Using computational methods to analyze communication

Damian Trilling

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

Afdeling Communicatiewetenschap
Universiteit van Amsterdam

1–5–2017

Today

1. What's Automated Content Analysis?
2. Basic ACA: Dictionary- and string-based methods
   - Regular expressions
3. Unsupervised Machine Learning
   - PCA
   - LDA
4. Supervised Machine Learning
   - You have done it before!
   - Applications
5. Examples
6. Take-home message

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

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

Automated content analysis using 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 editors (!), in the Terminal, in STATA . . . and in Python

An example

Cleaning up

- We wanted to remove everything but words from a tweet
- We could do this with a regular expression as well:
  `[^a-zA-Z]` would match anything that is not a letter

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

regexp quizz

Which words would be matched?

1. `[Pp]ython`

regexp quizz

Which words would be matched?

1. `[Pp]ython`
2. `[A-Z]+`

regexp quizz

Which words would be matched?

1. `[Pp]ython`
2. `[A-Z]+`
3. `RT :* @[a-zA-Z0-9]*`

What else is possible?

If you google `regexp` or `regular expression`, you'll get a bunch of useful overviews. The wikipedia page is not too bad, either.

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 (!)

Unsupervised Machine Learning

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

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

Unsupervised machine learning

You have no labels.

Some terminology

Supervised machine learning

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

Unsupervised machine learning

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

Some terminology

Unsupervised machine learning

You have no labels.

Again, you already know some techniques to find out how x_1, x_2,... x_i co-occur from other courses:

- Principal Component Analysis (PCA)
- Cluster analysis
- ...

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, $T_1 \dots T_k$
- 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

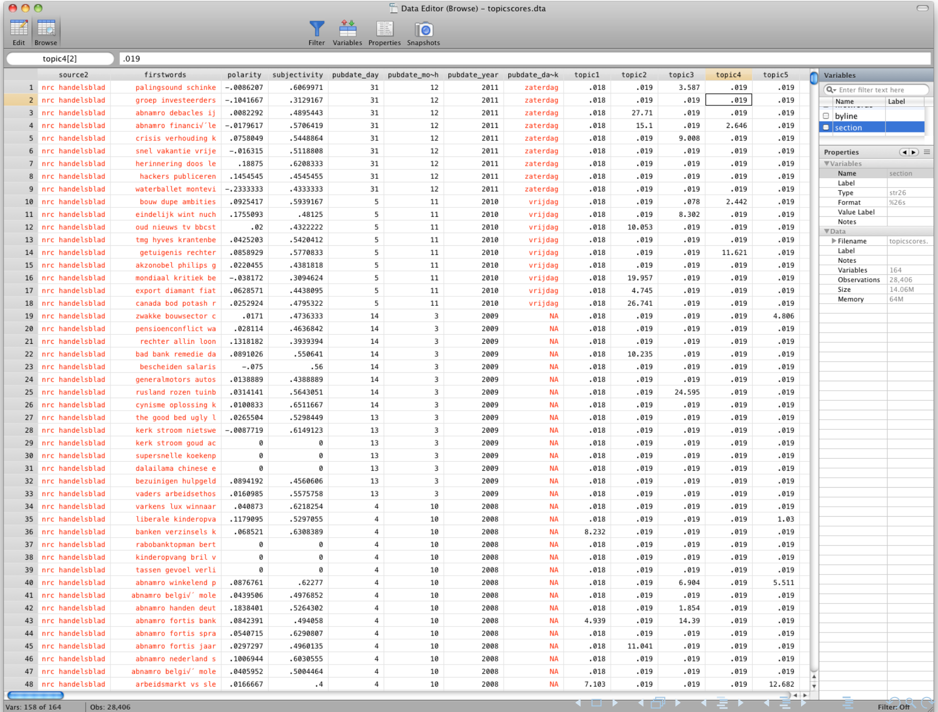
You can use gensim (Řehůřek & Sojka, 2010) for this.

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.

```python
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, alpha="auto")

# Print the topics.
for top in lda.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=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)

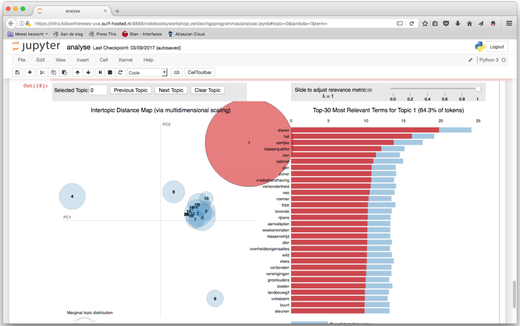
```
0.069*fusie + 0.058*brussel + 0.045*europesecommissie + 0.036*
    europese + 0.023*overname
0.109*bank + 0.066*britse + 0.041*regering + 0.035*financien +
    0.033*minister
0.114*nederlandse + 0.106*nederland + 0.070*bedrijven + 0.042*
    rusland + 0.038*russische
0.093*nederlandsespoorwegen +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



