A Practical Introduction to Machine Learning in Python
Day 4 – Thursday
»Supervised Machine Learning«

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Gesis

Today

- Recap: Top-down vs bottom-up
- Predicting things
  - You have done it before!
  - From regression to classification
- Supervised Machine Learning for Text Classification
  - (Traditional) non-SML approaches
  - Diving into SML
  - An implementation
  - Classifiers
  - Vectorizers
- Summing up
  - Revisiting the difference between the dictionary approach and

Recap

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

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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. (You did not measure y)

Again, you already know some techniques to find out how x1, x2,...x_i co-occur from other courses:

- Principal Component Analysis (PCA) and Singular Value Decomposition (SVD)
- Cluster analysis
- Topic modelling (Latent Dirichlet Allocation)

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Predicting things

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Regression

1. Based on your data, you estimate some regression equation $y_i = \alpha + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \epsilon_i$
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*: $\hat{y}_{man20} = -.8 + .4 \times 1 + .08 \times 20 = 1.2$ $\hat{y}_{woman40} = -.8 + .4 \times 0 + .08 \times 40 = 2.4$

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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)
  - 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×idf) (⇒BOW-representation)

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Predicting things

From regression to classification

In the machine learning world, predicting some continous value is referred to as a **regression** task. If we want to predict a binary or categorical variable, we call it a **classification** task.

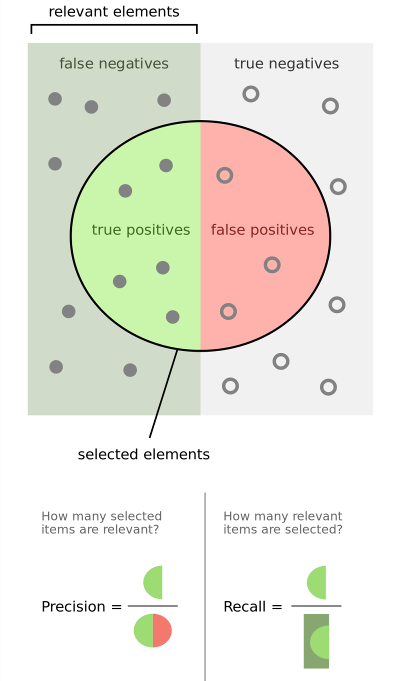
(quite confusingly, even if we use a logistic regression for the latter)

Classification tasks

For many computational approaches, we are actually not that interested in predicting a continuous value. Typical questions include:

- Is this article about topic A, B, C, D, or E?
- Is this review positive or negative?
- Does this text contain frame F?
- Is this satire?
- Is this misinformation?
- Given past behavior, can I predict the next click?

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



Some measures

- 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

Different classification algorithms

- It is an empirical question which one works best
- We typically try several ones and select the best
- (remember: we have a test dataset that we did *not* use to train the model, so that we can assess how well it predicts the test labels based on the test features)
- To avoid *p*-hacking-like scenario's (which we call "overfitting"), there are techniques available (cross-validation, later in this course)

(to make it easier, imagine a binary classfication ("positive"/"negative"), but it doesn't really matter whether there are two or more labels)

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Naïve Bayes

Bayes' theorem

$$P(A \mid B) = \frac{P(B \mid A) \times P(A)}{P(B)}$$

A = Text is about sports

B = Text contains 'very', 'close', 'game'. Furthermore, we simply multiply the probabilities for the features:

$$P(B) = P(very\ close\ game) = P(very) \times P(close) \times P(game)$$

We can fill in all values by counting how many articles are about sports, and how often the words occur in these texts. (Fully elaborated example on https://monkeylearn.com/blog/practical-explanation-naive-bayes-classifier/)

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Naïve Bayes

$$P(\text{label} \mid \text{features}) =$$
$$\frac{P(x_1 \mid label) \cdot P(x_2 \mid \text{label}) \ \cdot \mathrm{P}(\mathrm{x}_3 \mid \text{label}) \cdot \mathrm{P}(\text{label})}{P(x_1) \cdot P(x_2) \cdot P(x_3)}$$

.

- Formulas always look intimidating, but we only need to fill in how many documents containing feature x_n have the label, how often the label occurs, and how often each feature occurs
- Also for computers, this is *really easy and fast*
- Weird assumption: features are independent
- Often used as a baseline

Logistic Regression

Probability of a binary outcome in a regression model

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

Just like in OLS regression, we have an intercept and regression coefficients. We use a threshold (default: 0.5) and above, we assign the positive label ('good movie'), below, the negative label ('bad movie').

