Working with text: Topic modelling

Damian Trilling

d.c.trilling@uva.nl
@damian0604
www.damiantrilling.net

Afdeling Communicatiewetenschap
Universiteit van Amsterdam

18–1–2018

Today

1. Automated Content Analysis (ACA)
2. Basic top-down ACA: Dictionary- and string-based methods
   - Regular expressions
3. Unsupervised Machine Learning
   - PCA
   - LDA
4. Example and exercise

What's Automated Content Analysis?

	Methodological approach		
	Counting and Dictionary	*Supervised Machine Learning*	*Unsupervised Machine Learning*
Typical research interests and content features	visibility analysis sentiment analysis subjectivity analysis	frames topics gender bias	frames topics
Common statistical procedures	string comparisons counting	support vector machines naive Bayes	principal component analysis cluster analysis latent dirichlet allocation semantic network analysis

deductive → **inductive**

Boumans, J. W., & Trilling, D. (2016). Taking stock of the toolkit: An overview of relevant autmated content analysis approaches and techniques for digital journalism scholars. *Digital Journalism*, *4*(1), 8–23. doi:10.1080/21670811.2015.1096598

Basic ACA: Dictionary- and string-based methods

Regular expressions

Regular Expressions: What and why?

What is a regexp?

- a *very* widespread way to describe patterns in strings

Regular Expressions: What and why?

What is a regexp?

- a *very* widespread way to describe patterns in strings
- Think of wildcards like `*` or operators like `OR`, `AND` or `NOT` in search strings: a regexp does the same, but is *much* more powerful

Regular Expressions: What and why?

What is a regexp?

- a *very* widespread way to describe patterns in strings
- Think of wildcards like `*` or operators like `OR`, `AND` or `NOT` in search strings: a regexp does the same, but is *much* more powerful
- You can use them in many text editors (!), in STATA, R, Python, . . .

An example

We wanted to find references to companies in several years of news coverage

Problems:

- Spelling variations (ABN, ABN Amro, ABN-Amro, . . .)
- Shouldn't be in the middle of the word, but *can* be at the beginning of a word, optionally connected with a hyphen ("ABN-topman", "Shellstation")

For instance,

```
\bING(?:-.*?)?\b
```

allows to specify exactly this.

Strycharz, J., Strauss, N., & Trilling, D. (2017). The role of media coverage in explaining stock market fluctuations: insights for strategic financial communication. *International Journal of Strategic Communication, online first*. doi:10.1080/1553118X.2017.1378220
Jonkman, J. G., Trilling, D., Verhoeven, P., & Vliegenthart, R. (2016). More or less diverse: An assessment of the effect of attention to media salient company types on media agenda diversity in Dutch newspaper coverage between 2007 and 2013. *Journalism, online first*. doi:10.1177/1464884916680371

Basic regexp elements

Alternatives

`[TtFf]` matches either T or t or F or f

`Twitter|Facebook` matches either Twitter or Facebook

`.` matches any character

Basic regexp elements

Alternatives

`[TtFf]` matches either T or t or F or f

`Twitter|Facebook` matches either Twitter or Facebook

`.` matches any character

Repetition

`*` the expression before occurs 0 or more times

`+` the expression before occurs 1 or more times

Possible applications

Data preprocessing

- Remove unwanted characters, words, ...
- Identify *meaningful* bits of text: usernames, headlines, where an article starts, ...
- filter (distinguish relevant from irrelevant cases)

Possible applications

Data analysis: Automated coding

- Actors
- Brands
- links or other markers that follow a regular pattern
- Numbers (!)

This is top-down: we determined a priori what to look for. But what if we do not want to make such assumptions but want to look what 'emerges' from the data? Enter bottom-up approaches:

Unsupervised Machine Learning

Methodological approach

	Counting and Dictionary	*Supervised Machine Learning*	*Unsupervised Machine Learning*
Typical research interests and content features	visibility analysis sentiment analysis subjectivity analysis	frames topics gender bias	frames topics
Common statistical procedures	string comparisons counting	support vector machines naive Bayes	principal component analysis cluster analysis latent dirichlet allocation semantic network analysis

deductive → **inductive**

Boumans, J. W., & Trilling, D. (2016). Taking stock of the toolkit: An overview of relevant autmated content analysis approaches and techniques for digital journalism scholars. *Digital Journalism*, *4*(1), 8–23. doi:10.1080/21670811.2015.1096598

Supervised vs. unsupervised learning

Unsupervised

- No manually coded data
- We want to identify patterns or to make groups of most similar cases

Supervised vs. unsupervised learning

Unsupervised

- No manually coded data
- We want to identify patterns or to make groups of most similar cases

Example: We have a dataset of Facebook-massages on an organizations' page. We use clustering to group them and later interpret these clusters (e.g., as complaints, questions, praise, . . .)