	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(lda,mm,id2word)
pyLDAvis.display(vis_data)
```



predefined categories, but no predefined rules:
supervised machine learning

predefined categories, but no predefined rules:
supervised machine learning

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

Recap: supervised vs. unsupervised

Unsupervised

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

Recap: supervised vs. unsupervised

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, . . .)

Recap: supervised vs. unsupervised

Unsupervised

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

Supervised

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

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, . . .)

Recap: supervised vs. unsupervised

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.

You have done it before!

You have done it before!

Regression

You have done it before!

Regression

1. Based on your data, you estimate some regression equation $y_i = \alpha + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i$

You have done it before!

Regression

1. Based on your data, you estimate some regression equation $y_i = \alpha + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i$
2. Even if you have some *new unseen data*, you can estimate your expected outcome $\hat{y}$!

You have done it before!

Regression

1. Based on your data, you estimate some regression equation $y_i = \alpha + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i$
2. Even if you have some *new unseen data*, you can estimate your expected outcome $\hat{y}$!
3. Example: You estimated a regression equation where y is newspaper reading in days/week:
$y = -.8 + .4 \times man + .08 \times age$

You have done it before!

Regression

1. Based on your data, you estimate some regression equation $y_i = \alpha + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i$
2. Even if you have some *new unseen data*, you can estimate your expected outcome $\hat{y}$!
3. Example: You estimated a regression equation where y is newspaper reading in days/week:
   $y = -.8 + .4 \times man + .08 \times age$
4. You could now calculate $\hat{y}$ for a man of 20 years and a woman of 40 years – *even if no such person exists in your dataset*:
   $\hat{y}_{man20} = -.8 + .4 \times 1 + .08 \times 20 = 1.2$
   $\hat{y}_{woman40} = -.8 + .4 \times 0 + .08 \times 40 = 2.4$

This is Supervised Machine Learning!

. . . but. . .

- We will only use *half* (or another fraction) of our data to estimate the model, so that we can use the other half to check if our predictions match the manual coding ("labeled data","annotated data" in SML-lingo)

. . . but. . .

- We will only use *half* (or another fraction) of our data to estimate the model, so that we can use the other half to check if our predictions match the manual coding ("labeled data","annotated data" in SML-lingo)
  - e.g., 2000 labeled cases, 1000 for training, 1000 for testing — if successful, run on 100,000 unlabeled cases

. . . but. . .

- We will only use *half* (or another fraction) of our data to estimate the model, so that we can use the other half to check if our predictions match the manual coding ("labeled data","annotated data" in SML-lingo)
  - e.g., 2000 labeled cases, 1000 for training, 1000 for testing — if successful, run on 100,000 unlabeled cases
- We use many more independent variables ("features")

. . . but. . .

- We will only use *half* (or another fraction) of our data to estimate the model, so that we can use the other half to check if our predictions match the manual coding ("labeled data","annotated data" in SML-lingo)
  - e.g., 2000 labeled cases, 1000 for training, 1000 for testing — if successful, run on 100,000 unlabeled cases
- We use many more independent variables ("features")
- Typically, IVs are word frequencies (often weighted, e.g. tf$\times$idf) ($\Rightarrow$BOW-representation)

Applications

Applications

In other fields

A lot of different applications

