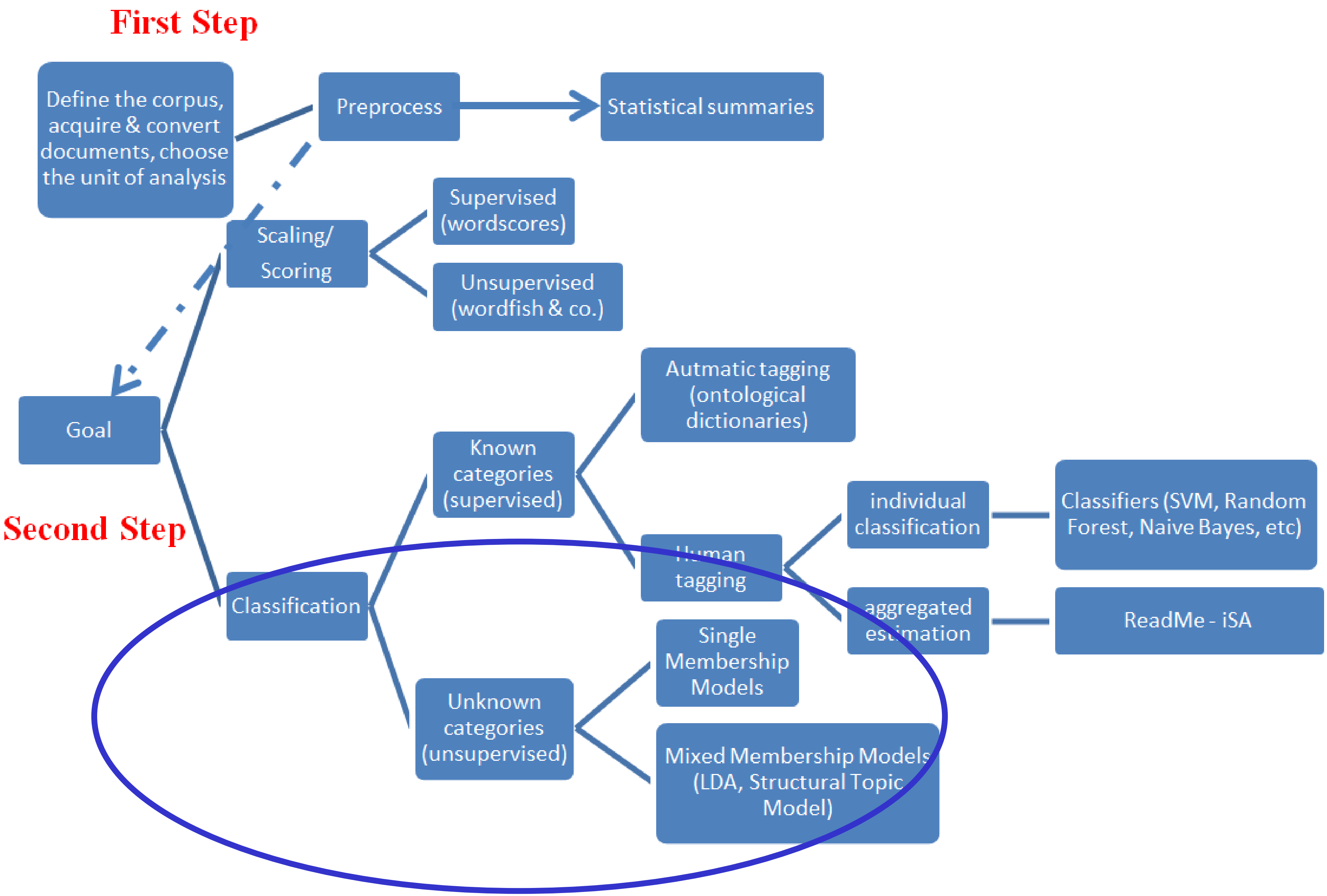
Applied Scaling & Classification Techniques in Political Science

Lecture 5 – Part 1

Unsupervised classification methods: the strucutural topic model

Assignment 4 solution

Our Course Map



Reference

- ✓ Roberts, Margaret E., Brandon M. Stewart, Dustin Tingley, Christopher Luca, Jetson Leder-Luis, Shana Kushner Gadarian, Bethany Albertson, David G. Rand (2014). Structural Topic Models for Open-Ended Survey Response, *American Journal of Political Science*, 58(4), 1064-1082
- ✓ Roberts, Margaret E., Brandon M. Stewart, Dustin Tingley(2014). STM: R Package for Structural Topic Models, *Journal of Statistical Software*, https://cran.r-project.org/web/packages/stm/vignettes/stmVignette.pdf

Classification methods

Structural Topic Model (STM) innovates on Topic models in two different ways:

First: topic proportions (θ) are allowed to be **correlated**: this is a reasonable assumption given that in documents topics discussed are correlated!

