Two-day workshop
Automated Content Analysis with Python
Day 2

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Afdeling Communicatiewetenschap
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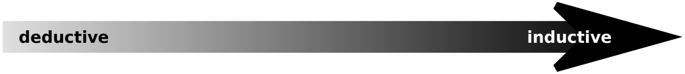
Today

Recap: 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



Some terminology

Supervised machine learning

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

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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

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Unsupervised machine learning

You have no labels.

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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

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

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

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

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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.
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:

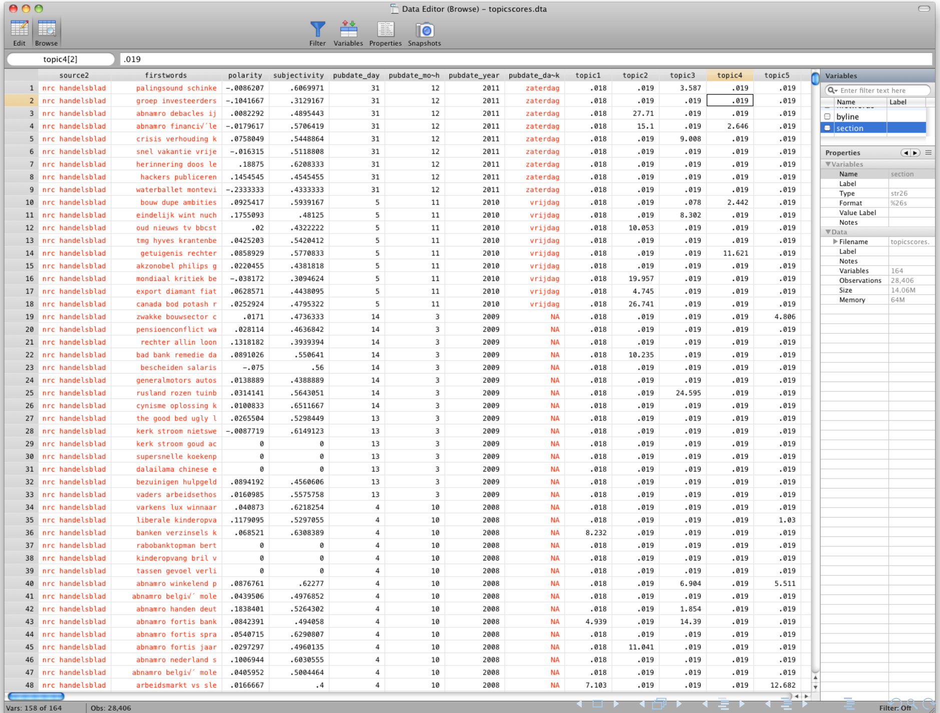
```
[['The', 'tax', 'deficit', 'is', 'higher', 'than', 'expected.', 'This',
    'said', 'xxx', '...'], ['Germany', 'won', 'the', 'World', 'Cup.', '
    After', 'a']]
```

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.
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
...
```



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	

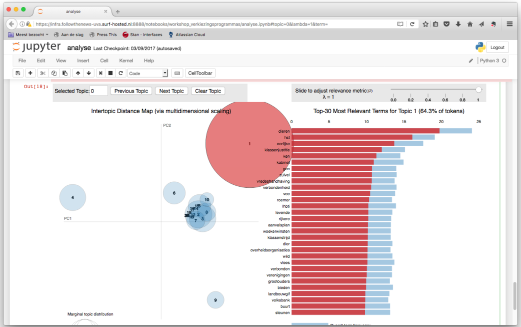
▼Data

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)
```



Try it yourself!

https://pastebin.com/xhTmBnp7

predefined categories, but no predefined rules:
supervised machine learning

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

Recap: supervised vs. unsupervised

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

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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!

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Regression

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Regression

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

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3. Example: You estimated a regression equation where y is newspaper reading in days/week: $y = -.8 + .4 \times man + .08 \times age$

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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. . .

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    - 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

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In other fields

A lot of different applications

- from recognizing hand-written characters to recommendation systems

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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, . . .)
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- **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

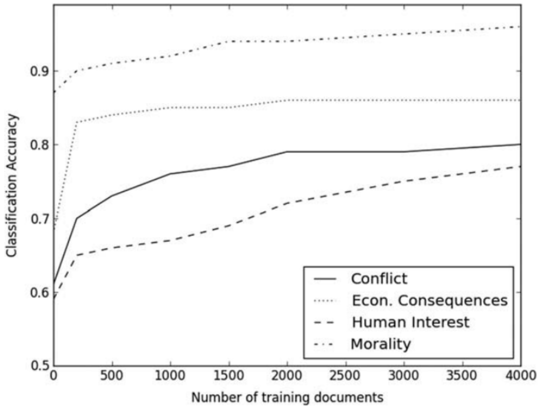


FIGURE 1 Relationship between classification accuracy and number of training documents.

