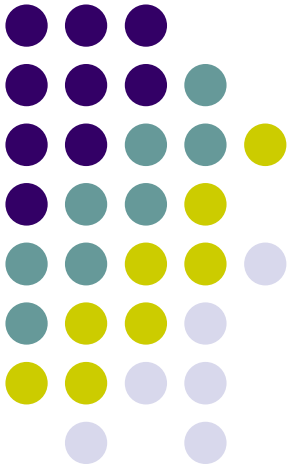
Applied Scaling & Classification Techniques in Political Science

Lecture 6 – Part 1

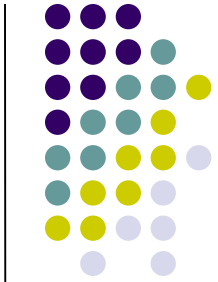
Semisupervised classification methods



Reference

- ✓ Kohei Watanabe and Yuan Zhou (2020) Theory-Driven Analysis of Large Corpora: Semisupervised Topic Classification of the UN Speeches, *Social Science Computer Review*, DOI: 10.1177/0894439320907027
- ✓ Shusei Eshimay Kosuke Imaiz Tomoya Sasakix (2020). Keyword Assisted Topic Models, arXiv:2004.05964v1

Semisupervised classification



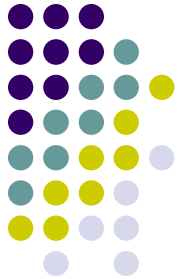
When using **topic models**, most researchers have the topics of interest in mind and possess (hopefully) a substantial amount of knowledge about them

After all, social scientists analyze textual data in order to empirically test hypotheses derived from substantive theories

Thus, researchers should find it natural to incorporate such **prior information** into topic models as keywords

In contrast, the standard topic models such are designed for the settings in which researchers wish to **explore** the contents of corpus, w/o any prior knowledge

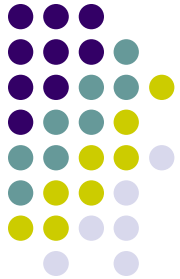
Semisupervised classification



Using topic models (i.e., unsupervised methods) produces therefore results that sometimes are difficult to make sense of (and perhaps not the topics you would be interest in as a researcher…)

Using **dictionary models** (i.e., automatic supervised methods) could also be problematic for the reasons just discussed in our previous class. Moreover, quite often you do not have any dictionary available for the research topic you have in mind!

Semisupervised classification



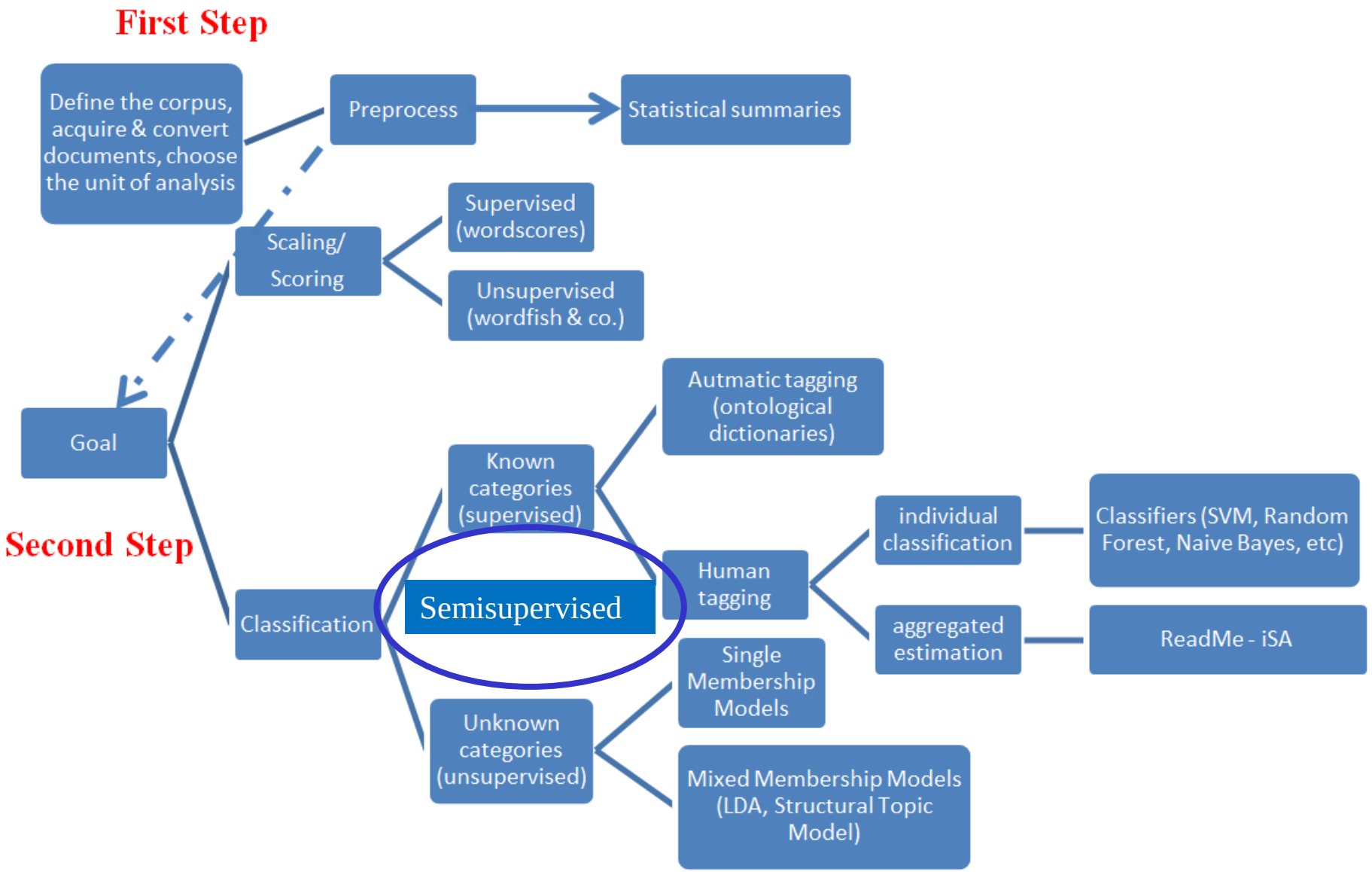
Should we then move to a human supervised methods?

