What the People Think: Advances in Public Opinion Measurement Using Modern Statistical Methods

Abstract

Surveys are a central part of political science. Without surveys, we would not know what people think about political issues. Survey experiments further enable us to test how people react to given treatments. Surveys and survey experiments are only as good as the measurements and analytical techniques we as researchers employ, though. For one particular survey variable called ordinal variables, some of our current measurements and techniques are insufficient. Ordinal variables consist of ordered categories where the spacing between each category is uneven and not known. Ordinal variables are highly important because the most important predictor of political behavior is an ordinal variable: education. Ordinal example categories for education could be "Some High School", "High School Graduate", and "Bachelor's Degree". The literature currently often does not take the special nature of ordinal variables, i.e. their uneven spacing, into account. This could misrepresent the data and potentially distort survey results. It is important that we measure and use education and other ordinal variables correctly. My dissertation develops two methods to do so and applies them in original survey research. Chapter 1 develops a new method to improve the use of ordinal variables in the assignment of treatment in survey experiments. Chapter 2 develops a new method to treat missing survey data with ordinal variables. Chapter 3 applies both methods in an online survey experiment on political framing.

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Summary

Chapter 1: Improving Blocking on Ordinal Variables in Survey Experiments

1.1 Background

Survey experiments attempt to uncover treatment effects. To do so, all treatment groups need to look the same, i.e. they must be balanced. This can be achieved through random assignment. Complete randomization probabilistically results in balance based on the Law of Large Numbers. For small samples, however, it can result in imbalance (Holland, 1986; Rubin, 1974). Blocking, i.e. arranging participants in groups that are equal in terms of demographic information, guarantees balance (Moore and Moore, 2013; Imai et al., 2009). However, researchers often simplify blocking on ordinal variables by making them numeric without justification (Urdan, 2010; Imai, 2018).

One of the most important predictors in political science is an ordinal variable: education. It is widely established that education represents one of the major driving forces behind political behavior in the U.S., such as turnout or donations (Dawood, 2015; Leighley and Nagler, 2014; Druckman et al., 2013). Ordinal variables consist of ordered categories where the spacing between each category is uneven and not known (Agresti, 2010, 1990; King et al., 2007). The spacing between "Some High School" and "High School Graduate", for instance, is arguably different than the spacing between "High School Graduate" and "Bachelor's Degree". It is difficult to measure the distances between the categories, so it is often ignored in academic usage (King et al., 1994; Fox, 2015). Blocking inadequately on such an important variable misrepresents the data and can distort the results, which puts any insights gained from an experiment in doubt. I propose a method that increases precision and removes this doubt.

1.2 Objectives

Hypothesis: Researchers misuse blocking on education by making it arbitrarily numeric.

Goal: Develop a method to block on education appropriately.

1.3 Methodology

I propose an ordered probit model threshold approach to estimate an underlying latent continuous structure underneath education. The re-estimated data-driven categories can then be used for blocking. In practice, I train the following linear model on the 2016 ANES data, one of the most respected and recognized externally and internally valid data sets:

$$Education \sim Gender + Race + Age + Income + Occupation + PartyID \tag{1}$$

In this model, I regress education on meaningful explanatory variables with the ordered probit function to create numerical thresholds. These thresholds partition education into regions corresponding to its categories and bin the data between these thresholds according to the explanatory variables. These binned cases then determine which of the original categories make sense given the underlying latent continuous structure. The result is a non-arbitrary re-estimated number of categories. Because of their data-driven justification, these categories can then be safely used for blocking. I demonstrate the benefits of this method with several Monte Carlo simulations. Simulations are crucial here as they allow comparison to the 'true' results, which is not possible with actual data. They show that the re-estimated ordered probit categories produce analytical results that are closer to the 'truth' than the original ANES categories.

Chapter 2: A New Method to Impute Missing Survey Data from Ordinal Variables

2.1 Background

Missing data are ubiquitous in surveys (Allison, 2002; Raghunathan, 2016). Respondents frequently refuse to answer questions, select "Don't Know" as a response option, or drop out during the response collection process (Honaker and King, 2010). Missing data pose a big problem for researchers because data can typically not be analyzed with statistical software if they contain missing values (Little and Rubin, 2002; Molenberghs and Kenward, 2007).

Scholars have developed several general ways to treat missing data. These range from deleting all observations with missing data (listwise deletion) over randomly drawing a 'similar' respondent to provide a fill-in value for a missing slot (hot decking) to estimating missing values from conditional distributions (multiple imputation) (Rubin, 1976; King et al., 2001; Fay, 1996).

