Machine Learning

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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

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

LDA Revisited

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

A General Hierarchical Structure

LDA:

Pop. Proportion

A General Hierarchical Structure

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Doc. Prop$_1$ **Doc. Prop**$_2$ $\cdots$ **Doc. Prop**$_N$

A General Hierarchical Structure

LDA:

Pop. Proportion

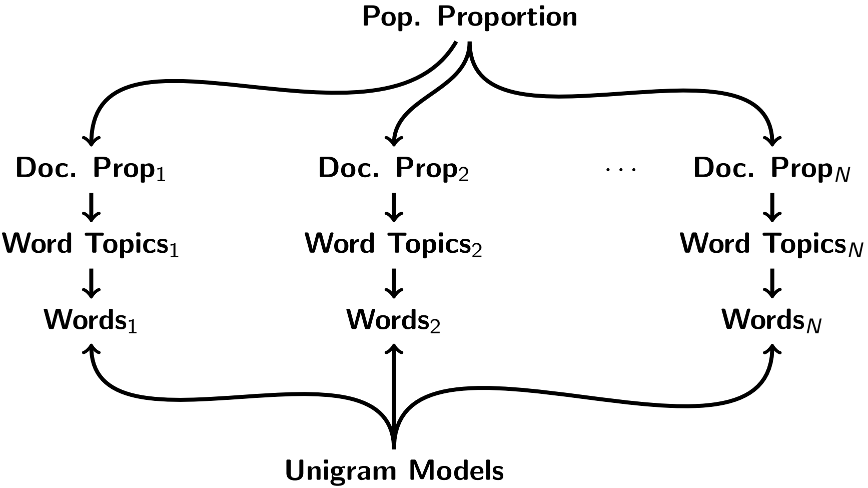
Doc. Prop$_1$ **Doc. Prop**$_2$ $\cdots$ **Doc. Prop**$_N$

$\downarrow$ $\downarrow$ $\downarrow$

Word Topics$_1$ **Word Topics**$_2$ **Word Topics**$_N$

A General Hierarchical Structure

LDA:



A General Hierarchical Structure

Dynamic Topic Model (Quinn et al 2010)

Dynamic Prior Across Days

A General Hierarchical Structure

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Dynamic Prior Across Days

Day Prop$_1$ **Day Prop**$_2$ $\cdots$ **Day Prop**$_N$

A General Hierarchical Structure

Dynamic Topic Model (Quinn et al 2010)

Dynamic Prior Across Days

Day Prop$_1$ → **Speech Topics$_1$**

Day Prop$_2$ → **Speech Topics$_2$**

$\cdots$

Day Prop$_N$ → **Speech Topics$_N$**

A General Hierarchical Structure

Dynamic Topic Model (Quinn et al 2010)

Dynamic Prior Across Days

Day Prop$_1$ **Day Prop$_2$** $\cdots$ **Day Prop$_N$**

$\downarrow$ $\downarrow$ $\downarrow$

Speech Topics$_1$ **Speech Topics$_2$**   **Speech Topics$_N$**

$\downarrow$ $\downarrow$ $\downarrow$

Speeches$_1$ **Speeches$_2$**   **Speeches$_N$**

Unigram Models

A General Hierarchical Structure

Expressed Agenda Model (Grimmer 2010)

Average Attention Across Authors

A General Hierarchical Structure

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Author Prop$_1$ **Author Prop$_2$** $\cdots$ **Author Prop$_N$**

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Text Topics$_1$ **Text Topics**$_2$ **Text Topics**$_N$

A General Hierarchical Structure

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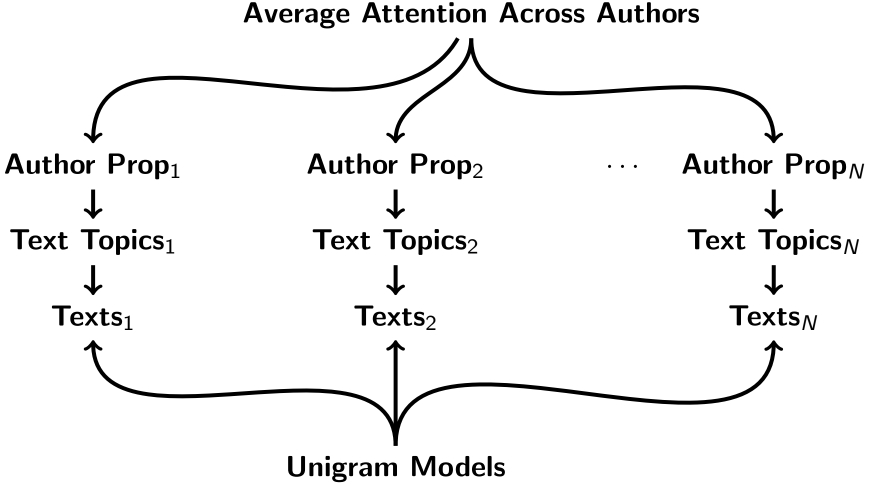

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Structural Topic Model (Roberts, Stewart, Airoldi 2014)

$$g(\boldsymbol{W}, \gamma)$$

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$$g(\boldsymbol{W}, \gamma)$$

$$\begin{array}{cccc}
\downarrow & \downarrow & & \downarrow \\
\textbf{Strata Prop}_1 & \textbf{Strata Prop}_2 & \cdots & \textbf{Strata Prop}_N \\
\downarrow & \downarrow & & \downarrow \\
\textbf{Text Topics}_1 & \textbf{Text Topics}_2 & & \textbf{Text Topics}_N
\end{array}$$

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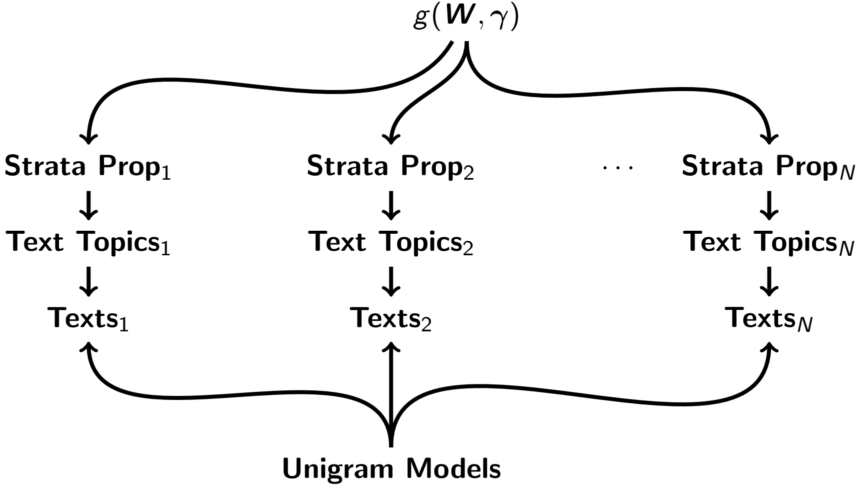

