

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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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

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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

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

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 k th 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
cducusu	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]

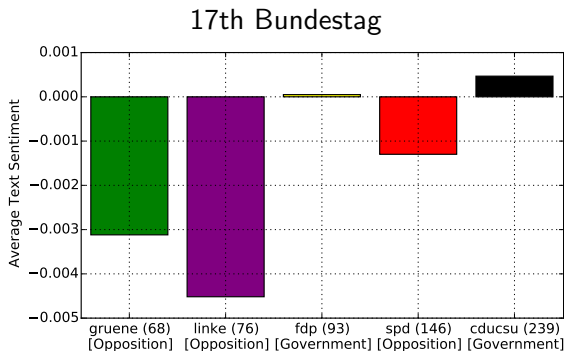
Effect of Text Domain

- 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?

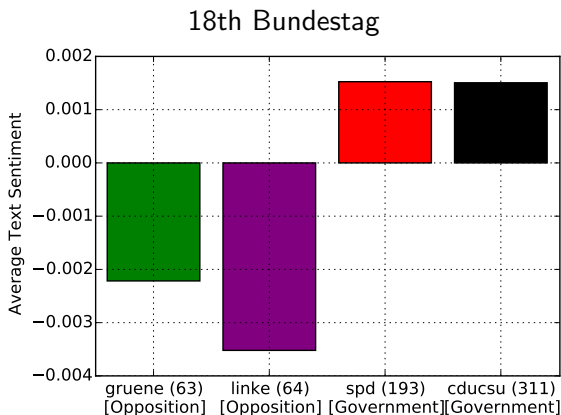
Some ML Tools for Leveraging Domain Knowledge

- 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



Sentiment correlates with political power

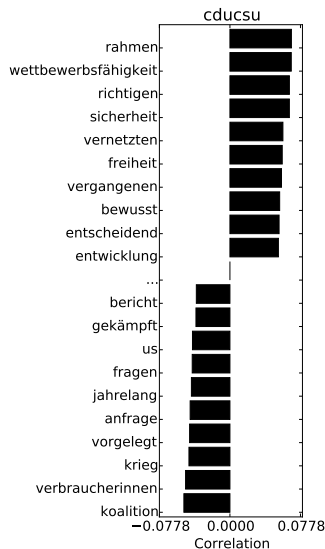


Sentiment correlates with political power

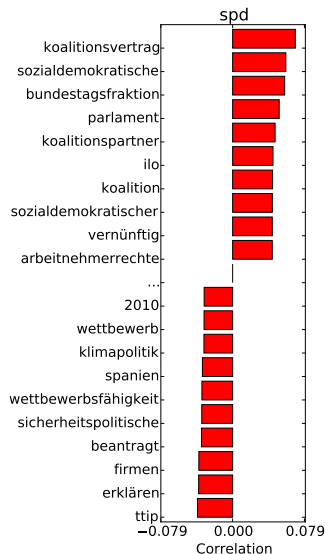
Table: Correlation coefficient between average sentiment with government membership and number of seats in the parliament.

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

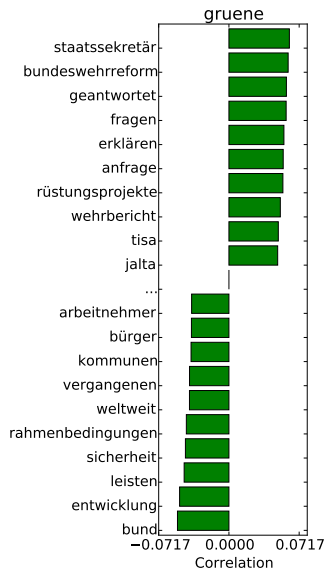
Finding Discriminative Features



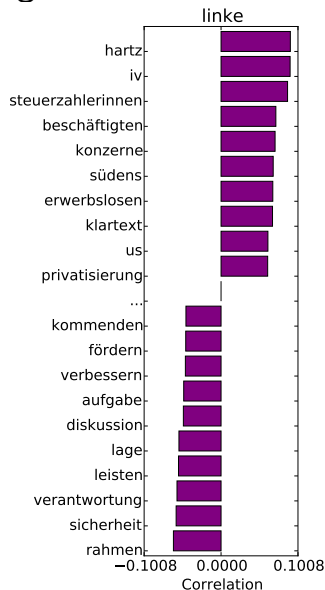
Finding Discriminative Features



Finding Discriminative Features



Finding Discriminative Features



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

The screenshot shows the 'linksrechts' website interface for 'Politische Gesinnungsanalyse'. The background features a word cloud with various political terms. The main heading 'linksrechts' is prominently displayed in a large, black, serif font. Below it, the subtitle 'Politische Gesinnungsanalyse' is centered. A paragraph of text explains the site's function: 'Auf dieser Seite können Sie die politische Gesinnung von Texten und Internetseiten analysieren*. Sie können einen Text in das erste Formular kopieren oder eine Internetseite analysieren, indem Sie eine URL in das zweite Formular kopieren. Wir analysieren auch kontinuierlich einige der großen Nachrichten-Seiten.' Below this, there are two analysis sections. The first, 'Analysiere einen Text', contains a text input field with the example text 'Reiche Banken und neoliberale gefährden den Sozialstaat.' and a blue 'Analyse starten' button. The second, 'Analysiere eine Internetseite', contains a URL input field with the placeholder 'Hier eine URL zu einem Text reinpaste[n]' and another blue 'Analyse starten' button. At the bottom, a semi-circular gauge chart displays the political distribution of the analyzed text. The chart is divided into four segments: a large purple segment labeled 'linke', a small green segment labeled 'gruene', a red segment labeled 'spd', and a small black segment labeled 'cdu'.

linksrechts

Politische Gesinnungsanalyse

Auf dieser Seite können Sie die politische Gesinnung von Texten und Internetseiten analysieren*. Sie können einen Text in das erste Formular kopieren oder eine Internetseite analysieren, indem Sie eine URL in das zweite Formular kopieren. Wir analysieren auch kontinuierlich einige der großen Nachrichten-Seiten.

Analysiere einen Text

Reiche Banken und neoliberale gefährden den Sozialstaat.

Analysiere eine Internetseite

Hier eine URL zu einem Text reinpaste[n]

Analyse starten

Analyse starten

linke gruene spd cdu

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 prääsidenten haftbefehl justiz
zurückgetreten immunität



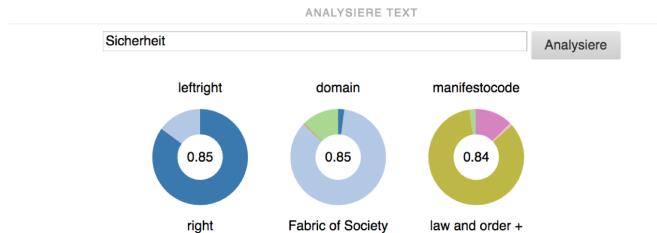
- 🇹🇷 Otto Pérez: Haftbefehl gegen Präsident von Guatemala erlassen
- 🇹🇷 Guatemala: Otto Pérez Molina tritt wegen Korruptionsaffäre zurück
- 🇹🇷 Guatemalas Präsident tritt zurück
- 🇹🇷 Lateinamerika: Guatemala braucht mehr als einen neuen Präsidenten

trump donald bush republikanischen spanisch republikaner
unabhängiger us kandidat präsidenschaftskandidaten



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

Some Web Applications



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

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.