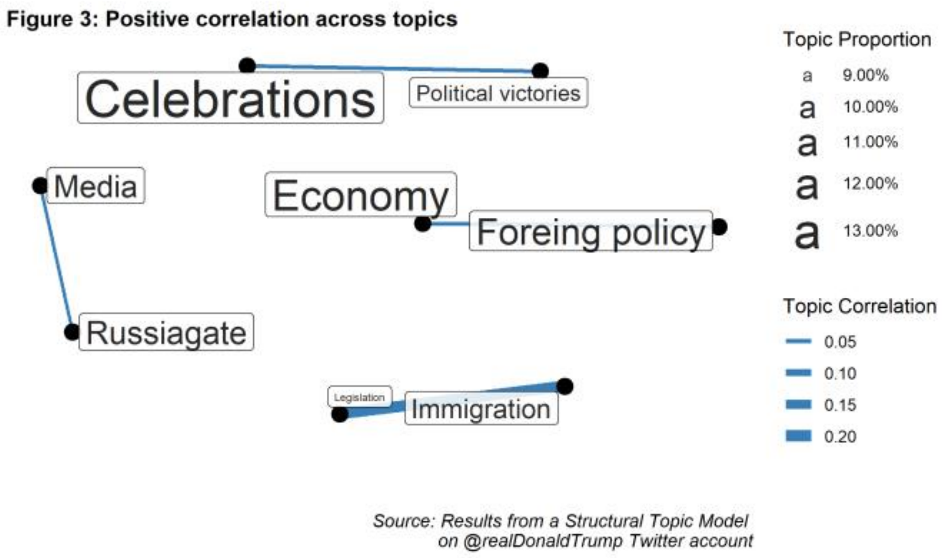
For example, if a manifesto contains discussion of Topic X (e.g. administrative reform), the probabilities that it will also contain discussion of Topics Y (e.g. curbing public works) and Z (e.g. reducing the number of Lower House members), are not independent of each other, but correlated

In this sense, STM fits a Correlated Topic Model (rather than a LDA)

Classification methods

Graphical depictions of the correlation between topics provide insight into the organizational structure at the corpus level

In essence, the model identifies when two topics are likely to co-occur (by focusing on positive correlation) within a document



Classification methods

Structural Topic Model (STM) innovates on the models just described in two different ways:

Second: in all topic models the analyst estimates for each document the proportion of words attributable to each topic, providing a measure of *topic prevalence*. The model also calculates the words most likely to be generated by each topic, which provides a measure of *topical content*

However, in standard LDA, the document collection is assumed to be **unstructured**; that is, each document is assumed to arise from the same data-generating process irrespective of additional information the analyst might possess

Classification methods

Suppose that after you run a Topic Model, you have the results for both **topic prevalance** and **topical content**

You could then start to ask yourself interesting questions such as:

a) is there any relationship between the ideology of the writer of a document and the emphasis/salience she devotes in her document(s) towards a particular topic (for example, a topic about social welfare or migrants?)?

b) is there any relationship between the language used to discuss a particular topic (for example, migrants) and the gender of the author of a document?

Classification methods

To answer these important questions you could either:

I) (a) run a Topic Model and then (b) run a set of OLS on your results using some Independent Variables (such as the ideology of the writer of a document or the gender, etc.)…or…

II) run (a) and (b) together!