This could present several advantages (as we will discuss!), however it is quite time-consuming: you have to create a training-set from scratch after all (more on this later on)

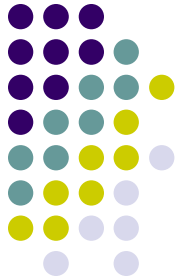
And so?

Perhaps we could give a try to **semisupervised classification**

Our Course Map



Semisupervised classification



How do they work? Let's first discuss **Newsmap**

Suppose we want to classify the news in our corpus according to two class-labels: either if they discuss about Ukraine or Iraq

First thing you have to do is to identify some words that would help us to automatically create a dictionary

Let's call these special words «**seed words**»

In our case, the seed words for countries such as Ukraine and Iraq could be {Ukraine, Ukrainian*, Kiev} and {Iraq, Iraqi*, Baghdad}

Seed words dictionary is the only manual input to the system, and serves as **semi-supervision**

Semisupervised classification

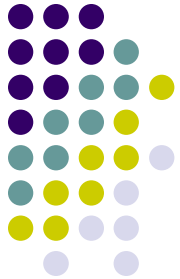
The researcher defines a list of labels/categories (Ukraine and Iraq in our example)

The researcher identifies the **seed-words** associated to each pre-defined categories (the only manual input to the system)

In the **training-stage** the algorithm takes advantage of these seed-words to automatically create a dictionary for each label

Then, in the **classification-stage** the algorithm classifies all the texts (also the texts that do not include any of our seed-words) into one of the pre-defined categories

Semisupervised classification



The training-stage

Firstly, we search individual documents for keywords in the seed dictionary (simple keyword matching) and gives them class labels (countries)

For example, suppose that in the corpus we have the following text: “This is an article about *Ukraine*”

We are going to **automatically label** such document as “Ukraine” given that it includes at least one of the seed-word {Ukraine, Ukrainian*, Kiev}

Semisupervised classification

Secondly, we aggregate the frequency of words according to the class labels to create **contingency tables**, i.e., the labels are used to estimate the association between the labels and features

In the contingency table below, c_j is a country of interest (i.e., Ukraine) and $\bar{C}_j$ is all other countries; w_i is the word for which scores are calculated (say word "article") and w'_i is all other words; *F* values are all raw frequency counts of words in respective classes

	c_j	$\bar{C}_j$
w_i	F_{11}	F_{01}
w'_i	F_{10}	F_{00}
$w_i + w'_i$	$F_{1.}$	$F_{0.}$