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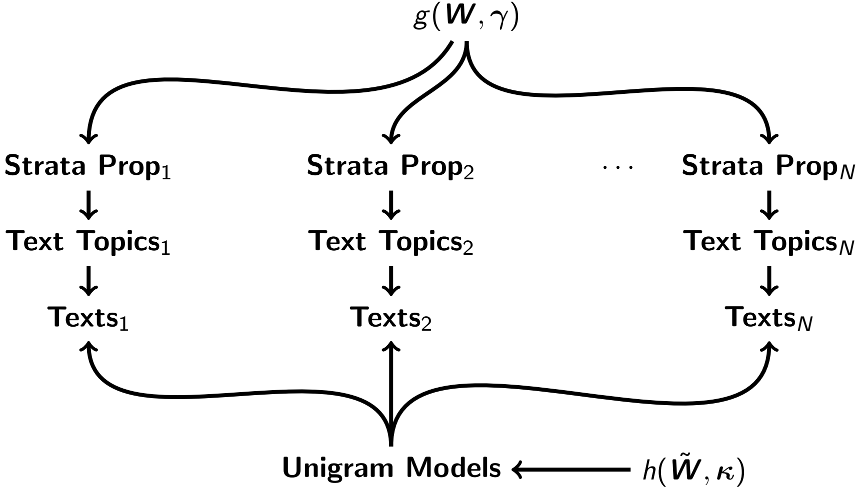

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R Code
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A General Hierarchical Structure

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

Mixture of Top. Attn. Models

A General Hierarchical Structure

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

Strata Indic. **Topic Attention Models**

A General Hierarchical Structure

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

Strata Indic. **Topic Attention Models**

Strata Prop$_1$ **Strata Prop$_2$** $\cdots$ **Strata Prop$_N$**

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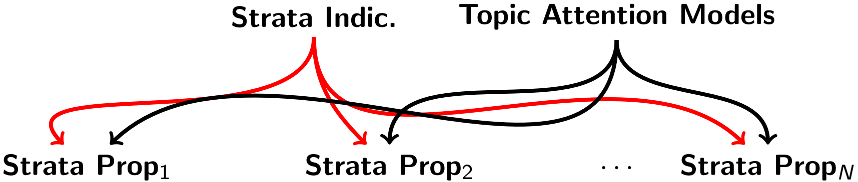

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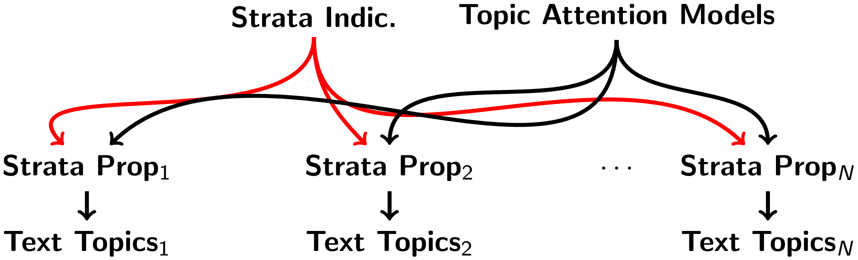

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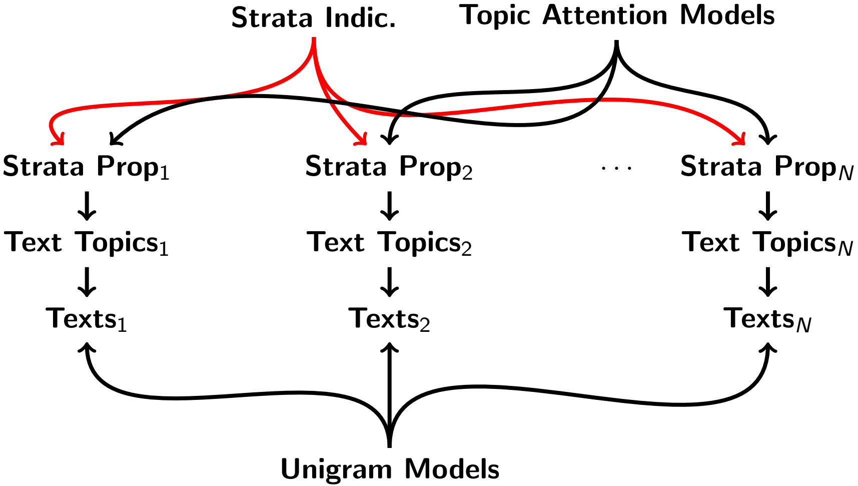

A General Hierarchical Structure

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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$$
\begin{tikzcd}
 & \textbf{Population attention} \arrow[dl] \arrow[d] \arrow[drr] & & \\
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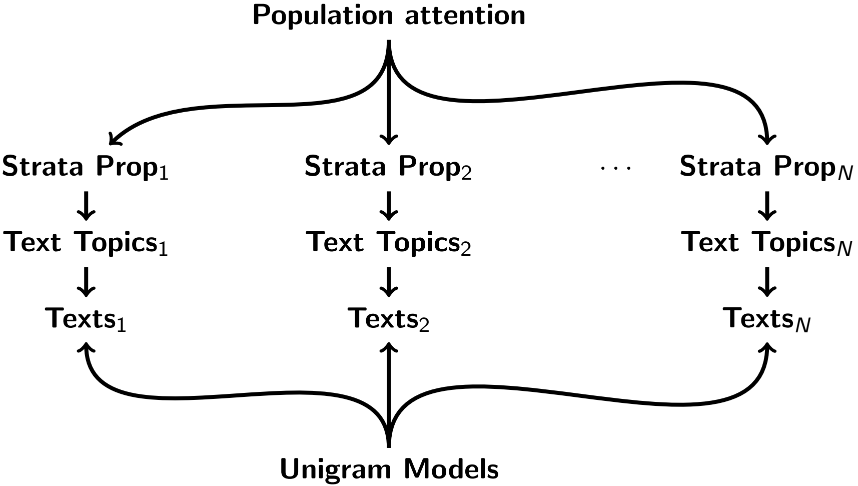

