Unsupervised approaches to detecting topics in news and politics

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Today

1. Types of Automated Content Analysis
2. PCA and Clustering
3. LDA Topic models
    - An introduction to LDA
    - Choosing the best (or a good) topic model
    - Using topic models
    - Other forms of topic models
4. Let's do it!

Types of 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

Some terminology

Supervised machine learning

You have a dataset with both predictor and outcome (independent and dependent variables; features and labels) — a *labeled* dataset.

Some terminology

Supervised machine learning

You have a dataset with both predictor and outcome (independent and dependent variables; features and labels) — a *labeled* dataset. Think of regression: You measured `x1`, `x2`, `x3` and you want to predict `y`, which you also measured

Some terminology

Supervised machine learning

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Unsupervised machine learning

You have no labels.

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Supervised machine learning

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Unsupervised machine learning

You have no labels. (You did not measure y)

Some terminology

Unsupervised machine learning

You have no labels.

You probably already know some techniques to find out how `x1`, `x2`,...`x_i` co-occur:

- Principal Component Analysis (PCA) and Singular Value Decomposition (SVD)
- Cluster analysis
- ...

PCA and Clustering

Let's assume we want to find out the topics in a large corpus of documents

We could, for example

- use PCA to find out related features (and interpret those as topics)
- or use clustering to find similar documents (and then look at the words they share to interpret as topics)

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- use PCA to find out related features (and interpret those as topics)
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Actually, we have *two* things we want to model:

1. Which topics can we extract from the corpus?
2. How present is each of these topics in each text in the corpus?

Recap: PCA

Document-term 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.

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```

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.

- 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?

Recap: clustering

- given a term-document matrix, we can easily find clusters of documents that resemble each other
- but also here does the goal of cluster analysis, assigning each document to *one* cluster, match real life?

We need other models to

1. model *simultaneously* (a) which topics we find in the whole corpus, and (b) which of these topics are present in which document; while at the same time

Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., . . . Adam, S. (2018). Applying LDA Topic Modeling in Communication Research: Toward a Valid and Reliable Methodology. *Communication Methods and Measures, 12*(2–3), 93–118. doi:10.1080/19312458.2018.1430754

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2. allowing (a) words to be part of multiple topics, and (b) multiple topics to be present in one document; and
3. being able to make connections between words "even if they never actually occured in a document together" (Maier et al, 2018, p. 96)

Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., . . . Adam, S. (2018). Applying LDA Topic Modeling in Communication Research: Toward a Valid and Reliable Methodology. *Communication Methods and Measures, 12*(2–3), 93–118. doi:10.1080/19312458.2018.1430754

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.
Let us assume you have a list of lists of words (!) called `texts`:

```
articles=[’The tax deficit is higher than expected. This said xxx ...’,
    ’Germany won the World Cup. After a’]
texts=[art.split() for art in articles]
```

which looks like this:

```
[[’The’, ’tax’, ’deficit’, ’is’, ’higher’, ’than’, ’expected.’, ’This’,
    ’said’, ’xxx’, ’...’], [’Germany’, ’won’, ’the’, ’World’, ’Cup.’, ’
    After’, ’a’]]
```

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.
mylda = models.ldamodel.LdaModel(corpus=mm, id2word=id2word, num_topics=
    NTOPICS, alpha="auto")

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

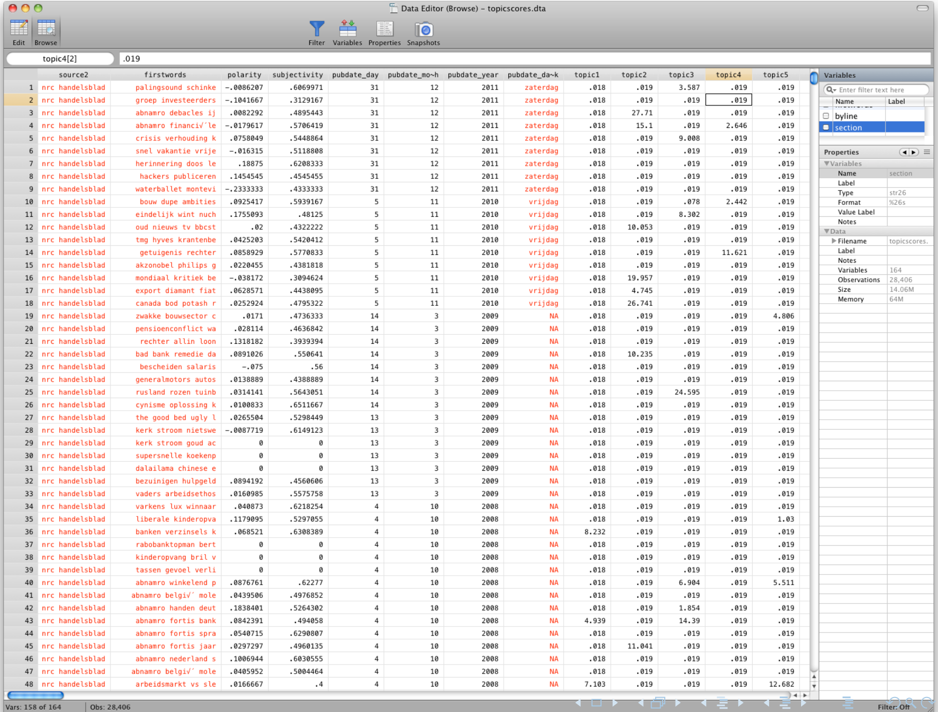
print ("\nFor further analysis, a dataset with the topic score for each
    document is saved to",LDAOUTPUTFILE)

scoresperdoc=mylda.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)

