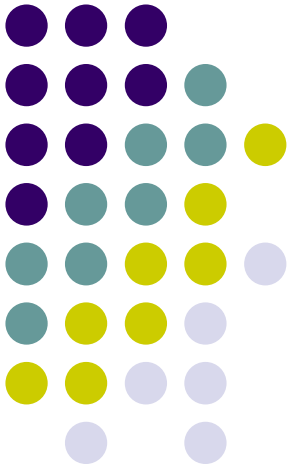
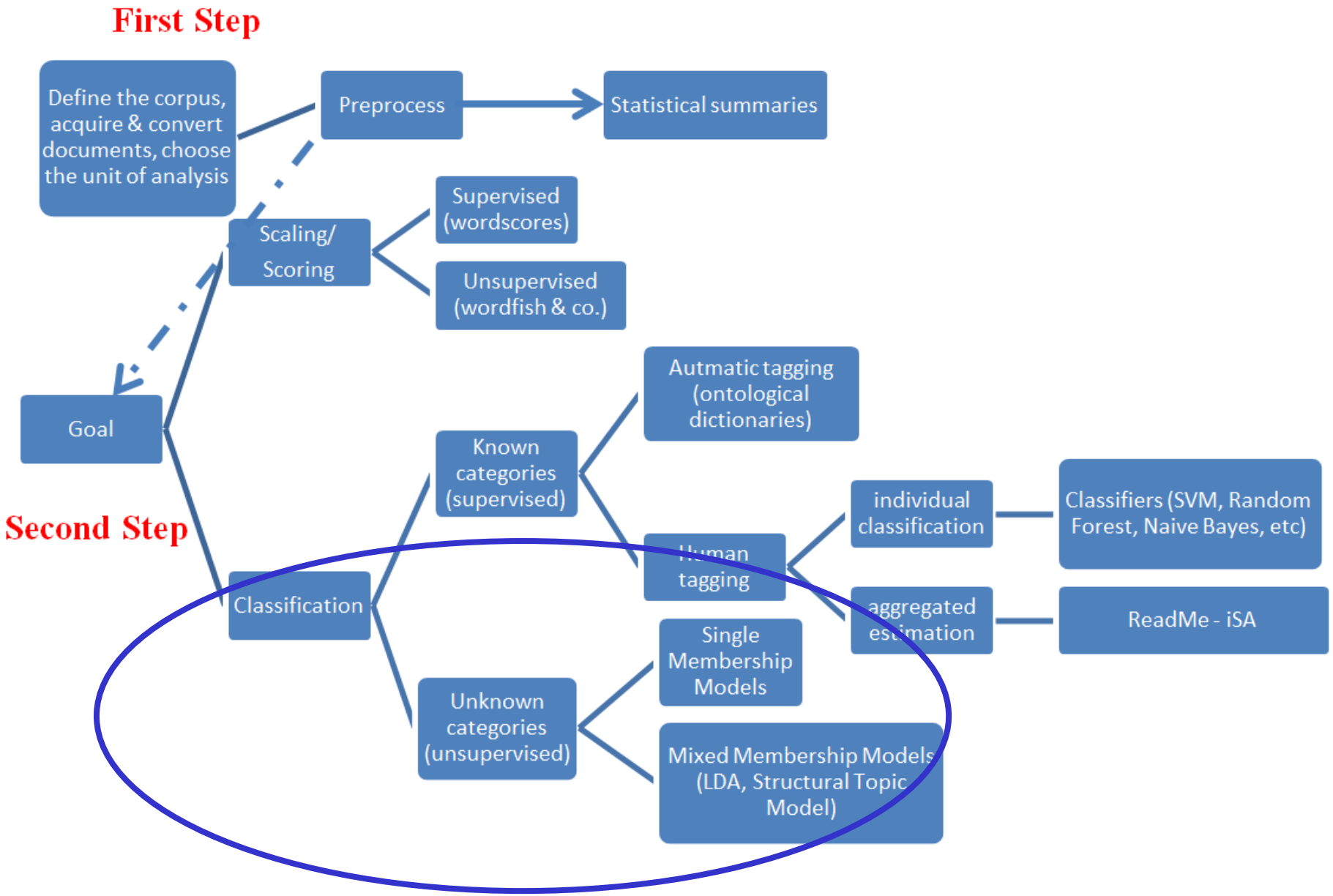
Big Data Analytics

