

KOALA: A new paradigm for election coverage

An opinion poll based “now-cast” of probabilities of events in multi-party electoral systems

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DAGStat | March 20, 2019 | Munich

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KoalitionsAnalyse

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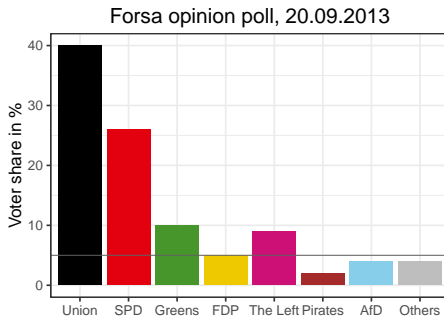
Outline

1. Motivation
2. Methods
3. Technical implementation
4. Conclusion

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1 Motivation



Questions of interest

- Which parties will pass the 5% hurdle and enter the parliament?
- Which parties will form the governing coalition?

① Motivation

Reported voter shares (Forsa, last pre-election poll 2013)

Union	SPD	Greens	FDP	The Left	Pirates	AfD	Others
40%	26%	10%	5%	9%	2%	4%	5%

Redistributed voter shares (based on 5% hurdle)

Union	SPD	Greens	FDP	The Left	Pirates	AfD	Others
44.44%	28.89%	11.11%	5.56%	10.00%	-	-	-

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- Stating that Union-FDP would thus miss a joint majority would neglect sample uncertainty

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We aim to do now-casting

We communicate sample uncertainty in a more natural way by calculating **event probabilities** that fully reflect sample uncertainty.

We do not aim to do for-casting

- Our approach simply communicates sample uncertainty in a novel way
- Also, a relevant share of voters is still undecided shortly before election day (Küchenhoff et al., 2018)

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② Methods

Estimating probabilities of events (POEs)

Given one opinion poll with sample size n :

$$\mathbf{X} = (X_1, \dots, X_P)^T \sim \text{Multinomial}(n, \theta_1, \dots, \theta_P),$$

with voter counts X_j and the true percentage of voters θ_j per party j .

A **Dirichlet posterior distribution** results for $\theta|\mathbf{x}$:

$$\theta|\mathbf{x} \sim \text{Dirichlet}(x_1 + 1/2, \dots, x_P + 1/2),$$

based on an **uninformative Dirichlet prior** (Gelman et al., 2013)

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Estimating probabilities of events (POEs)

Given the **posterior distribution of voter shares** we can use **Monte Carlo simulations** to estimate POEs:

1. Simulate 10 000 election outcomes from the posterior
(adding uniformly distributed random noise to account for rounding errors)
2. If necessary: Redistribute voter shares to get obtained seats in parliament
3.
$$\text{POE} = \frac{\text{\#events}}{\text{number of simulations}}$$

Example

Given the Forsa poll, the coalition of Union-FDP obtained a majority of seats in 2633 of 10 000 simulations

