# Election Forecasting Model

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Notation derives from (Cargnoni, Müller, & West, 1997), itself citing (West & Harrison, 1997).

## 1 Setup

Denote by  $\mathbf{p}_i = (p_{i1}, \dots, p_{i(r+1)})'$  a vector of r observed proportions on day  $t_i$ ,  $i = 1, \dots, n$ ,  $t_i \in \{0, \dots, T\}$ .  $\mathbf{p}_i$  gives voter responses to an opinion poll about their preference among r candidates, as well as an additional category for "Other". Accompanying  $\mathbf{p}_t$  is a sample size,  $N_i$ , so that an estimate of the number of respondents who prefer the  $j^{\text{th}}$  candidate may be calculated as  $y_{ij} = p_{ij}N_i$ ,  $j = 1, \dots, r$ . The data is reported in proportions, so to ensure the proper sample size after calculating  $y_{ij}$ , we define  $y_{i(r+1)} = N_i - \sum_{i=1}^r y_{ij}$ .

proper sample size after calculating  $y_{ij}$ , we define  $y_{i(r+1)} = N_i - \sum_{j=1}^r y_{ij}$ . We consider the vector of counts  $\mathbf{y}_i = (y_{i1}, \dots, y_{i(r+1)})$ , and we consider a multinomial likelihood:

$$[\mathbf{y}_i|\boldsymbol{\pi}_{t_i}, N_i] \sim \text{Mult.}(\boldsymbol{\pi}_{t_i}, N_i) \tag{1}$$

$$\eta_i = h(\pi_{t_i}) = (h_1(\pi_{t_{i1}}), \dots, h_r(\pi_{t_{ir}}))' \in \mathbb{R}^r, \quad i = 1, \dots, N.$$
(2)

$$h_j(\pi_{tj}) = \log \frac{\pi_{tj}}{\pi_{t(r+1)}}, \quad j = 1, \dots, r$$
 (3)

$$\boldsymbol{\pi}_{t_i} = h^{-1}(\boldsymbol{\eta}_i) = (h_1^{-1}(\boldsymbol{\eta}_i), \dots, h_{r+1}^{-1}(\boldsymbol{\eta}_i))' \in [0, 1]^r$$
 (4)

$$h_j^{-1}(\boldsymbol{\eta}_i) = \frac{e^{\eta_{ij}}}{1 + \sum_{j'=1}^r e^{\eta_{ij'}}}, \quad j = 1, \dots, r$$
 (5)

$$h_{r+1}^{-1}(\boldsymbol{\eta}_i) = \frac{1}{1 + \sum_{j'=1}^r e^{\eta_{ij'}}}$$
 (6)

where  $\sum_{j=1}^{r+1} \pi_{tj} = 1$ .

We model  $\eta_i$  using a dynamic linear model, which provides a structure to relate all polls that occur on the same day, i.e., the sets  $\{\mathbf{y}_i|t_i=t\}$ ,  $t=1,\ldots,T$ .

$$\eta_t = \beta_t + \nu_t, \quad \nu_t \sim N_r(\mathbf{0}, v\mathbf{I}_r)$$
(7)

$$\beta_t = \beta_{t-1} + \omega_t, \quad \omega_t \sim N_r(\mathbf{0}, w_t \mathbf{I}_r)$$
 (8)

and we assume  $\beta_0$  known. This model is a random walk for the daily multinomial proportion vectors.

In the notation and terminology of (West & Harrison, 1997), this is a constant dynamic linear model where

$$\mathbf{F} = \mathbf{I}_r \tag{9}$$

$$\mathbf{G} = \mathbf{I}_r \tag{10}$$

To construct a Bayesian model, we assign constant variance in the observation equation (v), and iid time-varying variances in the system equation  $(w_t)$ .

By the forward-filtering, backwards-sampling (FFBS) algorithm, the prior distributions for all  $\beta_t$  depend recursively only on  $\beta_0$ , so we complete the model by assigning priors to the parameters  $\{\beta_0, v, w_1, \dots, w_T\}$ .

$$\beta_0 \sim N_r(\mathbf{m}_0, C_0 \mathbf{I}_r)$$
 (11)

$$v \sim \text{Inv.-Gamma}(\alpha_0, \beta_0), \quad t = 1, \dots, T$$
 (12)

$$w_t \sim \text{Inv.-Gamma}(\alpha_0, \beta_0)$$
 (13)

We choose diffuse priors for v,  $w_t$ , with  $\alpha_0 = \beta_0 = 0.001$ .

We specify the mean structure of the model with the forward-filtering, backward-sampling procedure.

### 1.1 Forward-filtering

(West & Harrison, 1997) give the updates for the multivariate dynamic linear model on page 582.

We suppose  $\mathbf{m}_0, C_0$  known, so  $\boldsymbol{\beta}_0 \sim N_r(\mathbf{m}_0, C_0 \mathbf{I}_r)$ .

