Applied Scaling & Classification Techniques in Political Science

Lecture 6

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 Eshima, Kosuke Imai, Tomoya Sasaki (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 discussed so far are designed for the settings in which researchers wish to **explore** the contents of corpus, w/o any prior knowledge

Semisupervised classification

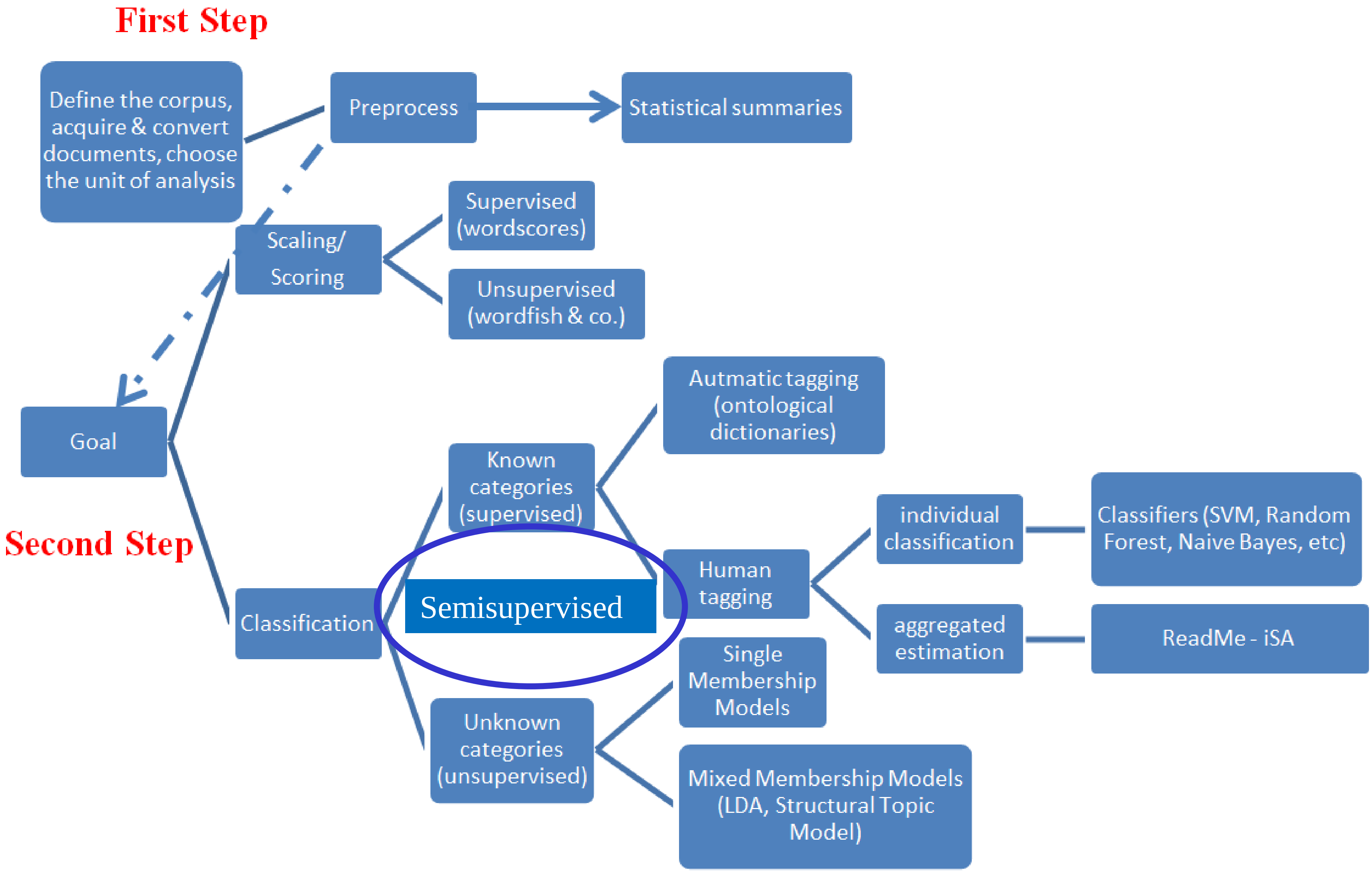
Using topic models (i.e., unsupervised methods) produces therefore results that sometimes are difficult to make sense of (and perhaps not the topics you would be interest in as a researcher…)

Moving to a **dictionary approach** could be therefore attractive (if you already know the category you are interest about)…but we know the challenges of using a dictionary. Plus, if you have to build your own dictionary, this is very time-consuming!