Semisupervised classification

The estimated score $\hat{S}$ of word w_i for class-label (country in our case) c_j is then estimated by focusing on **co-occurrences of words**

In particular $\hat{S}_{ij}$ (i.e., the "association score of word *i* for label *j*)" is calculated as the association between w_i and c_j subtracted by the association between w_i and $\overline{C_j}$:

$$\hat{S}_{ij} = log\frac{F_{11}}{F_{1.}} - log\frac{F_{01}}{F_{0.}}$$

Semisupervised classification

This table shows fictional scores given to the words most strongly associated with Ukraine and Iraq

	Ukraine	Score	Iraq	Score
1	Ukraine	11.84	Iraq	11.58
2	Ukrainian	10.36	Baghdad	10.56
3	Kiev	10.34	Iraqi	10.39
4	Ukrainians	7.94	Iraqis	8.15
5	Poroshenko	7.64	Anbar	8.14
6	Mariupol	7.15	Ramadi	7.55
7	Yatseniuk	6.94	Fallujah	7.51
8	Donetsk	6.92	Falluja	7.50
9	Slovyansk	6.84	Kirkuk	7.42
10	Lugansk	6.72	Tikrit	7.36

Many new words are identified based on **co-occurrences** both for Ukraine and Iraq! These words will be added to the **dictionary** you created starting from the original list of seed-words

Semisupervised classification

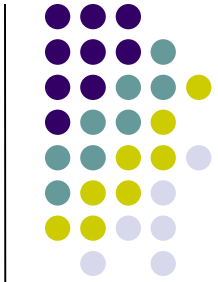
The classification-stage

Newsmap then predicts the class-label (i.e., $\hat{C}$ - countries in our case) most strongly associated with documents simply by finding a class-label that yields the largest total scores $\hat{S}$ weighted by the normalized frequency of word f_i in documents:

$$\hat{C} = \arg\max_j \sum_i \sum_j \hat{s}_{ij} f_i.$$

i.e., a given document will be assigned to Ukraine rather than Iraq if it presents words most frequently used in documents that use one of the seed-words related to Ukraine {Ukraine, Ukrainian*, Kiev} , even if it does not include **any of these seed-words**!

Semisupervised classification



This approach is advantageous because:

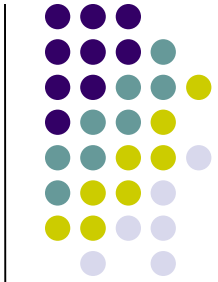
(1) training of new models **does not require** any manual coding but only a **seed word dictionary** used to train semisupervised document classifiers

(2) searching a corpus for dictionary words is not computationally intensive: creating a seed word dictionary for semisupervised models is easier because the number of words required for a seed word dictionary is a fraction of a keyword dictionary

(3) dictionaries can be ported to **different projects** without or little modification

(4) Finally, and contrary to a fully unsupervised model, you know ex-ante the content of the topics you are looking for!

Semisupervised classification



However:

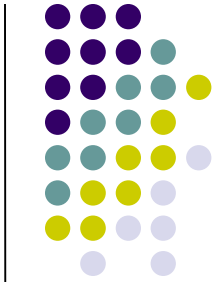
- ✓ use of semisupervised models requires knowledge of both methodology and substance of what you are analyzing!

In particular, your seed-words should be of high quality! And should be present in your corpus!!!

For some suggestions on how to improve a seed-words dictionary list see Watanabe and Zhou (2020)

For example seed word dictionaries should be constructed **based primarily on theory**, but they could also include **frequent words** in the corpus to produce good classification results

Semisupervised classification



However:

- ✓ Newsmap also requires users to define **all the relevant topics** in a seed dictionary because it estimates features' association with a topic by comparing between their frequencies in documents with the label and all other labels, **ignoring documents without labels**

So, for example, if in your corpus you have news discussing about Ukraine, Iraq, but also Italy, then if you have not identified seed-words about Italy as well, Newsmap will be ignore such documents in its training-stage!

Semisupervised classification

An alternative is employing a semi-supervised topic model (Eshimay et al. 2020; Curini and Vignoli 2020)

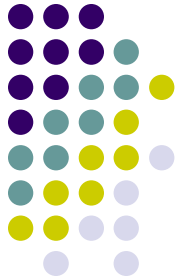
The main idea: we assume that in our corpus there are two types of topics

- ✓ **topics with keywords** (or seeded-words) defined ex-ante by the researcher, which are of primary interest to researchers and are referred to as *keyword topics*

For example, going back to our previous example, we can have 2 *keyword topics*:

a topic related to Ukraine defined by the keywords {Ukraine, Ukrainian*, Kiev} and a topic about Iraq defined by the keywords {Iraq, Iraqi*, Baghdad}

Semisupervised classification



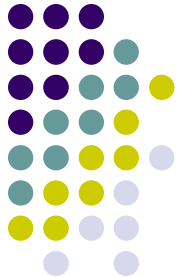
And..

