Predicting political party affiliation from text

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Disclaimers

- (For me) This is just a hobby – it has nothing to do with my job
- I did not know a lot of literature in the field
    - Some of this might sound naive (like the title)
    - I hope nobody (who has been active in the field for years) takes this personal

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- Methods
  - Data
  - Preprocessing
  - Classification Model
- Results
  - In-domain held-out data
  - Out-of-domain held-out-data
- Challenges of automated analyses
- Tools for better interpretability / leveraging domain knowledge
- Conclusion
- Web applications of political bias prediction

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Data

- In-domain data (training data domain)
  - `http://www.bundestag.de/plenarprotokolle`
- Out-of-domain data (test data domain)
  - `https://manifestoproject.wzb.eu/`
  - Texts from public Facebook pages of parties

Preprocessing

- Basic text cleaning (regexps, stopwords)
- Stemming
- n-grams (1-5)
- Tf-idf normalisation

Classification Model: Multinomial Logistic Regression

Party affiliation estimate is modelled as

$$p(y = k|\mathbf{x}) = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}} \text{ with } z_k = \mathbf{w}_k^\top \mathbf{x}. \tag{1}$$

With

- Labels $y \in \{1, 2, \ldots, K\}$ (true party affiliation)
- $\mathbf{w}_1, \ldots, \mathbf{w}_K \in \mathbb{R}^d$ weight vectors of kth party

Model Selection

All hyperparameters optimised with nested cross-validation.

Results: In-domain Predictions

Table: **17th Bundestag**

	precision	recall	f1-score	N
cducsu	0.62	0.81	0.70	706
fdp	0.70	0.37	0.49	331
gruene	0.59	0.40	0.48	298
linke	0.71	0.61	0.65	338
spd	0.60	0.69	0.65	606
total	0.64	0.63	0.62	2279

Results: Out-of-domain Predictions

Table: **Tested on manifesto quasi-sentences**

	prec.	recall	f1-score	N
cducsu	0.26	0.58	0.36	2030
fdp	0.38	0.28	0.33	2319
gruene	0.47	0.20	0.28	3747
linke	0.30	0.47	0.37	1701
spd	0.26	0.16	0.20	2278
total	0.35	0.31	0.30	12075

Why is out-of-domain classification so bad?

1. Length of texts

2. Text domain differences

Effect of Text Length

Table: (topic level) **Manifesto data predictions**

	precision	recall	f1-score	N
cducsu	0.64	1.00	0.78	7
fdp	1.00	1.00	1.00	7
gruene	1.00	0.86	0.92	7
linke	1.00	1.00	1.00	7
spd	0.80	0.50	0.62	8
total	0.88	0.86	0.86	36

Effect of Text Length

Table: **Facebook post predictions** (text length: 1000 words).

	precision	recall	f1-score	N
cducsu	0.65	1.00	0.79	50
gruene	0.67	0.12	0.20	50
linke	0.60	0.82	0.69	50
spd	1.00	0.92	0.96	50
avg / total	0.73	0.71	0.66	200

Effect of Text Length

- Longer texts are easier to predict
- Intuitively makes sense
- In line with previous findings, see e.g. Hirst et al. [2014]
- But still, accuracies are far from perfect

Effect of Text Length

What – except length – decreases generalization performance?

Effect of Text Domain

Table: Classification texts into government and opposition (long texts).

	In-Domain	**Out-of-Domain**	
	Parliament	Manifestos	Facebook Posts
Accuracy	0.88	0.60	0.76

- Despite less noisy, longer texts:
  Accuracy on manifesto data close to chance
- Recognized in previous work, see e.g. Yu et al. [2008]

Effect of Text Domain

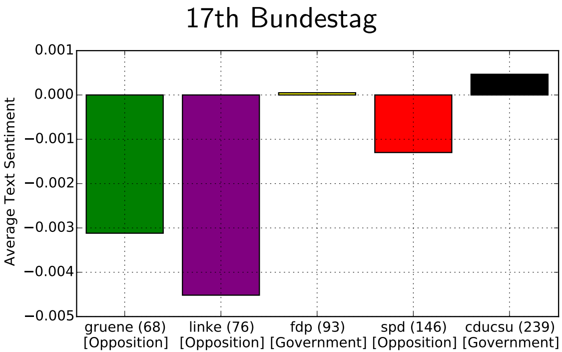
- Every ML model is biased by its training data
- Political scientists have less of a problem with varying domains
- Generalization from biased data is *the* central problem of ML
- Potential strategies to ensure generalization
  - Empirical risk minimization / Regularization
  - More (heterogeneous) data
  - Better models:
    Cov. shift adaptation, transfer/semi-supervised learning, ...
  - **Domain knowledge**

→ How can political scientists leverage domain knowledge for automatic text analysis models?

