

# Big Data & Automated Content Analysis

## Week 11 – Wednesday: »Unsupervised Approaches to Text Analysis«

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# Today

Recap: PCA and Clustering

LDA Topic models

- An introduction to LDA

- Choosing the best (or a good) topic model

- Using topic models

- Other forms of topic models

Next steps

## Recap

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# Recap

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## PCA and Clustering

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

We could either

- 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)

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?

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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

```
1      w1,w2,w3,w4,w5,w6 ...
2 text1, 2, 0, 0, 1, 2, 3 ...
3 text2, 0, 0, 1, 2, 3, 4 ...
4 text3, 9, 0, 1, 1, 0, 0 ...
5 ...
```

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?

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## 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
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 occurred 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

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# LDA Topic models

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An introduction to LDA

Enter topic modeling with Latent Dirichlet Allocation (LDA)

# LDA, what's that?

## No mathematical details here, but the general idea

- There are  $k$  topics,  $T_1 \dots T_k$
- Each document  $D_i$  consists of a mixture of these topics, e.g.  $80\% T_1, 15\% T_2, 0\% T_3, \dots 5\% T_k$
- 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:

```
1 articles=['The tax deficit is higher than expected. This said xxx ...',  
           'Germany won the World Cup. After a']  
2 texts=[[token for token in re.split(r"\W", art) if len(token)>0] for art  
          in articles]
```

which looks like this:

```
1 [['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.

```
1 from gensim import corpora, models
2
3 NTOPICS = 100
4 LDAOUTPUTFILE="topicscores.tsv"
5
6 # Create a BOW representation of the texts
7 id2word = corpora.Dictionary(texts)
8 mm=[id2word.doc2bow(text) for text in texts]
9
10 # Train the LDA models.
11 mylda = models.ldamodel.LdaModel(corpus=mm, id2word=id2word, num_topics=
    NTOPICS, alpha="auto")
12
13 # Print the topics.
14 for top in mylda.print_topics(num_topics=NTOPICS, num_words=5):
15     print ("\n",top)
16
17 print ("\nFor further analysis, a dataset with the topic score for each
    document is saved to",LDAOUTPUTFILE)
18
19 scoresperdoc=mylda.inference(mm)
20
21 with open(LDAOUTPUTFILE,"w",encoding="utf-8") as fo:
22     for row in scoresperdoc[0]:
23         fo.write("\t".join(["{:0.3f}".format(score) for score in row]))
```

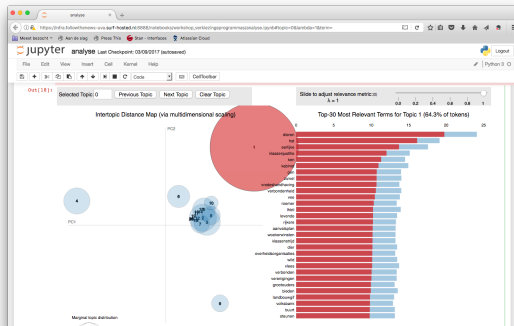
## Output: Topics (below) & topic scores (next slide)

