Automatic Classification by Topic Domain for Meta Data Generation, Web Corpus Evaluation, and Corpus Comparison

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Background

- Reliable metadata: not available for large crawled web corpora
- Topic domain (and genre/register): essential for many corpus linguists
- Also important for corpus evaluation and corpus comparison

- Automatic classification by genre/register: in unrestricted domains, disappointing results, even in recent experiments.
- Biber and Egbert (2016): acc.=0.42, prec.=0.27, rec.=0.3

Automatic classification by content

- Promising results years ago already (Sebastiani, 2002).
- Data-driven induction of topics: a very objective way of organizing a collection of documents by content.
- Topic classification through internal criteria: also advocated in the EAGLES (1996) guidelines

But:

- Topic modeling: no category labels
- from a linguist's viewpoint: categories should be 'intuitively' interpretable

Experiment

Idea

1. Infer a topic distribution over a corpus using topic modeling algorithms (unsupervised)
2. Do not interprete the inferred topical structure directly.
3. Instead, learn a small set of topic domains from the documents' assignment to the topics (supervised)

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Goals

- Development of a suitable annotation scheme for topic domain, grounded in lexical distributions
- Corpus comparison: web corpus vs. newspaper corpus (very little is known about the composition of crawled web corpora)

COWCat

Text classification schema (Schäfer and Bildhauer, 2012)

- No complex categories such as *genre*, *register* etc.
- Instead simple categories: *Aim*, *Mode*, *Topic Domain*
- Builds on previous work by Sharoff (2006)

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Topic Domain

- Design goal: moderate number (about 10–20) categories
- Basis for our classifcation experiments: 13 categories
- Developed in a cyclic fashion
  (repeated annotation processes, annotator feedback)

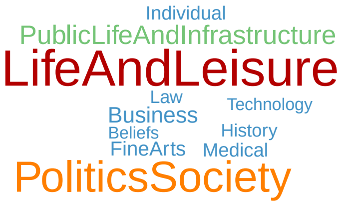
Step 1: Creating a gold standard data set

- 870 documents from DECOW14, crawled web corpus (Schäfer and Bildhauer, 2012; Schäfer, 2015)
- 886 documents from DeReKo, mostly newspaper texts (Kupietz et al., 2010)
- Manually annotated with COWCat for topic domain (COWCat)

- Annotators: Sarah Dietzfelbinger, Lea Helmers, Theresia Lehner, Kim Maser, Samuel Reichert, Luise Rißmann (FU Berlin); Monica Fürbacher (IDS Mannheim)

Distribution of topic domains

Comparison of DeReKo and DECOW14



Step 2: Topic modeling

- Starting point: term-document matrix
- Documents: weighted assignment to topics
- Topics: defined by a set of weighted words

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Our experiment:

- LSI (Landauer and Dumais, 1994)
  LDA (Blei et al., 2003)
  as implemented in `Gensim` (Řehůřek and Sojka, 2010)
- LDA topic distributions unstable (small gold standard corpora)
- Incrementally add other documents from the source copora

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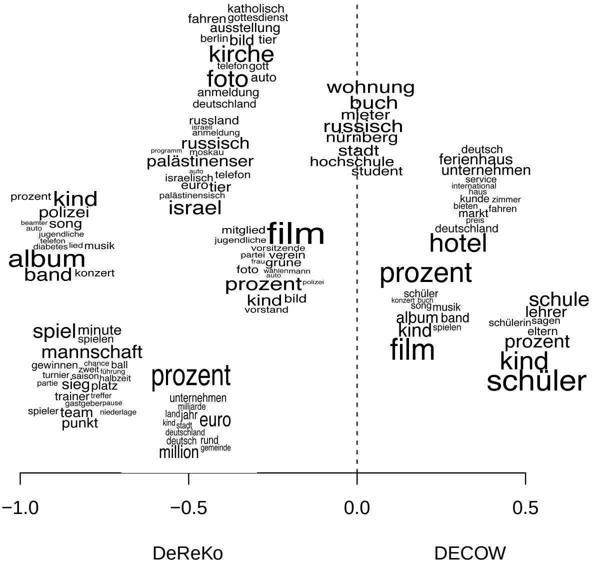
- Incrementally add other documents from the source copora
- Input terms: lemma + simplified POS tag (*kindergarten_nn*)
- Filtering: best results with lower-cased, purely alphabetic noun lemmas, 4–30 chars long

Corpus comparison: distribution of (selected) LSI-topics



Step 3: Learning topic domains from LSI-topics

- Supervised classifiers
- Permutation of virtually all available classifiers in `Weka` (Hall and Witten, 2011)
- Highest accuracy: SVMs with a Pearson VII kernel (Üstün et al., 2006)

