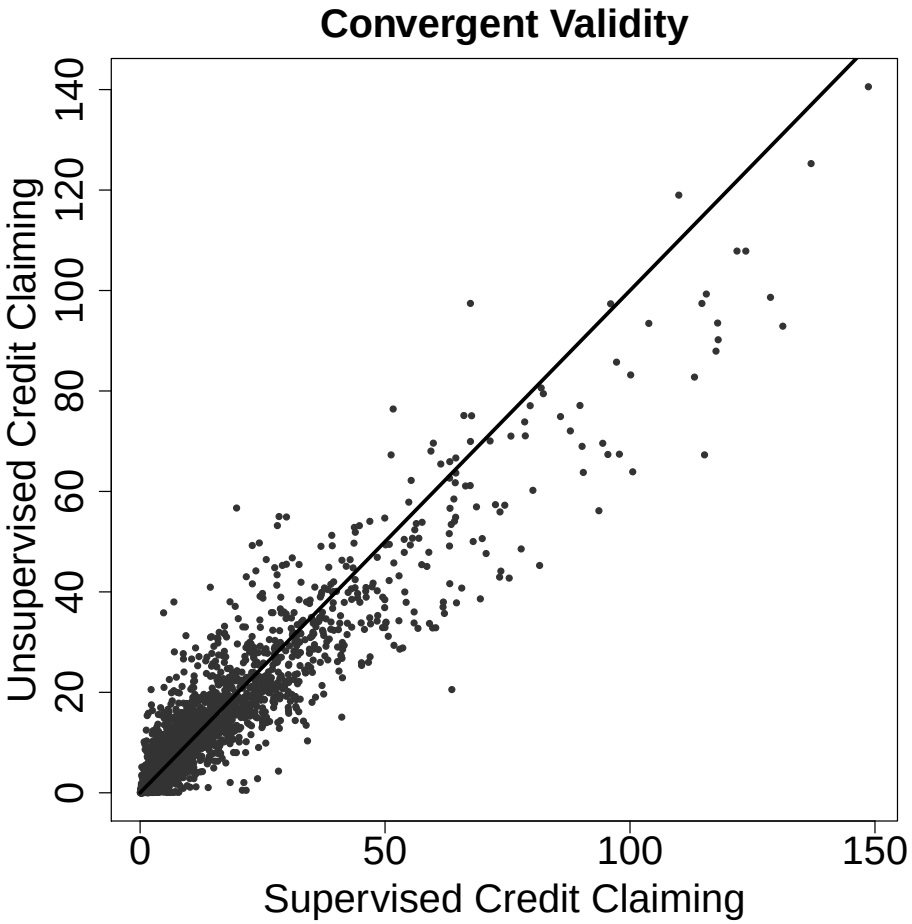


Home Style Measures, Convergent Validity

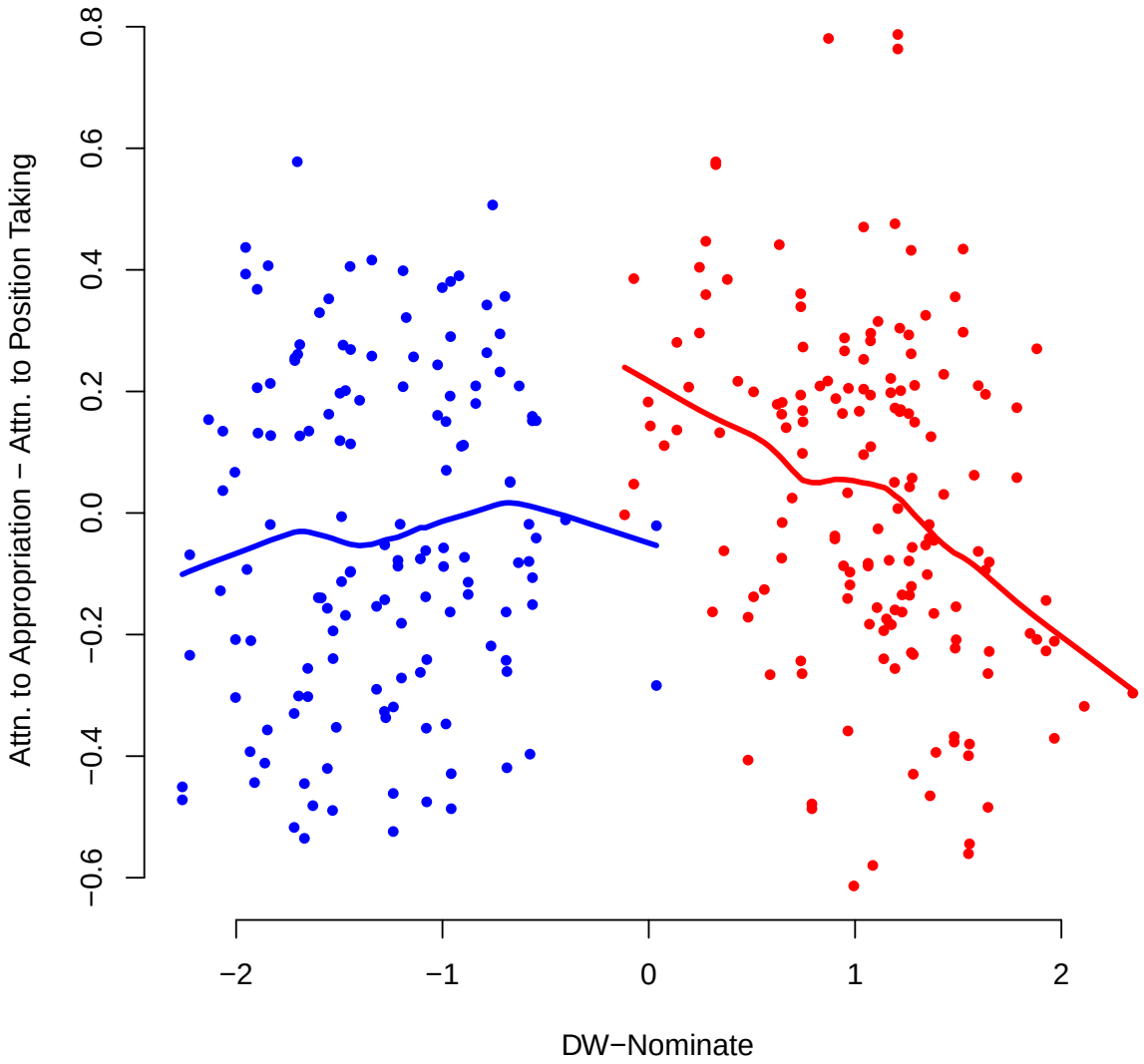
Supervised/Unsupervised Convergence



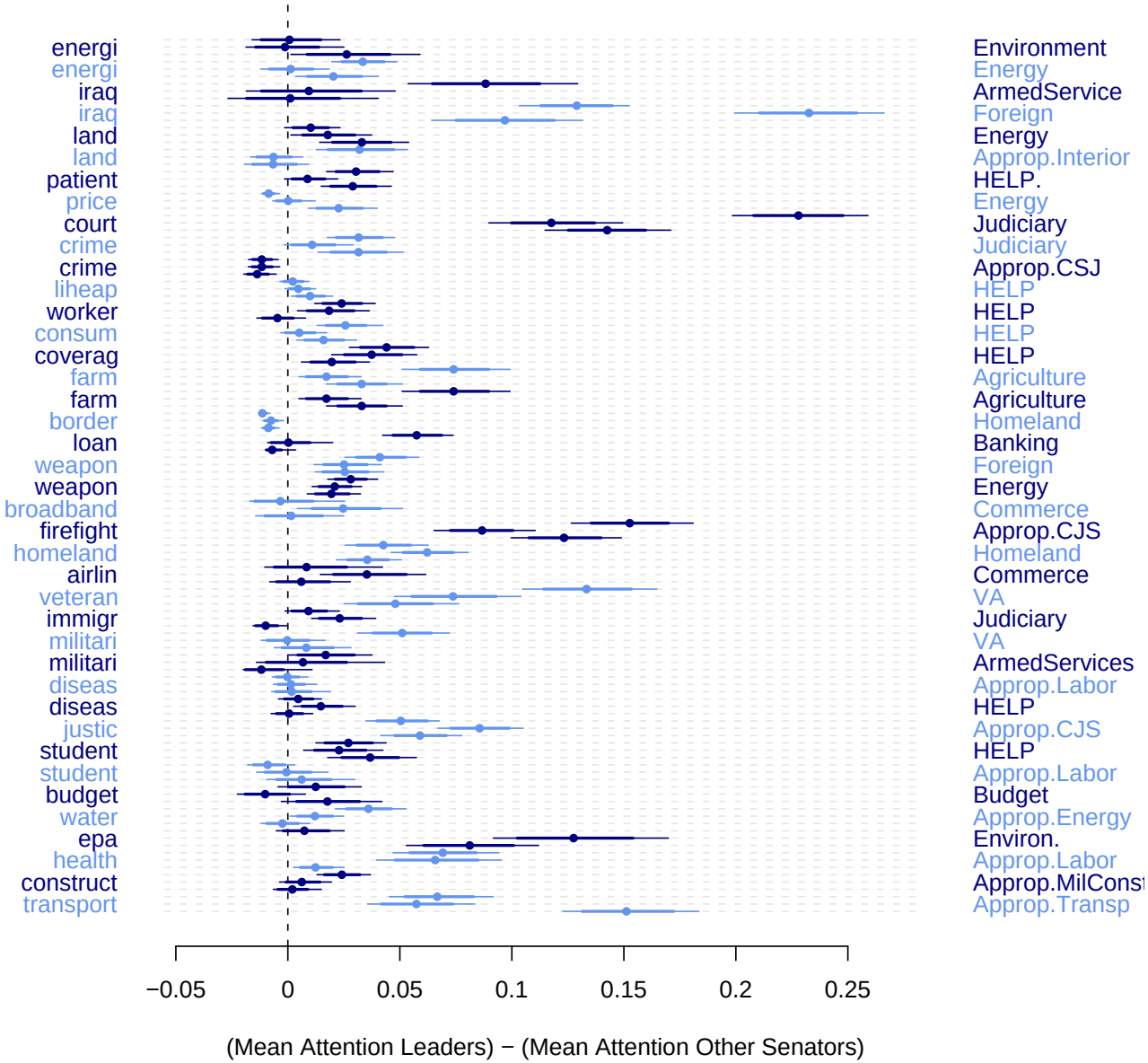
Home Style Measures, Convergent Validity