Logistic Regression

- The features are *not* independent.
- Computationally more expensive than Naïve Bayes
- We can get probabilities instead of just a label
- That allows us to say how sure we are for a specific case
- ...or to change the threshold to change our precision/recall-tradeoff

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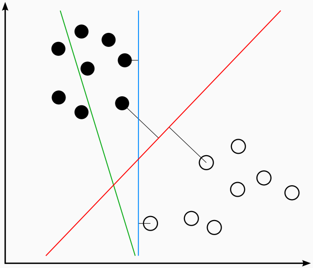
Support Vector Machines

- Idea: Find a hyperplane that best seperates your cases
- Can be linear, but does not have to be (depends on the so-called kernel you choose)
- Very popular



https://upload.wikimedia.org/wikipedia/commons/b/b5/Svm_separating_hyperplanes_%28SVG%29.svg

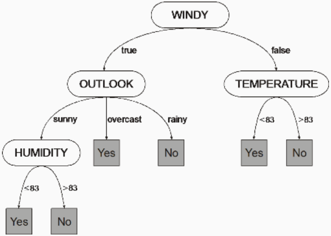
(Further reading: https://monkeylearn.com/blog/introduction-to-support-vector-machines-svm/)

SVM vs logistic regression

- for *linearly separable* classes not much difference
- with the right hyperparameters, SVM is less sensitive to outliers
- biggest advantage: with the *kernel trick*, data can be transformed that they *become* linearly separable

Decision Trees and Random Forests

- Model problem as a series of decisions (e.g., if cloudy then . . . if temperature > 30 degrees then . . .)
- Order and cutoff-points are determined by an algorithm
- Big advantage: Model non-linear relationships
- And: They are easy to interpret (!) (“white box”)



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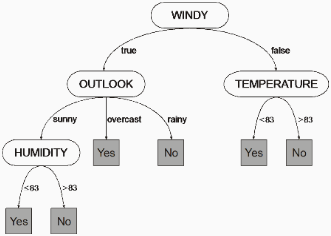

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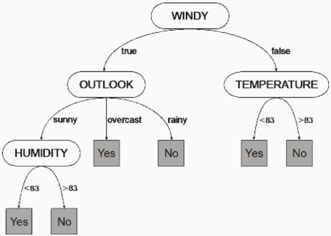

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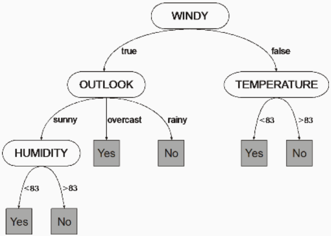

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Disadvantages of decision trees

- comparatively inaccurate
- once you are in the wrong branch, you cannot go 'back up'
- prone to overfitting (e.g., outlier in training data may lead to completely different outcome)

Therefore, nowadays people use *random forests*: Random forests *combine* the predictions of *multiple* trees ⇒ might be a good choice for your non-linear classification problem

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Supervised Machine Learning for Text Classification

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(Traditional) non-SML approaches

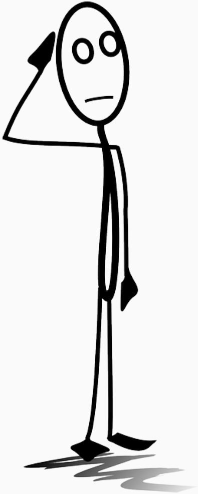
Let's consider three tasks

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], . . .



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
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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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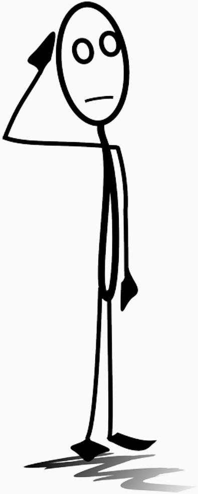

What do you think? Can this even work?

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 sentiment?

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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

	F_1	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.)

Supervised Machine Learning for Text Classification

Diving into SML

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!

