Big Data and Automated Content Analysis Part I+II

Week 9 – Wednesday
»Supervised Machine Learning I«

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Today

1. Recap: Types of Automated Content Analysis
2. Supervised Machine Learning
   - You have done it before!
   - Applications
   - An implementation
3. Vectorizers
4. Different models
5. Next meetings

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

deductive → **inductive**

Some terminology

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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

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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 `x1, x2,...x_i` co-occur from other courses:

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

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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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- We use many more independent variables ("features")
- Typically, IVs are word frequencies (often weighted, e.g. tf×idf) (⇒BOW-representation)

Applications

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In other fields

A lot of different applications

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In our field

It starts to get popular to measure latent variables

- frames
- topics

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- 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!

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

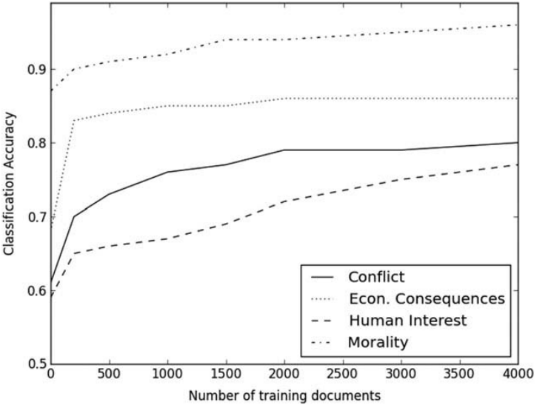


FIGURE 1 Relationship between classification accuracy and number of training documents.

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

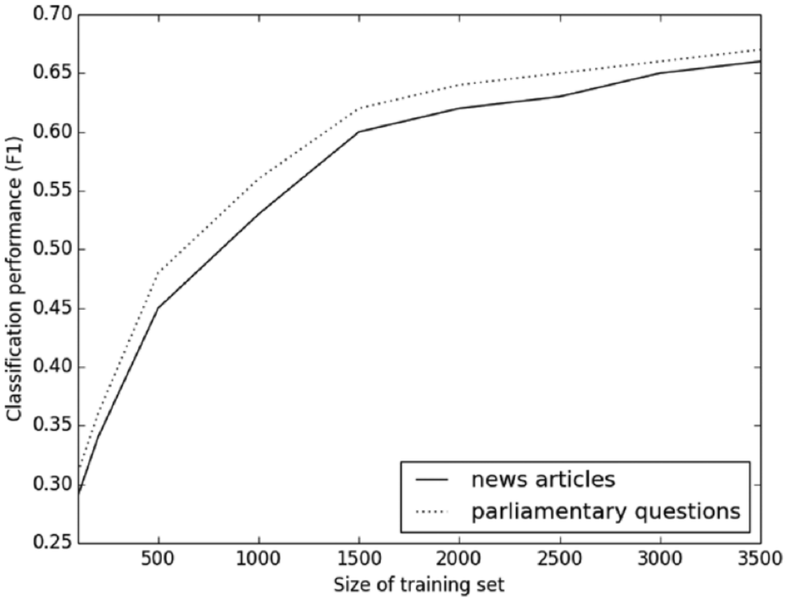
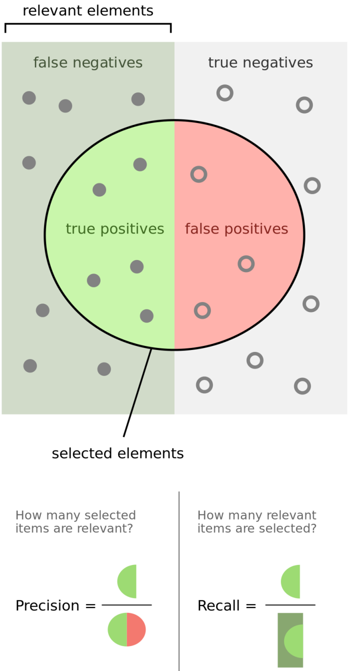


TABLE 1
F1 Scores for SML-Based Issue Coding in News Articles and PQs

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]

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

Vectorizers

Different vectorizers

1. CountVectorizer (=simple word counts)

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

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

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)

Models (Classifiers)

(When we want to predict a binary outcome, we often refer to this as a *classification problem*, while we often call predicting a continous outcome a *regression problem*.)

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).

Naïve Bayes

Bayes' theorem

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

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A = Text is about sports
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Bayes' theorem

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

A = Text is about sports
B = Text contains "a very good game" Furthermore, we simply multiply the propabilities for the features:

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

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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- It's fast and easy
- It's a good *baseline* for binary classification problems

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').

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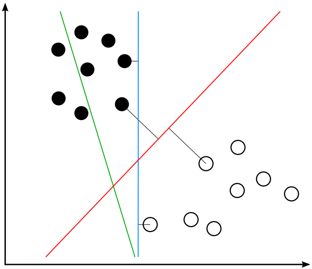
- ... or to change the threshold to change our precision/recall-tradeoff

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

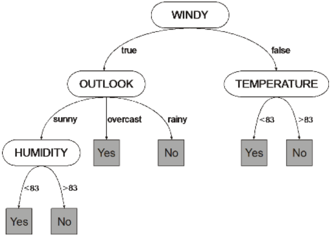


https://upload.wikimedia.org/wikipedia/commons/b/b5/Svm_separating_hyperplanes_%28SVG%29.svg

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

Decision Trees and Random Forests

- Model problem as a series of decisions (e.g., if cloudy then . . . if temperature > 30 degrees then . . .)



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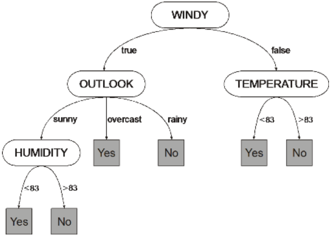

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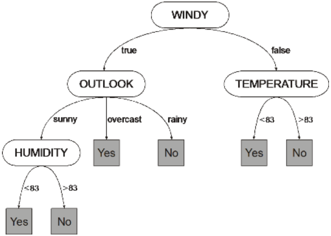

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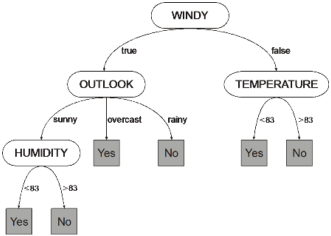
- Big advantage: Model non-linear relationships
- And: They are easy to interpret (!) ("white box")



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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)

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

https://scikit-learn.org/stable/supervised_learning.html

Next meetings

Friday

We'll write a supervised machine learning classifier (Chapter 10)

Next Wednesday: Supervised machine leraning 2

Creating the best model using Cross Validation, different thresholds, ROC curves, different feature sets, ...