Supervised vs. unsupervised learning

Unsupervised

- No manually coded data
- We want to identify patterns or to make groups of most similar cases

Example: We have a dataset of Facebook-massages on an organizations' page. We use clustering to group them and later interpret these clusters (e.g., as complaints, questions, praise, . . .)

Supervised

- We code a small dataset by hand and use it to "train" a machine
- The machine codes the rest

Supervised vs. unsupervised learning

Unsupervised

- No manually coded data
- We want to identify patterns or to make groups of most similar cases

Example: We have a dataset of Facebook-massages on an organizations' page. We use clustering to group them and later interpret these clusters (e.g., as complaints, questions, praise, . . .)

Supervised

- We code a small dataset by hand and use it to "train" a machine
- The machine codes the rest

Example: We have 2,000 of these messages grouped into such categories by human coders. We then use this data to group all remaining messages as well.

inductive and bottom-up:
unsupervised machine learning

inductive and bottom-up:
unsupervised machine learning

(something you aready did in your Bachelor – no kidding.)

Principal Component Analysis? How does *that* fit in here?

Principal Component Analysis? How does *that* fit in here?

In fact, PCA is used everywhere, even in image compression

Principal Component Analysis? How does *that* fit in here?

PCA in ACA

- Find out what word cooccur (inductive frame analysis)
- Basically, transform each document in a vector of word frequencies and do a PCA

A so-called term-document-matrix

```
      w1,w2,w3,w4,w5,w6 ...
text1, 2, 0, 0, 1, 2, 3 ...
text2, 0, 0, 1, 2, 3, 4 ...
text3, 9, 0, 1, 1, 0, 0 ...
...
```

A so-called term-document-matrix

```
     w1,w2,w3,w4,w5,w6 ...
text1, 2, 0, 0, 1, 2, 3 ...
text2, 0, 0, 1, 2, 3, 4 ...
text3, 9, 0, 1, 1, 0, 0 ...
...
```

These can be simple counts, but also more advanced metrics, like tf-idf scores (where you weigh the frequency by the number of documents in which it occurs), cosine distances, etc.

PCA: implications and problems

- given a term-document matrix, easy to do with any tool
- probably extremely skewed distributions
- some problematic assumptions: does the goal of PCA, to find a solution in which one word loads on *one* component match real life, where a word can belong to several topics or frames?

Enter **topic modeling with Latent Dirichlet Allocation (LDA)**

LDA, what's that?

No mathematical details here, but the general idea

- There are k topics, $T_1 \ldots T_k$
- Each document D_i consists of a mixture of these topics, e.g.$80\% T_1, 15\% T_2, 0\% T_3, \ldots 5\% T_k$
- On the next level, each topic consists of a specific probability distribution of words
- Thus, based on the frequencies of words in D_i, one can infer its distribution of topics
- Note that LDA (like PCA) is a Bag-of-Words (BOW) approach

Doing a LDA in Python

You can use gensim (Řehůřek & Sojka, 2010) for this.

Řehůřek, R., & Sojka, P. (2010). Software framework for topic modelling with large corpora. *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*, pp. 45–50. Valletta, Malta: ELRA.

```
from gensim import corpora, models

NTOPICS = 100
LDAOUTPUTFILE="topicscores.tsv"

# Create a BOW represenation of the texts
id2word = corpora.Dictionary(texts)
mm =[id2word.doc2bow(text) for text in texts]

# Train the LDA models.
lda = models.ldamodel.LdaModel(corpus=mm, id2word=id2word, num_topics=NTOPICS)

# Print the topics.
for top in lda.print_topics(num_topics=NTOPICS, num_words=5):
    print ("\n",top)

# save topic scores
scoresperdoc=lda.inference(mm)
with open(LDAOUTPUTFILE,"w",encoding="utf-8") as fo:
  for row in scoresperdoc[0]:
    fo.write("\t".join(["{:0.3f}".format(score) for score in row]))
    fo.write("\n")
```