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$$\begin{tikzcd}
 & \textbf{Population attention} \arrow[dl, bend right] \arrow[d] \arrow[drr, bend left] & & \\
\textbf{Strata Prop}_1 \arrow[d] & \textbf{Strata Prop}_2 \arrow[d] & \cdots & \textbf{Strata Prop}_N \arrow[d] \\
\textbf{Text Topics}_1 \arrow[d] & \textbf{Text Topics}_2 \arrow[d] & & \textbf{Text Topics}_N \arrow[d] \\
\textbf{Texts}_1 & \textbf{Texts}_2 & & \textbf{Texts}_N \\
 & \textbf{Unigram Models} \arrow[ul, bend left] \arrow[u] \arrow[urr, bend right] & & \textbf{Hierarchy of Topics} \arrow[ll]
\end{tikzcd}$$

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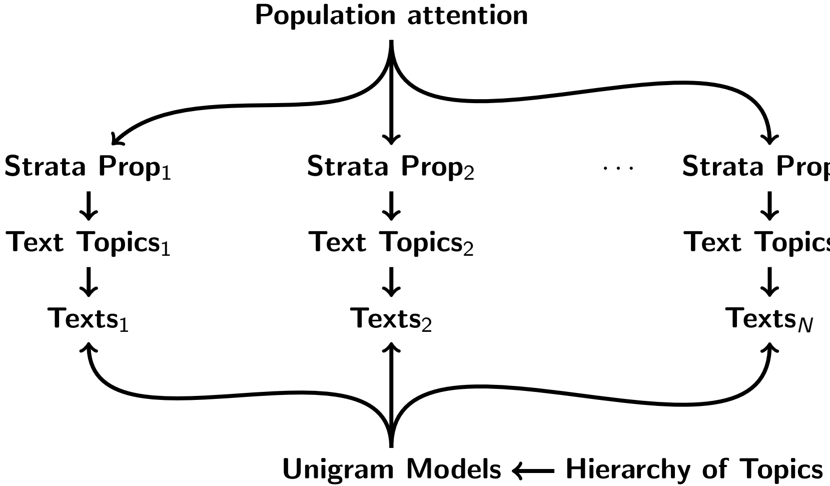

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  - Smoothing $\rightsquigarrow$ borrow information across groups intelligently
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  - Improved topics $\rightsquigarrow$ small word conditions, structure could help

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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Why? Hard to Measure
Describe model that facilitates estimation of presentational styles in Senate press releases

- 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
- $\pi_{itk} \equiv$ Probability press release is about issue k
- $\boldsymbol{\pi}_{it} = (\pi_{it1}, \ldots, \pi_{it44})$

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- If $\tau_{ijtk} = 1$ then

$$\boldsymbol{x}_{ijt} \sim \text{Multinomial}(n_{ijt}, \boldsymbol{\theta}_k).$$

Priors

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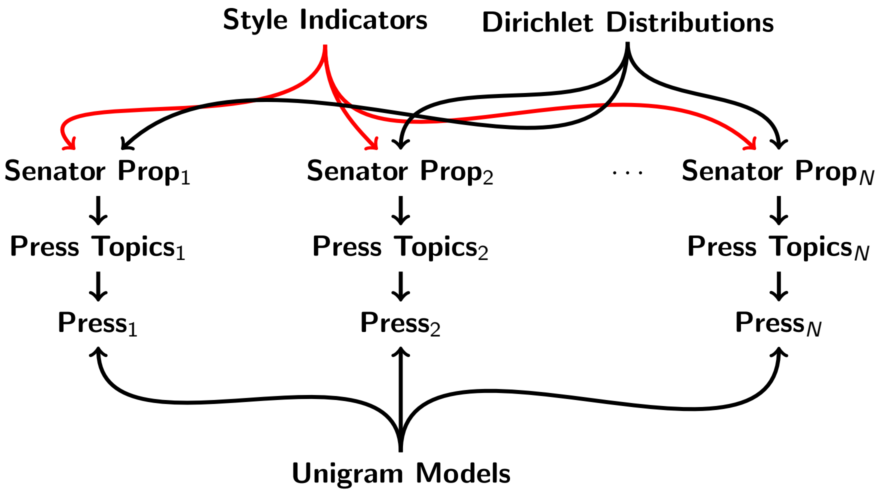
Mixture of Styles, Mixture of Topics



Posterior:

$$
\begin{aligned}
p(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\theta}, \boldsymbol{\sigma}, \boldsymbol{\pi}, \boldsymbol{\tau} | \boldsymbol{X}) \quad \propto \quad & \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

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\end{aligned}
$$

1) Estimate with Variational Approximation
2) Determining number of clusters at top? (Grimmer, Shorey, Wallach, and Zlotnick, In Progress)

Posterior:

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

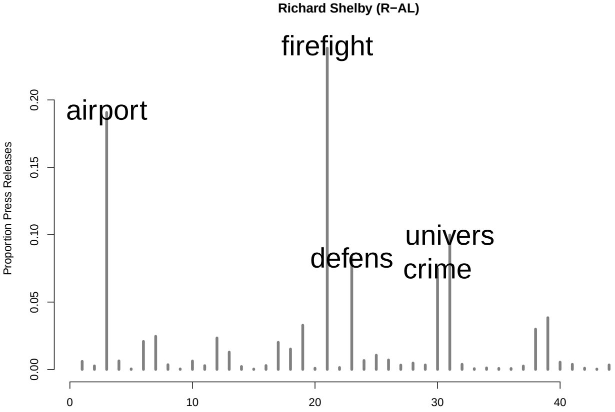
$$\prod_{i=1}^{N}\prod_{t=2005}^{2007}\prod_{s=1}^{S}\left[\beta_s \frac{\Gamma(\sum_{k=1}^{K}\alpha_{ks})}{\prod_{k=1}^{K}\Gamma(\alpha_{ks})}\prod_{k=1}^{K}\pi_{itk}^{\alpha_{ks}-1}\prod_{j=1}^{D_{it}}\prod_{k=1}^{K}\left[\pi_{itk}\prod_{w=1}^{W}\theta_{kw}^{x_{ijtw}}\right]^{\tau_{ijtk}}\right]^{\sigma_{its}}$$

