

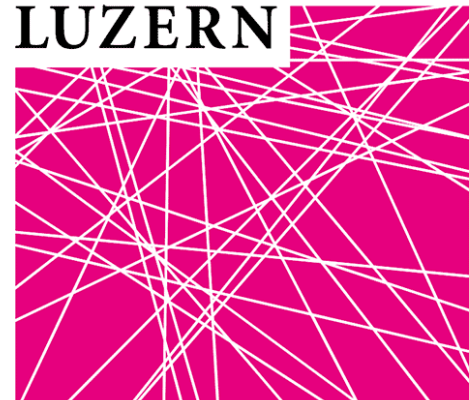
# *Big Data Analytics*

Lecture 2/C

Supervised classification methods:  
automatic tagging



UNIVERSITÄT  
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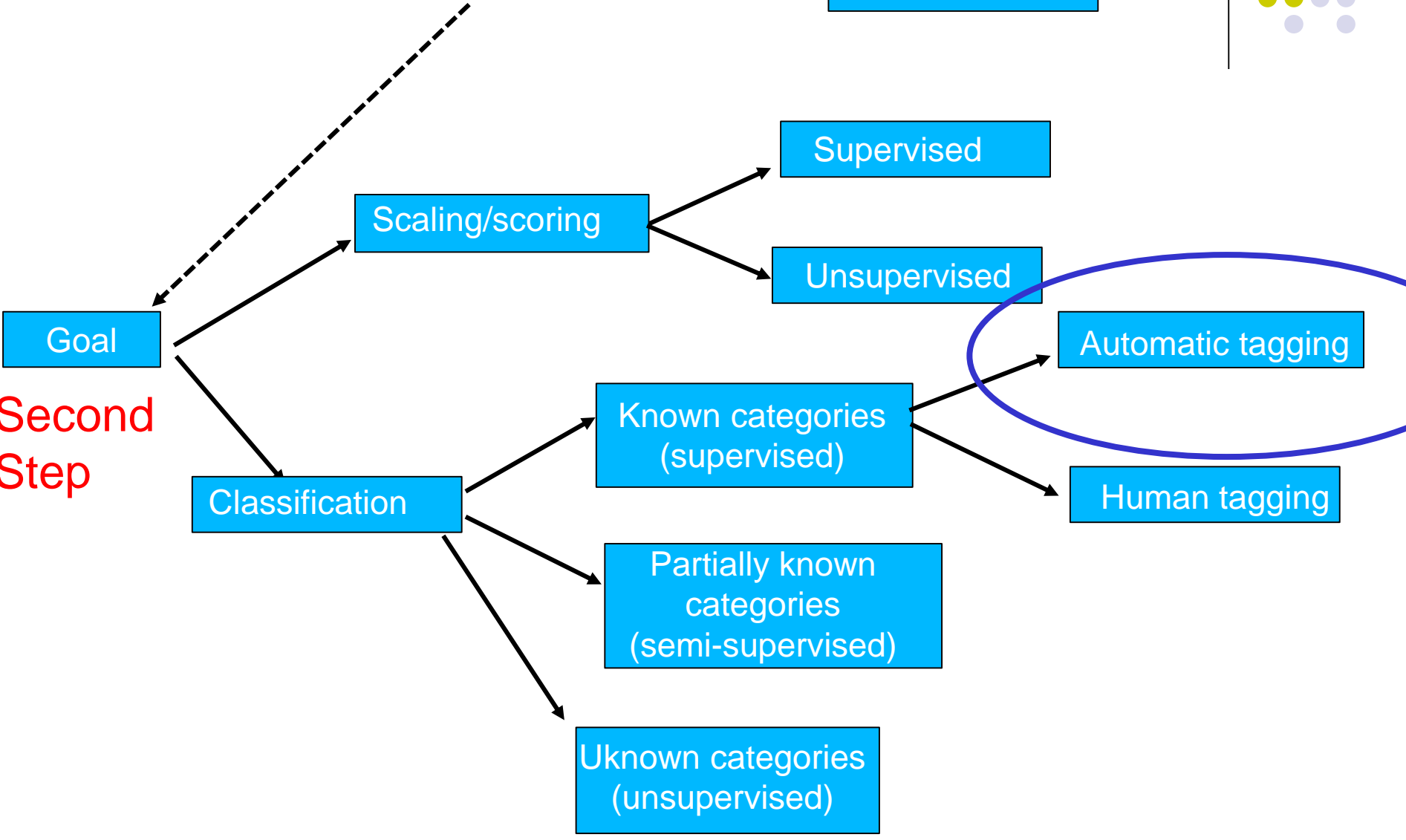