Listwise deletion has been shown to induce bias with political data, and hot decking does not reflect statistical uncertainty in the filled-in values since there is only one draw (Kroh, 2006; Gill and Witko, 2013; Rees and Duke-Williams, 1997). While multiple implementation has become and remains the state of the art in missing data management, it is not necessarily always suitable for all types of variables. Multiple hot deck imputation, an improvement over generic multiple imputation, solves this for non-granular discrete data (Gill and Cranmer, 2012; Reilly, 1993). However, the underlying algorithm assumes even distances between categories in discrete data, which makes it unsuitable for ordinal variables. I propose a method designed to impute missing data specifically from ordinal variables that fills this gap in multiple hot deck imputation.

2.2 Objectives

Hypothesis: Current methods to treat missing survey data are unsuitable for ordinal variables.
Goal: Develop a method to impute missing data specifically from ordinal variables.

2.3 Methodology

Multiple hot deck imputation uses draws of values from the variable with the missing values (hot decking) to impute them distributionally (multiple imputation) and estimate affinity scores. This score measures how close other respondents are to the one with the missing value. 'Closeness' is measured as the distance between respondents in the variables that do not contain missing values. This is best illustrated with simplified data shown in Table 1.

Respondent	Age	Party ID	Education	Income	Gender
A	25	Republican	High School Graduate	$40-50,000	Male
B	40	NA	Some High School	$30-40,000	Female
C	30	Democrat	Bachelor's Degree	$60-70,000	Female

Table 1: Illustrative Data

Respondent B shows missing data for party ID. To impute a fill-in value, we look at how close respondents A and C are to B in terms of age, education, income, and gender. C is closer to B in terms of age and they share the same gender. A is closer to B on education and income. Multiple hot deck imputation measures these distances and estimates affinity scores for respondents A and C. B then receives the party ID fill-in value from whichever respondent has the higher score. The algorithm building the affinity score, however, assumes evenly spaced distances between categories. This is the case for age, income, and gender, but not for education, since education is an ordinal variable. Applying multiple hot deck imputation here would misrepresent the data.

Instead, I propose a weighted distance solution with the estimated numeric thresholds from the ordered probit model approach in chapter 1 to measure the distances between the categories and calculate the affinity score. I demonstrate the benefits of this method with several Monte Carlo simulations. As in chapter 1, simulations are crucial as they allow comparison to the 'true' results, which is not possible with actual data. They show that weighted distance multiple hot decking imputation outperforms current general missing data techniques for ordinal variables.

Chapter 3: Moral Arguments as a Source of Frame Strength

Following the traditional structure of methods dissertations, this chapter applies the methods developed in chapters 1 and 2. I do so in an online survey experiment on political framing.

Framing is the practice of presenting an issue to affect the way people see it (Aaroe, 2011; Druckman, 2001). We learn about political issues through articles, reports, speeches, commercials, and social media. This mediated communication possesses tremendous potential influence on our perception of political issues (Iyengar, 1996; Kam and Simas, 2010). A variety of frames substantively influence how people view and think about issues (Entman, 2004; Slothuus and Vreese, 2010; Sniderman and Theriault, 2004), but we do not know why these frames elicit these effects. A major challenge for framing research thus "concerns the identification of factors that make a frame strong" (Chong and Druckman, 2007, p. 116). I propose an avenue of clarification by testing whether moral arguments are a part of what makes political frames strong.

Moralization theory claims that moral arguments and moral conviction possess enormous power to influence and guide development of public opinion (Haidt, 2003, 2012; Converse, 1964; Zaller, 1992). Moral arguments are defined as near-universal standards of truth and almost objective facts about the world (Skitka, 2010). They are essential to how people perceive and make sense of the world around them (Frank, 2005; Mooney, 2001). Moral arguments can also achieve a high emotional connection with people because they invoke feelings (Skitka et al., 2005; Tatalovich and Daynes, 2011). These conceptual definitions are encompassed in Moral Foundations Theory (MFT) presented in Table 2 below. MFT has not been applied to frame strength in experimental research. I propose to do so in an online survey experiment.

Positive		**Negative**	
Care	Cherishing, protecting others	*Harm*	Hurting others
Fairness	Rendering justice by shared rules	*Cheating*	Flouting justice, shared rules
Loyalty	Standing with your group	*Betrayal*	Opposing your group
Respect	Submitting to tradition, authority	*Subversion*	Resisting tradition, authority
Sanctity	Repulsion at disgust	*Degradation*	Enjoyment of disgust

Based on Haidt (2012). Positive and negative foundations are conceptual opposites.

Table 2: Foundations of Moral Arguments

3.1 Objectives

Hypothesis: Moral arguments form a part of what makes political frames strong.

Goal: Demonstrate the importance of moral arguments in frame strength.

3.2 Data

I design a questionnaire on several political issues that collects demographic information and applies several treatments. Each treatment consists of a moral frame based on MFT foundations. All frames are tested in an online poll on MTurk. This questionnaire is hosted online for a nationally representative sample of 2,331 respondents recruited through Lucid. Lucid has been shown to perform well on a national scale in survey experiments (Coppock and McClellan, 2019).