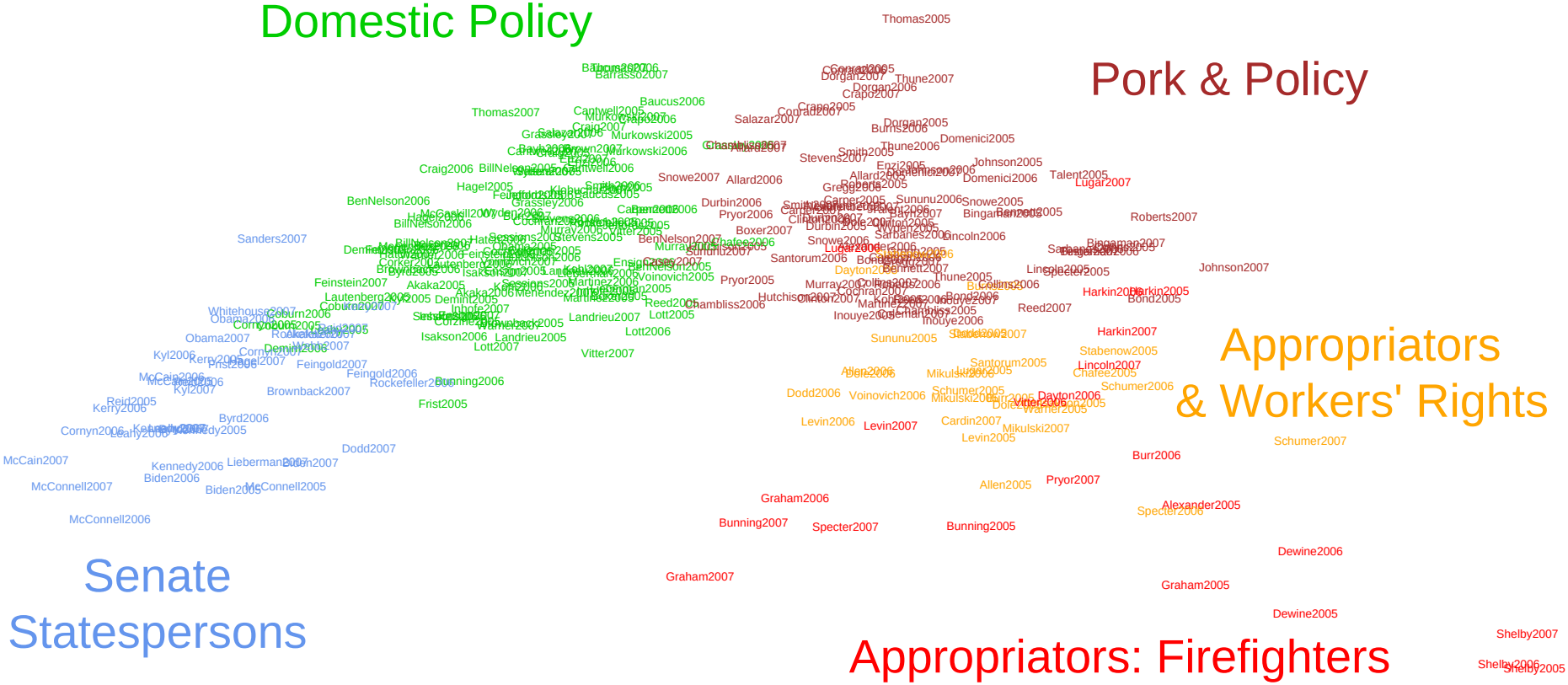
Discriminant Construct Validity



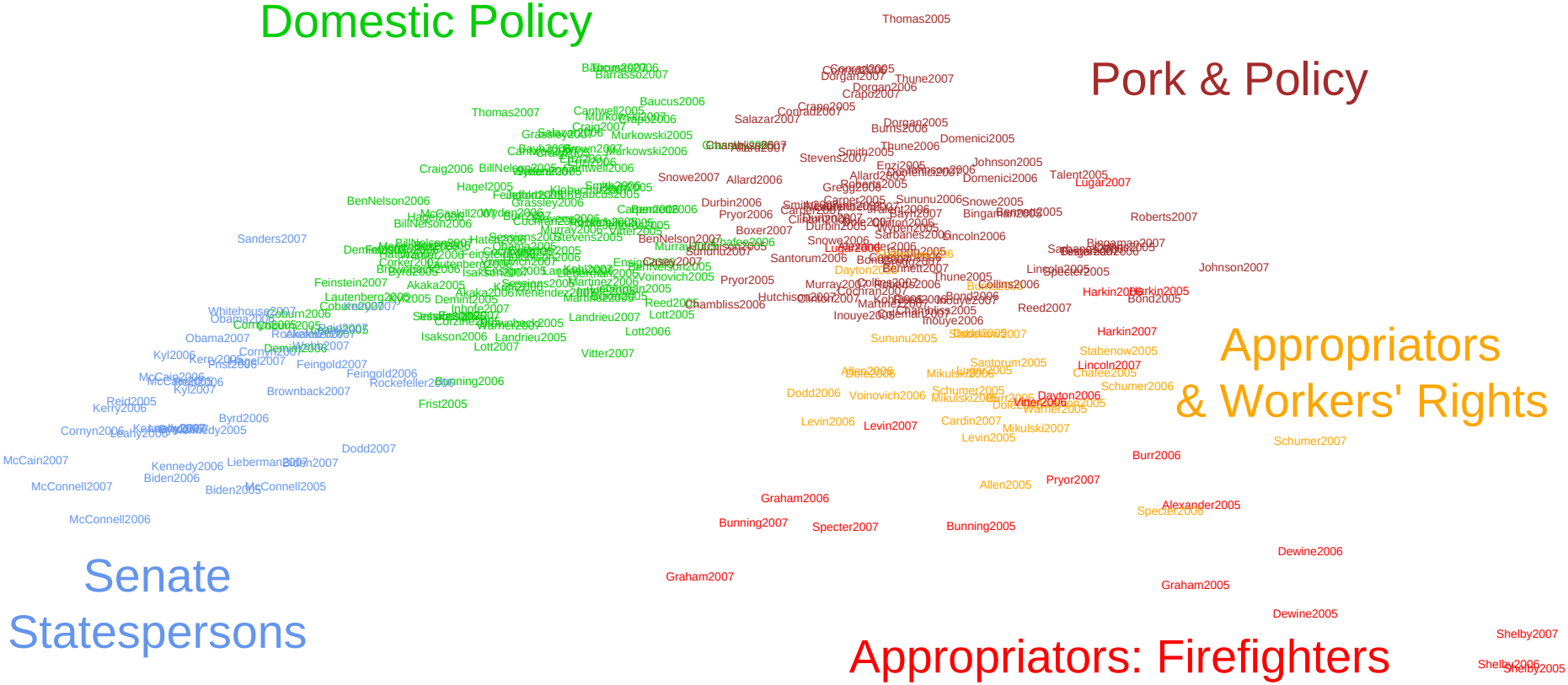
Predictive Validity



Hypothesis Validity



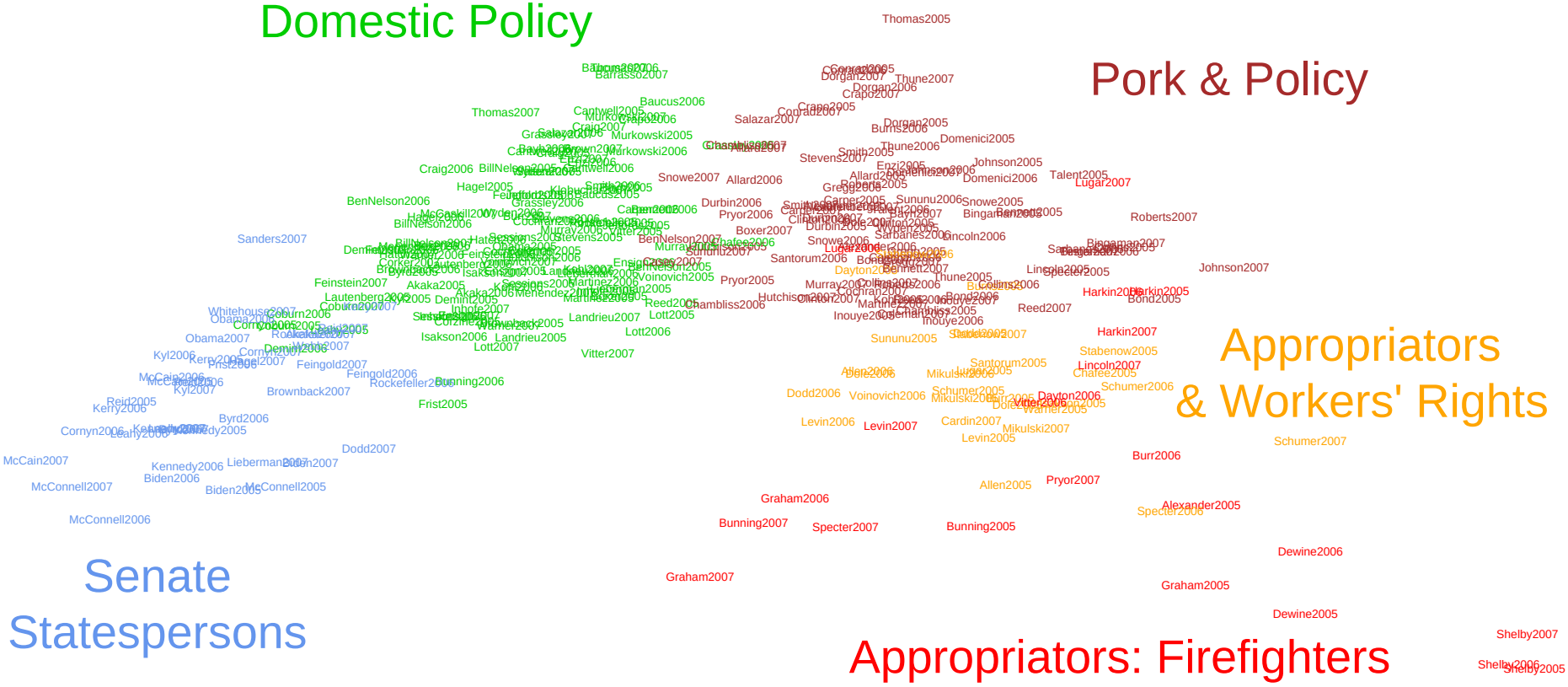
Hypothesis Validity



Senate Statesperson

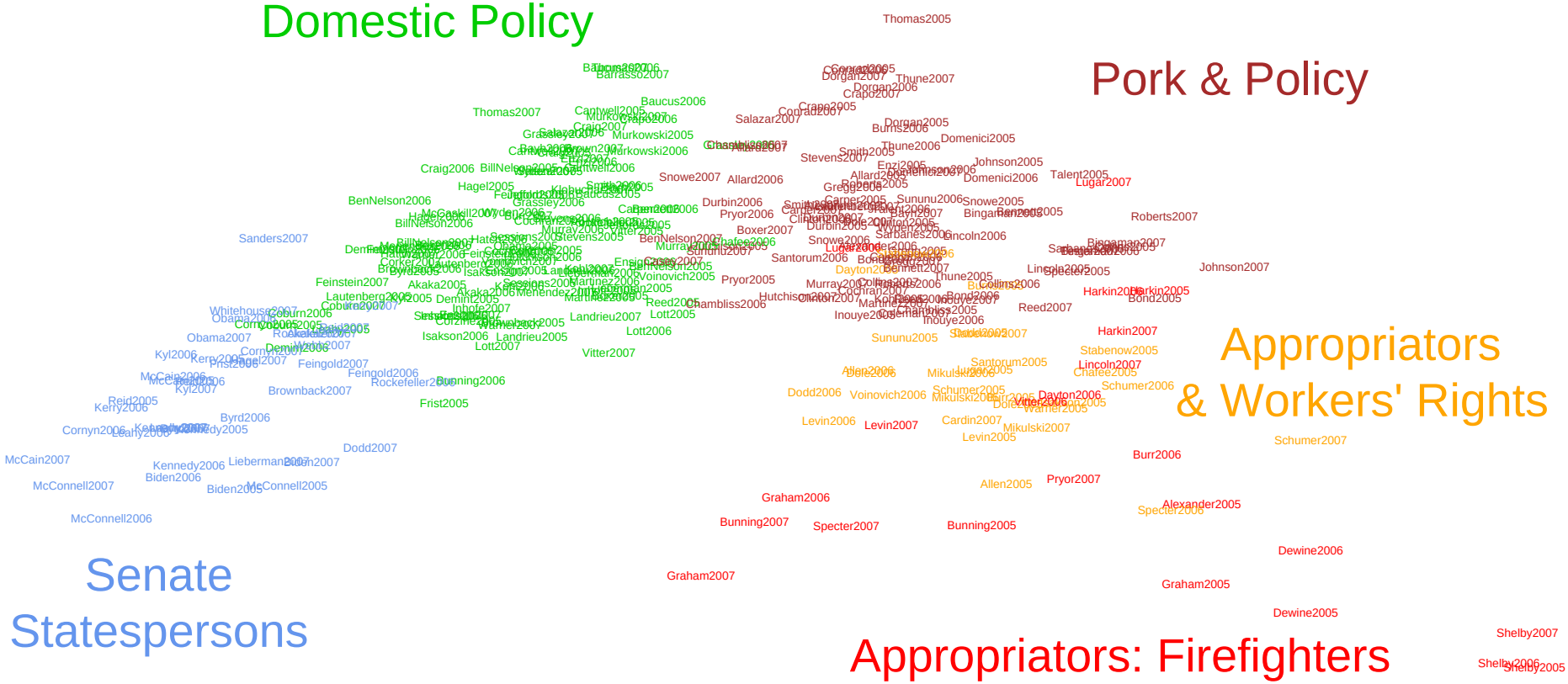
- Iraq War
- Intelligence
- Intl. Relations

Hypothesis Validity