Output: Topics (below) & topic scores (next slide)

```
0.069*fusie + 0.058*brussel + 0.045*europesecommissie + 0.036*europese + 0.023*overname
0.109*bank + 0.066*britse + 0.041*regering + 0.035*financien + 0.033*minister
0.114*nederlandse + 0.106*nederland + 0.070*bedrijven + 0.042*rusland + 0.038*russische
0.093*nederlandsespoorwegen + 0.074*den + 0.036*jaar + 0.029*onderzoek + 0.027*raad
0.099*banen + 0.045*jaar + 0.045*productie + 0.036*ton + 0.029*aantal
0.041*grote + 0.038*bedrijven + 0.027*ondernemers + 0.023*goed + 0.015*jaar
0.108*werknemers + 0.037*jongeren + 0.035*werkgevers + 0.029*jaar + 0.025*werk
0.171*bank + 0.122* + 0.041*klanten + 0.035*verzekeraar + 0.028*euro
0.162*banken + 0.055*bank + 0.039*centrale + 0.027*leningen + 0.024*financiele
0.052*post + 0.042*media + 0.038*nieuwe + 0.034*netwerk + 0.025*personeel
...
```

Data Editor (Browse) – topicscores.dta

Edit | Browse | Filter | Variables | Properties | Snapshots

topic4[2] .019

	source2	firstwords	polarity	subjectivity	pubdate_day	pubdate_mo~h	pubdate_year	pubdate_da~k	topic1	topic2	topic3	topic4	topic5
1	nrc handelsblad	palingsound schinke	-.0086207	.6069971	31	12	2011	zaterdag	.018	.019	3.587	.019	.019
2	nrc handelsblad	groep investeerders	-.1041667	.3129167	31	12	2011	zaterdag	.018	.019	.019	.019	.019
3	nrc handelsblad	abnamro debacles ij	.0082292	.4895443	31	12	2011	zaterdag	.018	27.71	.019	.019	.019
4	nrc handelsblad	abnamro financi√´le	-.0179617	.5706419	31	12	2011	zaterdag	.018	15.1	.019	2.646	.019
5	nrc handelsblad	crisis verhouding k	.0758049	.5448864	31	12	2011	zaterdag	.018	.019	9.008	.019	.019
6	nrc handelsblad	snel vakantie vrije	-.016315	.5118808	31	12	2011	zaterdag	.018	.019	.019	.019	.019
7	nrc handelsblad	herinnering doos le	.18875	.6208333	31	12	2011	zaterdag	.018	.019	.019	.019	.019
8	nrc handelsblad	hackers publiceren	.1454545	.4545455	31	12	2011	zaterdag	.018	.019	.019	.019	.019
9	nrc handelsblad	waterballet montevi	-.2333333	.4333333	31	12	2011	zaterdag	.018	.019	.019	.019	.019
10	nrc handelsblad	bouw dupe ambities	.0925417	.5939167	5	11	2010	vrijdag	.018	.019	.078	2.442	.019
11	nrc handelsblad	eindelijk wint nuch	.1755093	.48125	5	11	2010	vrijdag	.018	.019	8.302	.019	.019
12	nrc handelsblad	oud nieuws tv bbcst	.02	.4322222	5	11	2010	vrijdag	.018	10.053	.019	.019	.019
13	nrc handelsblad	tmg hyves krantenbe	.0425203	.5420412	5	11	2010	vrijdag	.018	.019	.019	.019	.019
14	nrc handelsblad	getuigenis rechter	.0858929	.5770833	5	11	2010	vrijdag	.018	.019	.019	11.621	.019
15	nrc handelsblad	akzonobel philips g	.0220455	.4381818	5	11	2010	vrijdag	.018	.019	.019	.019	.019
16	nrc handelsblad	mondiaal kritiek be	-.038172	.3094624	5	11	2010	vrijdag	.018	19.957	.019	.019	.019
17	nrc handelsblad	export diamant fiat	.0628571	.4438095	5	11	2010	vrijdag	.018	4.745	.019	.019	.019
18	nrc handelsblad	canada bod potash r	.0252924	.4795322	5	11	2010	vrijdag	.018	26.741	.019	.019	.019
19	nrc handelsblad	zwakke bouwsector c	.0171	.4736333	14	3	2009	NA	.018	.019	.019	.019	4.806
20	nrc handelsblad	pensioenconflict wa	.028114	.4636842	14	3	2009	NA	.018	.019	.019	.019	.019
21	nrc handelsblad	rechter allin loon	.1318182	.3939394	14	3	2009	NA	.018	.019	.019	.019	.019
22	nrc handelsblad	bad bank remedie da	.0891026	.550641	14	3	2009	NA	.018	10.235	.019	.019	.019
23	nrc handelsblad	bescheiden salaris	-.075	.56	14	3	2009	NA	.018	.019	.019	.019	.019
24	nrc handelsblad	generalmotors autos	.0138889	.4388889	14	3	2009	NA	.018	.019	.019	.019	.019
25	nrc handelsblad	rusland rozen tuinb	.0314141	.5643051	14	3	2009	NA	.018	.019	24.595	.019	.019
26	nrc handelsblad	cynisme oplossing k	.0100833	.6511667	14	3	2009	NA	.018	.019	.019	.019	.019
27	nrc handelsblad	the good bed ugly l	.0265504	.5298449	13	3	2009	NA	.018	.019	.019	.019	.019
28	nrc handelsblad	kerk stroom nietswe	-.0087719	.6149123	13	3	2009	NA	.018	.019	.019	.019	.019
29	nrc handelsblad	kerk stroom goud ac	0	0	13	3	2009	NA	.018	.019	.019	.019	.019
30	nrc handelsblad	supersnelle koekenp	0	0	13	3	2009	NA	.018	.019	.019	.019	.019
31	nrc handelsblad	dalailama chinese e	0	0	13	3	2009	NA	.018	.019	.019	.019	.019
32	nrc handelsblad	bezuinigen hulpgeld	.0894192	.4560606	13	3	2009	NA	.018	.019	.019	.019	.019
33	nrc handelsblad	vaders arbeidsethos	.0160985	.5575758	13	3	2009	NA	.018	.019	.019	.019	.019
34	nrc handelsblad	varkens lux winnaar	.040873	.6218254	4	10	2008	NA	.018	.019	.019	.019	.019
35	nrc handelsblad	liberale kinderopva	.1179095	.5297055	4	10	2008	NA	.018	.019	.019	.019	1.03
36	nrc handelsblad	banken verzinsels k	.068521	.6308389	4	10	2008	NA	8.232	.019	.019	.019	.019
37	nrc handelsblad	rabobanktopman bert	0	0	4	10	2008	NA	.018	.019	.019	.019	.019
38	nrc handelsblad	kinderopvang bril v	0	0	4	10	2008	NA	.018	.019	.019	.019	.019
39	nrc handelsblad	tassen gevoel verli	0	0	4	10	2008	NA	.018	.019	.019	.019	.019
40	nrc handelsblad	abnamro winkelend p	.0876761	.62277	4	10	2008	NA	.018	.019	6.904	.019	5.511
41	nrc handelsblad	abnamro belgi√´ mole	.0439506	.4976852	4	10	2008	NA	.018	.019	.019	.019	.019
42	nrc handelsblad	abnamro handen deut	.1838401	.5264302	4	10	2008	NA	.018	.019	1.854	.019	.019
43	nrc handelsblad	abnamro fortis bank	.0842391	.494058	4	10	2008	NA	4.939	.019	14.39	.019	.019
44	nrc handelsblad	abnamro fortis spra	.0540715	.6290807	4	10	2008	NA	.018	.019	.019	.019	.019
45	nrc handelsblad	abnamro fortis jaar	.0297297	.4960135	4	10	2008	NA	.018	11.041	.019	.019	.019
46	nrc handelsblad	abnamro nederland s	.1006944	.6030555	4	10	2008	NA	.018	.019	.019	.019	.019
47	nrc handelsblad	abnamro belgi√´ mole	.0405952	.5004464	4	10	2008	NA	.018	.019	.019	.019	.019
48	nrc handelsblad	arbeidsmarkt vs sle	.0166667	.4	4	10	2008	NA	7.103	.019	.019	.019	12.682

