Big Data & Automated Content Analysis Week 9 – Wednesday: »Supervised Approaches to Text Analysis I«

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Afdeling Communicatiewetenschap
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Today

Choosing the right method

SML for text classification

- An implementation
- Classifiers
- Vectorizers

Summing up

- Revisiting the difference between the dictionary approach and the SML
- A note on the input data

Choosing

A familiar picture by now

	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 and Trilling, 2016

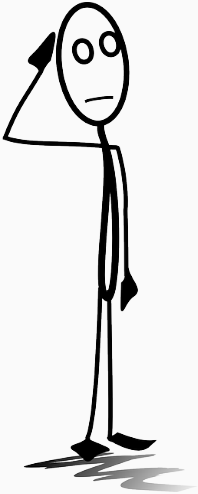
Let's consider three tasks

For a given text (say, a news article, a press release, a review), determine the

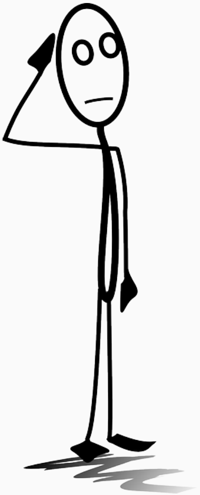
sentiment e.g., [positive|neutral|negative]

topic e.g., [sports|economy|politics|entertainment|other]

frames e.g., [economic|human|moral|conflict], or
non-exclusive: economic = [0|1], human = [0|1], . . .



What would be the strengths and weaknesses of different approaches for each of these tasks?



Imagine using a dictionary-based (list of keywords, list of regular expressions, or similar) approach to these tasks. How does the design (length, inclusiveness, etc.) of this list influence precision and recall?

Dictionary-based approaches for text classification

good for

- distinct, manifest things (names of organizations, pronouns, swearwords (?), ...)
- little room for interpretation/misunderstandings etc.
- "must-be-explainable-to-a-five-year-old"

bad for

- latent constructs and concepts
- implicit things

Hence, *not* state-of-the-art for

- topics
- frames
- sentiment

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From dictionary approaches to SML

- Early days of sentiment analysis: list of positive words, list of negative words, count what occurs most
- You can even *buy* lists of words that are meant to measure constructs like "positive emotions" or even "analytic" or "authentic" language use from a psychologist (LIWC, Pennebaker et al., 2007)

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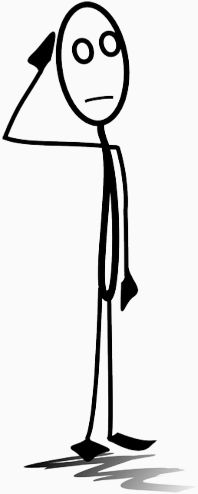

What do you think? Can this even work

Bag-of-words dictionary approaches to sentiment analysis

con

- simplistic assumptions
- e.g., intensifiers cannot be interpreted ("really" in "really good" or "really bad")
- or, even more important, negations.

Improving the BOW approach

Example: Sentistrenght (Thelwall et al., 2012)

- $-5 \ldots -1$ and $+1 \ldots +5$ instead of positive/negative
- spelling correction
- "booster word list" for strengthening/weakening the effect of the following word
- interpreting repeated letters ("baaaaaad"), CAPITALS and !!!
- idioms
- negation

VADER by Hutto and Gilbert, 2014 works in a similar way. Even though this is much less naïve than LIWC, for instance, the problem remains: Can we construct a dictionary that, *irrespective of the context*, gives us a meaningful estimate of

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Such an *off-the-shelf* dictionary does not (and probably cannot) exist.