SML to code frames and topics

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  (as in: code as 'Human Interest' if regular expression R is matched)

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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

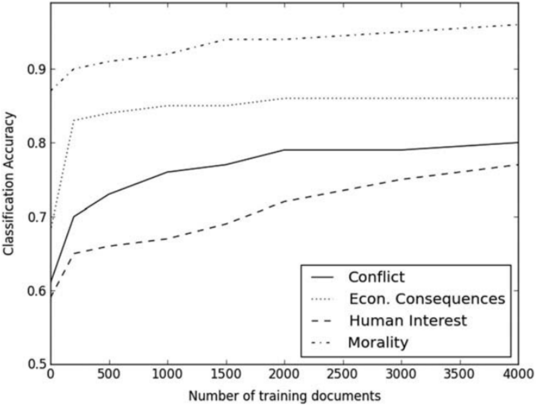

FIGURE 1 Relationship between classification accuracy and number of training documents.

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

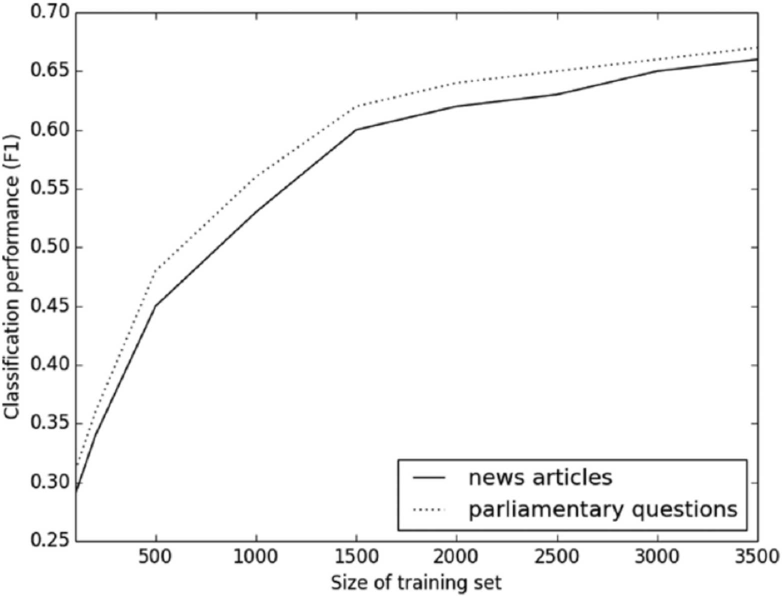

TABLE 1
F1 Scores for SML-Based Issue Coding in News Articles and PQs

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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Supervised Machine Learning for Text Classification

An implementation

An implementation

Let's say we have two lists, with movie reviews and their rating:

```
reviews_train = ["This is a great movie", "Bad movie", ... ...]
labels_train = [1,-1, ...]
```

And a second dataset with an identical structure:

```
reviews_test = ["Not that good","Nice film", ... ...]
labels_text = [-1,1, ......]
```

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

vectorizer = CountVectorizer(stop_words='english')
features_train = vectorizer.fit_transform(reviews_train)
features_test = vectorizer.transform(reviews_test)

# Fit a naive bayes model to the training data.
nb = MultinomialNB()
nb.fit(features_train, labels_train)

# Now we can use the model to predict classifications for our test
    features.
predictions = nb.predict(features_test)

print(f"Precision:\t{metrics.precision_score(labels_test, predictions,
    pos_label=1, labels = [-1,1])}"
print(f"Recall:\t{metrics.recall_score(labels_test, 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.

Supervised Machine Learning for Text Classification

Classifiers

Different classifiers

Typical options in a nutshell:

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

Supervised Machine Learning 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") ⇒ spelling mistakes etc.
- Remove words above a specific threshold ("occuring in more than 50% of all documents) ⇒ 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

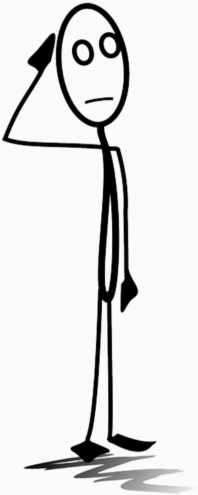
$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)}}$$

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)

[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!

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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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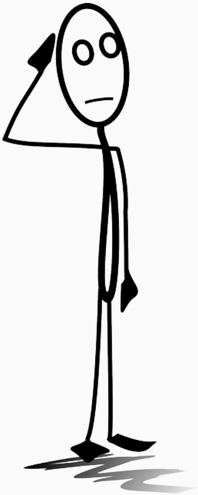

Any questions?

Things to remember

- unsupervised vs supervised
- rough understanding of different techniques and when to use them
- evaluation metrics (e.g., precision, recall)

Let's do an exercise!

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