Predicting political party affiliation from text

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July 9, 2016

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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 $y \in \{1, 2, \dots, K\}$ (true party affiliation)
- $\mathbf{w}_1, \dots, \mathbf{w}_K \in \mathbb{R}^d$ 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

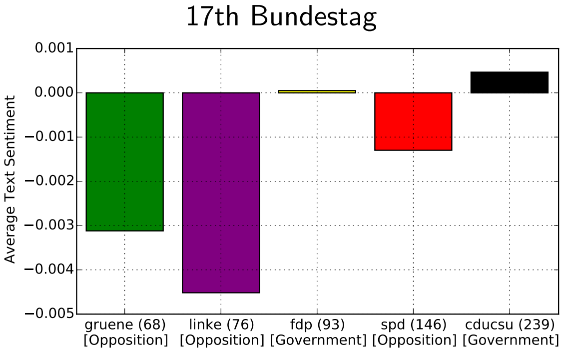
- Every ML model is biased by its training data
- Political scientists have less of a problem with varying domains
- Generalization from biased data is *the* central problem of ML
- Potential strategies to ensure generalization
  - Empirical risk minimization / Regularization
  - More (heterogeneous)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

$\rightarrow$ 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!**)
- Explicit tests of domain knowledge: Sentiment and Power

Sentiment correlates with political power



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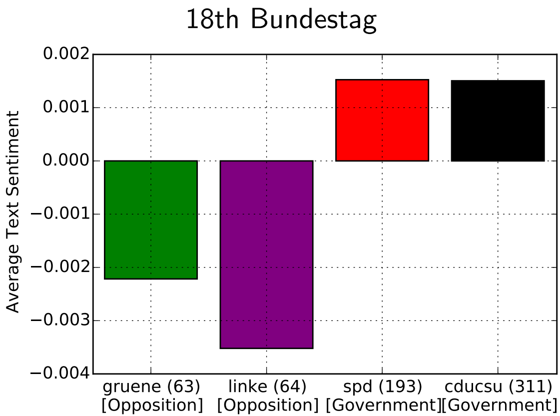
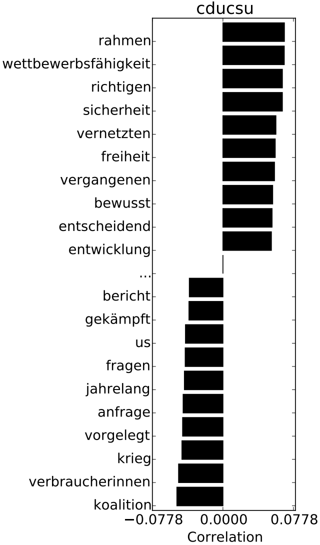


Sentiment correlates with political power

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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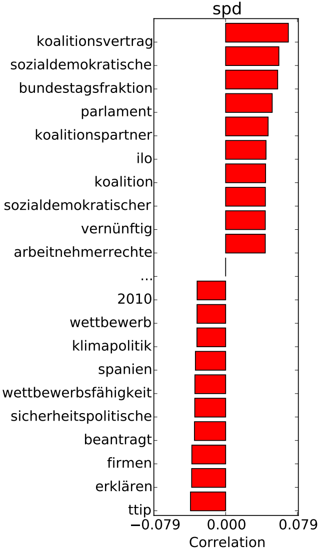

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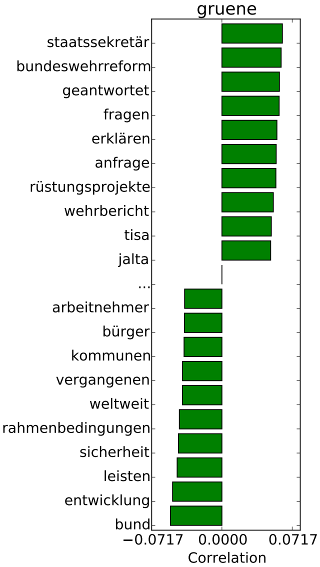

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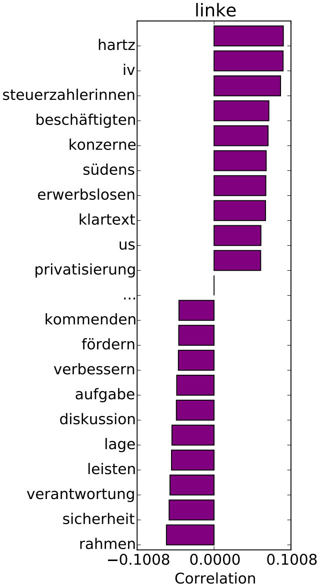

Misclassifications and Policy Change

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

Some Web Applications

ungarn flüchtlinge eu regierung für dublin orbán migranten jobbik polizisten

- Flüchtlinge in München: Ein freundliches, fröhliches Durcheinander
- Ungarn: Orbán droht mit Zaun an Grenze zu Kroatien
- Ungarn: Flüchtlinge treffen an der Grenze auf Rechtsradikale
- Flüchtlinge: "Deutschland hat eine mutige Entscheidung getroffen"
- Ungarns Ex-Premier nimmt Flüchtlinge auf
- Ungarische Polizei versucht Flüchtlinge in Aufnahmelager zu schleusen

pérez guatemala erlassen otto molina präsidenten haftbefehl justiz zurückgetreten immunität

- Otto Pérez: Haftbefehl gegen Präsident von Guatemala erlassen
- Guatemala: Otto Pérez Molina tritt wegen Korruptionsaffäre zurück
- Guatemalas Präsident tritt zurück
- Lateinamerika: Guatemala braucht mehr als einen neuen Präsidenten

trump donald bush republikanischen spanisch republikaner unabhängiger us kandidat präsidentschaftskandidaten

- Trump über Jeb Bush: "Er sollte wirklich Englisch sprechen"
- Donald Trump erklärt Loyalität zu US-Republikanern
- Donald Trump verpflichtet sich Republikanern
- US-Präsidentschaftskandidat: Donald Trump meint es ernst

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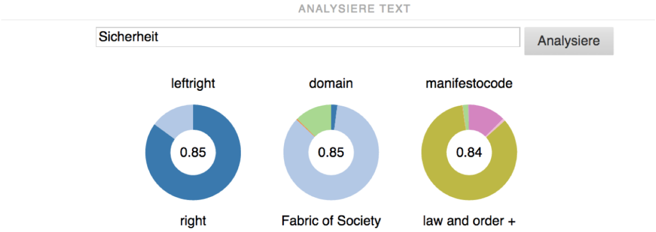

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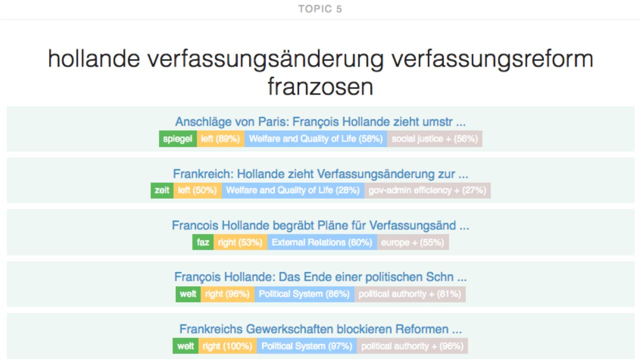

PyData Hackathon 2016 Berlin

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

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.