FIGURE 1
Learning Curves for the Classification of News Articles and PQs

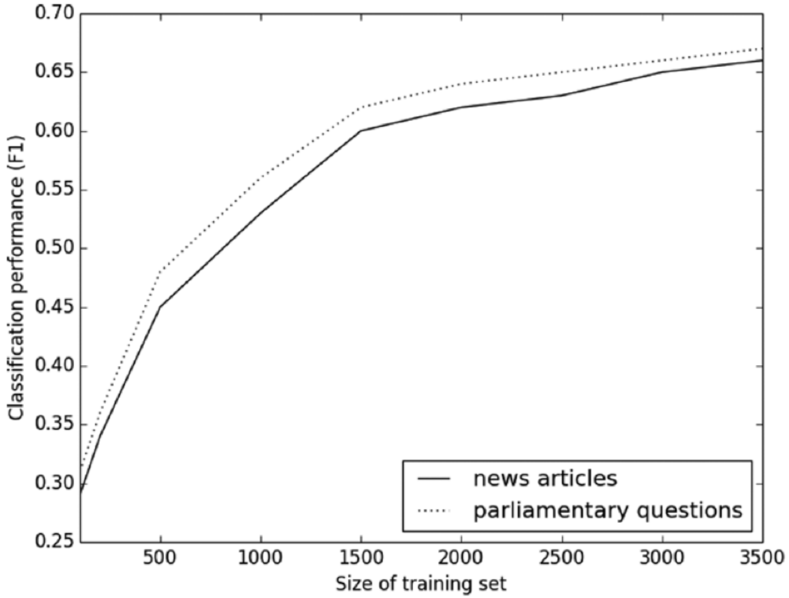


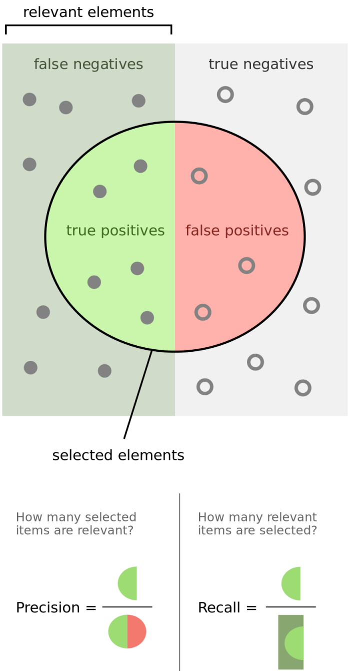
TABLE 1

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

What does this mean for our research?

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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.

An implementation

Let's say we have a list of tuples with movie reviews and their rating:

```
reviews=[("This is a great movie",1),("Bad movie",-1), ... ...]
```

And a second list with an identical structure:

```
test=[("Not that good",-1),("Nice film",1), ... ...]
```

Both are drawn from the same population, it is pure chance whether a specific review is on the one list or the other.

Based on an example from `http://blog.dataquest.io/blog/naive-bayes-movies/`

Training a A Naïve Bayes Classifier

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.feature_extraction.text import CountVectorizer
from sklearn import metrics

# This is just an efficient way of computing word counts
vectorizer = CountVectorizer(stop_words='english')
train_features = vectorizer.fit_transform([r[0] for r in reviews])
test_features = vectorizer.transform([r[0] for r in test])

# Fit a naive bayes model to the training data.
nb = MultinomialNB()
nb.fit(train_features, [r[1] for r in reviews])

# Now we can use the model to predict classifications for our test
    features.
predictions = nb.predict(test_features)
actual=[r[1] for r in test]

# Compute the error.
fpr, tpr, thresholds = metrics.roc_curve(actual, predictions, pos_label
    =1)
print("Multinomal naive bayes AUC: {0}".format(metrics.auc(fpr, tpr)))
```

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)*

Playing around with new data

```
newdata=vectorizer.transform(["What a crappy movie! It sucks!", "This is
      awsome. I liked this movie a lot, fantastic actors","I would not
     recomment it to anyone.", "Enjoyed it a lot"])
predictions = nb.predict(newdata)
print(predictions)
```

This returns, as you would expect and hope:

```
[-1  1 -1  1]
```

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/i5PmkUnq`

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