- ✓ **topics without keywords**, called *no-keyword topics*

One key-difference with Newsmap is that you can have therefore one or more of off-kewyords topics (beyond the ones you identify via your seed-words selection). And you can still recover them from the analysis!

Note that the algorithm we will employ is generally robust to the number of off-keywords topics (as long as they are >1)

Semisupervised classification



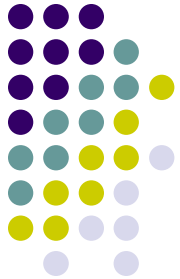
How it works? Going back to our example, let's suppose that we select k=3, with 2 keyword topics (Ukraine and Iraq) and 1 no-keyword topic

A semi-supervised topic model is a traditional topic model with the following difference in the **third step of the procedure** (i.e., after having extracted θ_i and β_k)

First, as usual, you draw a latent topic from θ_i

If the sampled topic is one of the no-keyword topics, then we draw word w_{im} (the *m*th word in document *i*) from the corresponding word distribution of the topic. And we follow our usual approach

Semisupervised classification

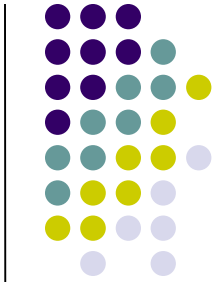


However, if the sampled topic is a keyword topics (i.e., either Ukraine or Iraq), we first draw a Bernoulli random variable with success probability *k* for word *m* in document *i*

If this variable is equal to 1, then word w_{im} is drawn from the set of keywords for the topic that we defined ex-ante

In contrast, if the Bernoulli random variable is equal to 0, then we sample the word from the standard topic-word distribution of the topic

Semisupervised classification



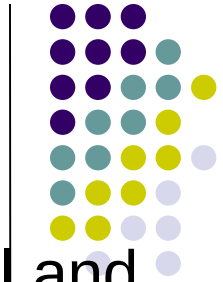
In other words, the semi-supervised topic is based on a mixture of two distributions, one with positive probabilities only for keywords and the other with positive probabilities for all words

It is straightforward to show that this mixture structure makes the prior means for the frequency of user-selected keywords (i.e., seeded-words) given a topic greater than those of non-keywords in the same topic

In addition, the prior variance is also larger for the frequency of keywords given a topic than for non-keywords

This encourages the algorithm to place a greater importance on keywords a priori while allowing the model to learn from the data about the precise degree to which keywords matter for a given topic

Semisupervised classification



As a result, each topic with keywords already has a label and so there is no need to interpret the resulting topics after model fitting (one topic is going to be Ukraine and the other is going to be Iraq)

In contrast, the no-keywords topics require as usual a post-hoc labeling (could it be related to Italy?)

Semisupervised classification

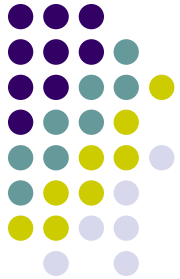
The selection of **high quality keywords** is once again critical for the successful application of such approach!

The keywords should be present in a non-negligible way in the corpus (this is something you can **check ex-ante**)

Moreover, the unique keywords selected for each topic should appear frequently in the keyword topic, i.e., they should discriminate their topics from others (this is something you can **check only ex-post**)

Note that the same keywords may be used for different keyword topics and keywords are a part of the total corpus unique words

Semisupervised classification

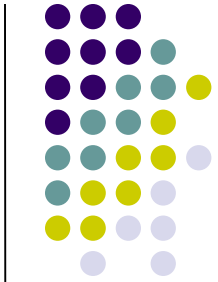


Interestingly, you can incorporate within a semi-supervised topic model also covariates for the document-topic distribution as social scientists often have meta information about documents

This is similar to what we discussed for STM. Do you remember?

We can have, in other words, a *structural* semisupervised classication algorithm!

Semisupervised classification



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

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

devtools::install_github("keyATM/keyATM", ref = "v0.4.0")

Note that also a seeded-LDA model is avaiable (Lu et al. 2011): the seeded LDA model is available in the R package, *topicmodels* or directly from Quanteda using *seededlda*