Variables

Enter filter text here

Name	Label
byline	
section	

Properties

Variables

Name	section
Label	
Type	str26
Format	%26s
Value Label	
Notes	

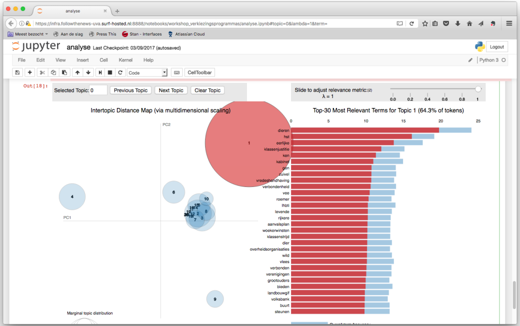
Data

Filename	topicscores.
Label	
Notes	
Variables	164
Observations	28,406
Size	14.06M
Memory	64M

Vars: 158 of 164 Obs: 28,406 Filter: Off

Visualization with pyldavis

```
import pyLDAvis
import pyLDAvis.gensim
% first estiate gensim model, then:
vis_data = pyLDAvis.gensim.prepare(lda,mm,id2word)
pyLDAvis.display(vis_data)
```



Supervised machine learning is something for another time . . .

Example and exercise

Let's have a look at the EU-speech dataset (Jupyter Notebook).
I'll first walk you through the example, afterwards, you have time to play with the data yourself.

Damian Trilling

d.c.trilling@uva.nl
@damian0604
www.damiantrilling.net