That's precisely the second advantage of running a STM

STM conducts (b) while **simultaneously** estimating the topics (a)

This is more efficient than doing the two processes in separated steps: aka, first the topic analysis, and then running an analysis on the topic extracted

Classification methods

That is, a STM framework is designed to incorporate directly additional information about the document or its author into the estimation process

Rather than assuming that **topic prevalence** (i.e., the frequency with which a topic is discussed) and **topical content** (i.e., the words used to discuss a topic) **are constant** across all documents, the analyst can incorporate covariates over which we might expect to see variance directly when estimating the topics

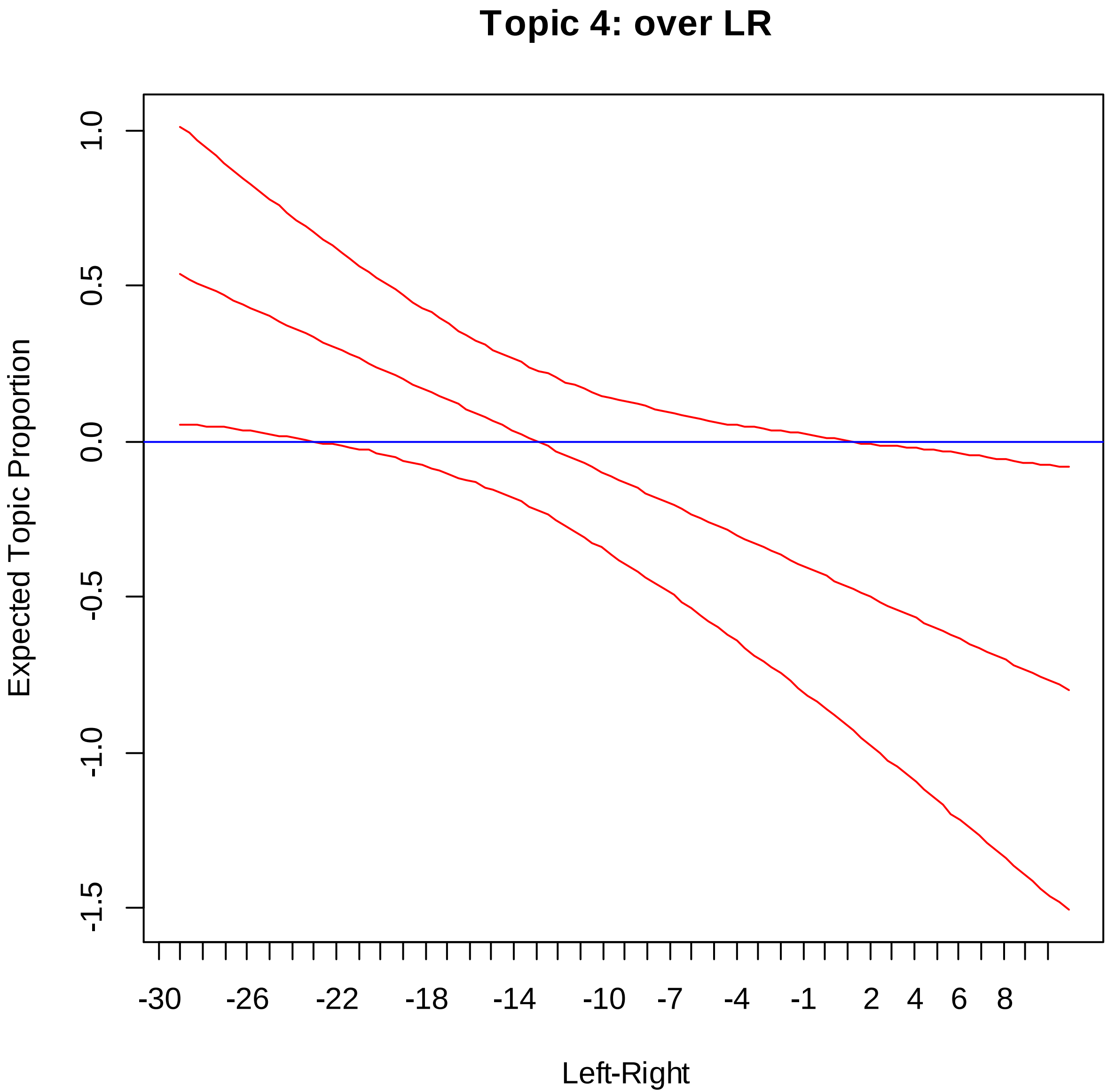
Classification methods

This allows to measure **systematic changes** in topical prevalence and topical content over the conditions in our experiment, as measured by the *X* covariates for prevalence and the *U* covariates for content

