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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Collaborators

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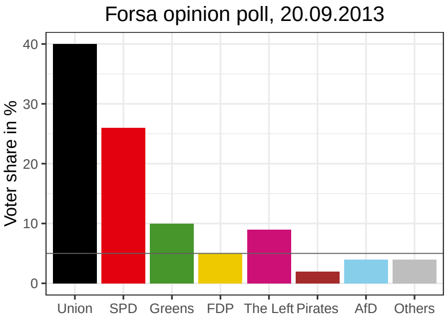
Outline

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

Outline

❶ Motivation



Questions of interest

- Which parties will pass the 5% hurdle and enter the parliament?
- Which parties will form the governing coalition?
- Which party will have the third largest share of votes?

❶ Motivation

Reported voter shares

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

Redistributed voter shares (based on 5% hurdle)

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44.44%	28.89%	11.11%	5.56%	10.00%	-	-	-

- Union-FDP have a joint seat share of exactly 50%
- Stating that Union-FDP would thus miss a joint majority would neglect sample uncertainty

⇒ We calculate event probabilities that fully reflect sample uncertainty

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We aim to do now-casting

- We incorporate the uncertainty as reported by the polling agencies
- Potential house biases or an industry bias are not accounted for

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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❷ Methods

Estimating probabilities of events (POEs)

Given one opinion poll with sample size n:

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

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

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

$$\boldsymbol{\theta} = (\theta_1, \dots, \theta_P)^T \sim Dirichlet(\alpha_1, \dots, \alpha_P),$$

$$\text{with} \qquad \alpha_1 = \dots = \alpha_P = \frac{1}{2},$$

a **Dirichlet posterior distribution** results for $\boldsymbol{\theta}|\boldsymbol{x}$:

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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
2. If necessary: Redistribute voter shares to get obtained seats in parliament
3. $\text{POE} = \frac{\#\text{event}}{\text{number of simulations}}$

Example

Given the Forsa poll, the coalition of Union-FDP obtained a majority of seats in 2 633 of 10 000 simulations

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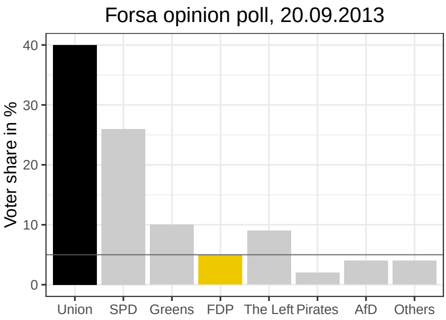
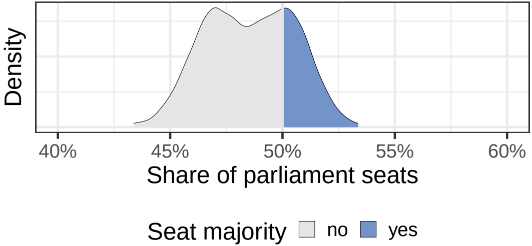


❷ Methods

Posterior distribution of joint CDU-FDP seat share



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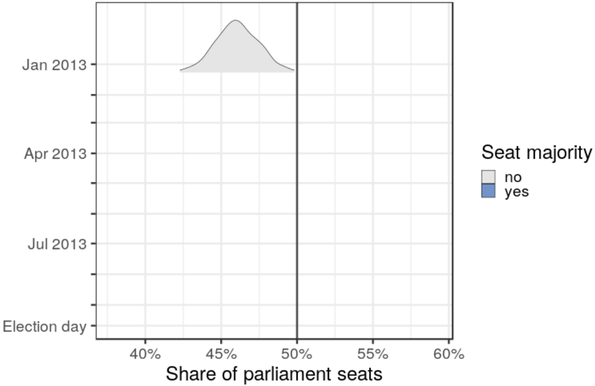
Visualization using ridgeline plots (Wilke, 2017)



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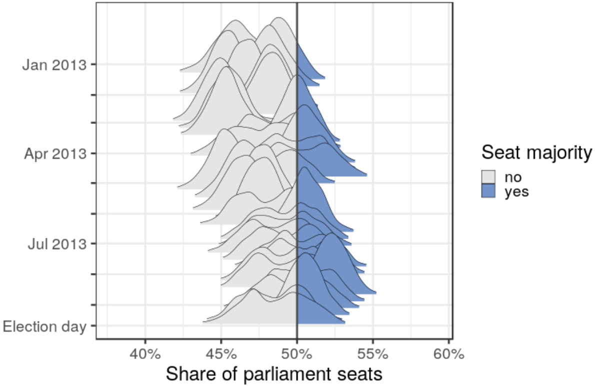

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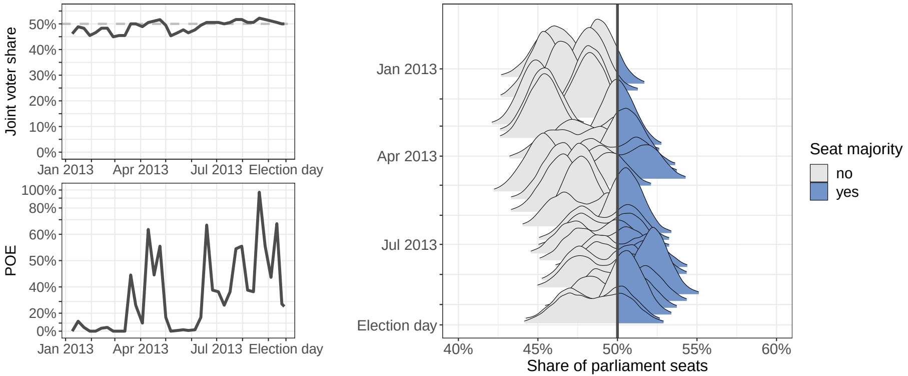

❷ Methods

Pooling

We aggregate multiple polls to reduce sample uncertainty.
In case of multiple random samples:

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

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 (where the strongest party obtained 40%), we get a conservative effective sample size of $n_{\text{eff}} = 2\,341$.

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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

Correction of rounding errors

Party shares are only published with a certain accuracy.
We add **uniformly distributed random noise** to avoid potential biases.

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❷ Technical implementation

R package `coalitions`

Functionality

- Scrapes wahlrecht.de for (new) polls
- Calculate pooled sample
- Calculate and sample from posterior distribution
- Redistribute votes below 5% threshold
  and calculate parliament seats (e.g. based on method by Sainte-Lague-Scheppers)
- Calculate coalition probabilities

More on github.com/adibender/coalitions

❷ Technical implementation

R package `coalitions`

```
> library(coalitions)
> library(tidyverse)

> surveys <- get_surveys()
> surveys

# A tibble: 7 x 2
  pollster   surveys
  <chr>      <list>
1 allensbach <tibble [42 x 5]>
2 emnid      <tibble [226 x 5]>
3 forsa      <tibble [236 x 5]>
...

> survey <- surveys %>% unnest() %>% slice(1)
> survey %>% get_probabilities(list(c("cdu","fdp")), nsim = 10000) %>%
  unnest()
# A tibble: 1 x 4
  pollster   date       coalition probability
  <chr>      <date>     <chr>           <dbl>
1 allensbach 2019-02-19 cdu_fdp             0
```

Web-Interface

Communicating the results

1. Website koala.stat.uni-muenchen.de
   ⇒ Automatic updates scraping data from wahlrecht.de
2. Twitter @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 do not make predictions

References

KOALA

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Further software

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