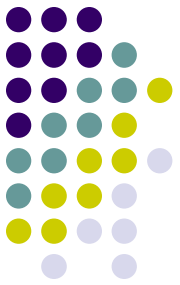


# First Step



# Second Step





# Reference

- ✓ Grimmer, Justin, and Stewart, Brandon M. (2013). Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts. *Political Analysis*, 21(3): 267-297



# Classification methods

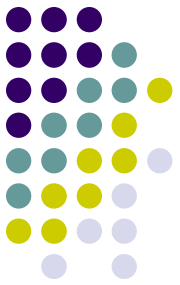
## Supervised Classification Methods

Assigning texts to **some known categories** (rather than to categories *discovered ex-post* the analysis – as it happens with unsupervised classification methods) is the most common use of content analysis methods in political science

For example, researchers may ask if local news coverage is positive or negative, if legislation is about the environment or some other issue area, if international statements are belligerent or peaceful, etc.

In each instance, the goal is to infer to which - among a given set of pre-defined categories - each document must be assigned

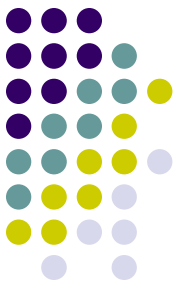
# Classification methods



There are **two broad groups of supervised classification methods** available according to the type of **tagging** (i.e., the assignation of a document to a given pre-defined category) **employed**:

We can have either:

- 1) human tagging - *supervised learning methods*
- 2) automatic tagging - *dictionaries*



# Human tagging

- ✓ **Supervised learning methods** replicate the familiar manual coding task, *but* with a machine

**First**, human coders are used to classify a subset of documents into a predetermined categorization scheme (*human tagging!!!*)

**Second**, this subset is used to train an automated method

**Finally**, the automated method then classifies the remaining unread documents

- ✓ **Dictionaries** use on the contrary the **relative rate** at which key words appear in a text to **classify documents into categories** (*automatic tagging!* No human intervention in the tagging procedure!)

Let's discuss first about automatic tagging...

# Dictionary methods



**Dictionary analysis** is very old but still one of the most popular methods in quantitative text analysis for its *technological simplicity*

Suppose the goal is to measure the **tone** (also called the “**sentiment**”) in newspaper articles: whether articles convey information positively or negatively about a given topic or a given politician

What is a **dictionary**? In this example, a **dictionary to measure sentiment** is simply a list of words that are either dichotomously classified as positive («good», «fantastic», etc.) or negative («bad», «horrible», etc.) or contain more continuous measures (via a set of weights) of their content (to take into account that *fantastic* >> *good* and *horrible* >> *bad*)

# Dictionary methods



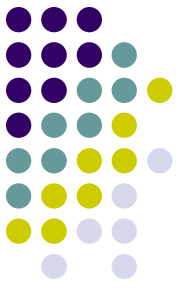
For example, the Lexicoder Sentiment Dictionary (as we will see tomorrow...) aggregates 4,567 sentiment words in the dictionary to two “negative” and “positive” categories

You can then use that dictionary to identify **the tone of a document** (either positive or negative) according to what???

To the **relative number of words** in that document identified by the dictionary as positive or negative ones!!!



# Dictionary methods

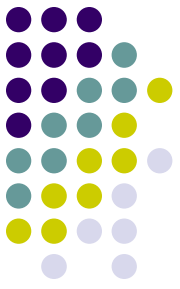


Formally, within a given dictionary  $Z$  each word  $m$  ( $m=1, \dots, M$ ) will have an associated score  $s_m$

For the simplest measures,  $s_m = -1$  if the word is associated with a negative sentiment and  $s_m = +1$  if associated with a positive sentiment

The analyst then applies some *decision rule*, such as summing over all the weighted feature values, to create a score for the document

# Dictionary methods

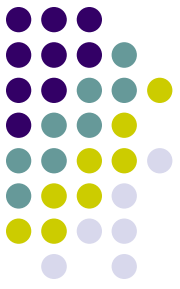


For example, if  $N_i = \sum_{m=1}^M W_{im}$  are the words included in dictionary  $Z$  that are **also** used in document  $i$ , then dictionary methods can use such list of words to measure the sentiment for any document  $t_i$  in the following way:

$$t_i = \sum_{m=1}^M \frac{s_m W_{im}}{N_i}$$

That is, if document  $i$  presents the words «good», «fantastic» and «bad», then  $t_i = (2-1)/3$  or 0.333