Senate Statesperson	Domestic Policy
- Iraq War	- Environment
- Intelligence	- Gas prices
- Intl. Relations	- DHS
	- Consumer

Hypothesis Validity



Senate Statesperson

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- Intl. Relations

Domestic Policy

- Environment
- Gas prices
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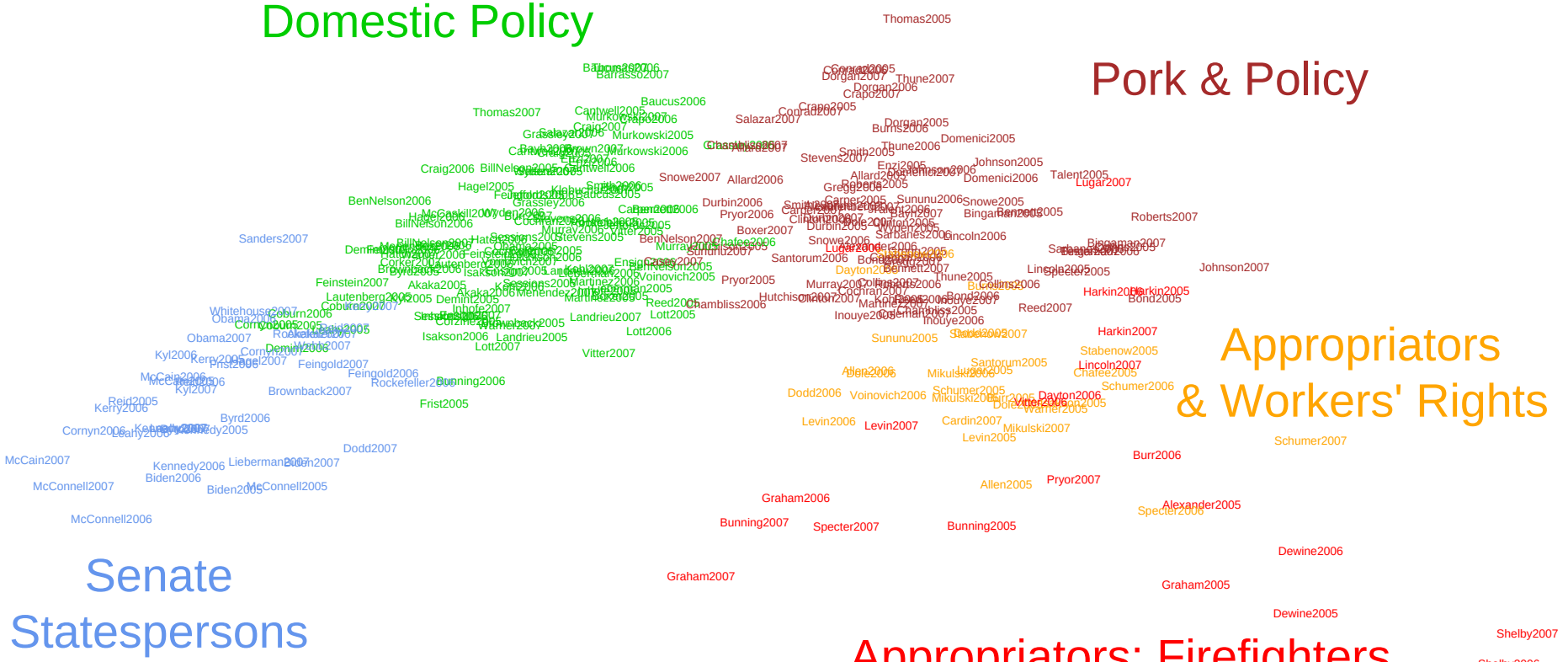
- Consumer

