A long-short term event memory state-space model for multi-party elections with (R)Stan

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Introduction

- State-space models are common choice for modelling voting intentions using poll data
- *Here:* Go beyond random-walk approaches by introducing long-short term event memory effect
- Vote shares tends to reverse to the party's long-term trend after larger short-term movements
- Empirical assessment by smoothing polls, calculating integrated acf's on weekly differences:

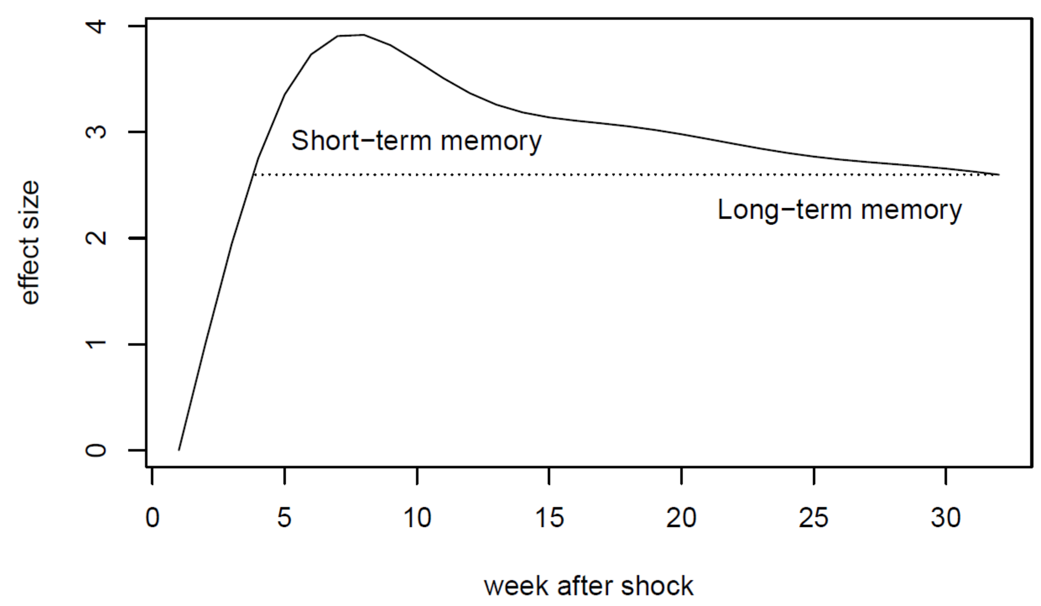

Fig. 1: Empirical effect of single shock or event on vote share in time course

- Max effect around 7 to 8 weeks after initial shock - wears off in the following weeks.
- Events influencing the vote share can be decomposed into:
  - A short-term effect due to e.g. media spreading
  - A smaller remaining long-term effect (new events, forgetfulness)
- Government parties tend to lose vote share between 1994 and 2017
  - In 10/12 cases government parties lost vote share
  - In 15/20 cases opposition parties gained vote share
- Sources of uncertainty in forecasting vote share:
  - Uncertainty about future events, i.e. shocks to vote share
  - Uncertainty in polling
    a) Common bias of all pollsters for a specific party
    b) House bias of a specific pollster for a specific party
    c) Polling uncertainty of a specific pollster

Data

- > 4000 polls beween 1994 and 2017 of German national elections ("Bundestagswahl")
- 7 pollsters (web-scraped) for 6 largest parties:
  - CDU/CSU (conservative; chancellor Angela Merkel)
  - SPD (social democratic party)
  - Die Grünen (green party)
  - FDP (liberal party)
  - Die Linke (left socialist party)
  - AfD (right populist party)
- Election outcome data since 1998
- Data on party status (government or opposition)

Model

- Features:
  - long- and short-term memory structure - mixture of a random walk and two contrasting AR-type processes
  - party status (government or opposition)
  - different sources of uncertainty (potential future events, common pollster error, pollster-party-house bias, polling uncertainty)
  - heavy-tail errors
  - correlations between errors (optional)
- $y_{pt,t}$: true vote share for specific party,pt time point t, if an election would be held (indexed on weekly basis).
- No direct measure of vote share except on election days ⇒ use of polling data $poll_{pt,t,pll}$ for party pt, time point t and pollster pll
- Logit scale to guarantee forecasts in (0,1) interval and variance regulation

$$logit(poll_{pt,t,pll}) \sim N(y_{pt,t} + bias_{pt,pll} + \epsilon_{\text{pollError}_{pt,t}}, \sigma_{pt,pll} + 1E-4)$$