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

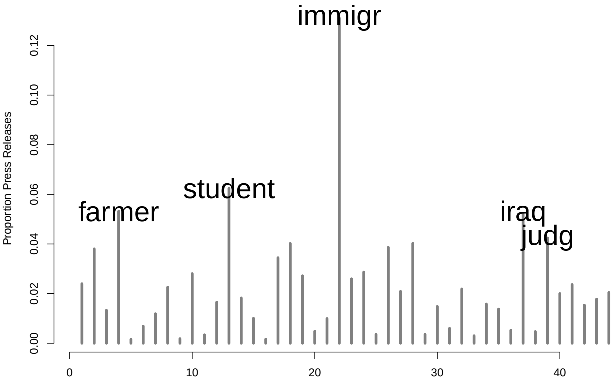
Posterior:

$$
\begin{aligned}
p(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\theta}, \boldsymbol{\sigma}, \boldsymbol{\pi}, \boldsymbol{\tau} | \boldsymbol{X}) \quad \propto \quad & \prod_{k=1}^{K} \prod_{s=1}^{S} \frac{\exp(-\frac{\alpha_{ks}}{1/4})}{1/4} \times \frac{\Gamma(\sum_{w=1}^{W} \lambda_w)}{\prod_{w=1}^{W} \Gamma(\lambda_w)} \prod_{w=1}^{W} \theta_{k,w}^{\lambda_w - 1} \times \\
& \prod_{i=1}^{N} \prod_{t=2005}^{2007} \prod_{s=1}^{S} \left[\beta_s \frac{\Gamma(\sum_{k=1}^{K} \alpha_{ks})}{\prod_{k=1}^{K} \Gamma(\alpha_{ks})} \prod_{k=1}^{K} \pi_{itk}^{\alpha_{ks}-1} \prod_{j=1}^{D_{it}} \prod_{k=1}^{K} \left[\pi_{itk} \prod_{w=1}^{W} \theta_{kw}^{x_{ijtw}} \right]^{\tau_{ijtk}} \right]^{\sigma_{its}}
\end{aligned}
$$

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)



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

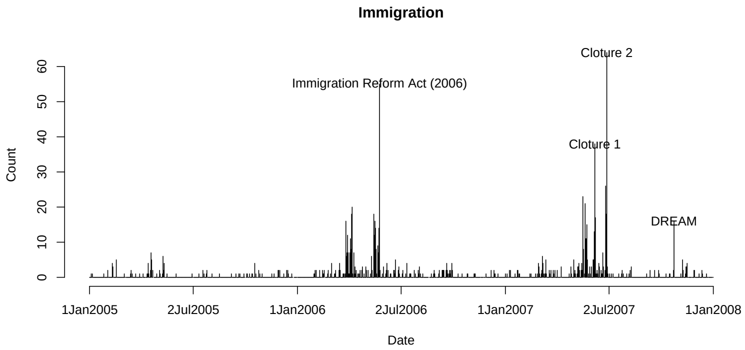
Must: Demonstrate to reader that topics are coherent and semantically meaningful

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.

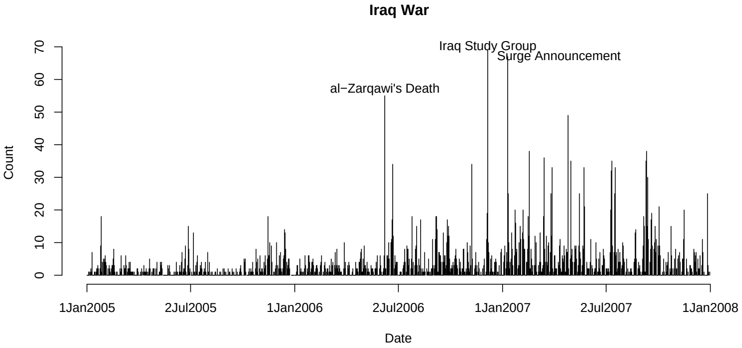
Home Style Measures, Convergent Validity

Over time variation



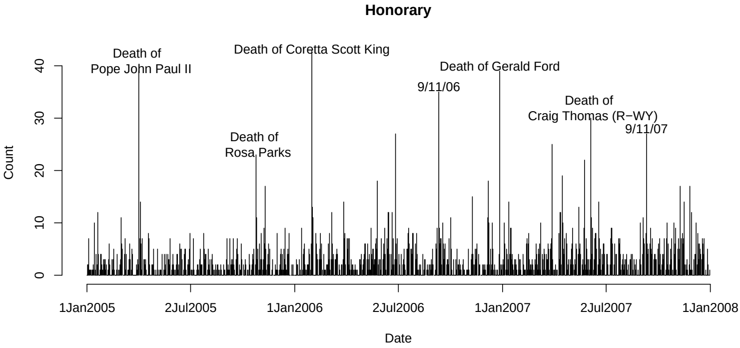
Home Style Measures, Convergent Validity

Over time variation



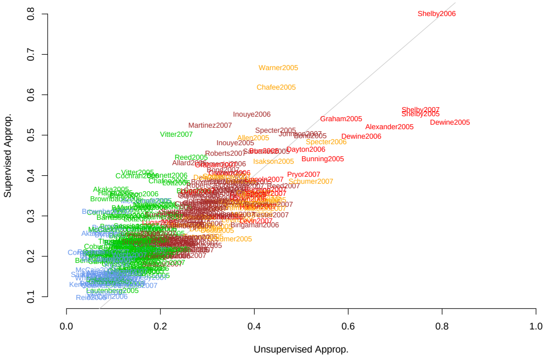
Home Style Measures, Convergent Validity