Pork & Policy

- WRDA grants
- Farming
- Health Care
- Education

Hypothesis Validity

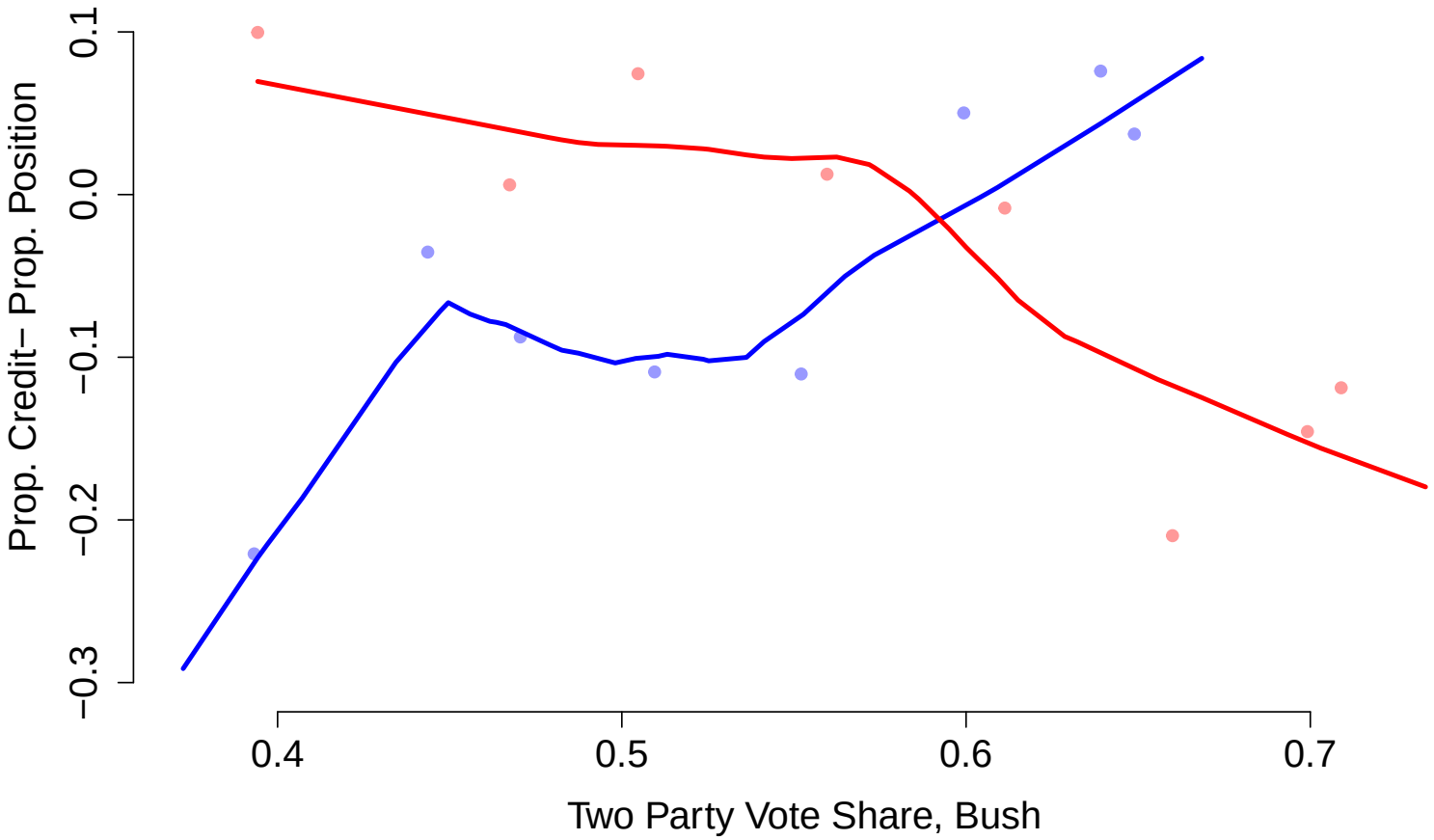


Senate Statesperson	Domestic Policy	Pork & Policy	Appropriators
- Iraq War	- Environment	- WRDA grants	- Fire Grants
- Intelligence	- Gas prices	- Farming	- Airport Grants
- Intl. Relations	- DHS	- Health Care	- University Money
	- Consumer	- Education	

Hypothesis Validity

Why do senators adopt different styles?

District Fit



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Blaydes, Grimmer, and McQueen 2018$\rightsquigarrow$ estimate nested topics to explore the Mirrors for Princes

The Mirrors Genre (BGM 2017)

26 Christian mirrors

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Work with translations

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Work with translations$\rightsquigarrow$ little evidence of selection

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Work with translations$\rightsquigarrow$ little evidence of selection

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- No difference on Year/Region

Preprocessing Texts

47 books

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47 books $\rightsquigarrow$ Each divided into paragraphs

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Create feature space

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We work with a normalized version of the documents,

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We work with a normalized version of the documents,

$$\mathbf{x}^*_{ij} = \frac{\mathbf{x}_{ij}}{\sqrt{\mathbf{x}'_{ij}\mathbf{x}_{ij}}}$$

Measuring Themes in the Mirrors

Model built around two hierarchies:

Measuring Themes in the Mirrors

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1) Books $\rightsquigarrow$ paragraphs (Blei, Ng, Jordan 2003; Wallach, 2008; Quinn et al 2010; Grimmer 2010; Roberts et al 2014)

Measuring Themes in the Mirrors

Model built around two hierarchies:

1) Books $\rightsquigarrow$ paragraphs (Blei, Ng, Jordan 2003; Wallach, 2008; Quinn et al 2010; Grimmer 2010; Roberts et al 2014)
2) Coarse topics $\rightsquigarrow$ granular topics (Li and McCallum 2006; Gopal and Yang 2014)

Measuring Themes in the Mirrors

Estimate four quantities of interest

Measuring Themes in the Mirrors

Estimate four quantities of interest

1) Granular topics (60)

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    - Each granular topic classified into one coarse topic

Measuring Themes in the Mirrors

Estimate four quantities of interest

1) Granular topics (60)
2) Coarse (broad) topics (3)
    - Each granular topic classified into one coarse topic
3) Each book i's $\mathbf{themes}_i$

$$\mathbf{themes}_i \quad = \quad (\text{theme}_{i1}, \text{theme}_{i2}, \ldots, \text{theme}_{i60})$$

Measuring Themes in the Mirrors

Estimate four quantities of interest

1) Granular topics (60)
2) Coarse (broad) topics (3)
    - Each granular topic classified into one coarse topic
3) Each book i's $\textbf{themes}_i$
4) Each short segment's granular (and coarse) topic

A Hierarchy of Topics

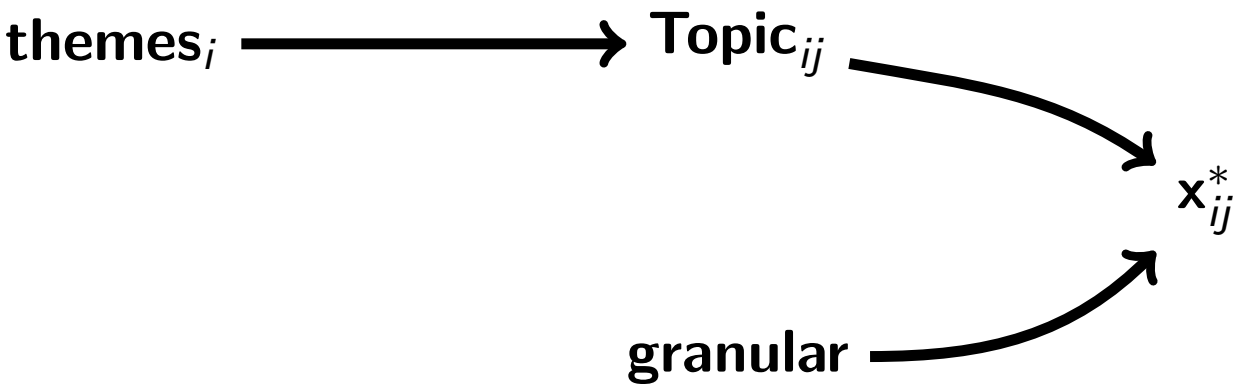
themes$_j$

A Hierarchy of Topics

$$\textbf{themes}_i \longrightarrow \textbf{Topic}_{ij}$$

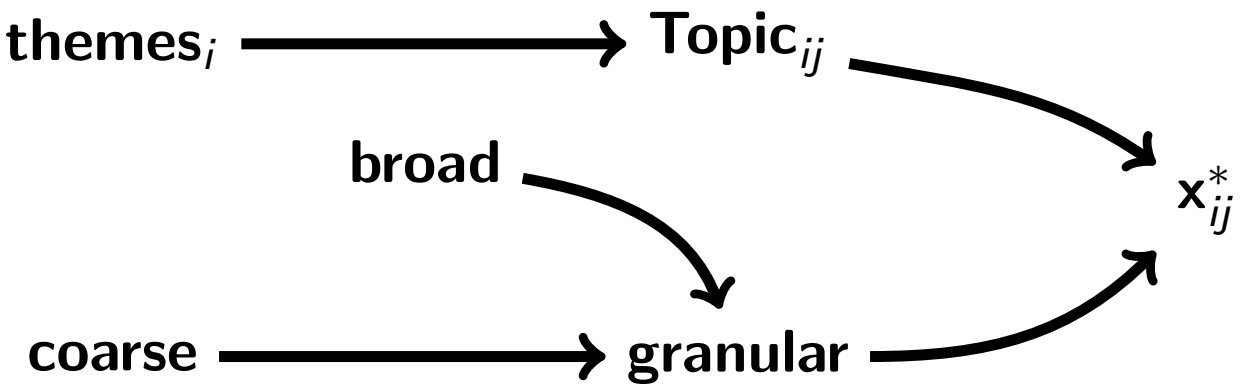
$$\textbf{Topic}_{ij} \sim \text{Multinomial}(1, \textbf{themes}_i)$$

A Hierarchy of Topics



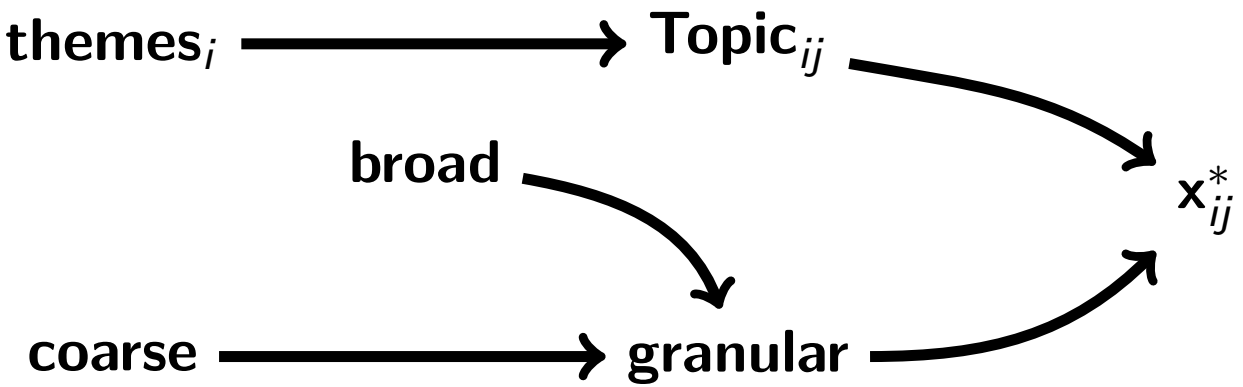
$$\begin{aligned} \textbf{Topic}_{ij} &\sim \text{Multinomial}(1, \textbf{themes}_i) \\ \mathbf{x}^*_{ij} | \text{Topic}_{ijk} = 1 &\sim \text{vMF}(\kappa, \textbf{granular}_k) \end{aligned}$$

A Hierarchy of Topics



$$
\begin{aligned}
\textbf{Topic}_{ij} &\sim \text{Multinomial}(1, \textbf{themes}_i) \\
\mathbf{x}^*_{ij} | \text{Topic}_{ijk} = 1 &\sim \text{vMF}(\kappa, \textbf{granular}_k) \\
\textbf{broad}_k &\sim \text{Multinomial}(1, \textbf{Broad Theme Prior}) \\
\textbf{granular}_k | \text{broad}_{km} = 1 &\sim \text{vMF}(\kappa, \textbf{coarse}_m)
\end{aligned}
$$