Some ML Tools for Leveraging Domain Knowledge

- Relation between misclassifications and party policy
- Covariation Text Features and Party labels
- Explicit tests of domain knowledge: Sentiment and Power

Sentiment correlates with political power



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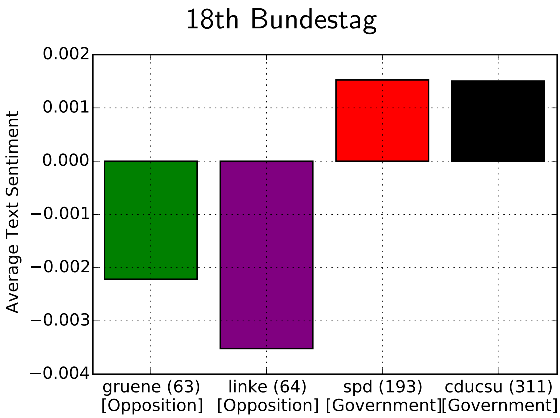
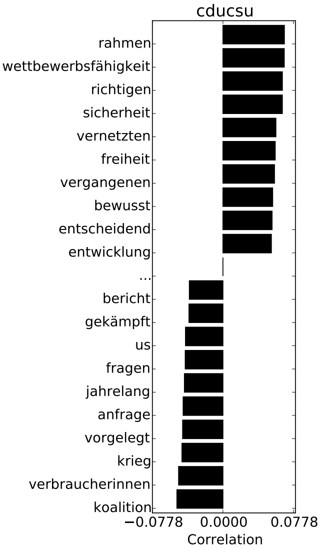


Sentiment correlates with political power

Table: Correlation coefficient between average sentiment with government membership and number of seats in the parliament.

Sentiment vs.	Gov. Member	Seats
17th Bundestag	0.84	0.70
18th Bundestag	0.98	0.89

Finding Discriminative Features



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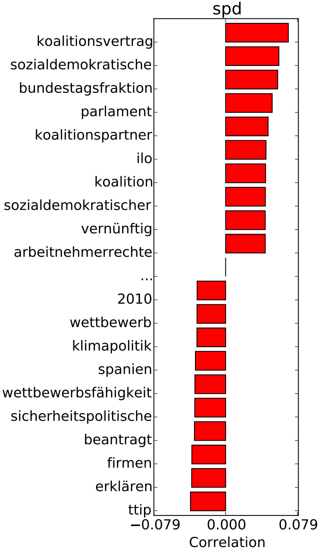

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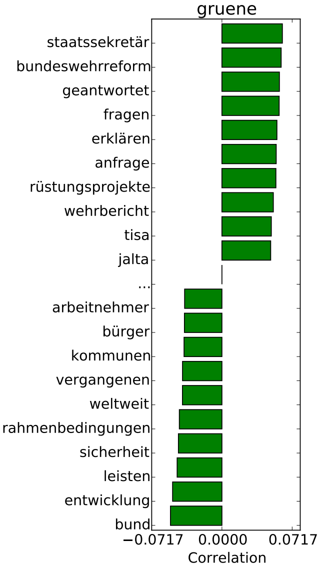

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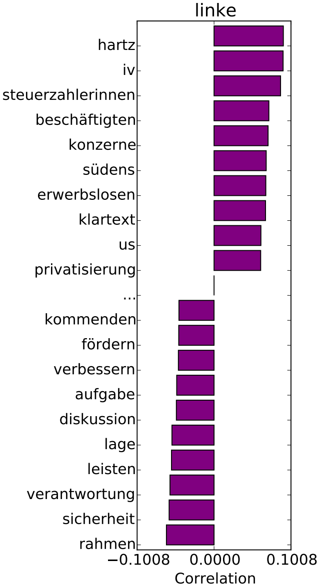

Misclassifications and Policy Change

Confusion Matrix 17th Bundestag

		Predicted				
		cducsu	fdp	gruene	linke	spd
True	cducsu	7	0	0	0	0
	fdp	0	7	0	0	0
	gruene	0	0	6	0	1
	linke	0	0	0	7	0
	spd	4	0	0	0	4

Conclusion

- Out-of-domain prediction of political bias possible
- Challenges
  - Text length, see also Hirst et al. [2014]
  - Domain transfer, see also Hirst et al. [2014]; Yu et al. [2008]
- Generalization should leverage domain knowledge
- Tools for leveraging domain knowledge
  - Relating misclassifications to policy changes
  - Interpreting discriminative features
  - Testing human experts' hypotheses explicitly

Some Web Applications

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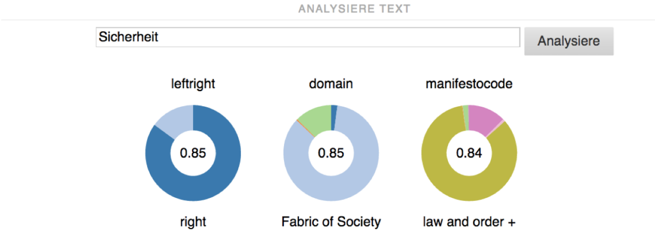

Some Web Applications

TOPIC 5

hollande verfassungsänderung verfassungsreform franzosen

Anschläge von Paris: François Hollande zieht umstr ...
spiegel | left (89%) | Welfare and Quality of Life (58%) | social justice + (56%)

Frankreich: Hollande zieht Verfassungsänderung zur ...
zeit | left (50%) | Welfare and Quality of Life (28%) | gov-admin efficiency + (27%)

Francois Hollande begräbt Pläne für Verfassungsänd ...
faz | right (53%) | External Relations (60%) | europe + (55%)

François Hollande: Das Ende einer politischen Schn ...
welt | right (96%) | Political System (86%) | political authority + (81%)

Frankreichs Gewerkschaften blockieren Reformen ...
welt | right (100%) | Political System (97%) | political authority + (96%)

PyData Hackathon 2016 Berlin

PyData Berlin 2016

What? Follow-up event of PyData Berlin 2016

Inviting Data Scientists, Social Scientists, UX Designers, . . .

Data Ambassadors for

1. Manifesto Data
2. Parliament Data
3. Social Network Data

When? First weekend of October 2016 (1.-2.)

Where? Berlin

References

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B. Yu, S. Kaufmann, and D. Diermeier. Classifying party affiliation from political speech. *Journal of Information Technology & Politics*, 5 (1):33–48, 2008.