

# Twitter in the Parliament - A Text-based Analysis of German Political Entities

Patrick Schulze, Simon Wiegrebe

Supervisors:

Prof. Dr. Christian Heumann, Prof. Dr. Paul W. Thurner

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# Covariate-level Topic Analysis

## Overview

- Explore estimated topical structure with respect to different dimensions, e.g. membership in political party, time, ...
- Precisely: examine relationship between document-level prevalence covariates  $\mathbf{x}_d$  and topic proportions  $\boldsymbol{\theta}_d$
- Natural idea: regress topic proportions on prevalence covariates
- Problem:  $\boldsymbol{\theta}_d$  is *latent* variable and has to be estimated itself!
- In following two approaches to address this problem:
  - ① Regression that takes into account uncertainty about  $\boldsymbol{\theta}_d$ : perform sampling technique known as "method of composition" in social sciences
  - ② Direct assessment of STM output via logistic normal distribution with estimated topical prevalence parameters  $\hat{\boldsymbol{\Gamma}}$  and  $\hat{\boldsymbol{\Sigma}}$

# Covariate-level Topic Analysis

## Method of Composition

- Let  $\theta_{(k)} := (\theta_{1,k}, \dots, \theta_{D,k})^T \in [0, 1]^D$  denote proportion of  $k$ -th topic for all  $D$  documents
- Method of Composition (repeat  $m$  times):
  - ① Sample  $\theta_{(k)}^*$  from (variational) posterior of  $\theta_{(k)}$  estimated by STM
  - ② Run regression model with response  $\theta_{(k)}^*$  and covariates  $\mathbf{X}$  to obtain estimate  $\hat{\xi}^*$  of regression coefficients  $\xi^*$  and covariance of  $\hat{\xi}^*$ ,  $\hat{\mathbf{V}}_{\xi}^*$
  - ③ Sample  $\tilde{\xi}^*$  from  $F(\hat{\xi}^*, \hat{\mathbf{V}}_{\xi}^*)$ , where  $F$  is (asymptotic) distribution of  $\hat{\xi}^*$
- Idea: samples  $\tilde{\xi}^*$  take into account uncertainty in  $\theta_{(k)}$
- Visualization of topic-metadata relationship: For observation  $\mathbf{x}_{\text{pred}}$ , plot  $\mathbf{x}_{\text{pred}}$  vs. predicted response with  $\mathbf{x}_{\text{pred}}^T \tilde{\xi}^*$  as linear predictor

# Covariate-level Topic Analysis

## Method of Composition: Problems

Several concerns with method of composition:

- ① In STM, regression model in step 2 is OLS; however OLS not appropriate to model (sampled) proportions in open unit interval
- ② Mixing of Bayesian and frequentist approach questionable:
  - From Bayesian perspective,  $\tilde{\xi}^*$  can only be considered sample from posterior of  $\xi$  in certain Bayesian regression models with questionable (uniform) prior assumptions
  - Using  $\mathbf{x}_{\text{pred}}^T \tilde{\xi}^*$  as linear predictor does *not* yield sample of posterior predictive distribution
- ③ Separate modeling of topic proportions neglects dependence of different topics among each other

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Method of Composition: Usage within R Package *stm*

- Problem: OLS regression not suitable for (sampled) proportions, which are restricted to interval  $(0,1)$
- Estimated relationship between proportions and prevalence covariates might even involve negative proportions:

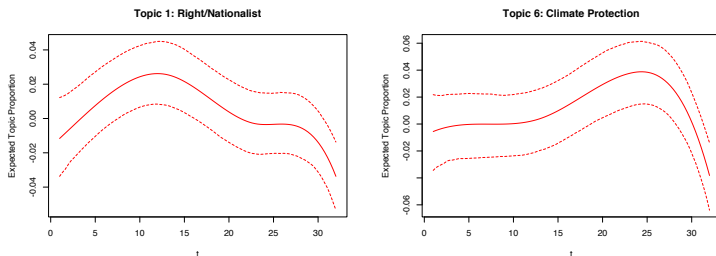


Figure: Empirical mean and 95% credible intervals for topics 1 and 6 over time, estimated using *estimateEffect* from the *stm* package.

# Covariate-level Topic Analysis

Method of Composition: Extension of existing approach

- Instead of OLS regression, we can use a beta regression or a quasibinomial GLM (both with logit-link) to adequately model proportions

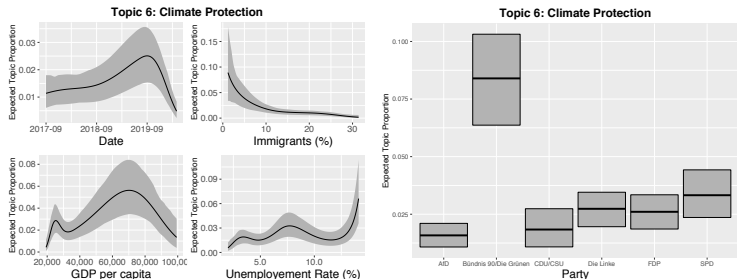


Figure: Empirical mean and 95% credible intervals, obtained using a quasibinomial GLM.