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 4 steps

1. The researcher pre-defines a list of labels/categories in which she is interested (Ukraine and Iraq in our example)

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

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

4. Then, in the **classification-stage** the algorithm classifies all the texts (also 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

Semisupervised classification

In the contingency table below, c_j is a country of interest (i.e., Ukraine) and $\bar{C}_j$ refers to all the other countries (i.e., Iraq in our example)

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 for different subset of texts (i.e., c_j: all those texts that report at least one of the seed-words we defined with respect to Ukraine; $\bar{C}_j$: all those texts that report at least one of the seed-words we defined with respect to Iraq)

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

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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

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

For example, if the word "`article`" appears 4 times in the subset of texts labelled as c_j and this subset includes 100 words, while it appears only once in the subset of texts labelled as $\overline{C}_j$ and this subset includes 300 words, then…

the score for "`article`" with respect to c_j will be: log 4/100 – log 1/300=+1.08

and with respect to $\overline{C}_j$ it will be: log 1/300 – log 4/100=-1.08

As a result, a text that includes only the word "`article`" will be classified, ceteris paribus, as belonging to c_j

Of course, you have to replicate this exercise to estimate a score for all the words in those texts that include at least one seed-word

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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

Through this approach, many new words are identified based on **co-occurrences** both for Ukraine and Iraq! These words will be added to the **dictionary** you created (with a given estimated weight) **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 *j* will be assigned to Ukraine rather than Iraq if it presents words most frequently used in the subset of 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

The classification-stage

From a given point of view, the logic of *Newsmap* is very similar to the logic employed in *Wordscores*:

a) you have a list of «reference texts» (i.e., the set of texts included in your corpus automatically labelled as belonging to a given class-label because they include at least one of your seed-word)

b) you then compute a score for each of the word included in such subset of texts

c) you then use such word-scores to predict the class-labels of all the texts (also those texts w/o any seed-word included in your corpus, i.e., the «virgin texts»)

Semisupervised classification

This approach is advantageous because:

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

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

(3) creating a seed word dictionary is relatively easy because the number of words required for a seed word dictionary is a **fraction of a standard dictionary approach**

(4) dictionaries trained via seed-words can then be ported to **different projects** without or little modification

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 (reasonably) present in your corpus

Semisupervised classification

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

Eshima et al. (2020), however, argue to be cautious about this latter option, because that would imply analyzing the same data as the one used to derive the seed words

Semisupervised classification

- ✓ 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**

Semisupervised classification

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 ignore such documents in its training-stage!

As a result, in the classification stage, the “true” texts discussing about Italy will be either a) classified as Iraq; or b) classified as Ukraine; or c) classified as NAs if they do not include any of the words that are present in the subset of texts that include at least one of your seed-word

Under a) and b) the possibility of false positives clearly can explode!

Semisupervised classification

Finally:

- ✓ Newsmap assigns one single topic to each single text, rather than assuming that each text is a *mixture of topics*. Under some given circumstances, as we already discussed with respect to topic models, this could be a limit (and a strong assumption), i.e., if we have a text discussing about Ukraine *and* Iraq as well

Semisupervised classification

An alternative is employing a semi-supervised topic model (Eshima 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 seed-words using the jargon of Newsmap) 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 discussion, 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!

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 a crucial difference in the **third step of the procedure** (i.e., after having extracted θ_i and β_k)

Classification methods

1. Choose $\theta_i \sim$DIRICHLET(α)
2. Choose $\beta_k \sim$DIRICHLET(δ)
3. Choose a topic z $\sim$Multinomial(θ_i)

If the sampled topic is one of the no-keyword topics, then we follow our usual approach. That is, we draw word w_i from the corresponding word distribution of the topic.:

➢ Choose a word $w_i \sim$Multinomial$\left(\beta_{i,k=z}\right)$

Classification methods

1. Choose θ_i~DIRICHLET(α)
2. Choose β_k~DIRICHLET(δ)
3. Choose a topic z ~Multinomial(θ_i)

If *however* the sampled topic is a keyword topics (i.e., either Ukraine or Iraq)…

- ✓ we first draw a Bernoulli random variable with success probability *p* for word *w* in document *i*
- ✓ If the Bernoulli random variable is equal to 0, then we sample the word from the standard topic-word distribution of the topic
- ➢ Choose a word w_i~Multinomial$\left(\beta_{i,k=z}\right)$
- ✓ **In contrast**, if this variable is equal to 1, then word w is drawn from the set of keywords for the topic that we defined ex-ante

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., seed words) given a topic greater than those of non-keywords in the same topic

Semisupervised classification

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 of a semisupervised topic model, 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

Note that the algorithm we will employ is generally robust to the number of no-keywords topics (as long as they are >0)

Why that? Cause if the keywords are of high quality (more on this below..) and they identify as 20% of document *i* as discussing about keyword topic X, it does not matter if the remaining 80% of document *i* is related to 3 or 10 no-keywords topic; the 20% devoted to topic X will remain still there

This of course also implies that everytime you are estimating a semi-supervised topic model, you are mainly interested in retrieving information about the keyword-topics, while the no-keyword topics are usually treated as simple "noise"

Semisupervised classification

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

1. The keywords selection should be theoretically sound! That also implies that (within each topic) keywords should refer to the same topic!
2. The keywords should be present in a non-negligible way in the corpus (this is something you can **check ex-ante**)
3. 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**)

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 semisupervised *structural* topic 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*