Boukes et al., 2020: Sentiment analysis of economic news

	F1	n (predicted)	n (human coding)	precision	recall
All tones combined (overall score)					
Recession	0.26		4640	0.30	0.43
Damstra and Boukes (2018)	0.32		4640	0.52	0.45
LIWC	0.42		4640	**0.53**	**0.48**
SentiStrength	0.42		4640	0.45	0.45
Pattern	0.41		4640	0.45	0.45
Polyglot	**0.43**		4640	0.44	0.44
DANEW	**0.43**		4640	0.46	0.45
Negative Tone					
Recession	0.00	6	1524	0.33	0.00
Damstra and Boukes (2018)	0.08	99	1524	**0.62**	0.04
LIWC	0.29	471	1524	**0.62**	0.19
SentiStrength	0.39	1158	1524	0.45	0.34
Pattern	0.30	692	1524	0.48	0.22
Polyglot	**0.42**	1158	1524	0.48	**0.37**
DANEW	0.36	794	1524	0.52	0.27
Neutral Tone					
Recession	**0.60**	4634	2008	0.43	**1.00**
Damstra and Boukes (2018)	**0.60**	4366	2008	0.44	0.96
LIWC	**0.60**	3750	2008	**0.46**	0.86
SentiStrength	0.55	3103	2008	0.45	0.70
Pattern	0.56	3260	2008	0.45	0.74
Polyglot	0.47	2231	2008	0.45	0.50
DANEW	0.53	2776	2008	**0.46**	0.63
Positive tone					
Recession	0.00	0	1108	0.00	0.00
Damstra and Boukes (2018)	0.14	175	1108	**0.53**	0.08
LIWC	0.29	419	1108	0.52	0.20
SentiStrength	0.22	379	1108	0.42	0.14
Pattern	0.30	688	1108	0.39	0.24
Polyglot	**0.39**	1251	1108	0.37	**0.42**
DANEW	0.36	1070	1108	0.37	0.35

Boukes et al., 2020: Sentiment analysis of economic news

Table A1. Correlations between sentiment scores using different methods for headlines (above) and full texts (below).

	Headline							
	Manual coding	Recession	D & B	LIWC	SentiStrength	Pattern	Polyglot	DANEW
Manual coding	1.00 ***							
Recession	-	-						
Damstra and Boukes (2018)	0.16 ***	-	1.00 ***					
LIWC	**0.30 *** **	-	0.16 ***	1.00 ***				
SentiStrength	0.24 ***	-	0.08 **	0.26 ***	1.00 ***			
Pattern	0.22 ***	-	0.00	0.30 ***	0.22 ***	1.00 ***		
Polyglot	0.30 ***	-	0.19 ***	0.32 ***	0.37 ***	0.26 ***	1.00 ***	
DANEW	0.24 ***	-	0.04	**0.43 *** **	0.33 ***	0.23 ***	0.32 ***	1.00 ***

	Full text							
	Manual coding	Recession	D & B	LIWC	SentiStrength	Pattern	Polyglot	DANEW
Manual coding	1.00 ***							
Recession	−0.06 *	1.00 ***						
Damstra and Boukes (2018)	0.27 ***	−0.16 ***	1.00 ***					
LIWC	0.39 ***	0.02	0.27 ***	1.00 ***				
SentiStrength	0.17 ***	−0.01	0.10 ***	0.18 ***	1.00 ***			
Pattern	0.13 ***	−0.02	0.04	0.28 ***	0.12 ***	1.00 ***		
Polyglot	0.26 ***	0.05	0.17 ***	0.41 ***	0.21 ***	0.30 ***	1.00 ***	
DANEW	0.15 ***	0.06 *	0.05	0.36 ***	0.18 ***	0.29 ***	0.37 ***	1.00 ***

The word “recession” did not occur in headlines of our sample, as such, no correlation coefficient is available for the recession classifier; *** $p < .001$, ** $p < .010$, * $p < .05$.

Boukes et al., 2020: Sentiment analysis of economic news

- Dictionaries have low agreement with each other, and also with human coders
- Even their own dictionary didn't agree
- **This is not because these dictionaries are particularly bad!**. Main point: For such a complex and context-dependent task, a dictionary is just not the right tool.

van Atteveldt et al., 2021: Extending Boukes et al., 2020 with SML

"manual coding (using undergraduate students) yields the best results

[...] A good second place is taken by crowd coding [...]

[...] machine learning performs worse than both students' manual coding and crowd coding. Reaching $\alpha = 0.50$ for deep learning (CNN) and slightly worse for classical machine learning (SVM; $\alpha = 0.41$, NB; $\alpha = 0.40$), machine learning still performs significantly better than chance. However, since these results are lower than generally accepted levels of inter-coder reliability [...]