# Dictionary methods



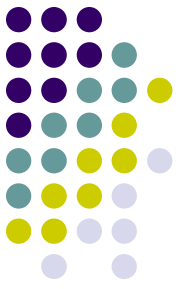
$t_i$  allows therefore to sort documents as to which are more or less positive or negative relative to one other

$t_i$  can also be used to classify documents into **sentiment categories** if a decision rule that identifies a cut point is assumed along with the dictionary method

Perhaps the simplest coding rule would assign all documents with  $t_i > 0$  to a positive sentiment category and  $t_i < 0$  to a negative sentiment

And if  $t_i = 0$ ? Either neutral category or NC

# Dictionary methods

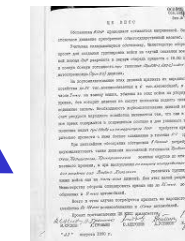
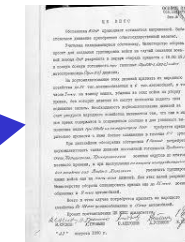
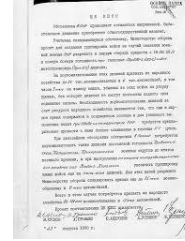
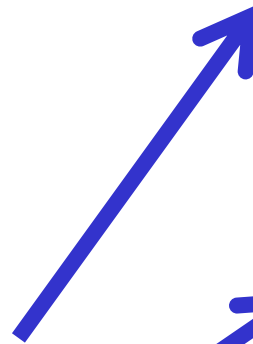
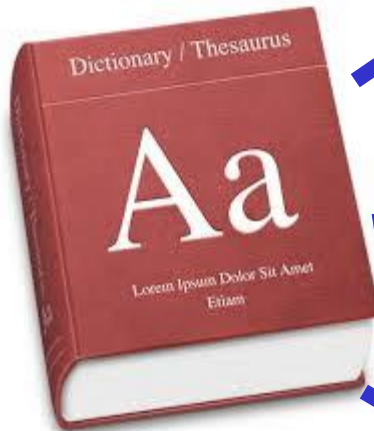
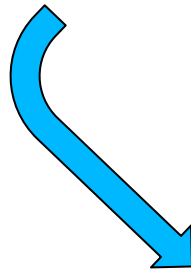


Of course, the words included in the texts you are analyzing that are **not also included** in the dictionary, will not provide any additional information for your classification aim (we will discuss more about this point later on)

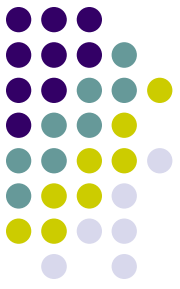
This is similar to what happens with Wordscores! Do you remember?

This also explains why the list of words included in a dictionary should be **relatively large!!!**

# Dictionary methods



# Dictionary methods

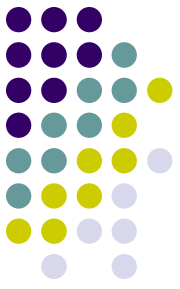


**Sentiment analysis** is just one type of analysis a dictionary method can perform

The general idea of dictionaries is indeed always the same in each given circumstance: identify **words that separate categories** (for example *policy categories*) and measure **how often those words occur in texts**

For example, the Lexicoder Topic Dictionary (Albugh et al., 2013) contains 1,387 keywords under 28 topics (e.g., macroeconomics, civil rights, health care, agriculture) based on the Comparative Agenda Project's coding scheme. If you are interested about it, just let me know!

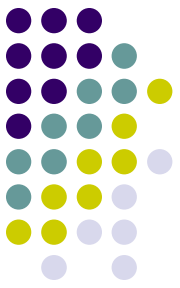
# Dictionary methods



Using a dictionary clearly **minimizes** the amount of labor needed to classify documents (no human involved in the tagging proces after all!)

This is very attractive! Once you have for example a sentiment dictionary, you can apply it to any corpus you have

# Dictionary methods



Users can moreover produce meaningful results easily with dictionaries **regardless of the size** of the corpus

This is because the selection of words is based solely on the pre-defined list

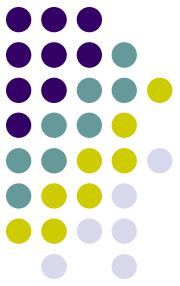
This is a clear advantage when analyzing a *large and noisy corpus* (containing unusual words, tags, etc.), such as a collection of social media posts

Dictionary analysis also works well with *small corpora*, such as responses to open-ended questions, where frequency of words is often too low to perform statistical analysis

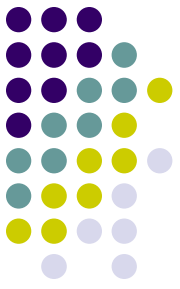


# Dictionary methods

But...beware of the **challenges** of using a dictionary!