Lecture 5 – Part 1

Unsupervised classification methods: the strucutural topic model



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

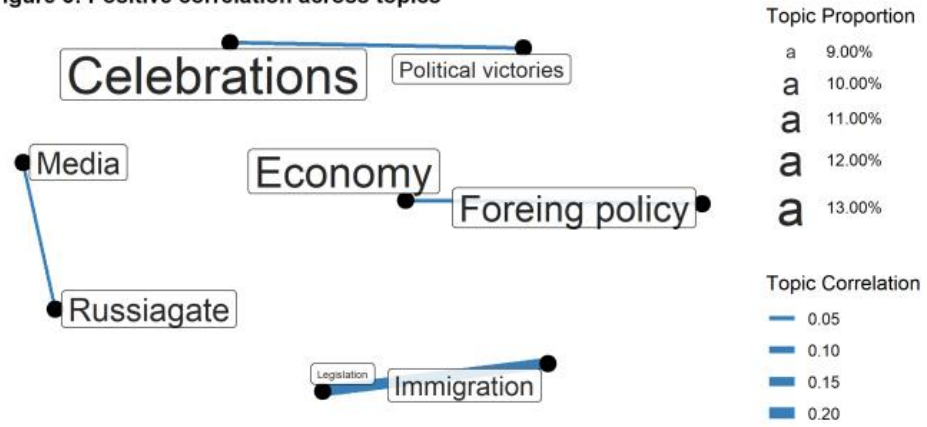
In this sense, STM fits a Correlated Topic Model (rather than a LDA)

Classification methods

Graphical depictions of the (*positive*) 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

Figure 3: Positive correlation across topics



Source: Results from a Structural Topic Model on @realDonaldTrump Twitter account

Classification methods

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 (about the corpus) the analyst might possess. And that shouldn't be always the case…