A Hierarchy of Topics



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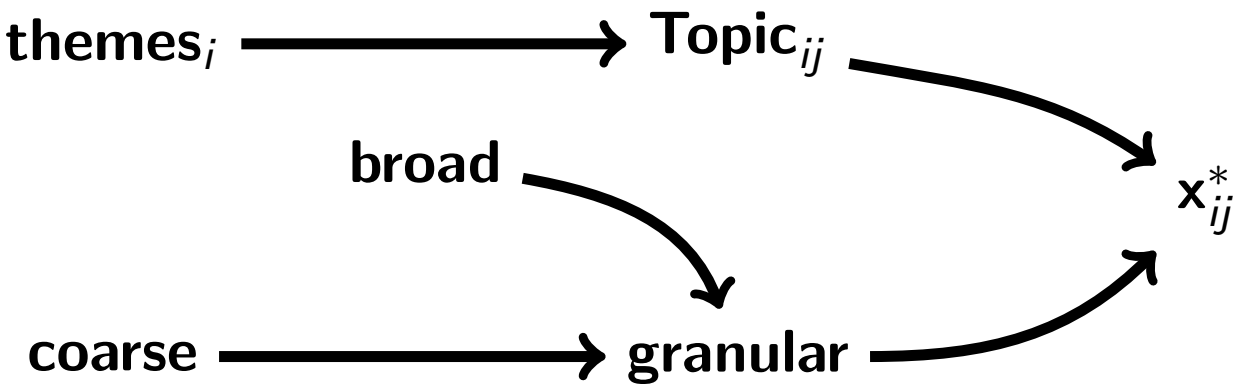
\end{aligned}
$$

Estimate model with Variational Approximation

A Hierarchy of Topics



$$
\begin{aligned}
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\end{aligned}
$$

Estimate model with Variational Approximation
Model selection: automatic model fit, qualitative evaluation

Interpreting Unsupervised Models

Two approaches to labeling output

Interpreting Unsupervised Models

Two approaches to labeling output

1) Computational: identify discriminating words

Interpreting Unsupervised Models

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2) Manual: Segments classified to coarse, granular topics. Read, discuss, and label

Interpreting Unsupervised Models

Two approaches to labeling output

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Unsupervised models structure and guide our reading

Art of Rulership

Practices and ideals of political rule

Art of Rulership

Practices and ideals of political rule

king

Art of Rulership

Practices and ideals of political rule

king,princ

Art of Rulership

Practices and ideals of political rule

king,princ,citi

Art of Rulership

Practices and ideals of political rule

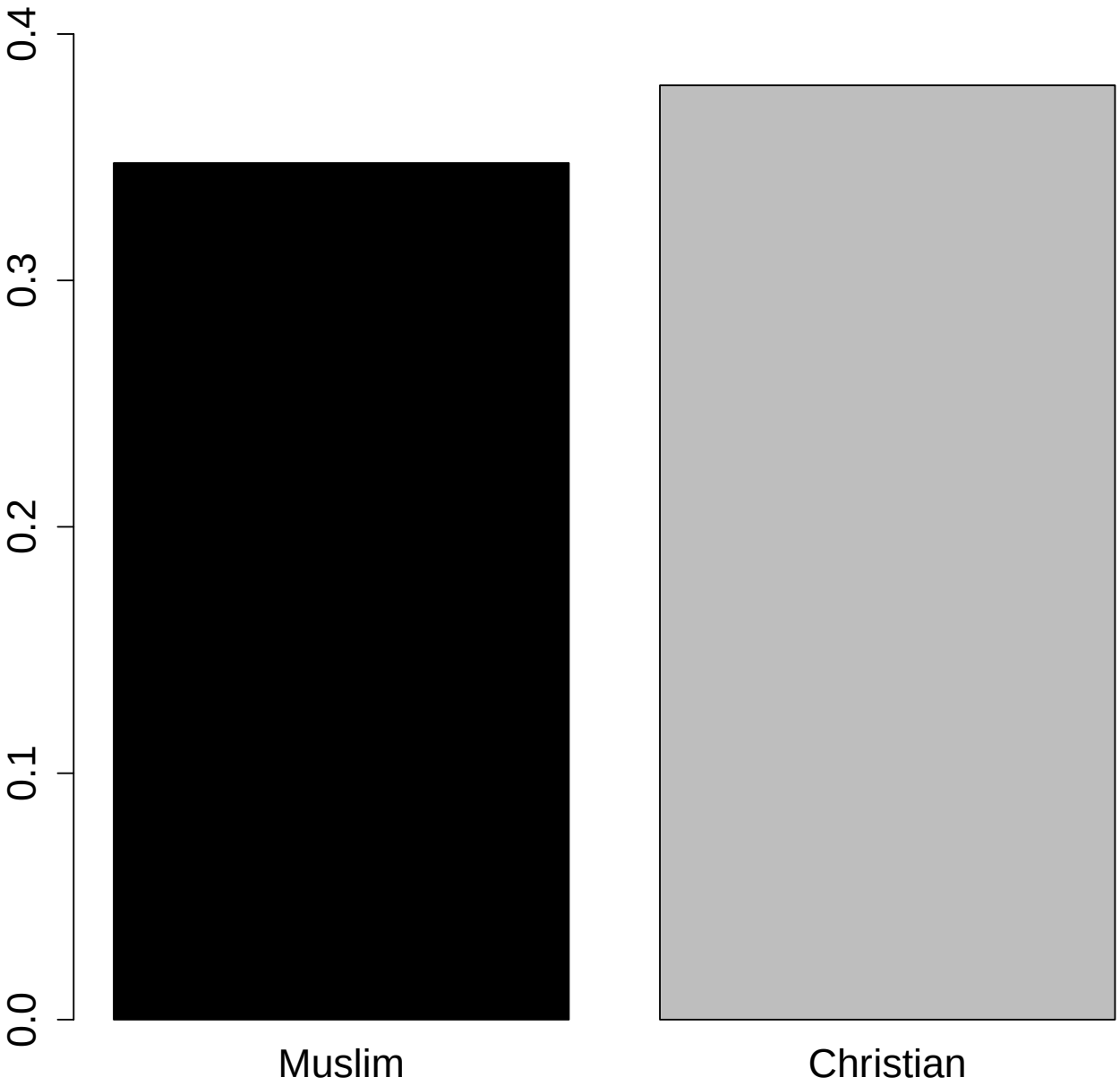
king,princ,citi,great,place,work,emperor,enemi,armi,letter

Art of Rulership

Practices and ideals of political rule

king,princ,citi,great,place,work,emperor,enemi,armi,letter

36.5% of paragraphs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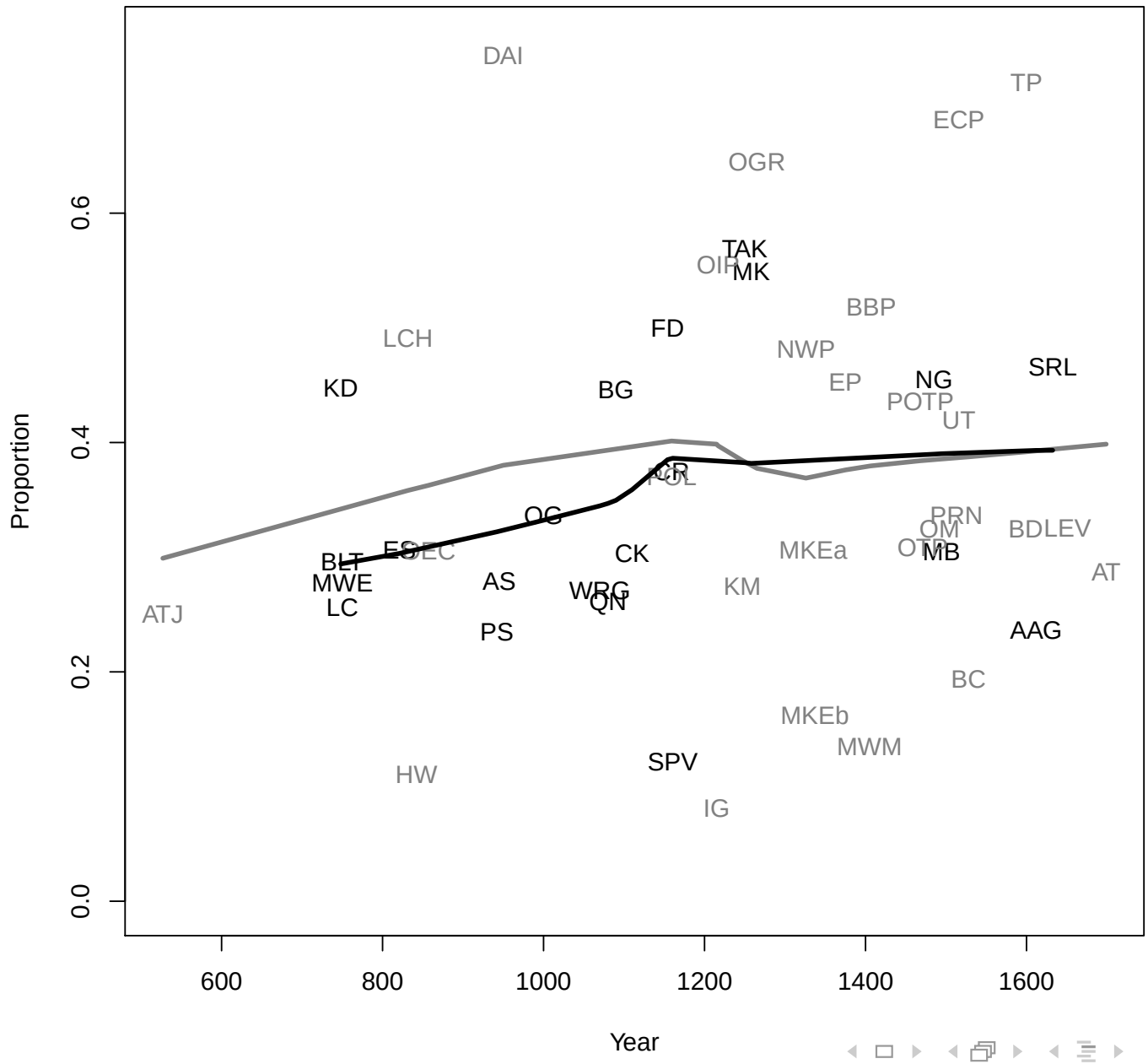
Muslim
Christian