- from recognizing hand-written characters to recommendation systems

Applications

In other fields

A lot of different applications

- from recognizing hand-written characters to recommendation systems

In our field

It starts to get popular to measure latent variables

- frames
- topics

SML to code frames and topics

Some work by Burscher and colleagues

- Humans can code generic frames (human-interest, economic, ...)
- Humans can code topics from a pre-defined list

SML to code frames and topics

Some work by Burscher and colleagues

- Humans can code generic frames (human-interest, economic, ...)
- Humans can code topics from a pre-defined list
- **But it is very hard to formulate an explicit rule**
  (as in: code as 'Human Interest' if regular expression R is matched)

SML to code frames and topics

Some work by Burscher and colleagues

- Humans can code generic frames (human-interest, economic, . . .)
- Humans can code topics from a pre-defined list
- **But it is very hard to formulate an explicit rule** (as in: code as 'Human Interest' if regular expression R is matched)

$\Rightarrow$ This is where you need supervised machine learning!

Burscher, B., Odijk, D., Vliegenthart, R., De Rijke, M., & De Vreese, C. H. (2014). Teaching the computer to code frames in news: Comparing two supervised machine learning approaches to frame analysis. *Communication Methods and Measures, 8*(3), 190–206. doi:10.1080/19312458.2014.937527
Burscher, B., Vliegenthart, R., & De Vreese, C. H. (2015). Using supervised machine learning to code policy issues: Can classifiers generalize across contexts? *Annals of the American Academy of Political and Social Science, 659*(1), 122–131.

TABLE 4
Classification Accuracy of Frames in Sources Outside the Training Set

	VK/NRC →*Tel*	*VK/TEL* →*NRC*	*NRC/TEL* →*VK*
Conflict	.69	.74	.75
Economic Cons.	.88	.86	.86
Human Interest	.69	.71	.67
Morality	.97	.90	.89

Note. VK = Volkskrant, NRC = NRC/Handelsblad, TEL = Telegraaf

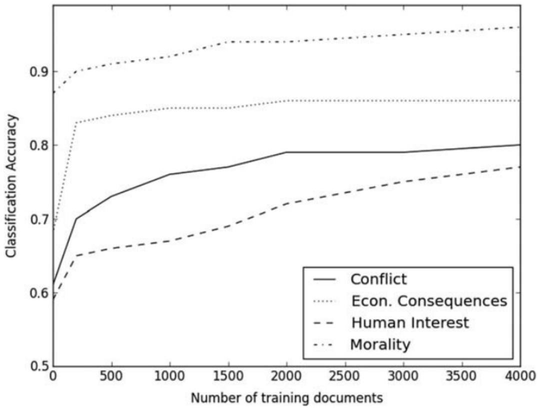


FIGURE 1 Relationship between classification accuracy and number of training documents.

FIGURE 1

Learning Curves for the Classification of News Articles and PQs

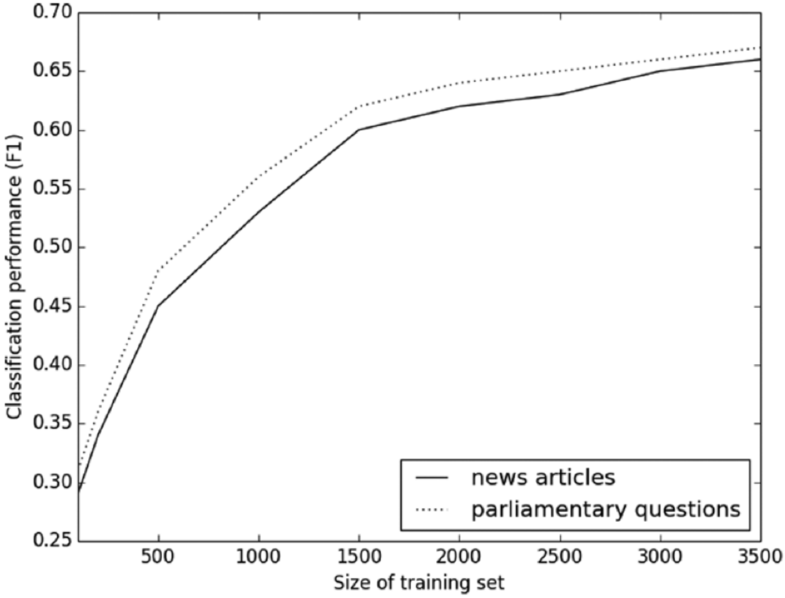
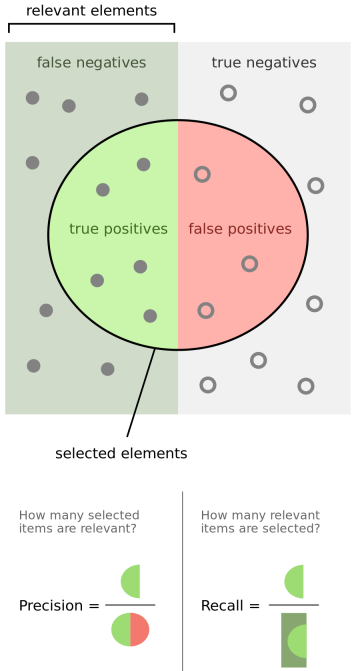


TABLE 1
F1 Scores for SML-Based Issue Coding in News Articles and PQs

Issue	News Articles			PQs	
		All Words	Lead Only		All Words
Features	*N*	F1	F1	*N*	F1
Macroeconomics	413	.54	.63	172	.46
Civil rights and minority issues	327	.34	.28	192	.53
Health	444	.70	.71	520	.81
Agriculture	114	.72	.76	159	.66
Labor and employment	217	.43	.49	174	.58
Education	188	.79	.71	229	.78
Environment	152	.34	.44	237	.59
Energy	81	.35	.59	67	.66
Immigration and integration	150	.50	.57	239	.78
Transportation	416	.58	.67	306	.81
Law and crime	1198	.70	.69	685	.77
Social welfare	115	.33	.34	214	.54
Community development and housing	113	.45	.44	136	.72
Banking, finance, and commerce	622	.62	.67	188	.58
Defense	393	.59	.55	196	.71
Science, technology, and communication	426	.64	.59	57	.53
International affairs and foreign aid	1,106	.70	.64	352	..65
Government operations	1,301	.71	.72	276	.48
Other issue	3,322	.84	.80	360	.51
Total	11,089	.71	.68	4,759	.69

NOTE: The F1 score is equal to the harmonic mean of recall and precision. Recall is the fraction of relevant documents that are retrieved, and precision is the fraction of retrieved documents that are relevant.

http://commons.wikimedia.org/wiki/File:Precisionrecall.svg



Some measures of accuracy

- Recall
- Precision
- $\text{F1} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$
- AUC (Area under curve) $[0, 1]$, $0.5 =$ random guessing

What does this mean for our research?

What does this mean for our research?

It we have 2,000 documents with manually coded frames and topics. . .

- we can use them to train a SML classifier
- which can code an unlimited number of new documents
- with an acceptable accuracy