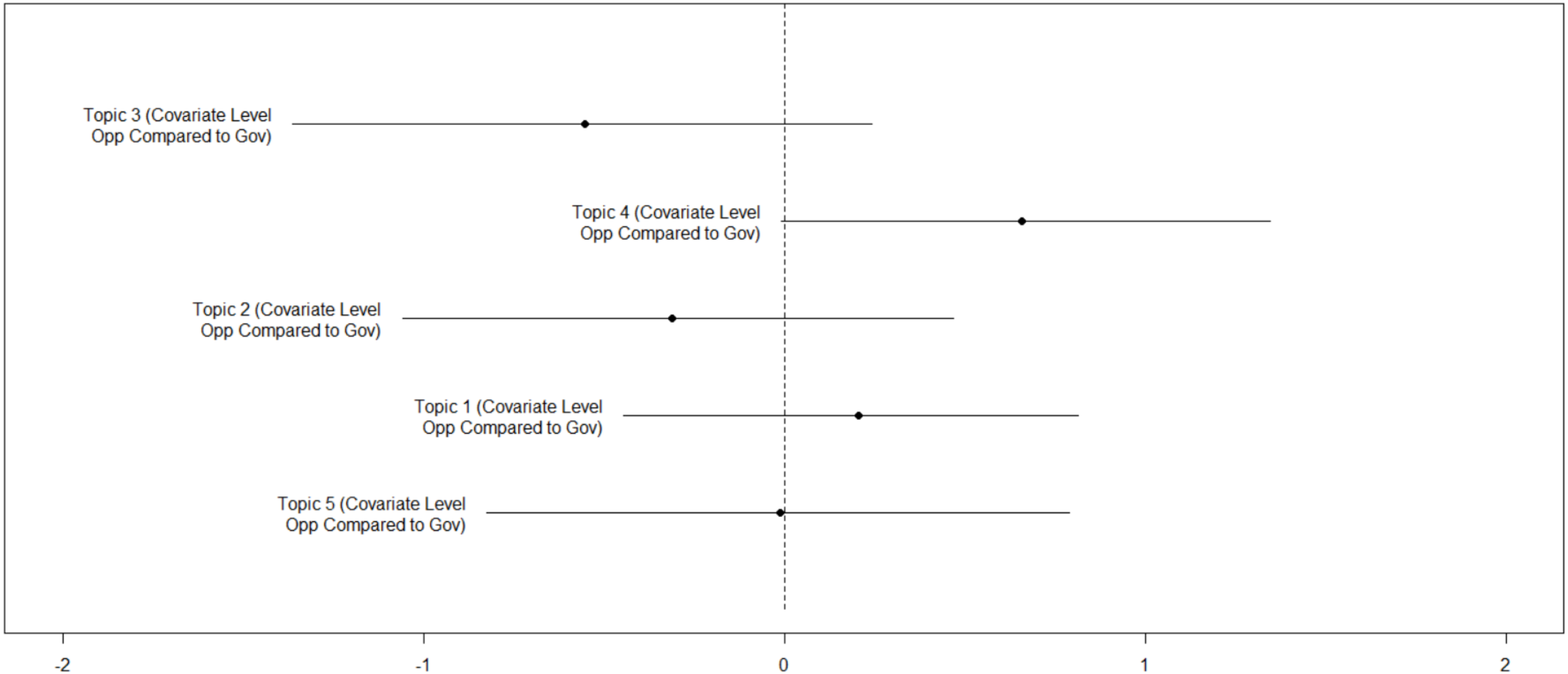
Thus, for example, we can easily obtain measures of how our treatment condition affects how often a topic is discussed (prevalence)!

- for example, do documents of left parties discuss more about a given topic than documents of right parties?