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

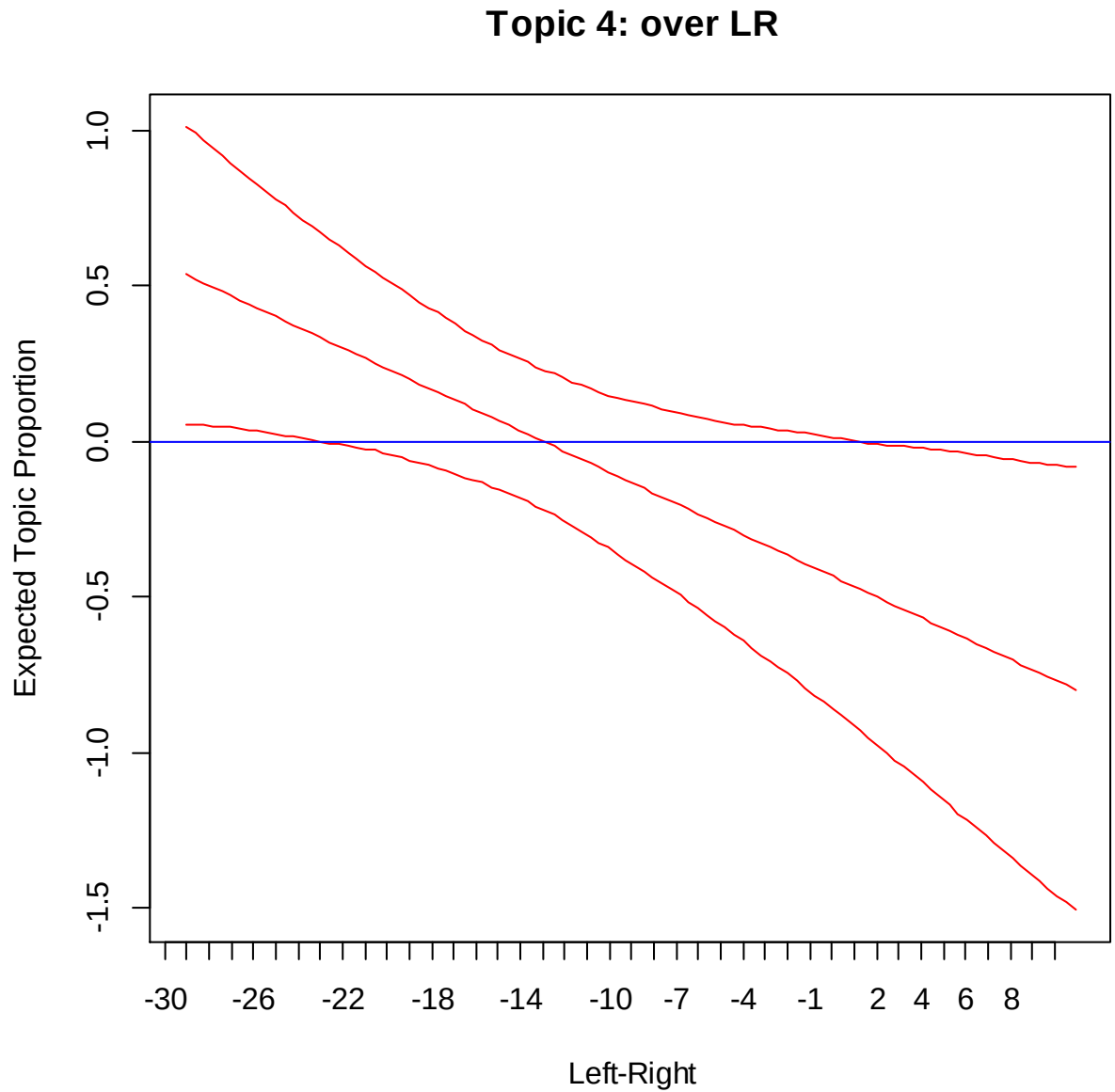
Classification methods

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

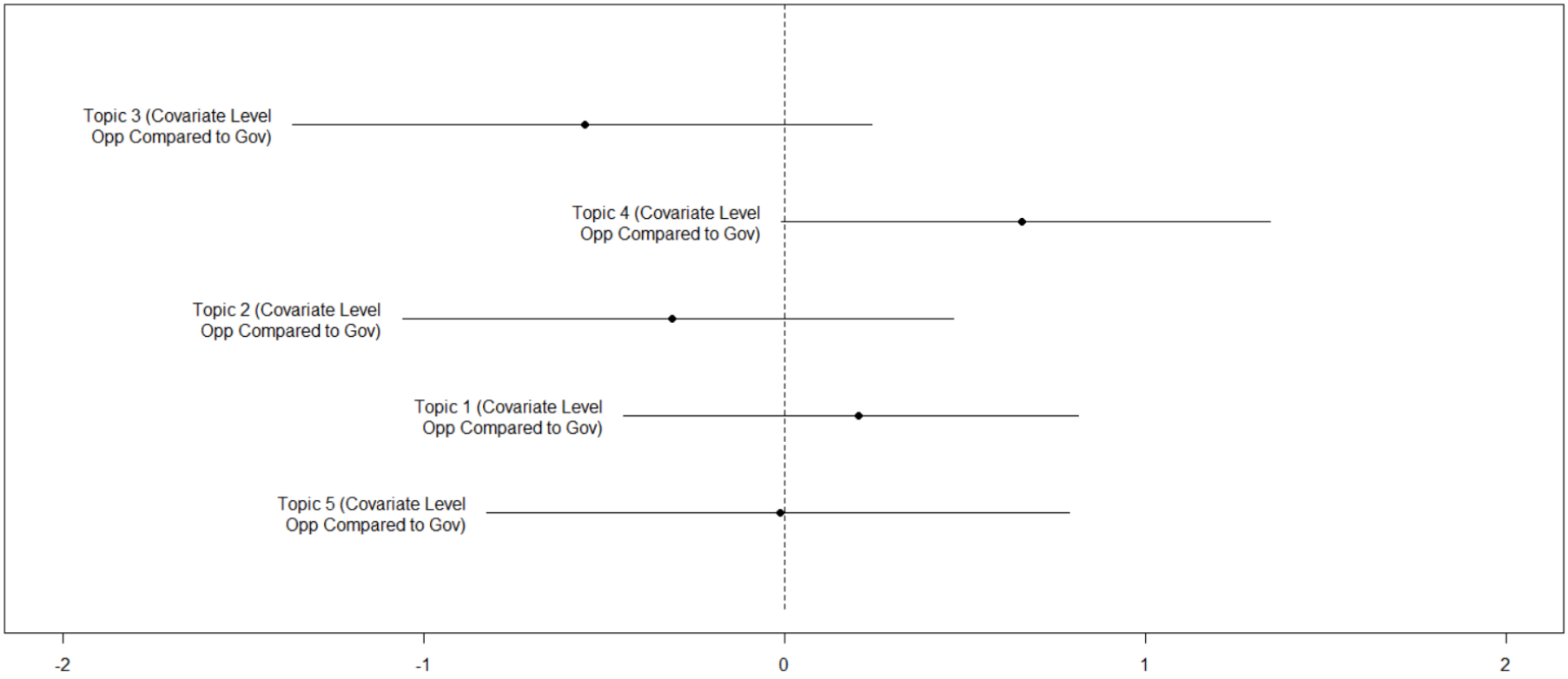
Thus, for example, we can easily obtain measures of how our treatment condition affects how often a topic is discussed (prevalence)!