Over time variation

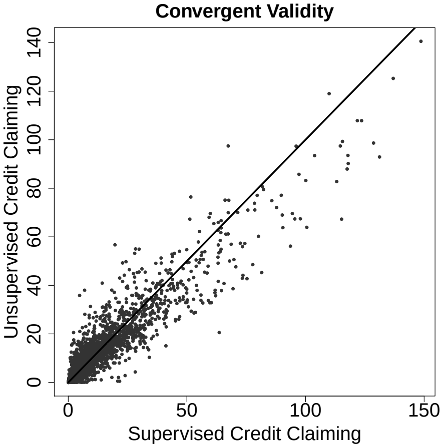


Home Style Measures, Convergent Validity

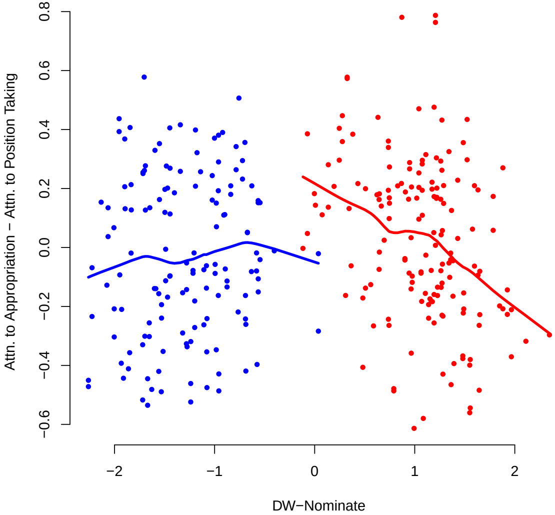
Supervised/Unsupervised Convergence



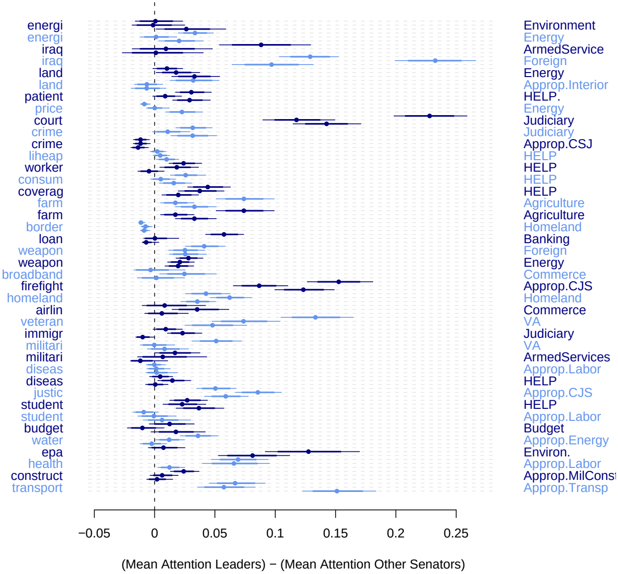
Home Style Measures, Convergent Validity



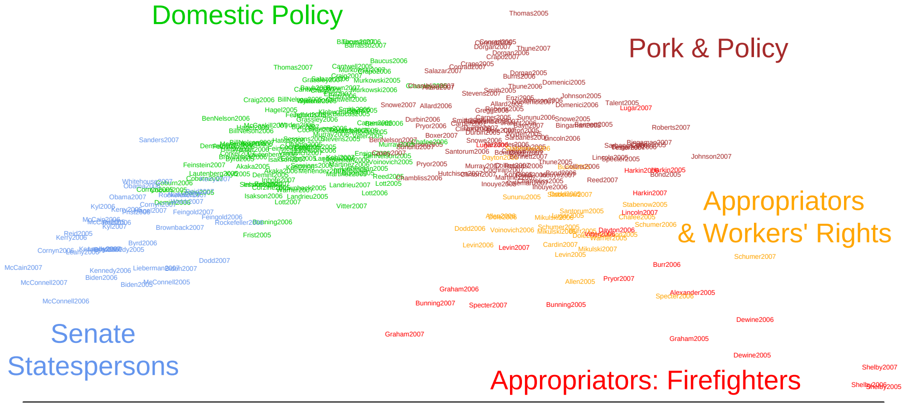
Discriminant Construct Validity



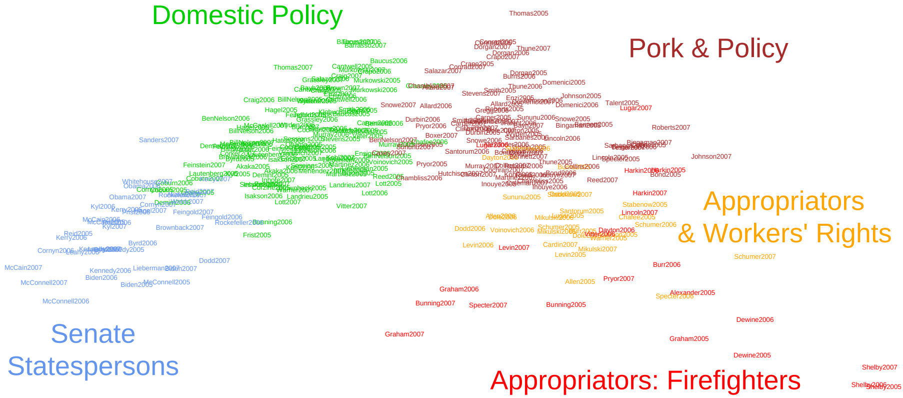
Predictive Validity



Hypothesis Validity



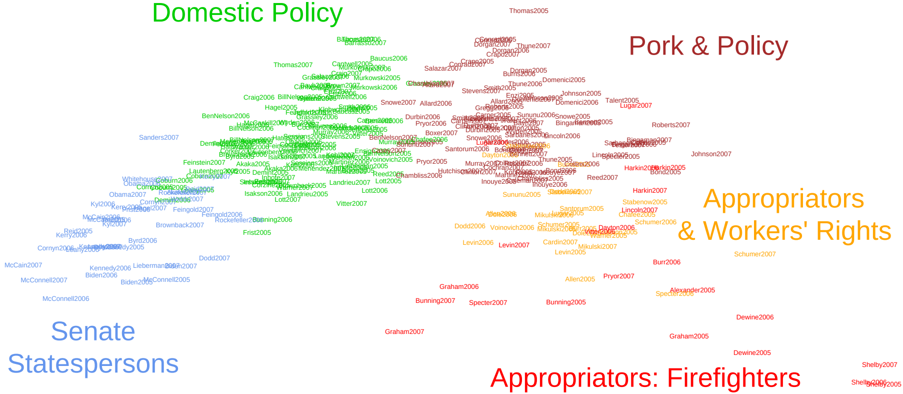
Hypothesis Validity



Senate
Statesperson

- Iraq War
- Intelligence
- Intl.
  Relations

Hypothesis Validity



Senate Statesperson

- Iraq War
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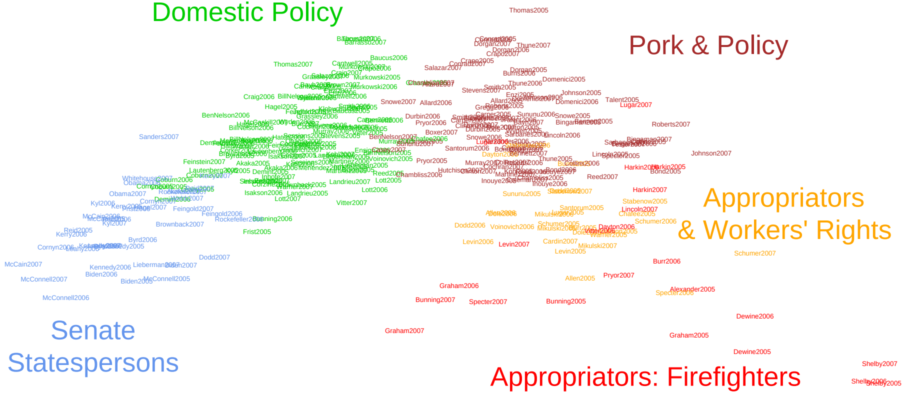
Domestic Policy