Classification methods



Classification methods



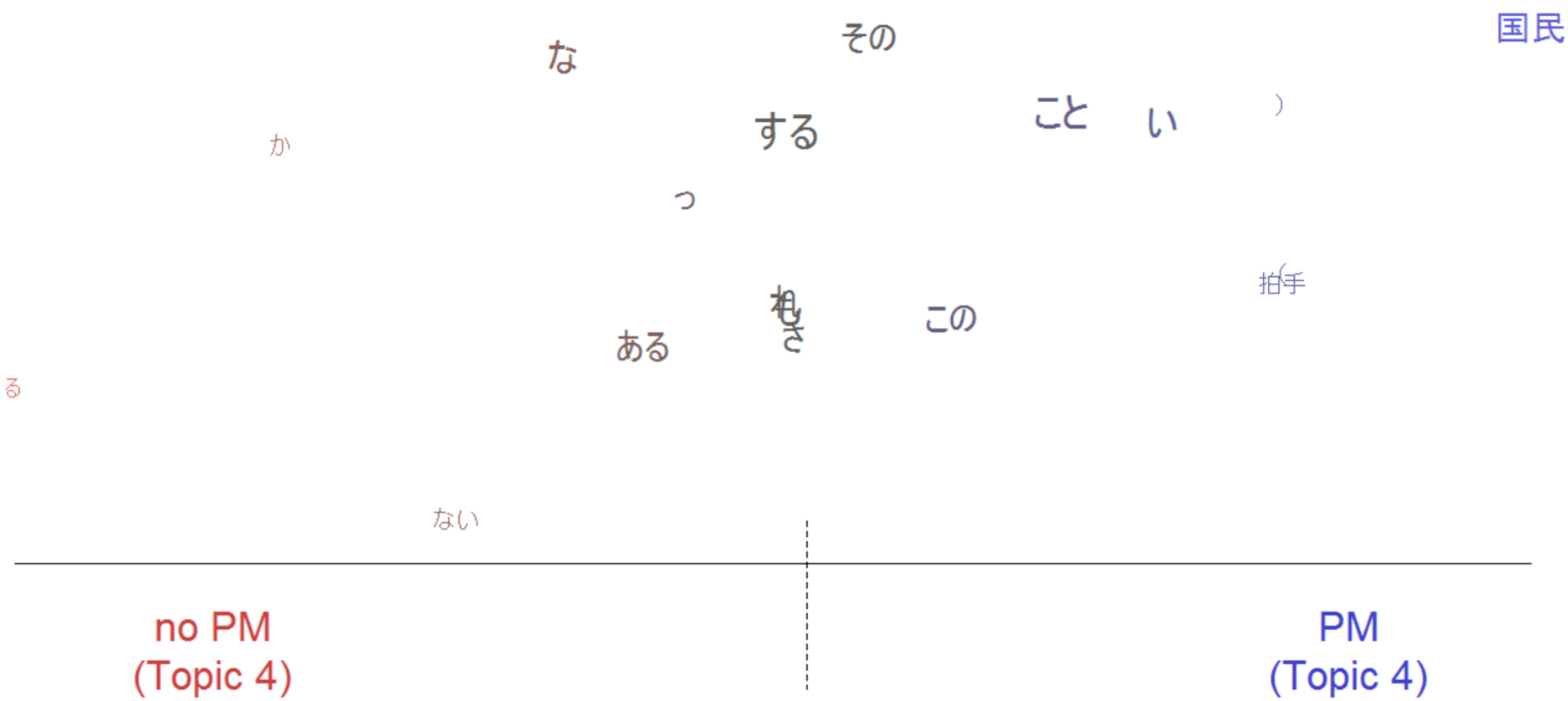
Reported coefficient:
«opposition – government»

Classification methods

Moreover, we can easily obtain measures of how the language used to discuss the same topic (content)

- for example, when men politicians discuss about a particular topic do they use the same words than female politicians?

Classification methods



Classification methods

In the STM framework, the researcher has therefore the option to choose covariates to incorporate in the model

These covariates inform either the **topic prevalence** or the **topical content** latent variables with observed information about the respondent

The analyst will want to include a covariate in the topical prevalence portion of the model (*X*) when she believes that the observed covariate will affect *how much* the respondent is to discuss a particular topic

The analyst also has the option to include a covariate in the topical content portion of the model (*U*) when she believes that the observed covariate will affect *the words which a respondent uses* to discuss a particular topic

Classification methods

These two sets of covariates can overlap, suggesting that the topic proportion and the way the topic is discussed change with particular covariate values

Classification methods

The quantities of interest from a **Structural** Topic Model (beyond θ and β_k of any Topic Model)

QOI: Topical Prevalence Covariate Effects

- Level of Analysis: Corpus
- Part of the Model: θ, X
- Description: Degree of association between a document covariate X and the average proportion of a document discussing each topic.
- Example Finding: Subjects receiving the treatment on average devote twice as many words to Topic 2 as control subjects.