# Dictionary methods



First, there is the **problem of availability!**

The very possibility of performing dictionary analysis is dependent on the existence of *suitable dictionaries in the target domain* of your research

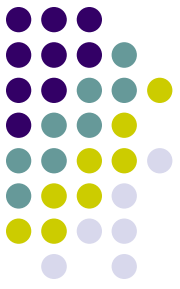
Indeed, for dictionary methods to work well, the scores attached to words must closely align with **how** the words are used in a particular context

If a dictionary is developed for a **specific application**, then this assumption should be easy to justify

But when dictionaries are **created in one substantive area and then applied to another**, serious errors can occur

Why that?

# Dictionary methods

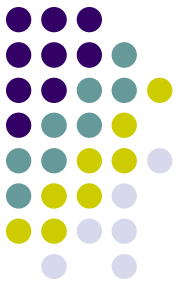


To build a “good” dictionary you need to be sure that all relevant terms are included in it (**no false negatives**, i.e., terms we should have included in the dictionary cause they are relevant given our research topic, but failed to do so)...

...and no irrelevant or wrong terms are (**no false positives**, i.e., terms we have included in the dictionary but should not have, being them irrelevant given our research topic)

In other words, you want to minimize both false negatives as well as false positives

# Dictionary methods



But language do **change across topics!** And when this happens, false negatives and false positives proliferate!

For example, a word like `cancer` may have a positive connotation in a health-care company documents, but negative in many other contexts

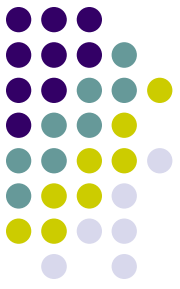
# Dictionary methods



Note that the possibility of performing dictionary analysis is dependent on the existence of *suitable dictionaries* also with respect to languages!

The English language has the largest collection of dictionaries. Several of them also implemented in European languages but not so many in non-European languages

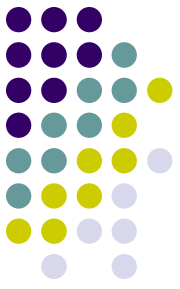
# Dictionary methods



A notable effort has been made in recent years to increase the availability of dictionaries in non-English languages using computational tools (such as Google translator: see Proksch et al. 2019)

However, machine translation of a dictionary from English to non-European languages is not always possible because of the absence of one-to-one correspondence of words and the ambiguity of word semantics out of context

# Dictionary methods



As a result of this *first problem*, quite often you are called to create your own dictionary from scratch to employ dictionary analysis in new domains or languages

But it is not an easy job to collect usually thousands of words that are related to the target concepts...moreover, you need to validate it (more on this later on)

# Dictionary methods



Second, there is the problem of the **complexity of language!**

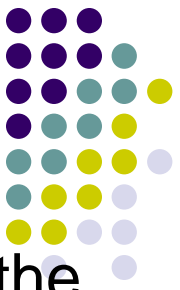
Dictionary methods work pretty well when you study texts that use a **standardized language** (i.e., legal text!).

In other contexts, things become more complex...given that **language evolves continuously**: it is a social construction after all!

That implies, for example, that the list of words included in the dictionary you want to employ (developed at time  $t-1$ ) can be already (partly) outdated (at time  $t$ ), unless you keep updated it...

Moreover, it is almost impossible to code all possible semantic rules in a pre-defined dictionary (double meaning sentences, specific jargons, neologisms, irony)





# Dictionary methods

This last point brings us to our third, and final, challenge: the **problem of implementation!**

**Counting the number of positive and negative terms in a sentence may lead to paradoxical effects**

*"This movie has good premises. Looks like it has a nice plot, an exception"*

5 POSITIVE  
TERMS  
VS 1 NEGATIVE



# Dictionary methods



Dictionaries, therefore, should be used with **substantial caution**, or at least coupled with **explicit validation**

If using dictionaries, choose therefore a dictionary **appropriate** to the task at hand, and **validate** the utility of the dictionary, for example by confirming that a sample of dictionary-generated scores of text in the corpus conform to human coding of the text for the measure of interest (i.e., contrast automatic with human tagging)

On the contrary, **avoid** to assume the measures created from a dictionary are correct and then apply them to the problem

The consequence of **domain specificity and lack of validation** can make your analysis built on shaky foundations...