- Environment
- Gas prices
- DHS
- Consumer

Hypothesis Validity



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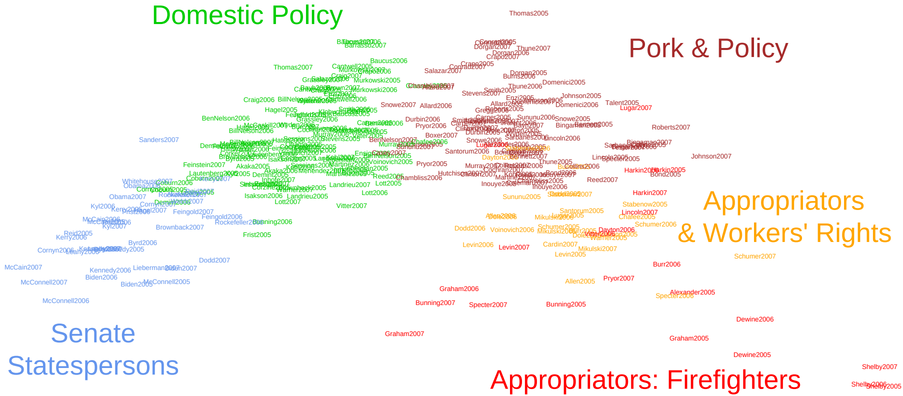
Pork & Policy

- WRDA grants
- Farming
- Health Care
- Education

Hypothesis Validity



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- Education

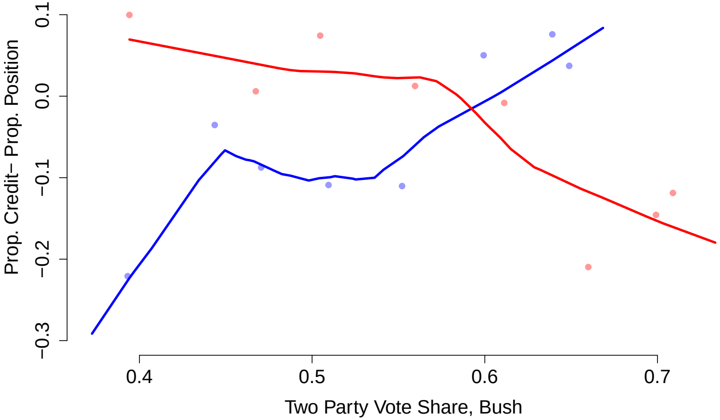
Appropriators

- Fire Grants
- Airport Grants
- University Money

Hypothesis Validity

Why do senators adopt different styles?

District Fit



What are the right number of topics?

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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

- Collect data on collection of 98 (51 Christian, 47 Islamic, some not translated)
- No difference on Year/Region

Preprocessing Texts

47 books

Preprocessing Texts

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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$$\mathbf{x}_{ij} = (x_{ij1}, x_{ij2}, \ldots, x_{ij2124})$$

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)

Measuring Themes in the Mirrors

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3) Each book i's $\textbf{themes}_i$

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

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 **themes**$_i$
4) Each short segment's granular (and coarse) topic

A Hierarchy of Topics

themes$_i$

A Hierarchy of Topics

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

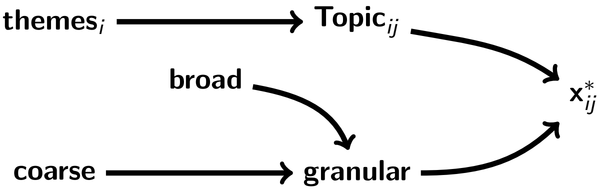
$$\textbf{Topic}_{ij} \sim \text{Multinomial}(1, \textbf{themes}_i)$$

A Hierarchy of Topics

$$
\begin{tikzcd}
\textbf{themes}_i \arrow[r] & \textbf{Topic}_{ij} \arrow[dr] & \\
 & & \mathbf{x}^*_{ij} \\
 & \textbf{granular} \arrow[ur] &
\end{tikzcd}
$$

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

A Hierarchy of Topics



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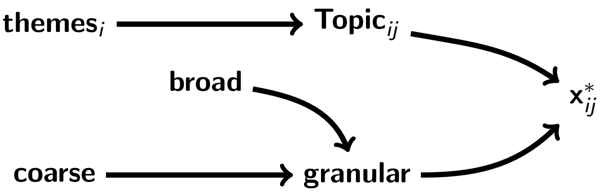
\mathbf{x}^*_{ij} | \text{Topic}_{ijk} = 1 &\sim \text{vMF}(\kappa, \textbf{granular}_k) \\
\textbf{broad}_k &\sim \text{Multinomial}(1, \textbf{Broad Theme Prior}) \\
\textbf{granular}_k | \text{broad}_{km} = 1 &\sim \text{vMF}(\kappa, \textbf{coarse}_m)
\end{aligned}
$$

A Hierarchy of Topics



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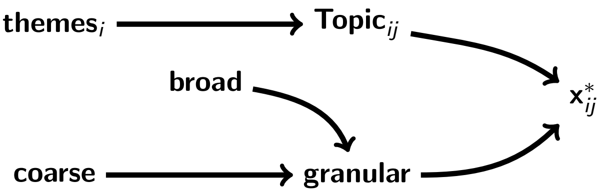
Estimate model with Variational Approximation

A Hierarchy of Topics



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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

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1) Computational: identify discriminating words

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

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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

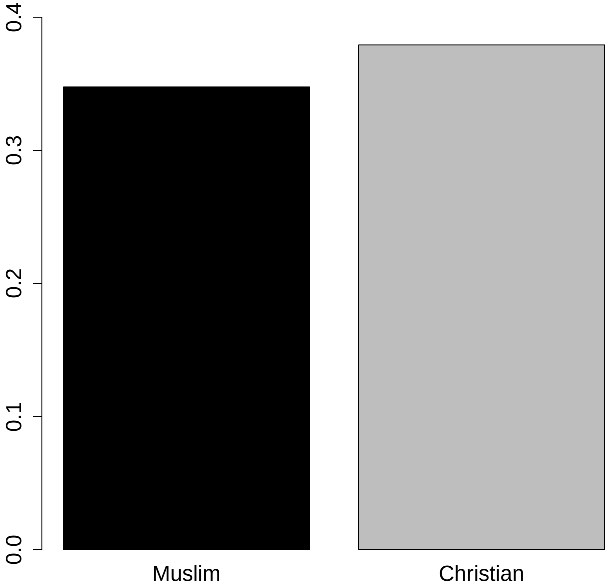
king,princ,citi,great,place,work,emperor,enemi,armi,letter