Classification methods

The quantities of interest from a **Structural** Topic Model (beyond θ and β_k of any Topic Model)

QOI: Topical Content Covariate Effects

- Level of Analysis: Corpus
- Part of the Model: κ, U
- Description: Degree of association between a document covariate U and the rate of word use within a particular topic.
- Example Finding: Subjects receiving the treatment are twice as likely to use the word "worry" when writing on the immigration topic as control subjects.

Novel applications of STM

Matching procedure!

Suppose you are interested in analyzing **media-bias**

A fundamental challenge in this domain is how to disentangle the component of bias relating to how a story is covered, i.e., “*presentation bias*”, from the component relating to what is covered, also known as “*selection bias*”

In particular, systematic comparisons of how stories are covered by different news sources (e.g., comparing the level of positive sentiment expressed in the article) may be biased by differences in the content being compared

Novel applications of STM

How to deal with this?

STM (as well as a TM) could help us in this regard!

Suppose you have a corpus of news from different media sources (such as WasPos, NyT, WSJ, etc.) that have been manually codified as presenting a liberal or a conservative view

If we compare the average score obtained by each media source, we can only say something about the relative “liberal” or “conservative” bias of each media source (for example, “the NyT is more liberal than the WSJ”) but we cannot say anything about the source of such media-bias (selection or presentation bias?)

Novel applications of STM

And so?

First, we could run a STM analysis to identify the topics covered in the corpus

Second, we can identify a subset of articles within each media source that discuss highly the same topic (i.e., with a high topic prevalence on the same topic) and therefore similar to each other

This second step allows us to identify the degree of "presentation bias" given that now we are comparing news articles mainly discussing the same topic!

The remaining "bias" is of course to be due to "selection bias"

Novel applications of STM

Of course this is just a possibility

More sophisticated approaches to text matching are available (more or less based on STM)

This is an exciting new area for text analysis that allows to produce more robust observational causal inference (exactly as matching procedures do for a survey for example)

Novel applications of STM

Let’s think about another example:

Social media users living under an authoritarian regime are very often censored every day, but it is largely unknown how the experience of being censored affects their future online experience

Do social media users avoid writing after being censored? Do they continue to write on sensitive topics or do they avoid them? Are social media users who are censored for the first time flagged by censors for increased scrutiny in the future? Is censorship “targeted” and “customized” toward specific users?

Novel applications of STM

Inferring causal effects in observational settings per-se is challenging due to **confounding**

The types of users who are censored **might have different opinions** that drive them to write differently than the types of users who are not censored

This in turn might affect both the users' rate of censorship as well as future behavior and outcomes

So how to deal with that?

Novel applications of STM

Matching on texts!

By conditioning on text, we can match bloggers with similar posts (info obtained via STM) and similar histories of posting for example to identify censorship mistakes: i.e., where one post was censored and the other was not by writing more or less similar things!

By doing that, Roberts et al. (2020) show that censorship increases the probability of future censorship, but it does not have an effect on the number of posts the user writes. This provides evidence that censorship is targeted toward users who are recently censored, but that it does not induce a chilling effect on the number of posts written.

Novel applications of STM

Other applications:

How the gender of international relations scholars affects citations to their articles?

Which is the race effect of similar college admissions profiles and essays on college admissions?

Novel applications of STM

To learn more about this fascinating topic (R packages are available!):

Roberts, M.E. Stewart, B.M., Nielsen R.A. (2020). Adjusting for Confounding with Text Matching, *American Journal of Political Science*, DOI: 10.1111/ajps.12526

Mozer, R. et al. (2020). Matching with Text Data: An Experimental Evaluation of Methods for Matching Documents and of Measuring Match Quality. *Political Analysis*, DOI: 10.1017/pan.2020.1

STM and R

install.packages("stm", repos='http://cran.us.r-project.org')

install.packages("igraph", repos='http://cran.us.r-project.org')

install.packages("wordcloud", repos='http://cran.us.r-project.org')

install.packages("dplyr", repos='http://cran.us.r-project.org')