Finally, [...] dictionaries [...] perform worse than the machine learning results and much worse than manual annotation [...] [and] approximate chance agreement"

Vermeer et al., 2019: Satisfaction with brands

Category	Technique	Accuracy	Precision	Recall
Satisfaction ($N = 854$)				
Sentiment analysis	LIWC	0.05	0.06	0.04
	P	0.04	0.04	0.04
	SN	0.07	0.07	0.08
Dictionary-based	D	0.15	0.30	0.10
Machine learning	BNB	0.38	0.44	0.34
	MNB	0.32	0.67	0.21
	LR	0.51	0.38	0.76
	SGD	0.49	0.38	0.69
	SVM	0.52	0.41	0.63
	PA	0.50	0.40	0.68
Neutral ($N = 760$)				
Sentiment analysis	LIWC	0.13	0.16	0.10
	P	0.13	0.13	0.14
	SN	0.19	0.16	0.22
Dictionary-based	D	0.14	0.35	0.09
Machine learning	BNB	0.28	0.25	0.32
	MNB	0.15	0.34	0.10
	LR	0.37	0.25	0.74
	SGD	0.33	0.23	0.60
	SVM	0.36	0.24	0.69
	PA	0.34	0.24	0.60
Dissatisfaction ($N = 267$)				
Sentiment analysis	LIWC	0.20	0.15	0.29
	P	0.19	0.12	0.40
	SN	0.22	0.14	0.54
Dictionary-based	D	0.09	0.41	0.05
Machine learning	BNB	0.26	0.20	0.40
	MNB	0.25	0.48	0.16
	LR	0.35	0.23	0.77
	SGD	0.39	0.32	0.48
	SVM	0.04	0.02	1.00
	PA	0.35	0.23	0.71

Note. LIWC *Linguistic Inquiry and Word Count;* P *Pattern;* SN *Sentiment Net*; D *Dictionary-based;* BN *Bernoulli Naïve Bayes*; MNB *Multinomial Naïve Bayes*; LR *Logistic Regression*; SGD *Stochastic Gradient Descent*; SVM *Support Vector Machine*; and PA *Passive Aggressive*. Performance scores ≥0.60 have been highlighted. Results merely derived from the test set.

SML is no panacea, but the most promising approach to analyzing large quantities of texts. Don't believe off-the-shelf packages that claim to do the work for you. (For small datasets, just do it by hand.)

SML for text classification

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

Unsupervised machine learning

You have no labels.

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SML to code frames and topics

Some work by Burscher et al., 2014 and Burscher et al., 2015

- 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)

⇒ This is where you need supervised machine learning!

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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

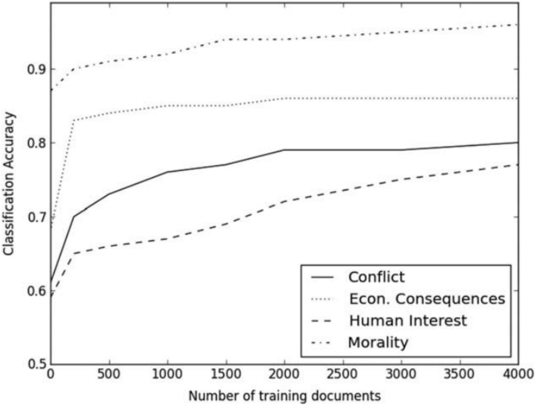

FIGURE 1 Relationship between classification accuracy and number of training documents.