For t = 1, ..., T,

1. Posterior at t-1

$$\beta_{t-1}|\mathcal{D}_{t-1} \sim N_r(\mathbf{m}_{t-1}, C_{t-1}\mathbf{I}_r) \tag{14}$$

2. Prior at t

$$\beta_t | \mathcal{D}_{t-1} \sim N_r(\mathbf{m}_{t-1}, R_t \mathbf{I}_r)$$
 (15)

3. One-step forecast

$$\eta_t | \mathcal{D}_{t-1} \sim N_r(\mathbf{m}_{t-1}, Q_t \mathbf{I}_r)$$
(16)

4. Posterior at t

$$\beta_t | \mathcal{D}_t \sim N_r(\mathbf{m}_t, C_t)$$
 (17)

$$\mathbf{m}_t = \mathbf{m}_{t-1} + A_t(\boldsymbol{\eta}_t - \mathbf{m}_{t-1}) \tag{18}$$

$$R_t = C_{t-1} + w_t (19)$$

$$Q_t = (R_t + v) \tag{20}$$

$$A_t = R_t / (R_t + v) \tag{21}$$

$$C_t = R_t - A_t^2 Q_t \tag{22}$$

When filtering, also calculate  $B_t$  given below.

#### 1.1.1 Missing observations

Most series are comprised of unequally spaced time points, that is, there may be "missing observations". In this case, we have no data, but the state vector is not of interest: by properties of a normal distribution we can "solve out" the intervening time periods. Practically speaking, this means the variance increases, but the mean remains the same:

$$\mathbf{m}_t = m_{t-1} \tag{23}$$

$$R_t = C_{t-1} + w_t (24)$$

## 1.2 Backward-sampling

As written on page 570 of (West & Harrison, 1997), we can then sample backwards by the procedure procedure is then:

- Sample  $\beta_T | \mathcal{D}_T \sim N_r(\mathbf{m}_T, C_T \mathbf{I}_r)$
- For  $t = n 1, n 2, \dots, 1, 0$ , sample

$$\beta_t | \beta_{t+1}, \mathcal{D}_t \sim N_r(\mathbf{h}_t, H_t \mathbf{I}_r)$$
 (25)

$$\mathbf{h}_t = \mathbf{m}_t + B_t(\boldsymbol{\beta}_{t+1} - \mathbf{m}_{t+1}) \tag{26}$$

$$H_t = C_t - B_t^2 R_{t+1} (27)$$

$$B_t = \frac{C_t}{R_{t+1}} \tag{28}$$

## References

Cargnoni, C., Müller, P., & West, M. (1997). Bayesian forecasting of multinomial time series through conditionally Gaussian dynamic models. *Journal of the American Statistical Association*, 92(438), 640–647.

West, M., & Harrison, J. (1997). Bayesian Forecasting and Dynamic Models. Springer-Verlag New York.

# 2 Example dataset

This dataset was scraped for informational and research purposes from RealClearPolitics<sup>1</sup>.

Date	MoE Poll	Year	N	VoterType	Start	StartDate	End	EndDate	Abrams.D	Kemp.R	Other
<chr></chr>	<dbl> <chr></chr></dbl>	<int></int>	<dbl></dbl>	<chr></chr>	<chr></chr>	<date></date>	<chr>&gt;</chr>	<date></date>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>
1 10/29 - 10/31	3.7 Emerson	2018	724	LV	10/29	2018-10-29	10/31	2018-10-31	0.47	0.49	0.04
2 10/21 - 10/30	3 Atlanta Journal-Constitution	2018	1091	LV	10/21	2018-10-21	10/30	2018-10-30	0.47	0.47	0.06
3 10/28 - 10/29	3.9 FOX 5 Atlanta/Opinion Savvy*	2018	623	LV	10/28	2018-10-28	10/29	2018-10-29	0.48	0.47	0.05
4 10/21 - 10/22	3.4 FOX 5 Atlanta/Opinion Savvy*	2018	824	LV	10/21	2018-10-21	10/22	2018-10-22	0.48	0.48	0.04
5 10/14 - 10/18	4.8 NBC News/Marist	2018	554	LV	10/14	2018-10-14	10/18	2018-10-18	0.47	0.49	0.04
6 9/30 - 10/9	2.8 Atlanta Journal-Constitution*	2018	1232	LV	9/30	2018-09-30	10/9	2018-10-09	0.46	0.48	0.06
7 10/3 - 10/8	4.9 WXIA-TV/SurveyUSA	2018	655	LV	10/3	2018-10-03	10/8	2018-10-08	0.45	0.47	0.08
8 10/1 - 10/1	3.2 Landmark Communications*	2018	964	LV	10/1	2018-10-01	10/1	2018-10-01	0.46	0.48	0.06
9 8/26 - 9/4	3.1 Atlanta Journal-Constitution*	2018	1020	LV	8/26	2018-08-26	9/4	2018-09-04	0.45	0.45	0.1
10 7/27 - 7/29	3.8 Gravis	2018	650	LV	7/27	2018-07-27	7/29	2018-07-29	0.46	0.44	0.1
11 7/15 - 7/19	4.3 WXIA-TV/SurveyUSA	2018	1199	LV	7/15	2018-07-15	7/19	2018-07-19	0.44	0.46	0.1

https://www.realclearpolitics.com/epolls/latest\_polls/