- The Common pollster bias follows AR1-process. Set to zero just after an election, as pollsters adjust for the bias afterwards:

$$\epsilon_{\text{pollError}_{pt,t}} = 0.98 \cdot \epsilon_{\text{pollError}_{pt,t-1}} + \epsilon_{\text{polls}_{pt,t}}$$

- Shifts in the common bias of the pollsters for a specific party follow a t-distribution with five degrees of freedom and a standard deviation $\sigma_{pollbias}$ that is different for each party pt:

$$\epsilon_{\text{polls}_{pt,t}} \sim t(0, \sigma_{\text{pollbias}_{pt}}, df = 5)$$

- True vote shares $y_{pt,t}$ follow a random walk (with drift), but two additional terms $\upsilon_{pt,t}$ and $\eta_{pt,t}$, modeling short and long-term memory effects:

$$y_{pt,t} = y_{pt,t-1} + \epsilon_{pt,t} + \nu_{pt,t} - \eta_{pt,t}$$

- 5-df t-distribution chosen for shocks in vote share. Expectation $\mu_{pt,t}$ depends on government or opposition state, the sd $\sigma_{shift_{pt}}$ is different for each party pt :

$$\epsilon_{pt,t} \sim t(\mu_{pt,t}, \sigma_{\text{shift}_{pt}}, df = 5)$$

- The positive short-term memory effect $\upsilon_{pt,t}$ follows a process resembling AR(1) :

$$\nu_{pt,t} = \theta_2 \cdot (\nu_{pt,t-1} + \epsilon_{pt,t-1})$$

- $\eta_{pt,t}$ represents a diminishing short-term effect. The amount of "forgetting" is set by α :
  - α = 1: the long-term effect is zero
  - α = 0: the long-term = short-term effect

$$\eta_{pt,t} = \theta \cdot \eta_{pt,t-1} + (1-\theta) \cdot \alpha(\nu_{pt,t} + \epsilon_{pt,t-1})$$

Results

- Forecast three months prior 2017 election:

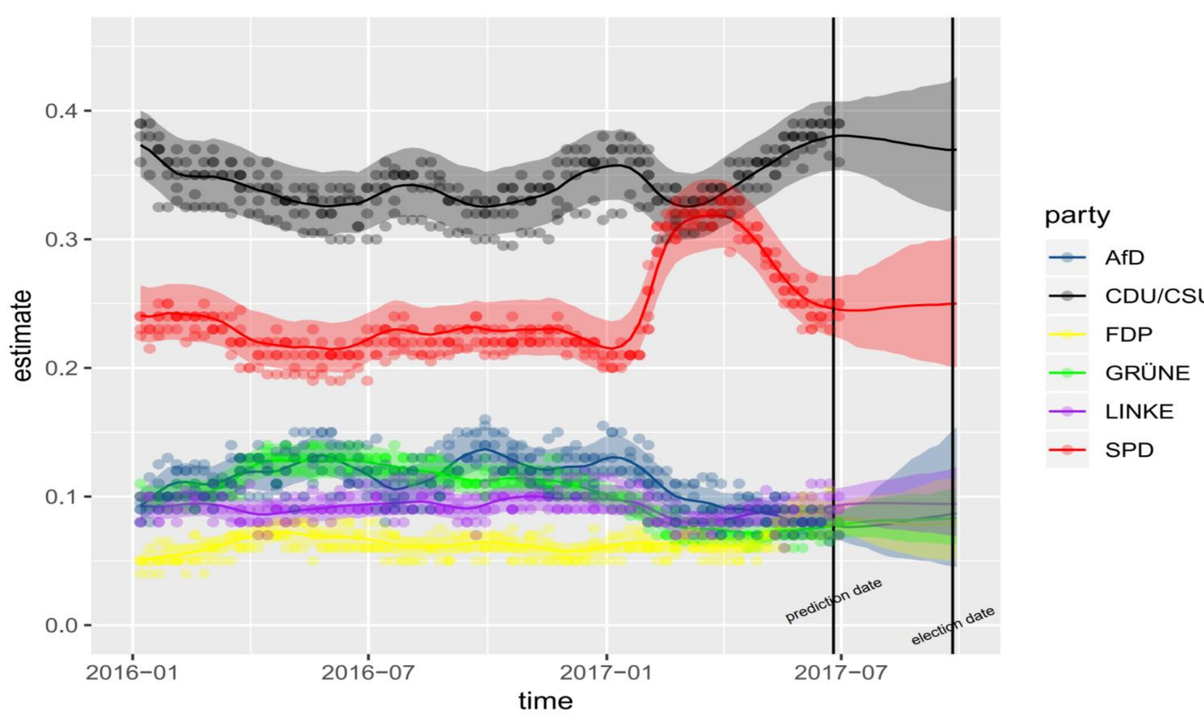

Fig. 2: Solid lines: vote share estimates $y_{pt,t}$ + 95% credible bands, points: polls, vertical lines: date of prediction (2017-06-25), election date (2017-09-24)