Coarse Topic 1
DAI
TP
ECP
OGR
TAK
OIP
MK
BBP
FD
LCH
NWP
SRL
KD
BG
EP
NG
POTP
UT
PRL
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MKEa
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ESLEC
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Proportion
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0.2
0.4
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800
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1200
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1600
Year

Religion and Virtue

Connection between religion, virtue, justice and political rule

Religion and Virtue

Connection between religion, virtue, justice and political rule

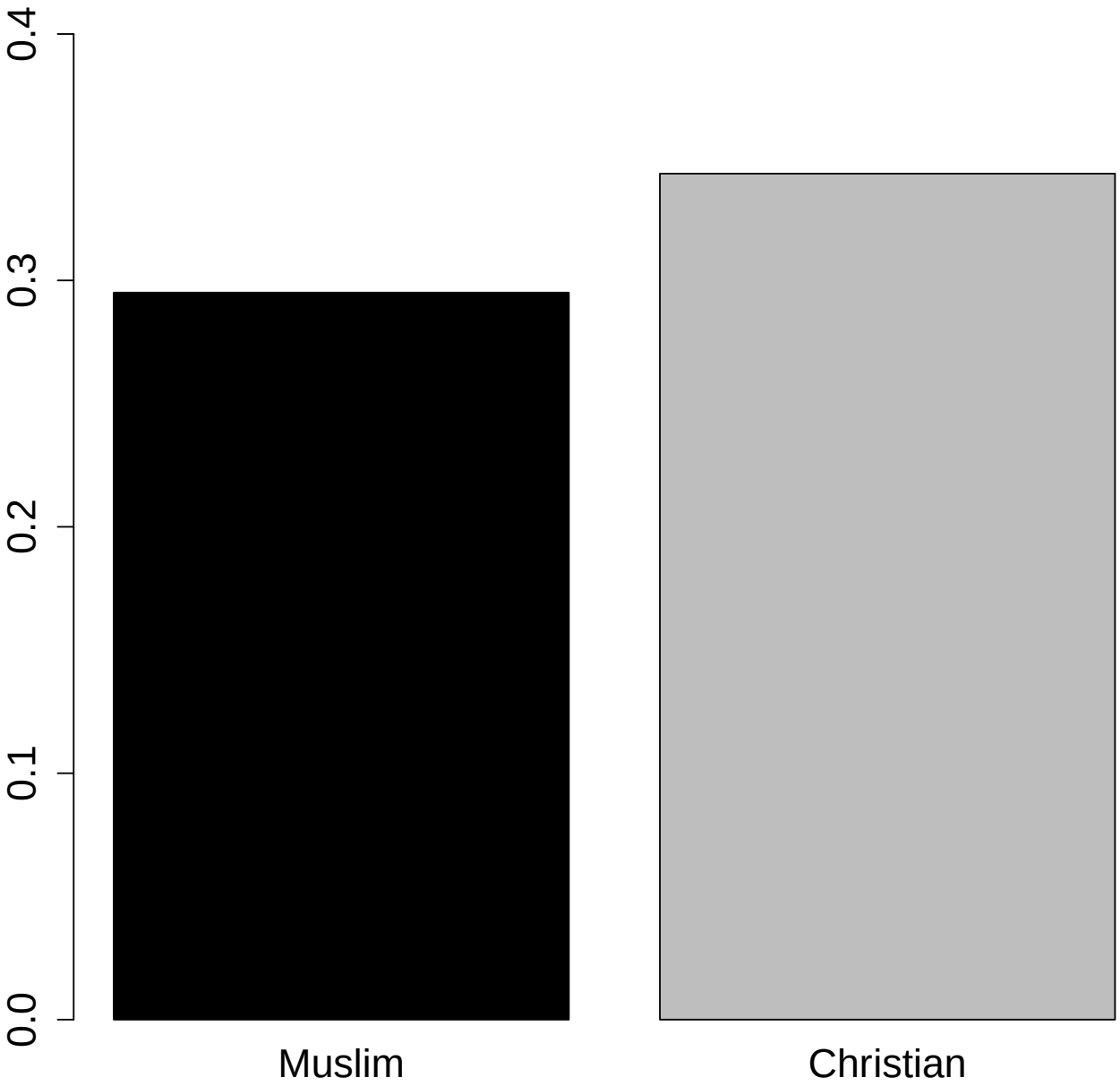
almighti,good,virtu,power,ruler,justic,prayer,rule,prophet,mena

Religion and Virtue

Connection between religion, virtue, justice and political rule

almighti,good,virtu,power,ruler,justic,prayer,rule,prophet,mena

32.2% of pargraphs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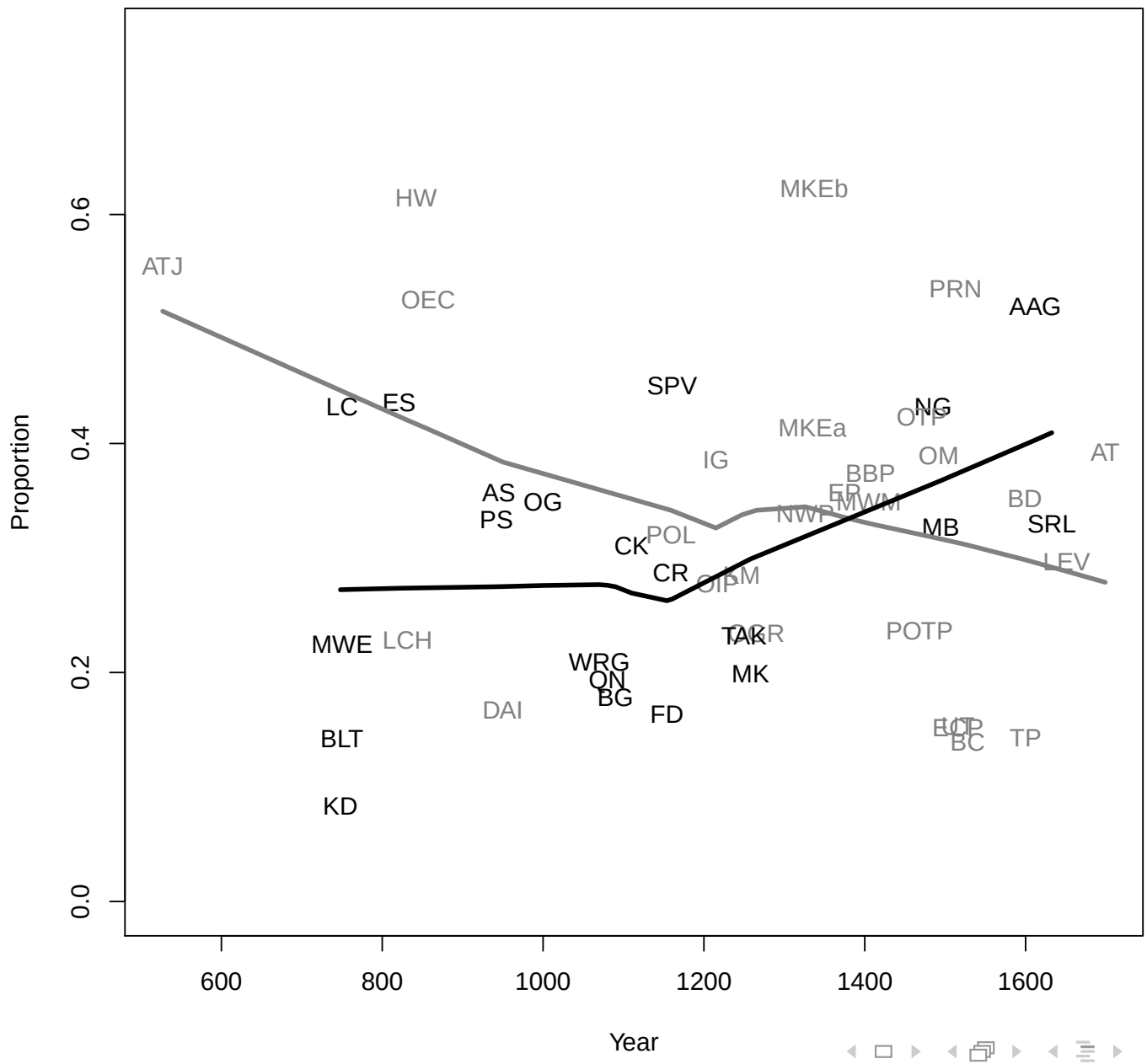
Muslim
Christian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0.2
0.4
0.6
600
800
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ATJ
OEC
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CK
CR
LEV
MWE
LCH
TAK
POTP
WRG
ON
MK
BG
DAI
FD
BLT
TP
BC
KD

Inner Life of the Ruler

Personal relationships, care for and practices of the self, and ultimate fate of the soul

Inner Life of the Ruler

Personal relationships, care for and practices of the self, and ultimate fate of the soul