```
1 0.069*fusie + 0.058*brussel + 0.045*europese commissie + 0.036*europese +
   0.023*overname
2 0.109*bank + 0.066*britse + 0.041*regering + 0.035*financien + 0.033*
   minister
3 0.114*nederlandse + 0.106*nederland + 0.070*bedrijven + 0.042*rusland +
   0.038*russische
4 0.093*nederlandsespoorwegen + 0.074*den + 0.036*jaar + 0.029*onderzoek +
   0.027*raad
5 0.099*banen + 0.045*jaar + 0.045*productie + 0.036*ton + 0.029*aantal
6 0.041*grote + 0.038*bedrijven + 0.027*ondernemers + 0.023*goed + 0.015*
   jaar
7 0.108*werknemers + 0.037*jongeren + 0.035*werkgevers + 0.029*jaar +
   0.025*werk
8 0.171*bank + 0.122* + 0.041*klanten + 0.035*verzekeraar + 0.028*euro
9 0.162*banken + 0.055*bank + 0.039*centrale + 0.027*leningen + 0.024*
   financiële
10 0.052*post + 0.042*media + 0.038*nieuwe + 0.034*netwerk + 0.025*
    personeel
11 ...
```

Data Editor (Browse) - topicscores.data													
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	.3129194	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	.5118008	31	12	2011	zaterdag	.018	.019	.019	.019	.019
7	nrc handelsblad	herinnering doos le	.18875	.6200333	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 nontevi	-.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 nuh	.1755093	.48125	5	11	2010	vrijdag	.018	.019	8.302	.019	.019
12	nrc handelsblad	oud nieuws tv bbct	.02	.4322222	5	11	2010	vrijdag	.018	10.053	.019	.019	.019
13	nrc handelsblad	tag hyves krantenb	.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	.3894624	5	11	2010	vrijdag	.018	19.957	.019	.019	.019
17	nrc handelsblad	export diamant fiat	.0628571	.4438895	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	cynisae oplossing k	.0100033	.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 koekn	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	.040073	.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	1.83
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 winklend 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	.6830555	4	10	2008	NA	.018	.019	.019	.019	.019
47	nrc handelsblad	abnamro belgi' mole	.0405952	.5804464	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

```
1 import pyLDAvis
2 import pyLDAvis.gensim_models as gensimvis
3 # first estiate gensim model, then:
4 vis_data = gensimvis.prepare(mylda,mm,id2word)
5 pyLDAvis.display(vis_data)
```



## Visualization with pyldavis

Short note about the  $\lambda$  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  $\lambda$  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  $\lambda$ -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

## Code examples

[https://github.com/damian0604/bdaca/blob/master/  
rm-course-2/week12/lda.ipynb](https://github.com/damian0604/bdaca/blob/master/rm-course-2/week12/lda.ipynb)

# LDA Topic models

---

Choosing the best (or a good) topic model



## Choosing the best (or a good) topic model

- There is no single best solution (e.g., do you want more coarse of 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?

## 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()`)

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- 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()`)

## So, how do we do this?

- Basically, similar to the idea behind our grid search from two weeks ago: estimate multiple models, store the metrics for each model, and then compare them (numerically, or by plotting)
- Idea: We select some candidate models, and then look whether they can be interpreted.
- But what can we tune?

## So, how do we do this?

- Basically, similar to the idea behind our grid search from two weeks ago: estimate multiple models, store the metrics for each model, and then compare them (numerically, or by plotting)
- Idea: We select some candidate models, and then look whether they can be interpreted.
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## So, how do we do this?

- Basically, similar to the idea behind our grid search from two weeks ago: estimate multiple models, store the metrics for each model, and then compare them (numerically, or by plotting)
- Idea: We select some candidate models, and then look whether they can be interpreted.
- But what can we tune?

## 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 peculiarities 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 $\alpha$ : how sparse should the document-topic distribution $\theta$ be?

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

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

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



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## Choosing $\eta$ : how sparse should the topic-word distribution $\lambda$ 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.

## Choosing $\eta$ : how sparse should the topic-word distribution $\lambda$ be?

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

# LDA Topic models

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Using topic models

# 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).

# LDA Topic models

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Other forms of topic models

## Other forms of topic models

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

## Next steps

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## Exercise for this week

- Work through the example notebook on LDA: <https://github.com/damian0604/bdaca/blob/master/12ec/week11/lda.ipynb>
- But most importantly: **Use a dataset of your choice** and find a suitable topic model. You can also try to compare multiple approaches (e.g., clustering vs LDA). Possible inspiration:  
<https://github.com/annekroon/gesis-ml-learning/blob/master/03wednesday/livecoding.ipynb>

## Next week: Word embeddings

Models that learn that 'teacher' and 'instructor' are more similar than 'teacher' and 'plumber'; or that 'king' - 'man' + 'woman' = 'queen'.

## Final project

If you haven't done so yet, talk with me about your topic

Recap  
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LDA Topic models  
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Next steps  
○○

**Good luck with the take-home exam!**