

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

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

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
- L_2 norm regularization of weights

Model Selection

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

⁴This 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
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

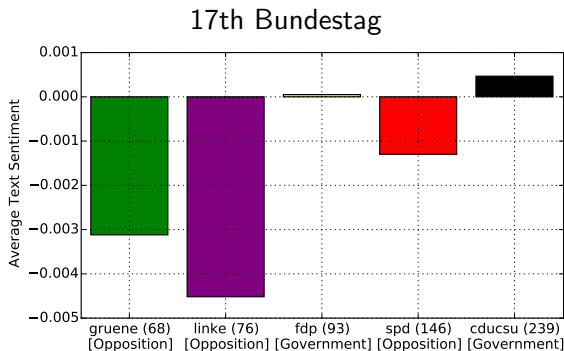
Effect of Text Domain

- 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?

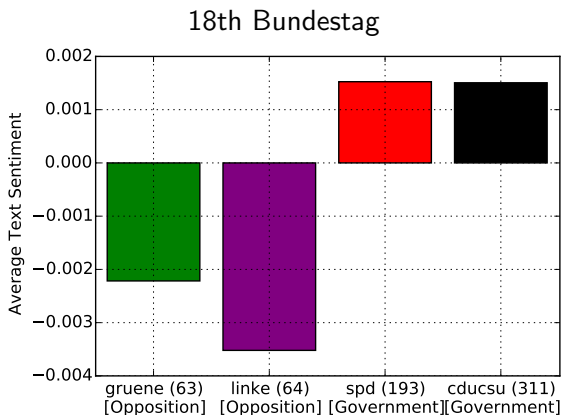
Some ML Tools for Leveraging Domain Knowledge

- 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



Sentiment correlates with political power

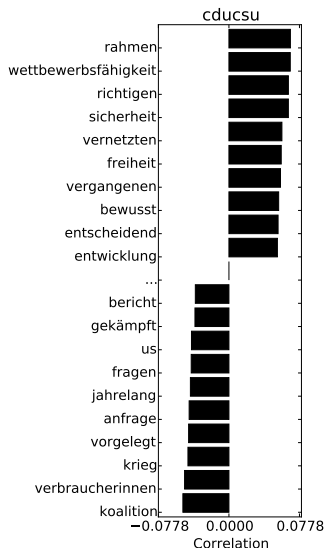


Sentiment correlates with political power

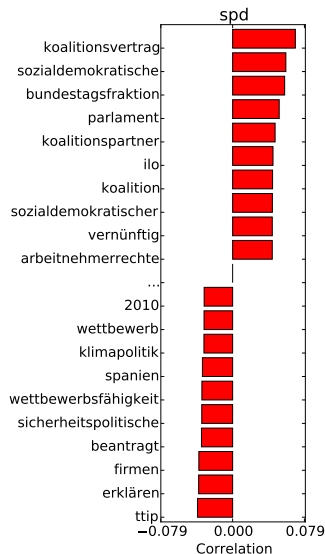
Table: Correlation coefficient between average sentiment with government membership and number of seats in the parliament.

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

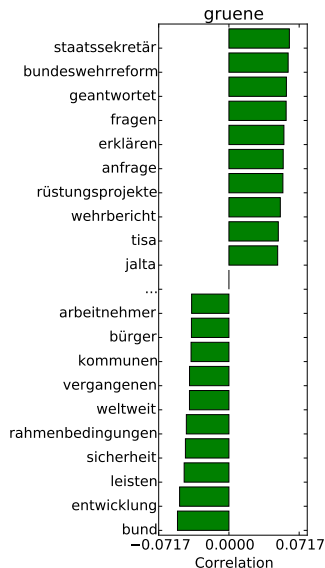
Finding Discriminative Features



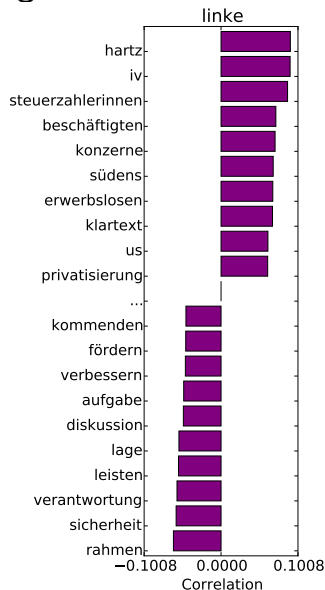
Finding Discriminative Features



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 displays the 'linksrechts' website, which is dedicated to 'Politische Gesinnungsanalyse' (Political Sentiment Analysis). The page features a large, stylized title 'linksrechts' at the top, with a background of floating letters and numbers. Below the title, the subtitle 'Politische Gesinnungsanalyse' is prominently displayed. A paragraph of text explains the tool's purpose: '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.' (On this page, you can analyze the political sentiment of texts and websites*. You can copy a text into the first form or analyze a website by pasting a URL into the second form. We also continuously analyze some of the major news websites.)

There are two main input sections:

- Analysiere einen Text**: A text input field containing the example text 'Reiche Banken und neoliberale gefährden den Sozialstaat.' Below this field is a blue button labeled 'Analyse starten'.
- Analysiere eine Internetseite**: A text input field with the placeholder 'Hier eine URL zu einem Text reinpaste'. Below this field is a blue button labeled 'Analyse starten'.

At the bottom of the page, there is a semi-circular gauge chart representing the political spectrum. The chart is divided into five segments, each representing a different political party:

- linke** (left): A large purple segment on the far left.
- grüne** (green): A small green segment next to the 'linke' segment.
- spd** (socialist): A red segment next to the 'grüne' segment.
- cdu** (conservative): A black segment next to the 'spd' segment.
- rechts** (right): An unlabeled white segment on the far right.

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



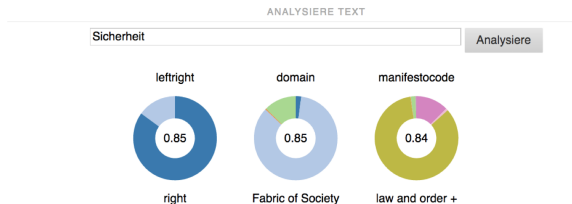
- Otto Pérez: Haftbefehl gegen Präsident von Guatemala erlassen
- Guatemala: Otto Pérez Molina tritt wegen Korruptionsaffäre zurück
- Guatemalas Präsident tritt zurück
- Lateinamerika: Guatemala braucht mehr als einen neuen Präsidenten

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 (56%) 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 (88%) political authority + (81%)

Frankreichs Gewerkschaften blockieren Reformen ...

welt right (100%) Political System (87%) 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

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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.