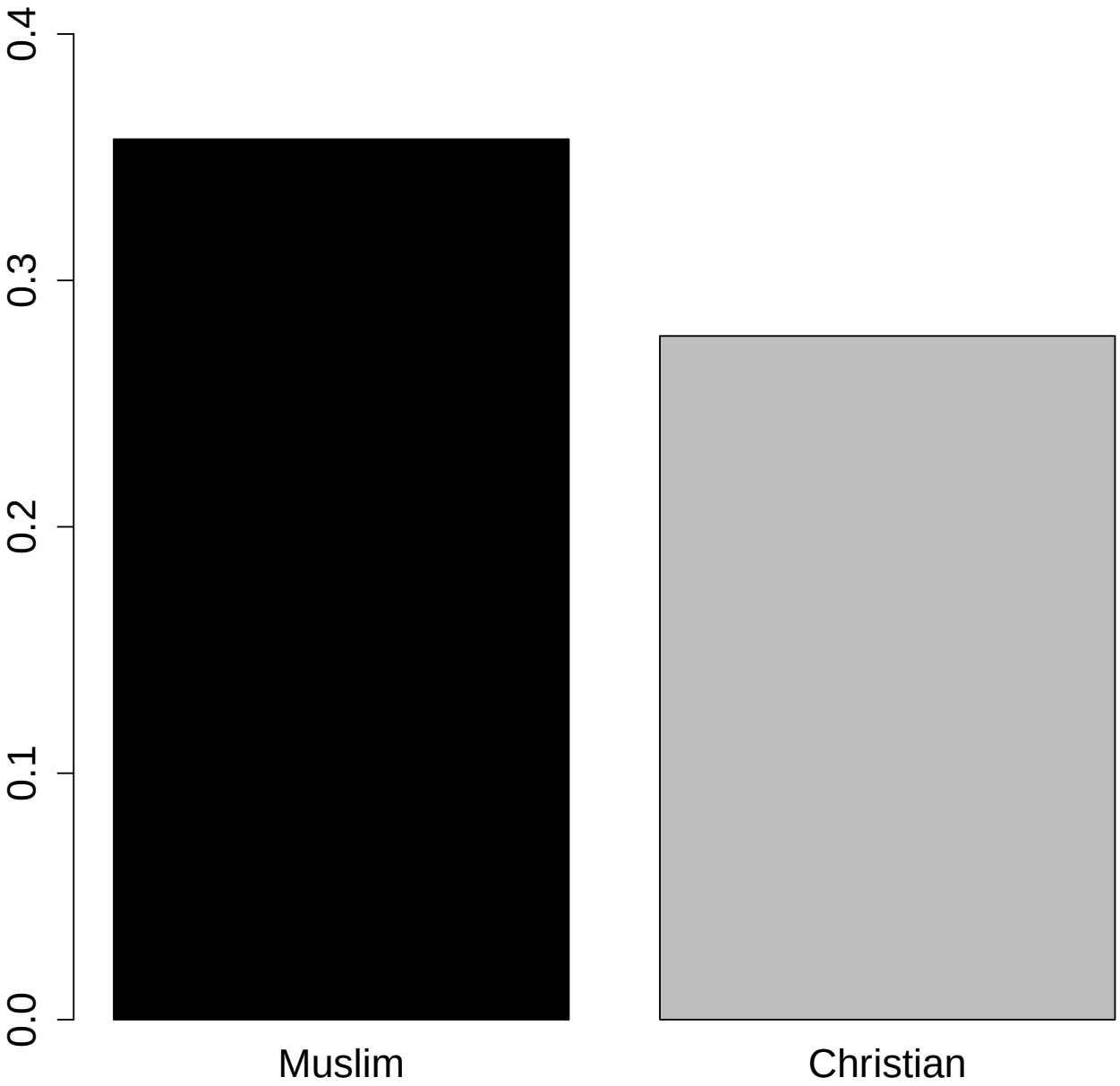
man,land,woman,know,bodi,eye,ladi,love,faculti,old

Inner Life of the Ruler

Personal relationships, care for and practices of the self, and ultimate fate of the soul

man,land,woman,know,bodi,eye,ladi,love,faculti,old

31.2% of paragraphs


0.0
0.1
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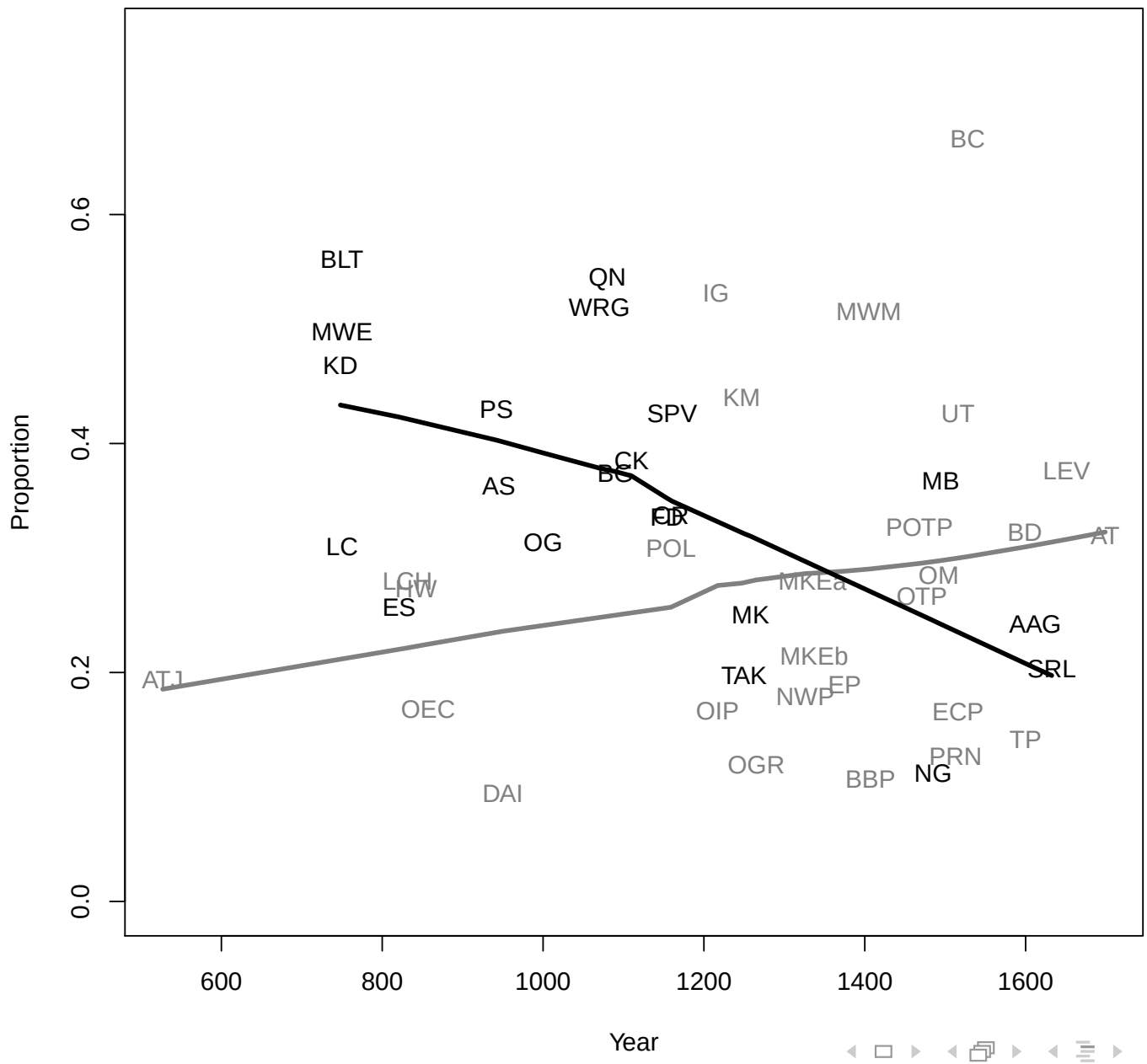
0.3
0.4
Muslim
Christian


Coarse Topic 3
Proportion
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SPV
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MKEa
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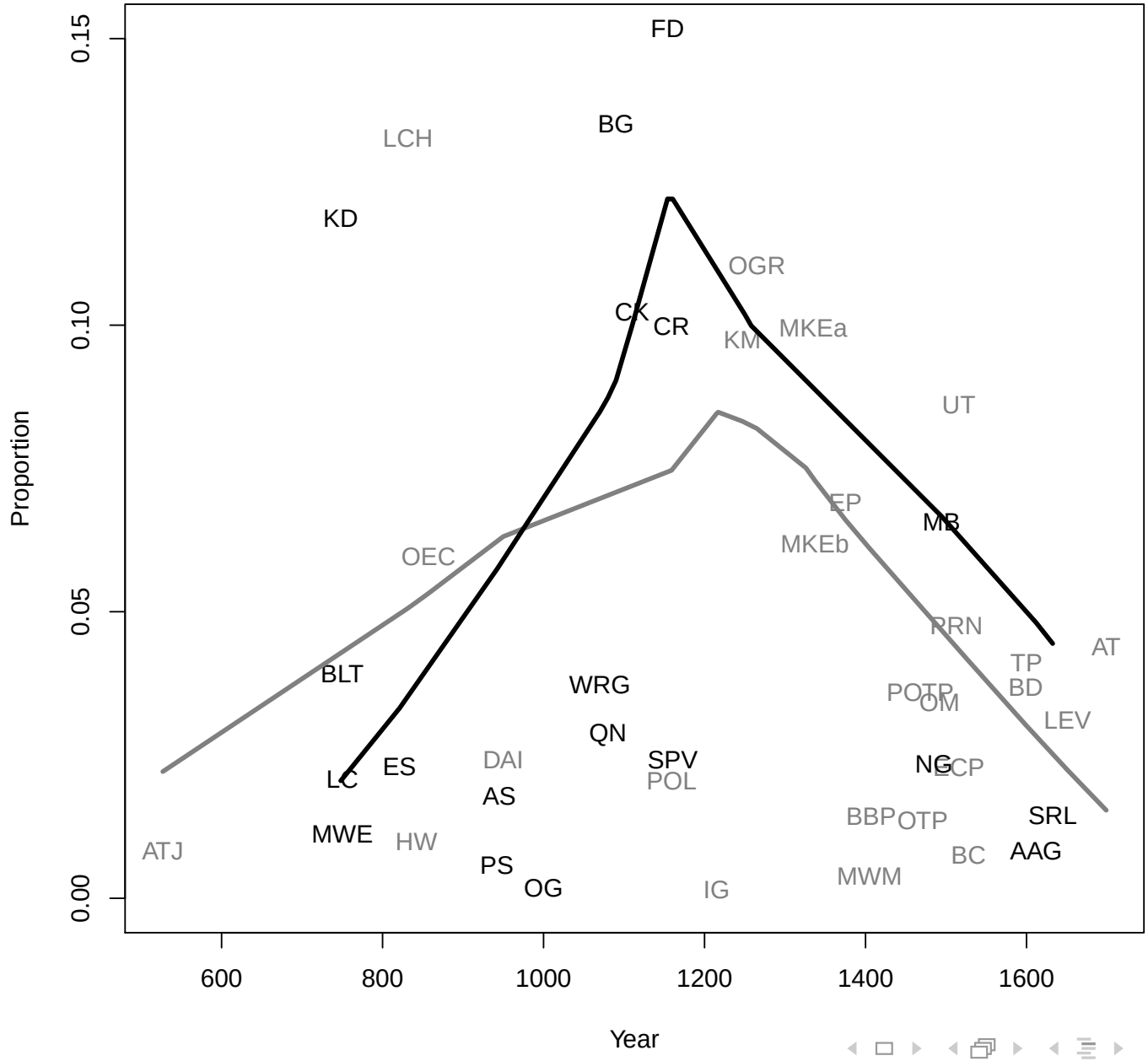
AAG
MKEb
SRL
TAK
EP
NWP
OEC
OIP
ECP
TP
PRN
OGR
BBP
NG
DAI