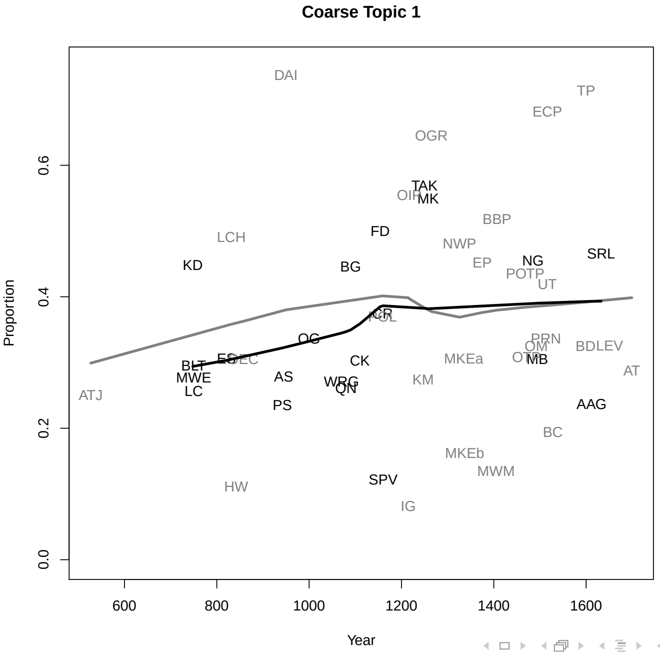
Art of Rulership

Practices and ideals of political rule

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

36.5% of paragraphs


0.0
0.1
0.2
0.3
0.4
Muslim
Christian


Coarse Topic 1
Proportion
Year
0.0
0.2
0.4
0.6
600
800
1000
1200
1400
1600
DAI
TP
ECP
OGR
TAK
OIR
MK
BBP
FD
LCH
NWP
SRL
KD
BG
EP
NG
POTP
UT
CR
POL
OG
PRN
OM
BDLEV
ES
DEC
BLT
CK
MKEa
OTP
MB
AT
MWE
AS
WRG
KM
LC
QN
ATJ
PS
AAG
BC
MKEb
MWM
SPV
HW
IG

Religion and Virtue

Connection between religion, virtue, justice and political rule

Religion and Virtue

Connection between religion, virtue, justice and political rule

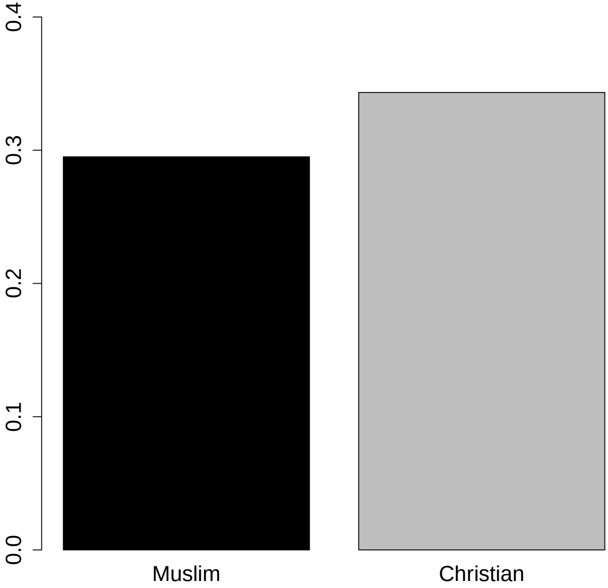
almighti,good,virtu,power,ruler,justic,prayer,rule,prophet,mena

Religion and Virtue

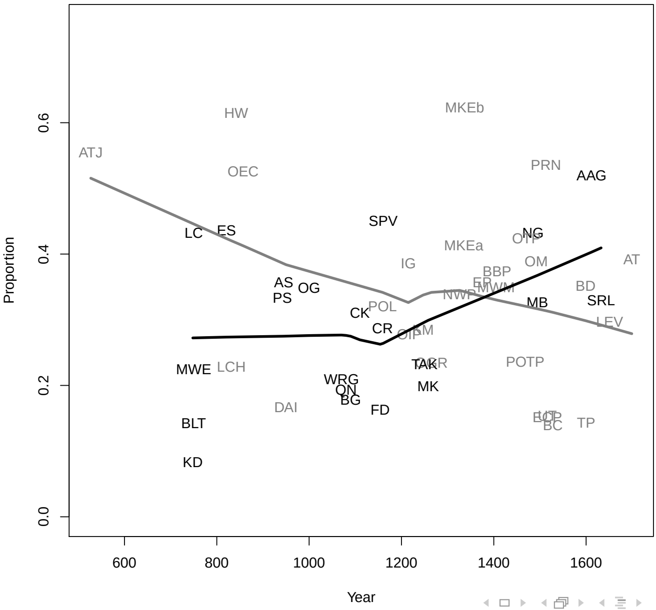
Connection between religion, virtue, justice and political rule

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

32.2% of pargraphs


0.0
0.1
0.2
0.3
0.4
Muslim
Christian

Coarse Topic 2



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

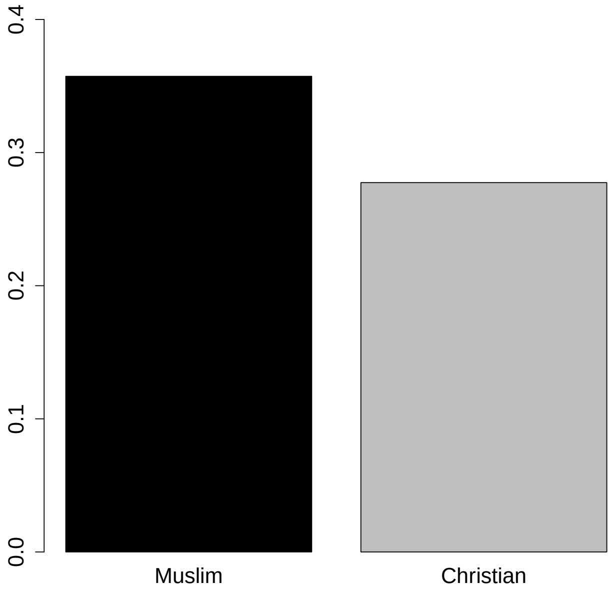
man,land,woman,know,bodi,eye,ladi,love,faculti,old