Some easier tasks even need only 500 training documents, see Hopkins, D. J., & King, G. (2010). A method of automated nonparametric content analysis for social science. *American Journal of Political Science, 54*(1), 229–247.

And it works!

Using 50,000 IMDB movies that are classified as either negative or positive,

- I created a list with 25,000 training tuples and another one with 25,000 test tuples and
- trained a classifier
- that achieved an AUC of .82.

Dataset obtained from `http://ai.stanford.edu/~amaas/data/sentiment`, Maas, A.L., Daly, R.E., Pham, P.T., Huang, D., Ng, A.Y., & Potts, C. (2011). Learning word vectors for sentiment analysis. *49th Annual Meeting of the Association for Computational Linguistics (ACL 2011)*

But we can do even better

We can use different vectorizers and different classifiers.

Different vectorizers

- CountVectorizer (=simple word counts)
- TfidfVectorizer (word counts ("term frequency") weighted by number of documents in which the word occurs at all ("inverse document frequency"))
- additional options: stopwords, thresholds for minimum frequencies etc.

Different classifiers

- Naïve Bayes
- Logistic Regression
- Support Vector Machine (SVM)
- ...

Typical approach: Find out which setup performs best (see example source code in the book).

Try it yourself!

https://pastebin.com/KLeq6SGT

Examples

Putting these techniques into practice

Examples

The following examples were implemented in Python.
(Alternative: R).
burggraaff trilling
shareworthiness tolochko
evtl strycharz

What explains how often an article is shared on social media?

Trilling, D., Tolochko, P., & Burscher, B. (2017). From Newsworthiness to Shareworthiness. *Journal of Mass Communication Quarterly, 94*(1), 38–60. doi:10.1177/1077699016654682

The research design

The data

- Subscribe to RSS feeds of major news outlets
- Query feeds 1x/hour for a year, follow links and download
- Parse downloads (i.e., extract title, text, . . .)
- Use Twitter and Facebook API to retrieve number of shares

The research design

The automated content analysis

- written by press agency?: regular expressions
- geographical location: regular expressions
- positivity/negativity: sentiment analysis package
- topic: supervised machine learning
- economic and human-interest frames: supervised machine learning
- topic popularity: part-of-speech tagging, calculation of overlap of nouns in time frame

The research design

The final models

- negative binomial regression to predict the number of shares

What did we find?

- it's not true that mostly soft topics are shared
- geographical closeness matters
- differences between Facebook and Twitter (e.g., more skewed towards popular stories on FB, more long tail on Twitter)

How do online and offline news differ?

Burggraaff, C., & Trilling, D. (2017). Through a different gate: An automated content analysis of how online news and print news differ. *Journalism, online first*. doi:10.1177/1464884917716699

The research design

The data

- Online: as in previous study, but longer time period
- Plus offline articles from a newspaper database

The research design

The automated content analysis

- As in previous study, additionally:
- Follow-up news?: cosine similarity
- References to persons: Named entity recognition (NER)
- Entertainment news: supervised machine learning
- Celebrity news: NER + SPARQL-queries on DBpedia (=Wikipedia)

The research design

The final models

- regression models that predict the presence of news values (based on among other things online/offline-dummy)

What did we find?

- significant differences between online and offline
- e.g., online more follow-up
- but: no evidence for common perception that online is more entertainment and celebrity news

Take-home message

Take-home message

- There is more than one form of ACA
- top-down (deductive) vs bottom-up (inductive)
- You can start simple!
- No need to use specialized software, it's all available in Python (or R)

Tomorrow

Workshop: A bit of ACA in Python

Damian Trilling

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