Granular: Best Practices for Ruling

king,princ,citi,great,place,work,emperor,enemi,armi,letter
king,kingdom,royal,minist,reign,father,court,majesti,presenc,war

6.2% of paragraphs


Coarse Topic 1 Granular Topic 1
Proportion
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OEC
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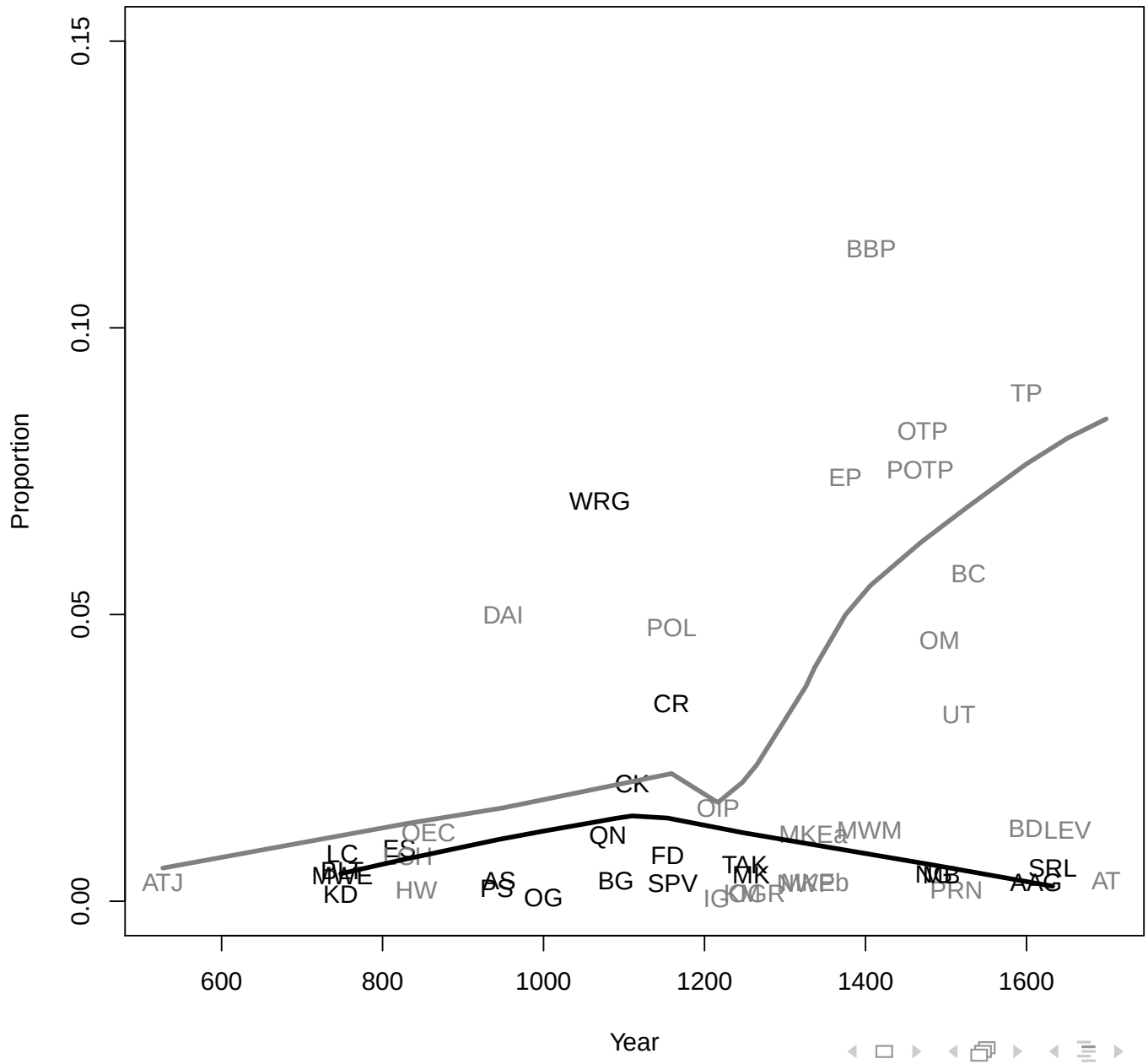
SRL
MWE
HW
ATJ
PS
BC
AAG
OG
IG
MWM

Granular: Characteristics that distinguish Just Ruler from Tyrant

king,princ,citi,great,place,work,emperor,enemi,armi,letter
king,kingdom,royal,minist,reign,father,court,majesti,presenc,war
princ,good,peopl,christian,tyranni,war,mind,ought,state,public

3.1% of paragraphs


Coarse Topic 1 Granular Topic 2
Proportion
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AAG
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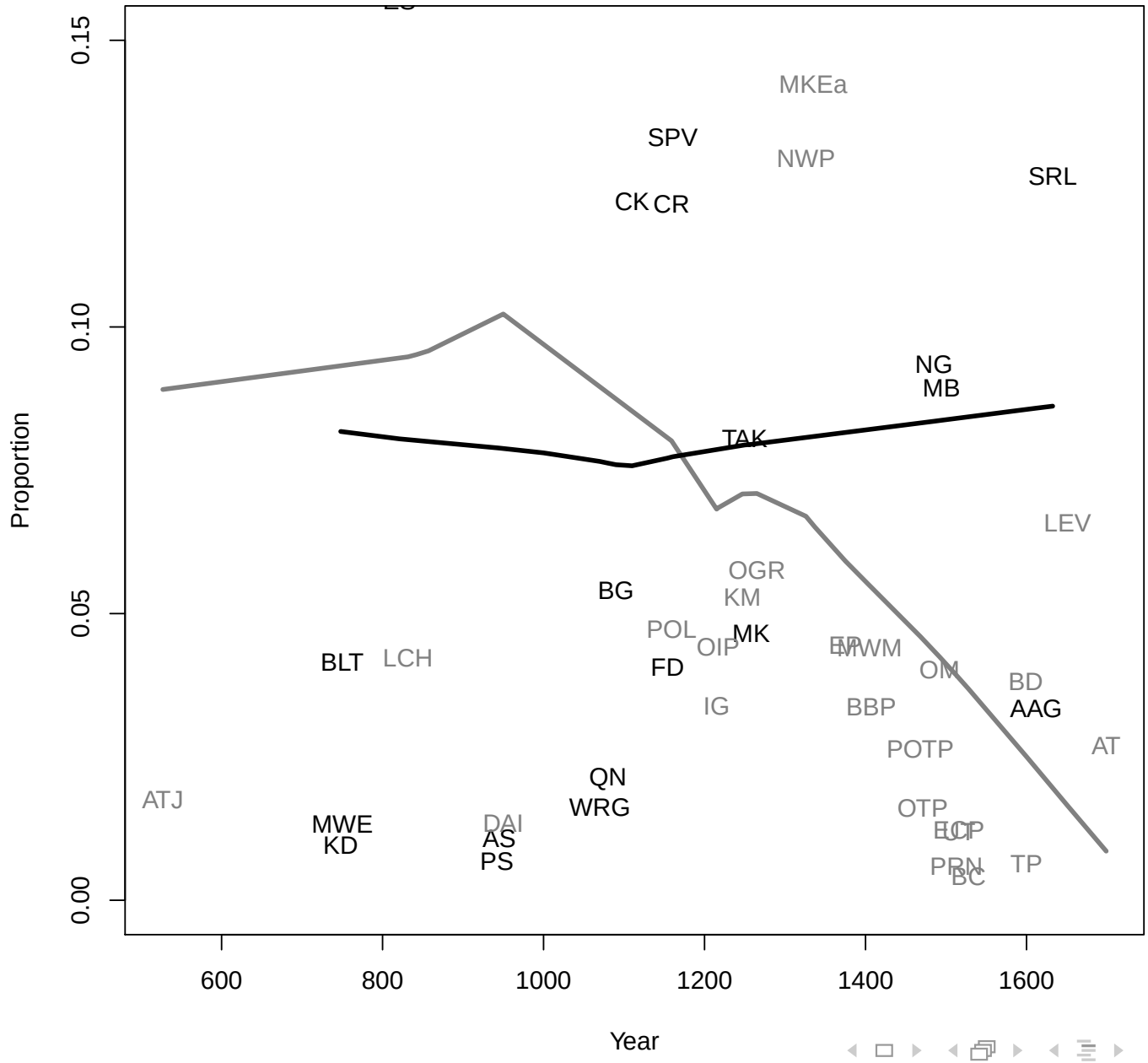
WRG
DAI
POL
CR
CK
QN
OIP
FD
BBP
TP
OTP
POTP
EP
BC
OM
UT
MWM
BDLEV
SRL

Granular: Religious Virtues and Political Ideals

almighti,good,virtu,power,ruler,justic,prayer,rule,prophet,mena
almighti,bless,grant,peac,messeng,prophet,merci,holi,command,grace

6.9% of paragraphs


Coarse Topic 2 Granular Topic 1
Proportion
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SRL
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LEV
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