# Covariate-level Topic Analysis

## Mixing of Bayesian and Frequentist Approach

- Regression within of method of composition is *frequentist* regression
- However, in STM  $\tilde{\xi}^*$  considered samples from (marginal, i.e., integrated over latent topic proportions) posterior of regression coefficients; only true by assuming uniform priors for  $\xi$
- Caution: uncertainty from previous plots with respect to prediction of mean  $\Rightarrow$  does *not* reflect variation of topic proportions in data!
- Better idea: fully Bayesian approach with more realistic priors and sampling from posterior predictive distribution to reflect variation of data

# Covariate-level Topic Analysis

## Fully Bayesian Approach: Idea

- Idea: *explicitly* perform Bayesian regression in second step of each iteration of method of composition
- Modeling via beta regression (with normal priors centered around zero) in order to model proportions in  $(0, 1)$
- Visualization: Sample proportions from posterior predictive distribution at end of each step of method of composition (i.e., conditioning on previously sampled  $\theta_{(k)}^*$ ) with covariate values  $\mathbf{x}_{\text{pred}}$



# Covariate-level Topic Analysis

## Fully Bayesian Approach: Results

- Predicted (empirical) mean mostly in line with results from previous analysis
- Uncertainty now w.r.t. variation of topic proportions in data
- Observed variation for topic proportions corresponds well to variation according to predictive posterior

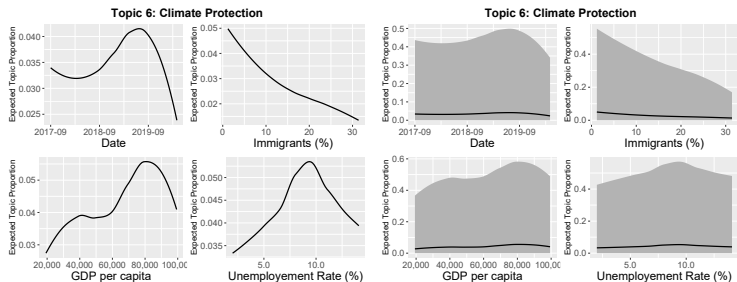


Figure: Smooth effects without credible intervals (left) and smooth effects with 95% credible intervals (right)

# Covariate-level Topic Analysis

## Multivariate Modeling of Proportions

- Remember, by assumption:  $\theta_d \sim \text{LogisticNormal}(\Gamma^T \mathbf{x}_d^T, \Sigma)$
- Logistic normal distribution assumes high dependence among individual components  $\Rightarrow$  not fully taken into account in univariate modeling via, e.g., the beta distribution
- Inference within STM involves finding estimates  $\hat{\Gamma}$  and  $\hat{\Sigma} \Rightarrow$  Idea: plug estimates into logistic normal distribution
- For given covariate value  $\mathbf{x}_{\text{pred}}$ , obtain topic proportion as  $\theta_d^* \sim \text{LogisticNormal}(\hat{\Gamma}^T \mathbf{x}_{\text{pred}}^T, \hat{\Sigma})$

# Covariate-level Topic Analysis

## Multivariate Modeling of Proportions

- Plugging in  $\Gamma$  and  $\hat{\Sigma}$  is "naïve" method: ideally sample prevalence parameters from their posterior  $\Rightarrow$  would yield higher variation
- However, not easily possible  $\Rightarrow$  should be addressed in future implementations

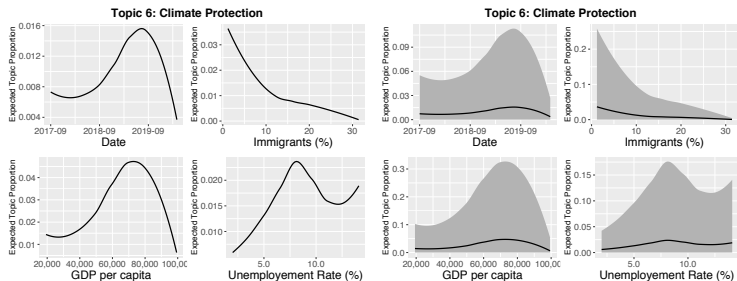


Figure: Smooth effects without credible intervals (left) and smooth effects with credible intervals (right)

# Bibliography