A Bayesian Model for Inference on Multiple Panel Public Opinion Surveys

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Overview

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Abstract

Public opinion polling data has unique features that make modelling it challenging. Polling data is often non-representative of the population it aims to estimate. It is also common for individual polls to have a large enough measurement error to make identifying the most popular response difficult. Previous research has developed various methods for analyzing individual polls and some methods for aggregation. Some of these methods are Bayesian but there are unsolved problems. This dissertation will focus on three distinct but related models. The first is a model to predict American presidential election data. The second is a combination of Bayesian model averaging and multiple imputation to create regressions based on a panel survey about terrorism policy preferences. The last is a Bayesian model based on combining two distinct panel surveys about terrorism with different sampling frames and measurement schedules.

Data

- Both surveys have similar questions asked about various topics regarding terrorism including: different types of concern about terrorism, likelihood of attacks, support for federal/local counterterrorism spending, support for certain counterterrorism policies. Population is US adults
- Both surveys have over 25 questions and 100 items per wave varying slightly across surveys and waves
- Survey 1: Two wave (May 2016 & November 2016) Probability based internet survey ran on KnowledgePanel (then at GFK), had 1730 respondents in first wave, 1210 in second wave, generally nationally representative.
- Survey 2: Six wave (monthly from June-November 2016) non-probability panel recruit from web advertisements, 700 respondents, 110 were replenishment sample, 562 completed all waves
- Both surveys have item non-response, but on average less than 5 items are missing from the survey per respondent per wave
- These surveys happened during the rise of ISIS, and multiple attacks occurred between waves. These surveys also happened in a presidential campaign where terrorism was a key issue
- There are 7 time points: May, June, July, August, September, October, November

Data Continued

There are a series of key variables in the survey that regressions were fit on. This presentation will focus on policy support. The survey asked about 7 different counter terrorism policies using a Likert scale of Strongly oppose, Somewhat oppose, Neutral, Somewhat support, Strongly support coded as 1 to 5.
The goal is to track changes over time in the population and in individuals.
Data was split into 80% training and 20% testing to validate the model.
There are four response patterns: T1 only (S=1), T1 & T7 (S=2), T2-T7 (S=3), T7 only (S=4) that represent proxies of four different "surveys".

The Three Main Challenges

1. Integrate two very different surveys
2. Handle item level non-response
3. Handle differential non-response especially in the non-probability sample

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Analyzing Panel Surveys

- Individual panel surveys can be easily analyzed in a mixed model with a random coefficient for time and subject in both Bayesian and classical contexts
- The repeated measurements in a panel survey allow change over time to be more accurately measured since the samples are identical
- Dropouts are common and can affect the analysis
- Combining separate panel surveys is difficult due to different dates and rates of measurement but can provide a better picture
- Panel surveys are becoming more common with the rise of internet survey companies that use a common group to draw samples from

Multilevel Regression with Poststatification (MRP)

MRP fits a multilevel regression on demographic characteristics and then predicts a response for each combination of characteristics (stratification cells) and a weighted average across those values predicts the population value. Wang et al (2015) demonstrated that MRP produced reliable estimates of the election outcome using a highly unrepresentative online convenience sample.
MRP is designed primarily for fixed time points. Gelman et al (2016) extended MRP to the form of a mixed model with a coefficient for time, but all the data used to fit the model was independent surveys without repeated measures.
Stan is a probabilistic programming language that efficiently implements multilevel regression using Hamiltonian Monte Carlo and was used to run the model.

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Model

- Impute the data with mi package external to the model
- Use normal likelihood for individuals with one wave of responses, and MVN for individuals with two or more waves of responses, 32 different variance structures on normal distribution based on interaction of age, gender, race to improve normality.
- Put hierarchical priors on the regression coefficients to allow for pooling across time and pooling across demographic groups
- Use Hamiltonian Monte Carlo in Stan to fit the model (non-centered parameterization)
- Use MRP to handle non-representative data

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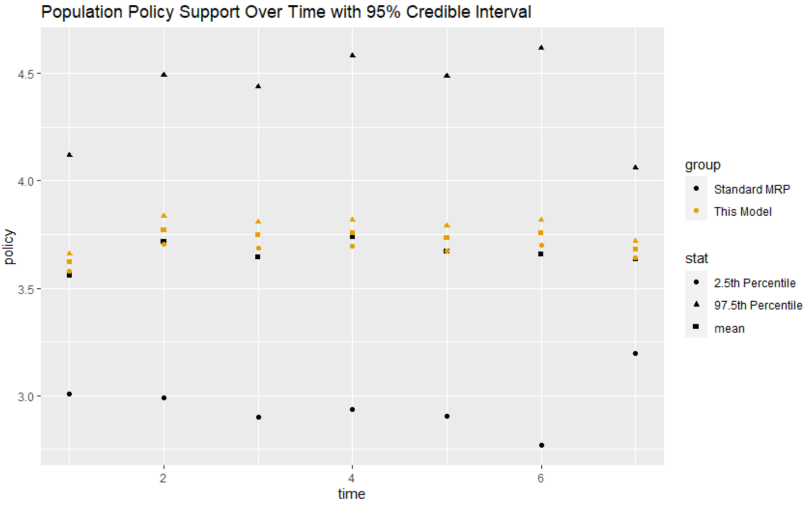
Results: Average Absolute Residuals Compared to Standard MRP fit at each Time point

In this table, the average absolute residual of this model is compared to standard MRP fit using rstanarm at each time point.

	MRP	This Model
T1	0.627	0.670
T2	0.697	0.671
T3	0.663	0.672
T4	0.644	0.616
T5	0.653	0.669
T6	0.600	0.610
T7	0.610	0.644
Average	0.642	0.652

Plot of Change over time in population

Below is a plot showing the mean and endpoints of a 95% credible intervals of the population estimate for This model and standard MRP fit at each time point.



Conclusion

- This model presents a way to track changes of opinion over time in a way that is more precise than standard MRP.
- A combination probability and non-probability sample is also more economical
- Multi-wave surveys have distinct advantages in measuring change over time
- A survey with a similar design of a multi-wave probability survey with a smaller non-probability survey conducted in the middle, may be able to better detect changes over time while being more cost affordable than a large multi-wave probability survey.
- This model could also be extended to track categorical data over time with a higher degree of precision than individual polls

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