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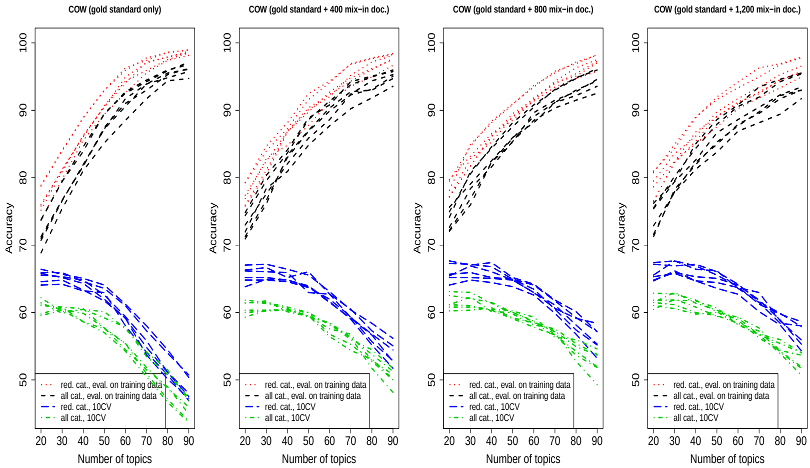
Set of experiments with:

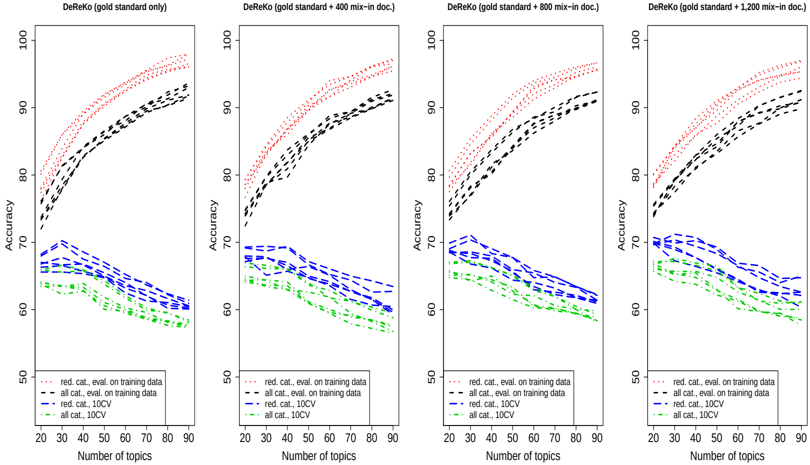
- varying number of LSI-topics
- topics induced from
  - gold standard data plus varying amounts of additional documents
  - several pre-processing variants
- evaluation on the *full* data set and on a *reduced* data set (with rare categories removed)

Results: Web (accuracy)



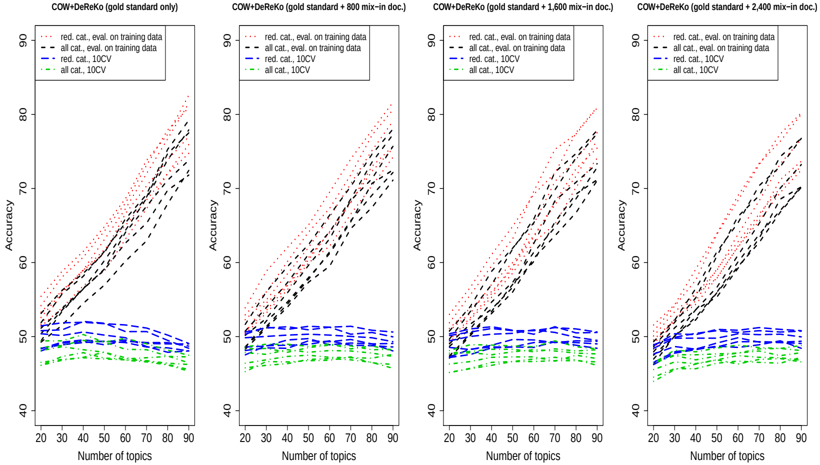
Mixed-in	Attribute	Topics	Accuracy	Precision	Recall	F-Measure
3,200	token	20	68.765%	0.688	0.688	0.674

Results: News (accuracy)



Mixed-in	Attribute	Topics	Accuracy	Precision	Recall	F-Measure
3,600	lemma + POS	40	72.999%	0.725	0.730	0.696

Results: Web + News (accuracy)



Mixed-in	Attribute	Topics	Accuracy	Precision	Recall	F-Measure
0	lemma + POS	30	51.872%	0.431	0.519	0.417

Results: all

Corpus	Mixed-in	Attribute	Topics	Accuracy	Precision	Recall	F-Measure
Web	3,200	token	20	68.765%	0.688	0.688	0.674
News	3,600	lemma + POS	40	72.999%	0.725	0.730	0.696
Web + News	0	lemma + POS	30	51.872%	0.431	0.519	0.417

- Web + News: larger training set does not increase accuracy
- Web + News: mixing in more documents for topic modeling does not increase accuracy
- News: higher accuracy (4.23%) probably a side effect of the more skewed distribution of topic domains in gold standard data

Confusion matrices

COW		Classified							
		PolSoc	Busi	Life	Arts	Public	Law	Beliefs	Hist
Annotated	**PolSoc**	**26**	12	10	1	1	0	1	0
	Busi	5	**105**	40	7	1	2	1	1
	Life	3	14	**286**	6	4	1	1	1
	Arts	3	2	36	**78**	1	0	2	6
	Public	0	3	11	0	**9**	1	0	0
	Law	3	9	8	0	1	**8**	0	0
	Beliefs	4	3	11	6	1	0	**30**	1
	Hist	9	0	9	7	1	1	2	**15**

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