	CDU	SPD	Grüne	Linke	FDP	AfD	*RMSE*
Bayes - Model	**36.96**	**25.01**	**8.31**	**9.42**	**7.91**	**8.69**	**3.17**
ForschG	39	25	8	9	8	7	4.02
Insa	36,5	25	6,5	11	9	9	3.11
EMNID	39	24	8	9	7	8	3.77
GMS	39	23	7	11	9	8	3.52
Infra	39	24	7	8	9	8	3.62
Forsa	39	23	8	10	8	7	3.73
Allensbach	40	24	7	8.5	10.5	6.5	4.16
Election Result	**32.9**	**20.5**	**8.9**	**9.2**	**10.7**	**12.6**	**0**

Tab. 1: Comparison of model forecast with most recent polls of pollsters and election result (in %)

- Model predicts a mean-reversing trend for CDU/CSU (black) and AfD (blue), i.e. decrease/increase in vote share until election
- AfD forecasts: much larger credible intervals compared to the other three smaller parties on election day (party founded some years ago, less stable)
- Simulation of single shock effect with model parameters:

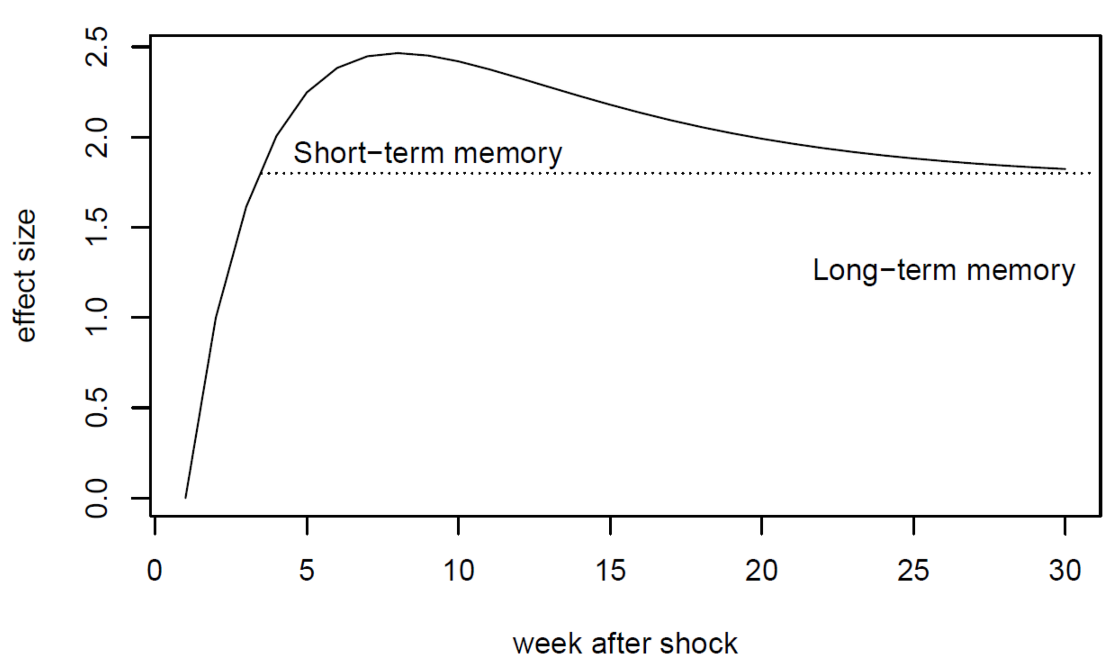

Fig. 3: Simulated effect of single shock or event on vote share in time course

- Very similar to empirical results!