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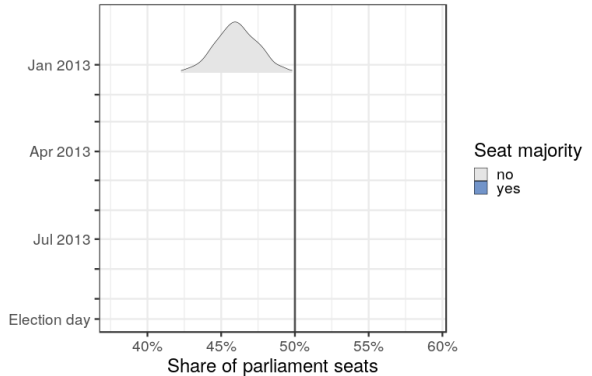
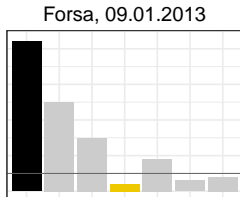
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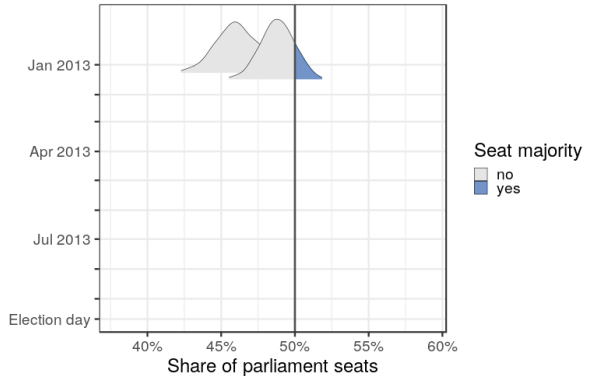
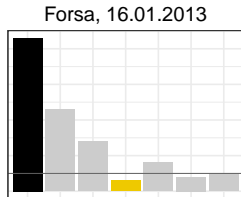
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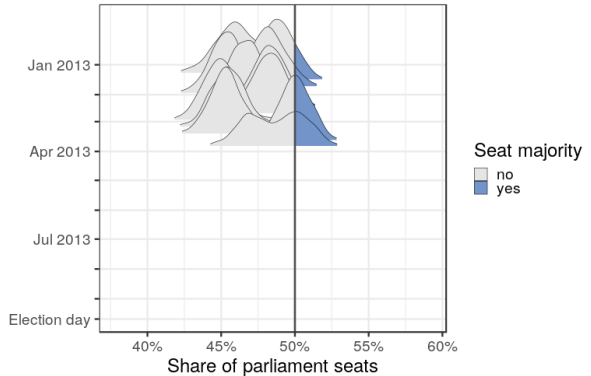
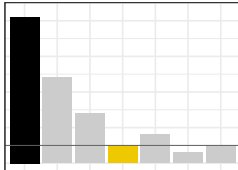
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② Methods

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Forsa, 26.03.2013



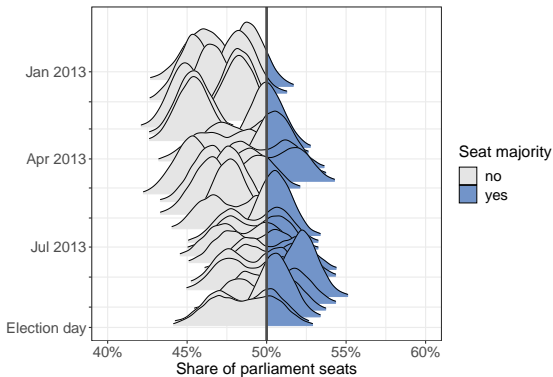
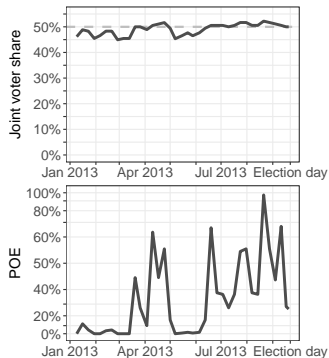
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② Methods

Pooling

We aggregate multiple polls to reduce sample uncertainty.

In case of multiple random samples:

$$\left(\sum_i X_{i1}, \dots, \sum_i X_{iP} \right)^T \sim \text{Multinomial} \left(\sum_i n_i, \theta_1, \dots, \theta_P \right).$$

We account for correlations between polling agencies by using an **effective sample size** (Hanley et al., 2003).

Example

Pooling two polls with 1 500 and 2 000 respondents we get an effective sample size of $n_{\text{eff}} = 2\,341$ (based on a strongest party share of 40%).

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Pooling in practice

- We only pool surveys published in the last 14 days
- We only include one survey per polling agency

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③ Technical implementation



R package coalitions

Functionality

- Scrape wahlrecht.de for (new) polls
- Calculate pooled sample
- Sample from posterior distribution
- Redistribute votes below 5% threshold
and calculate parliament seats (e.g. based on method by [Sainte-Laguë-Schepers](#))
- Calculate coalition probabilities

More on github.com/adibender/coalitions

③ Technical implementation

Web-Interface



Communicating the results

1. Website koala.stat.uni-muenchen.de
⇒ Automatic updates scraping data from wahlrecht.de
2. Twitter [@KOALA_LMU](https://twitter.com/KOALA_LMU)
⇒ Automatic tweets of new results
3. Blog koala-blog.netlify.com

Technical implementation in R

- User interface was built with the `shiny` package
- Server is based on `Shiny Server Open Source`
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The KOALA approach

- New paradigm for opinion poll coverage
- Bayesian approach to now-cast POEs
- Sample uncertainty is reduced by pooling multiple polls
- Communication to the general public
- **Keep in mind:** We calculate now-casts, not for-casts

References

KOALA

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