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

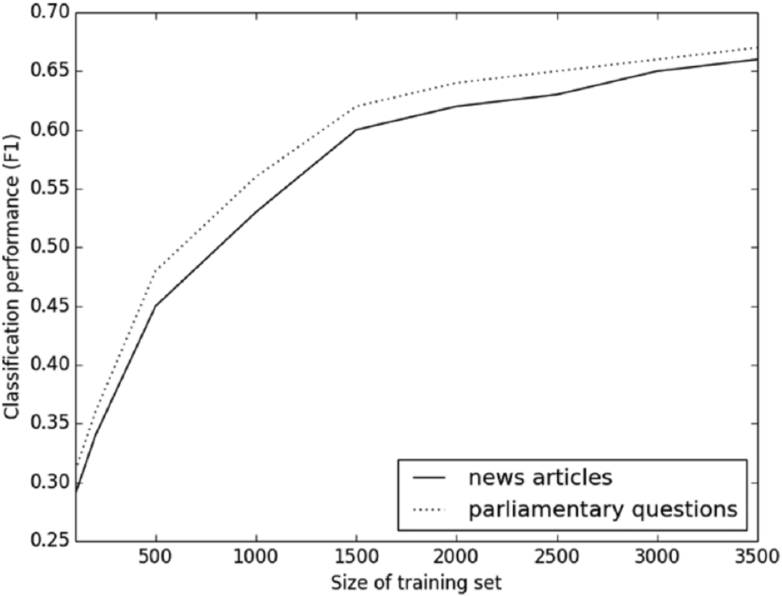

TABLE 1
F1 Scores for SML-Based Issue Coding in News Articles and PQs

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.

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 (at least for some of them)

Some easier tasks even need only 500 training documents, see Hopkins and King, 2010.

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SML for text classification

An implementation

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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]