I apply my ordered probit method from chapter 1 by blocking on education. One half of the sample is blocked with arbitrary numeric values, while the other uses my method. Subsequent ordered probit regression on an ordinal response variable on a 5-point Likert scale, ranging from "Strongly oppose" to "Strongly support", shows the differences in performance. Since there currently is no way to block online, I created an online survey environment based on statistical software code to implement blocking. Missing data in the form of "Don't Know" or "Refused" are imputed separately with general methods and my specific ordinal variable adaptation of multiple hot deck imputation from chapter 2. Visual displays of the resulting variable distributions show the differences in performance. Substantively, the regression results provide insights into the importance of moral arguments in political framing and in political messaging overall.

Implications and Limitations

Education is the most important predictor of political behavior in political science. It is crucial that we measure and use this variable correctly to obtain results that reflect the true data structure. As an ordinal variable, education contains special characteristics: Its categories are ordered, but unevenly spaced. We need modern statistical methods to fully utilize all this information contained in this variable. So far, this aspect has been largely ignored in the literature. If we want to know what people think and how they act, we need to make sure our measurements are as good as they can possibly be. My dissertation outlines two new methods that contribute to this undertaking. They significantly improve how we handle ordinal variables in surveys and survey experiments in political science and thus increase precision when we analyze public opinion.

Whether my methods are suitable in a specific survey or survey experiment depends on the situation, as no method works for all circumstances. For a survey experiment with a very large sample and few treatment groups, there is no need for my ordered probit method and blocking. Simple randomization does the job here. Similarly, if survey results do not contain important ordinal predictor variables, my method to impute missing data from ordinal variables is not applicable. Overall, my dissertation adds two important new tools to the empirical political scientist's toolbox to choose from.

Timetable for Completion

July 2019 – May 2020

August	Completed chapter 1
November	Completed chapter 2
December	Run framing survey experiment applying the methods in chapters 1 and 2 Analyze experiment results and draft chapter 3
February	Completed chapter 3
March	Advanced draft of complete dissertation
April-May	Defend dissertation

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CV

Education

PH.D., **Political Science**. American University, Washington, D.C., 2020 (expected)

Fields: American Politics, Quantitative Methods, Comparative Politics
Dissertation: "What the People Think: Advances in Public Opinion Measurement Using Modern Statistical Methods"
Dissertation Chair: Jeff Gill

M.A., **Social and Political Thought**, *magna cum laude*. University of Warwick, UK, 2014

Dissertation: "Fighting 'Socialism': The Koch Brothers, the Tea Party, and Obamacare" (15,000 words), *magna cum laude*

MAGISTER, **English Linguistics, Communication.** University of Munich, Germany, 2011

Dissertation: "From Candidate to President: The Use of Metaphors and Pronouns in Speeches by Barack Obama" (40,000 words), *magna cum laude*

Publications

2019. "Insufficiencies in Data Material: A Replication Analysis of Muchlinski, Siroky, He and Kocher (2016)". *Political Analysis* 27 (1), 114-118 (Paper).

"Bayesian Modeling and Inference: A Postmodern Perspective" with Jeff Gill. In Luigi Curini and Robert J. Franzese, Jr. (editors), *Handbook of Research Methods in Political Science & International Relations*. SAGE, *forthcoming*.

Teaching Experience

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Introduction to Political Research (`R`) (2018 Syllabus, Evaluations)	Spring 2020, Fall 2018
Seminar for Teaching Assistants	Fall 2019
Political Action and Public Policy (Online, Syllabus)	Summer 2019
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Teaching Assistant

Bayesian Statistics for Social and Biomedical Sciences (`R`), Jeff Gill (Syllabus)	Fall 2018
Introduction to Political Research (`R`), Ryan T. Moore (Syllabus, Guide to R)	Spring 2017
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Research Experience

Editorial Assistant 2017-Present
Political Analysis Journal (Jeff Gill, R. Michael Alvarez, Jonathan Katz)

Data Replication of Journal Submissions
Code Debugging and Quality Control in `R`, `Python`, `Stata`
Dataverse Organizational Management

Research Assistant 2015-Present
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Strength and Effectiveness of Framing Measures in Political Behavior
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List Experiments on Social Desirability Bias
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Data Analysis

`Eagledown`: `R` Package to Write a PhD Thesis at AU in `R Markdown` (GitHub)
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Awards and Grants

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Graduate Leadership Council Conference Travel Grant, 2017, 2018, 2019
Award from the Vice Provost and Dean of Graduate Studies, "The Impact of Information and Emotions on Voter Turnout and Civic Engagement," with Jan E. Leighley, 2016
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