Predicting political party affiliation from text

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Disclaimers

- (For me) This is just a hobby / open source project
- It has nothing to do with my job
- I did not know a lot of literature in the field
- So some of this might sound naive (like the title)

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Motivation

- Media generate loads of data
- Too much text to handle by humans

→ Automated political bias prediction required for

  - Political scientists
  - Political education of average media consumer

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Overview

- 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

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
- L_2 norm regularization of weights

Model Selection

All hyperparameters optimised with **nested** cross-validation.[4]

[4] This is not a technical detail. It's a crucial requirement for any ML system.

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

Effect of Text Domain

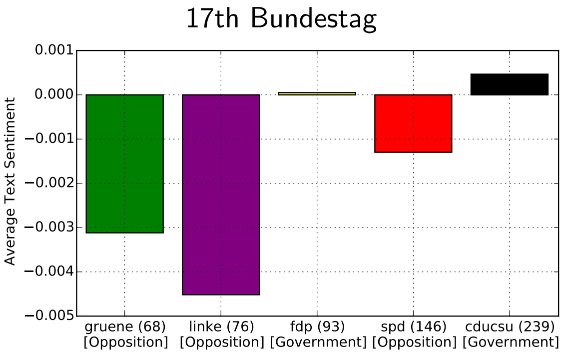
- Recognized in previous work, see e.g. Yu et al. [2008]
- Every ML model is biased by its training data
- Generalization from biased data is *the* central problem of ML
- Strategies to improve generalization
    - Empirical risk minimization / Regularization
    - More (heterogeneous) data
    - Better 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 (**not model coefficients!**) Haufe et al. [2014]
- Explicit tests of domain knowledge: Sentiment and Power

Sentiment correlates with political power



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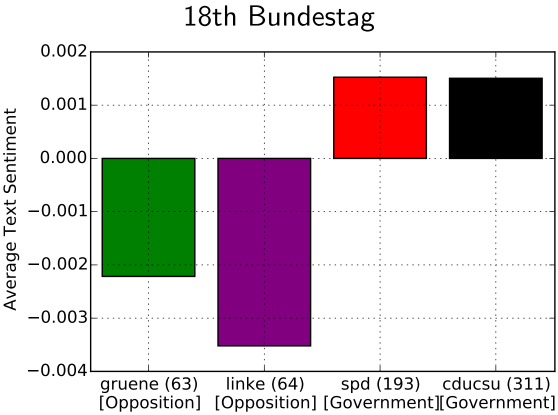
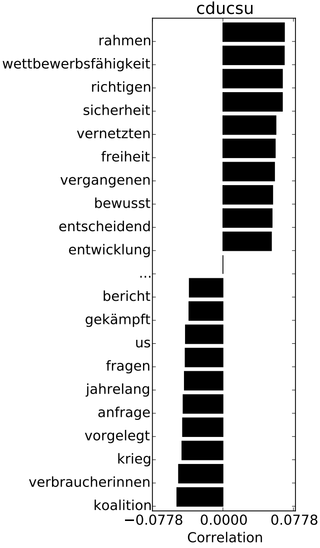


Sentiment correlates with political power

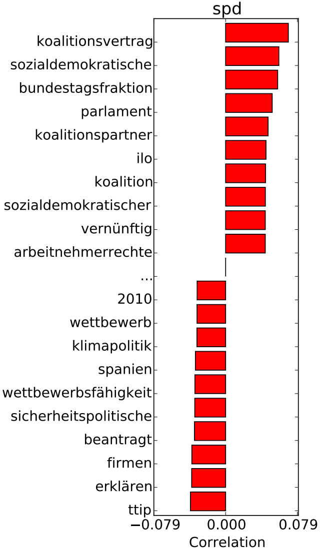
Table: Correlation coefficient between average sentiment with government membership and number of seats in the parliament.

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

Finding Discriminative Features



Finding Discriminative Features



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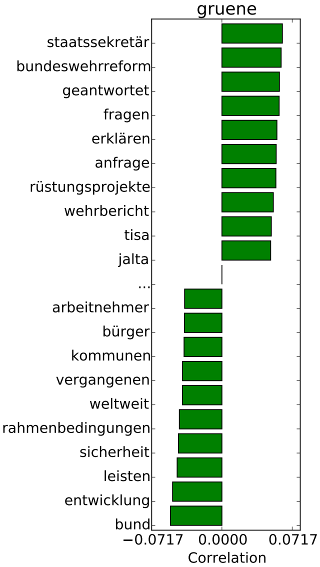

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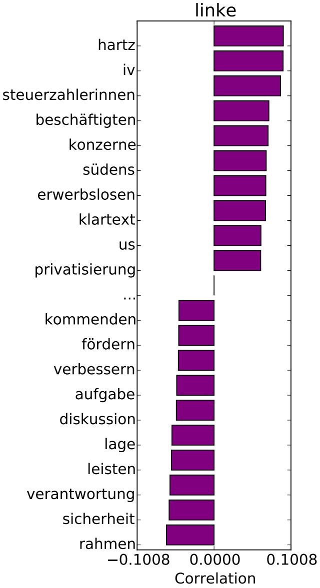

Misclassifications and Policy Change

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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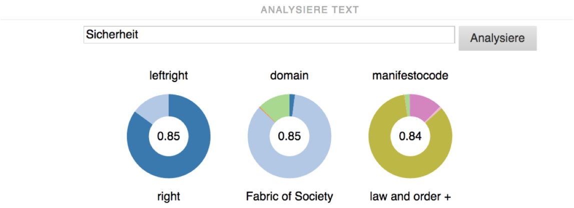
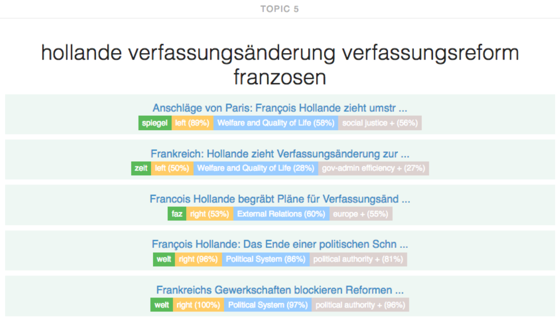


Some Web Applications



PyData Hackathon 2016 Berlin

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

S. Haufe, F. Meinecke, K. Görgen, S. Dähne, J.-D. Haynes, B. Blankertz, and F. Biessmann. On the interpretation of weight vectors of linear models in multivariate neuroimaging. *Neuroimage*, 87:96–110, 2014.

G. Hirst, Y. Riabinin, J. Graham, and M. Boizot-Roche. Text to ideology or text to party status? In I. M. Bertie Kaal and A. van Elfrinkhof, editors, *From Text to Political Positions: Text analysis across disciplines*, pages 47–70, 2014.

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