- Government ⇒ negative drift in random walk part; opposition ⇒ positive drift:

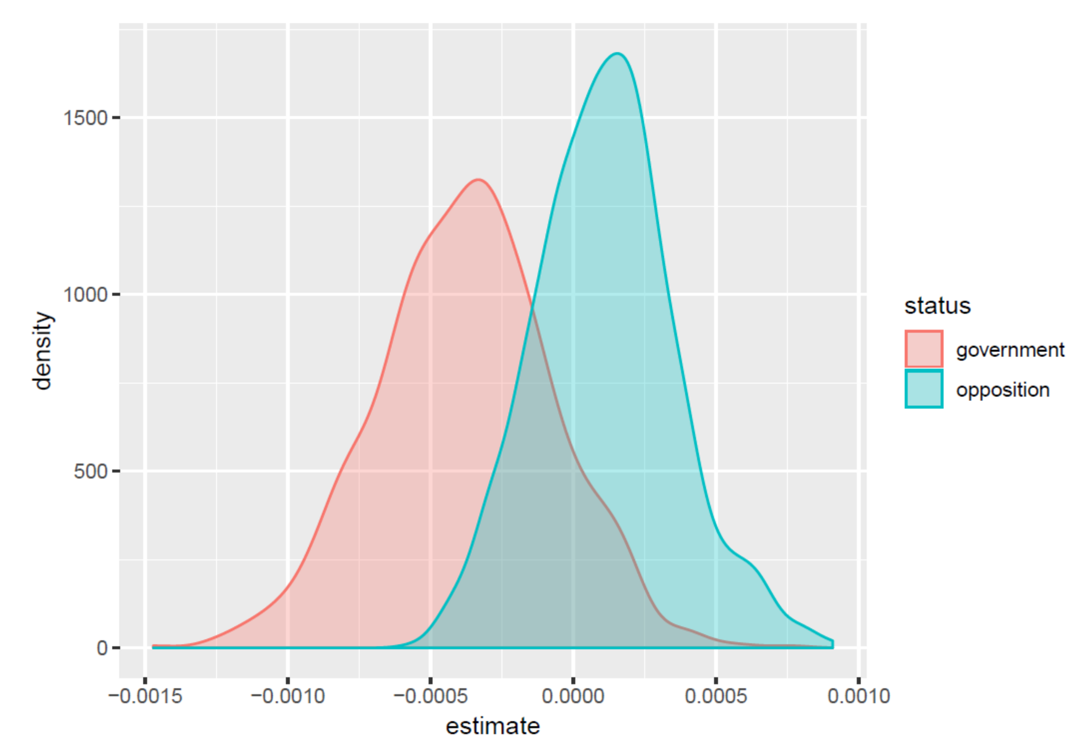

Fig. 4: Kernel density of government and opposition effect

- House bias of pollster for specfic parties can be substantial:

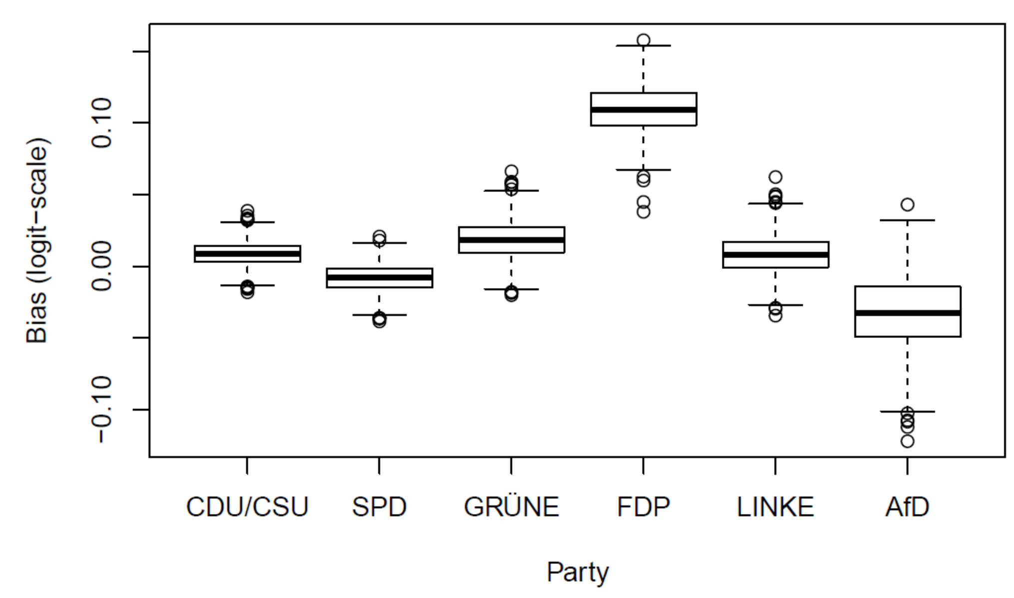

Fig. 5: House bias estimates of „Allensbach" pollster

Summary

Model performance evaluation:

- Fit model and forecast election each month for year prior to 2017 federal election
- Two competitors:
  1. Avg. of the most recent poll of the 7 pollsters
  2. Most recent poll
- In average, model outperforms poll average by *15%* and by *20%* compared to the most recent poll:

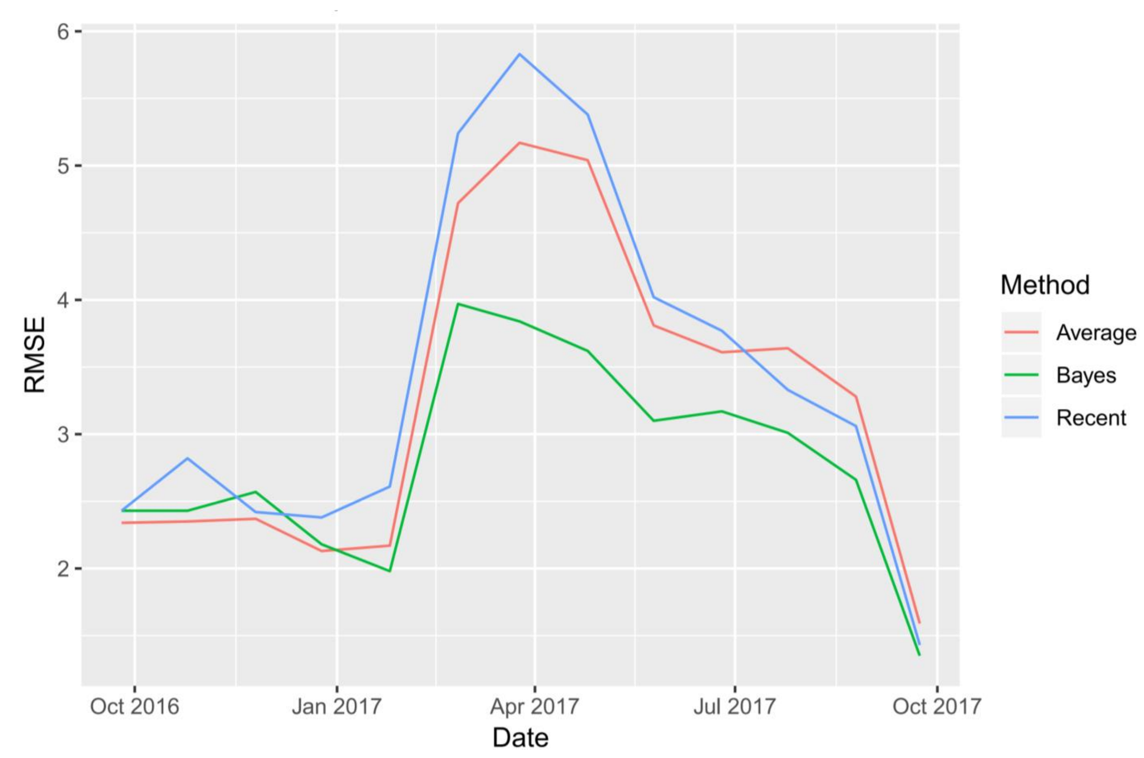

Fig. 6: Root Mean Square Error (RMSE) in monthly intervals for the proposed model (green), the average of the most recent polls (red) and the most recent poll (blue) for the year prior the 2017 german federal election.

- Even unfair hindsight competitors (using best pollster for this particular election and best pollster for each prediction date) worse or on par with proposed model
- Similar results for 2013 election

Troubleshooting and outlook:

- The model iterations exceed maximum tree size, for tree_depth < 18 (but results are o.k. for tree_depth larger than 15) ⇒ very slow computation (ca. one week)
- Usage of map_rect should speed up comptutation
- Extension of model by multivariate t-distributions for both vote share shocks $\epsilon_{pt,t}$ and common poll bias $\epsilon_{polls_{pt,t}}$
- Introduction of mid-term effect seems to improve for modelling forgetting of events

Stan-Code, examples and more on GitHub: https://github.com/INWTlab/lsTerm-election-forecast