Inner Life of the Ruler

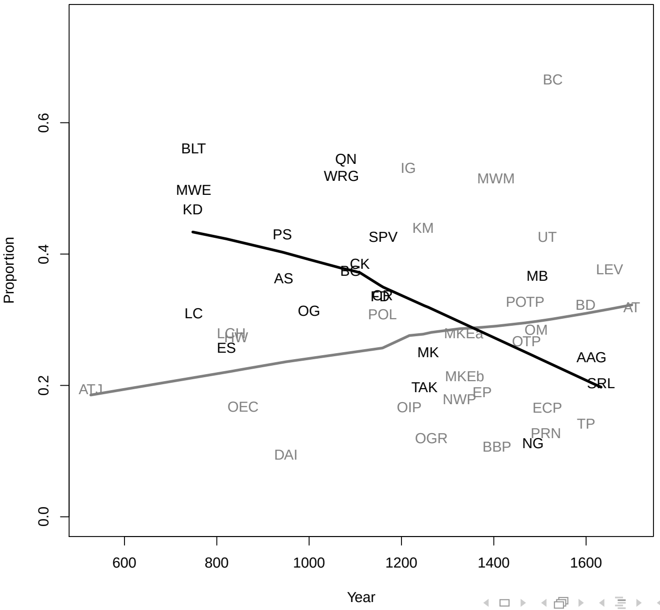
Personal relationships, care for and practices of the self, and ultimate fate of the soul

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

31.2% of paragraphs


0.0
0.1
0.2
0.3
0.4
Muslim
Christian

Coarse Topic 3

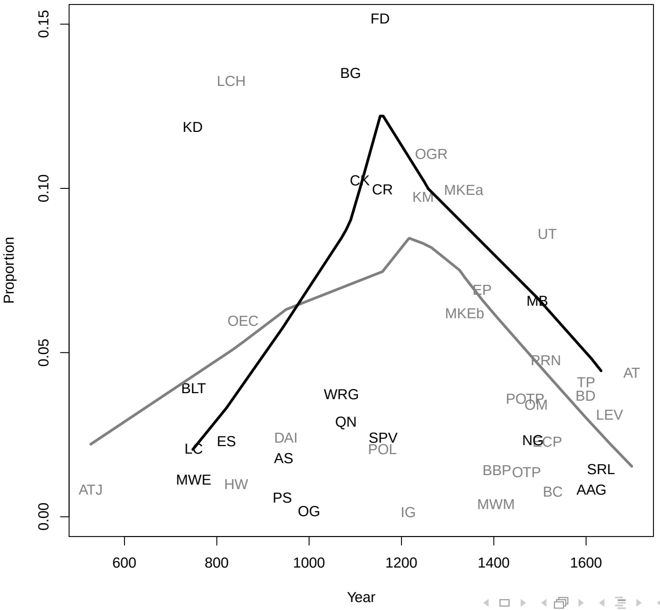


Granular: Best Practices for Ruling

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

6.2% of paragraphs

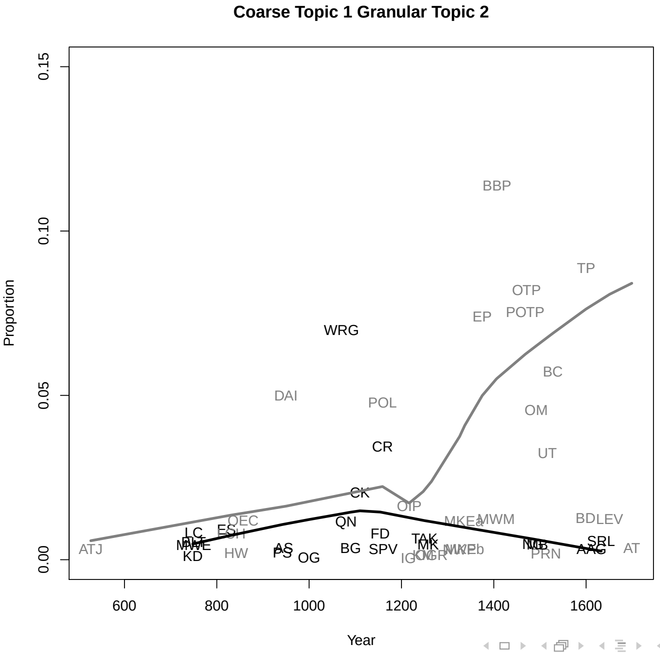
Coarse Topic 1 Granular Topic 1



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
Year
0.00
0.05
0.10
0.15
600
800
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1200
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1600
BBP
TP
OTP
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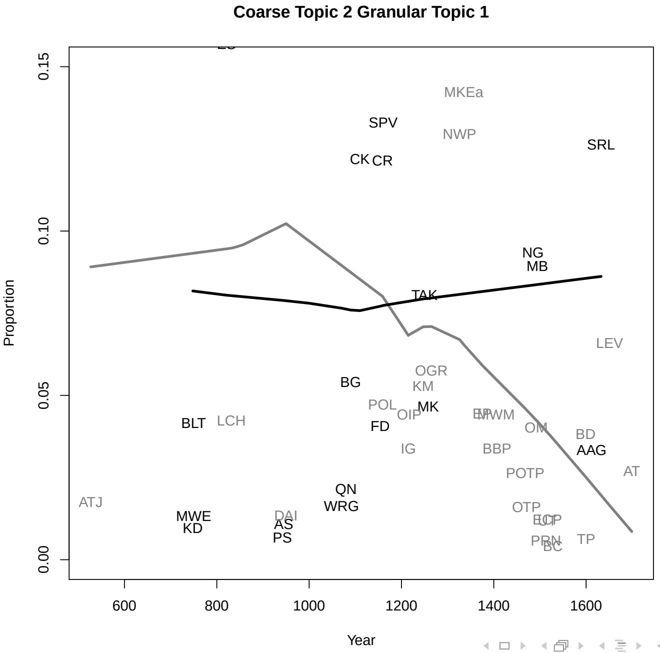
POTP
WRG
BC
DAI
POL
OM
CR
UT
CK
OIP
QEC
QN
MKEa
MWM
BDLEV
LC
ES
FD
TAK
SRL
MWE
KD
HW
AS
PS
OG
BG
SPV
IG
MK
PRN
AAG
ATJ
AT

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
Year
0.00
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600
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1600
MKEa
SPV
NWP
SRL
CK
CR
NG
MB
TAK
LEV
OGR
BG
KM
POL
MK
OIP
MWM
BLT
LCH
FD
OM
BD
IG
BBP
AAG
POTP
AT
QN
ATJ
WRG
OTP
MWE
DAI
KD
AS
PS
TP
BC