Dynamic Linear Election Model for Icelandic Parliamentary Elections Forecast

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## Introduction

This report outlines the methodology behind forecasting the outcome of the upcoming Icelandic Parliamentary Elections scheduled for November 30th. The forecast is based on a dynamic linear model implemented in Stan, incorporating polling data over time and adjusting for polling house effects.

## Model Specification

We model the polling percentages for each political party over time using a dynamic linear model with a multinomial observation component. The model captures the evolution of party support and accounts for variations between different polling houses.

### Notation

* : Number of political parties.
* : Number of time points (dates).
* : Number of polling houses.
* : Number of observations (polls).
* : Count of responses for party in poll .
* : Latent support for party at time .
* : Effect of polling house for party .
* : Scale parameter for the random walk of party .

### Dynamic Party Effects

The latent support for each party evolves over time following a random walk:

where , and is the time difference between polls at and .

### Polling House Effects

Polling house effects are modeled to account for biases:

where election results are assigned to the the first polling house and therefore the first polling house’s effect is set to zero. A soft sum-to-zero constraint is applied to the remaining effects to allow for small amounts of industry-level bias.

## Data and Likelihood

The observed counts are modeled using a multinomial distribution with a logit link:

where , is the date of poll , and is the polling house of poll .

## Prior Distributions

The priors are specified as follows:

* Initial party effects: .
* Random walk innovations: .
* Polling house effects: , with as a soft constraint.
* Scale parameters: .

## Inference

Bayesian inference is performed using Markov Chain Monte Carlo (MCMC) sampling via Stan. Posterior distributions of the latent variables and are obtained, allowing for probabilistic forecasting of election outcomes.

## Posterior Predictive Checks

To assess the model’s fit, posterior predictive simulations are conducted:

These simulations generate replicated data under the model to compare with the observed data.

## Conclusion

The dynamic linear model effectively captures the temporal evolution of party support and adjusts for polling house biases. By leveraging Bayesian methods, we obtain a comprehensive probabilistic forecast of the election outcomes, accounting for uncertainty in the estimates.