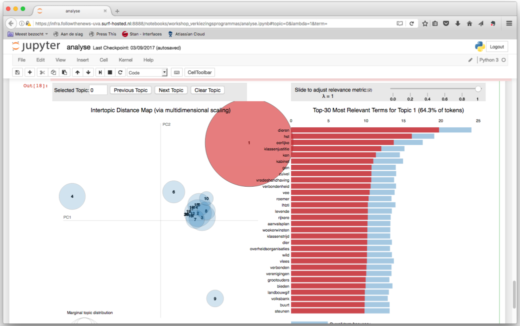
```
0.069*fusie + 0.058*brussel + 0.045*europesecommissie + 0.036*europese +
     0.023*overname
0.109*bank + 0.066*britse + 0.041*regering + 0.035*financien + 0.033*
     minister
0.114*nederlandse + 0.106*nederland + 0.070*bedrijven + 0.042*rusland +
     0.038*russische
0.093*nederlandsespoorwegen + 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
...
```



	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

Visualization with pyldavis

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



Visualization with pyldavis

Short note about the λ setting:
It influences the ordering of the words in pyldavis.

> *"For $\lambda = 1$, the ordering of the top words is equal to the ordering of the standard conditional word probabilities. For λ close to zero, the most specific words of the topic will lead the list of top words. In their case study, Sievert and Shirley (2014, p. 67) found the best interpretability of topics using a λ-value close to .6, which we adopted for our own case" (Maier et al., 2018, p. 107)*

Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., ... Adam, S. (2018). Applying LDA Topic Modeling in Communication Research: Toward a Valid and Reliable Methodology. *Communication Methods and Measures, 12*(2–3), 93–118. doi:10.1080/19312458.2018.1430754

Choosing the best (or a good) topic model

- There is no single best solution (e.g., do you want more coarse or fine-grained topics?)
- Non-deterministic
- Very sensitive to preprocessing choices
- Interplay of both metrics and (qualitative) interpretability

See for more elaborate guidance:

Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., . . . Adam, S. (2018). Applying LDA Topic Modeling in Communication Research: Toward a Valid and Reliable Methodology. *Communication Methods and Measures, 12*(2–3), 93–118. doi:10.1080/19312458.2018.1430754

Evaluation metrics (closer to zero is better)

perplexity

A goodness-of-fit measure, answering the question: If we do a train-test split, how well does the trained model fit the test data?

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coherence

- mean coherence of the whole model: attempts to quantify the interpretability
- coherence per topic: allows to get topics that are most likely to be coherently interpreted (`.top_topics()`)

Choosing k: How many topics do we want?

- Typical values: $10 < k < 200$
- Too low: losing nuance, so broad it becomes meaningless
- Too high: picks up tiny pecularities instead of finding general patterns
- There is no inherent ordering of topics (unlike PCA!)
- We can throw away or merge topics later, so if out of $k = 50$ topics 5 are not interpretable and a couple of others overlap, it still may be a good model

Choosing α: how sparse should the document-topic distribution θ be?

- The higher α, the more topics per document
- Default: $1/k$
- But: We can explicitly change it, or – really cool – even learn α from the data (`alpha = "auto"`)

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Takeaway: It takes longer, but you probably want to learn alpha from the data, using multiple passes:

```
mylda LdaModel(corpus=tfidfcorpus[ldacorpus], id2word=id2word,
    num_topics=50, alpha='auto', passes=10)
```

Choosing η: how sparse should the topic-word distribution λ be?

- Can be used to boost specific words
- Can also be learned from the data

Choosing η: how sparse should the topic-word distribution λ be?

- Can be used to boost specific words
- Can also be learned from the data

Takeaway: Even though you can do `eta="auto"`, this usually does not help you much.

Using topic models

You got your model – what now?

1. Assign topic scores to documents
2. Label topics
3. Merge topics, throw away boilerplate topics and similar (manually, or aided by cluster analysis)
4. Compare topics between, e.g., outlets
5. or do some time-series analysis.

Example: Tsur, O., Calacci, D., & Lazer, D. (2015). A Frame of Mind: Using Statistical Models for Detection of Framing and Agenda Setting Campaigns. *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing* (pp. 1629–1638).

Other forms of topic models

Other forms of topic models

- Author-topic models
- Structural topic models
- Non-negative matrix factorization
- ...

Let's do it!

(go to Google colab)