print("Precision: {0}".format(metrics.precision_score(actual,
    predictions, pos_label=1, labels = [-1,1])))
```

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
- with precision and recall values $> .80$

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.

SML for text classification

Classifiers

Check out the overview from last week

Different classifiers

Typical options in a nutshell:

- Naïve Bayes
- Logistic Regression
- Support Vector Machine (SVM/SVC)
- Random forests

SML for text classification

Vectorizers

Different vectorizers

1. CountVectorizer (=simple word counts)
2. TfidfVectorizer (word counts ("term frequency") weighted by number of documents in which the word occurs at all ("inverse document frequency"))

$$tfidf_{t,d} = tf_{t,d} \cdot idf_t$$

There are different ways to weigh the idf score. A common one is taking the logarithm:

$$idf_t = \log \frac{N}{n_t}$$

where N is the total number of documents and n_t is the number of documents containing term t

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Different vectorizer options

- Preprocessing (e.g., stopword removal)
- Remove words below a specific threshold ("occurring in less than $n = 5$ documents") $\Rightarrow$ spelling mistakes etc.
- Remove words above a specific threshold ("occuring in more than 50% of all documents) $\Rightarrow$ de-facto stopwords
- Not only to improve prediction, but also performance (can reduce number of features by a huge amount)

Which one would you (not) use for which purpose?

NB with Count

	precision	recall
positive reviews:	0.87	0.77
negative reviews:	0.79	0.88

NB with TfIdf

	precision	recall
positive reviews:	0.87	0.78
negative reviews:	0.80	0.88

LogReg with Count

	precision	recall
positive reviews:	0.87	0.85
negative reviews:	0.85	0.87

LogReg with TfIdf

	precision	recall
positive reviews:	0.89	0.88
negative reviews:	0.88	0.89

Summing up

Summing up

Revisiting the difference between the dictionary approach and the SML

What *is* our fitted classifier again?

Essentially, just a formula

$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)}}$$

where β_0 is an intercept[1], β_1 a coefficient for the frequency (or tf·idf score) of some word, β_2 a coefficient some other word.

If our fitted *vectorizer* contains 5,000 words, we thus have 5,001 coefficients.

(for logistic regression in this case, but same argument applies to other classifiers as well)

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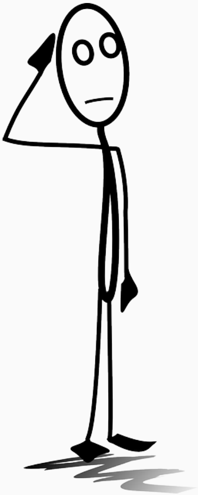
[1] Machine Learning people sometimes call the intercept "bias" (yes, I know, that's confusing)



But isn't that then essentially very much like a dictionary, except that the words have different weights?

In some sense, yes.

- But we don't pretend that we can construct the dictionary *a priori*.
- It's specifically tailored to our use-case.
- The weights are *really* essential here.

We *could* print all coefficients-word pairs, but probably it's enough to just look at those with the largest absolute value:

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ELI5

In [98]:
```
import eli5
eli5.show_weights(pipe, top=10)
```

Out[98]:

y=1 top features

Weight?	Feature
+9.043	great
+8.487	excellent
+6.908	perfect
… 37662 more positive …	
… 37178 more negative …	
-6.507	worse
-7.347	poor
-8.341	boring
-8.944	waste
-8.976	bad
-9.152	awful
-12.749	worst

In [111]:
```
eli5.show_prediction(clf, test[0][0],vec=vec)
```

Out[111]:

y=1 (probability **0.844**, score **1.689**) top features

Contribution?	Feature
+1.920	Highlighted in text (sum)
-0.232	<BIAS>

it is a rare and fine spectacle, an allegory of death and transfiguration that is neither preachy nor mawkish. a work of mature and courageous insight, northfork avoids arthouse distinction by refusing to belong to a kind. unlike the most memorable and accomplished film to impose an obvious comparison, wim wenders' 1987 wings of desire (der himmel über berlin), it sustains an ambivalence in a narrative spectrum spanning from the mundane to the supernatural. this story of earthly and celestial eminent domains in the american west withholds the fairytale literalness that marked its german predecessor in the ad hoc genre of angels shedding their wings with obsequious sentimentalism. its celestial transcendence, be it inspired by doleful faith or impelled by a fever dream, never parts ways with crud and rot. this firm grounding redounds to great credit for writers and directors mark and michael polish.

ELI5

- Inspecting *all* coefficients of a ML model usually doesn't make much sense
- But that does not mean that we cannot understand how the model makes its predictions
- We can look at the most important coefficients
- We can look which words in a given text contributed most to its classfication

But have we solved all problems of dictionaries?

No.

For instance, the negation and/or intensifier problem.

Possible approaches

- *n*-grams as features
- preprocessing (?)
- deep learning
- ...

⇒ But ultimately, it's just an empirical question how big the problem is!

But have we solved all problems of dictionaries?

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- ...

⇒ **But ultimately, it's just an empirical question how big the problem is!**

Summing up

A note on the input data

The input scikit-learn expects

A training dataset consisting of:

1. an array (e.g., a list) of labels (`y_train`)
2. a corresponding array (e.g., a list) of feature vectors (`X_train`)

A test dataset consisting of:

1. an array (e.g., a list) of labels (`y_test`)
2. a corresponding array (e.g., a list) of feature vectors (`X_test`)

The feature vectors can be created via a *vectorizer*, but could in principle also just be lists themselves.

We use a lowercase `y` because it is a onedimensional vector, and an uppercase `X` because it is a two-dimensional matrix.

The input scikit-learn expects

- **It does not matter *how* you create `y` and `X`!**
- Getting data into the right shape can be as much work (or more) as training the classifier itself

Typical techniques:

- Reading text files from folders into lists of strings (looping over folder contents)
- Reading from csv file either directly into lists (`csv` module) or via pandas
- List comprehension to restructure or process data
- Potentially, you need to split into train and test dataset yourself (with slicing, or with scikit-learn itself)

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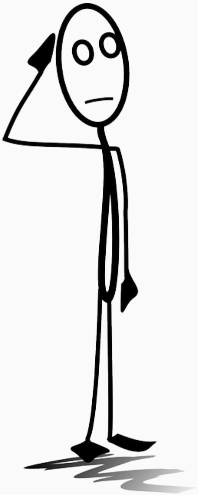

Any questions?

Friday

- Reproduce examples from the book for SML on the IMDB data (11.2, 11.3, 11.4) (check `week09/codefrombook.py` on github if you do not want to type over the code)
- Play around with different options! Can you tweak the models and make them even better? Take a look back at week 7 when we compared different vectorizers as well!
- **Download the files `train.csv` and `test.csv` from the module "Files week 9" on Canvas. Train a classifier on them as well!** (Data from Vermeer et al., 2020)

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