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

Classification methods



Classification methods



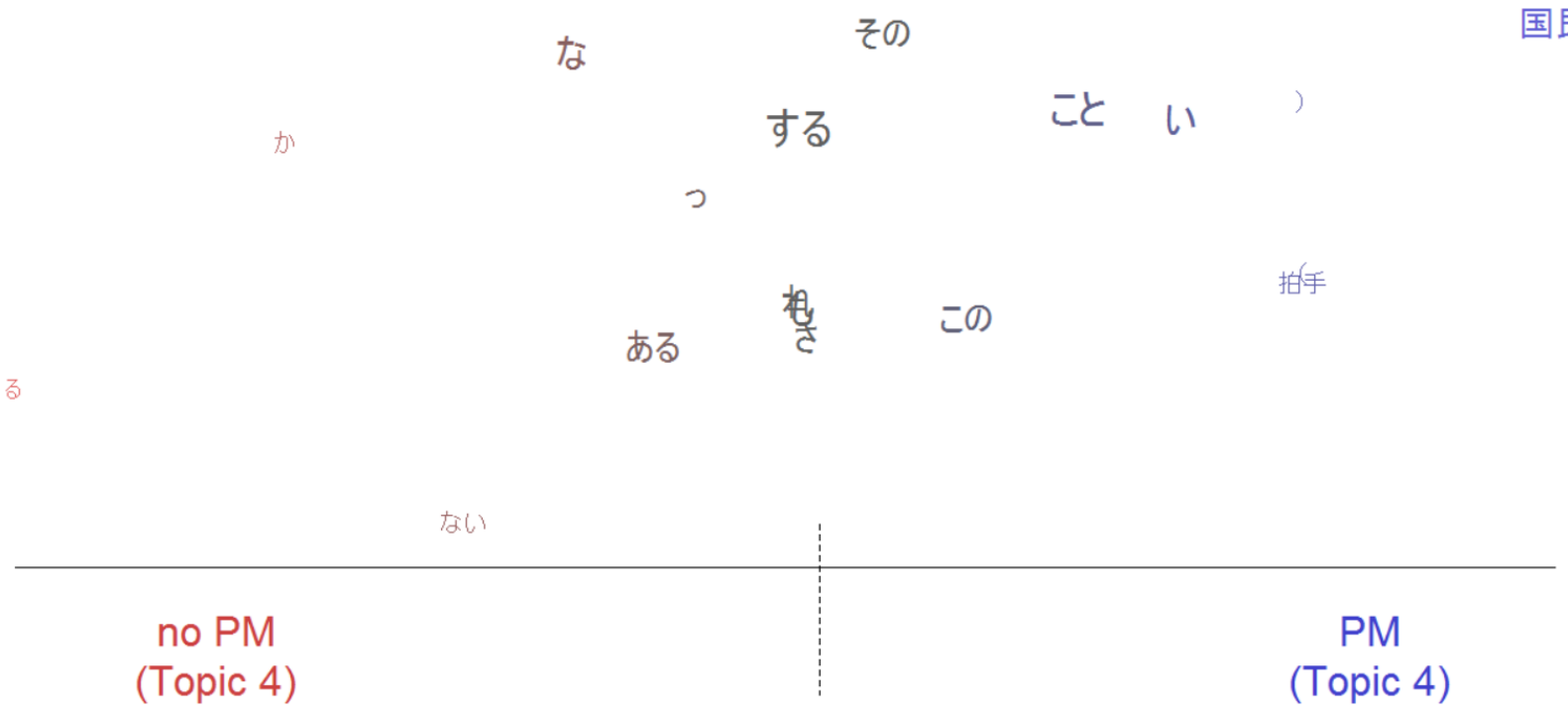
Reported coefficient:
«opposition – government»

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

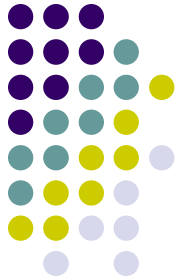
These covariates inform either the **topic prevalence** or the **topical content** latent variables with observed information about the respondent

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.

STM and R

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

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

devtools::install_github("cpsievert/LDAvis")

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

devtools::install_github("mroberts/stmBrowser",dependencies=TRUE)