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CHAPTER

Intersectional Quantitative Methods

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Abstract

This chapter reviews the major advances in accounting for intersectionality empirically and embracing methodological pluralism within Political Science and related Social Sciences. Intersectionality, or approaching identity categories rooted in structural power such as race, gender, and class as inseparable, remains a site of intellectual promise particularly because of its utility for explaining the big questions in American politics. This chapter focuses on intersectional quantitative methods as a site for new innovations as it is the natural step after demonstrating the current literature's advances of frameworks to operationalize intersectionality. After outlining these advances in approaching identity, the chapter explores how ideas on statistical learning within Political Methodology can help inform both new modeling and statistical paradigm choices for intersectional research. The new avenues posed by multilevel modeling and Bayesian frameworks show a small window into the promise of this emerging field.

Keywords: intersectionality, quantitative methods, Bayesianism, multilevel modeling, identity

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Introduction

> I am encouraging political methodologists to step up to the challenge of answering questions in Political Science where data is not as easy to access and where methodological questions are paramount.
>
> (Roberts 2018)

Political methodologists are charged with analyzing the questions and methods being asked within the discipline to look at their utility for understanding politics, as well as their ability to promote a pluralism of approaches and cutting across disciplinary boundaries (Box-Steffensmeier, Brady, and Collier 2008). Intersectionality research, or research that utilizes conceptions of identity where race, gender, and class create unique sets of lived experience, represents a burgeoning field of pluralist and interdisciplinary Political Science research. Intersectional quantitative methods, therefore, are arguably one of the most fruitful avenues for political methodologists to pursue given their promise in understanding politics and the methodological scope of approaches that current scholars utilize. This work blends both interpretive and quantitative priorities and promotes interdisciplinary research across Social Science boundaries. The focus of this chapter is thus outlining the existing approaches to intersectional quantitative methods, and explaining the new frontiers posed by new modeling tactics and statistical frameworks. I will focus on how choice of the functional form of intersectionality can address some data limitations facing intersectional work, and that Bayesinianism allows the intersectional researcher to blend interpretive priorities with quantitative methods in innovative ways.

Intersectionality and Methods

Intersectionality represents a growing and vibrant field of Political Science. The methodological operationalization of intersectionality is pluralist at its core as it embodies pluralism in both the definition and in the approach. The origins of intersectionality are located in a long lineage of Black feminism and praxis which assessed the multiplicities of oppression and relative power (Gloria Anzaldua, Combahee River Collective, Patricia Hill Collins, Anna Julia Cooper, Ida B. Wells, and Maria Stewart). This intellectual lineage and experience was made concrete by Crenshaw's interventionist and practitioner oriented approach to the legal system to critique conceptions of identity and White feminism for a lack of understanding of the interwoven nature of race/ethnicity, gender, and class with respect to Black women (Crenshaw 1989, 1991). In particular, Crenshaw highlights how the lived experience of both racism and sexism didn't align with the societal understanding of these "separate" concepts. Since then, intersectionality has grown to be arguably the most important concept in the study of relative power and identity. Within Political Science, its visibility has grown as a vital research paradigm, particularly in the American context, as well as remaining a political and radical project for some scholars (Mügge et al. 2018).

In addition to this research growth, the importance of social identities to understanding politics is also both long documented and timely, given the importance of race and gender in elections with candidates like Obama, Trump, and Clinton (Berelson, Lazarsfeld, and McPhee 1954; Converse et al. 1961; Dawson 1994; Kinder and Sanders 1996; Mason 2018; Tesler 2016; Sides, Tesler, and Vavreck 2018; Jardina 2019; Phoenix 2019). Intersectional research within Political Science shines in its application in where scholars analyze women of color in Congress, political behavior and attitudes of women of color, and the effectiveness of U.S. democracy and voting rights for minority groups (Hawkesworth 2003; Smooth 2011; Brown 2012; Junn and Masuoka 2008; Junn 2017; Junn and Masuoka 2020; Brown 2014; Ojeda and Slaughter 2019; Montoya 2020; Frasure-Yokley 2018 ; Gershon et al. 2019). Intersectionality has also traveled to the Comparative Politics subfield and has shaped survey methodology at the forefront of the American Politics subfield (Weldon 2006; Barreto et al. 2018; Spry 2018).

There are a subset of pioneers who outline how to apply intersectionality quantitatively despite some scholars having posed that the nuance demanded by intersectionality is incompatible with quantitative methods. These researchers often cite that intersectionality was created to understand Black women, and must acknowledge research that shows that Black Americans have distinct epistemology which is rooted in dialogue, expressiveness, personal accountability, and experiences as meaning making (Jordan-Zachery 2007). To best capture the distinct experiences of Black women, scholars often turn to tools such as discourse analysis and interpretive methods (Jordan-Zachery 2007). Past research was marked with debates on what methodologies best capture intersectionality, but many have sought to leave these battles behind, instead focusing on all opportunities to combat power imbalances provided they are rooted in liberating marginalized voices (Cho, Crenshaw, and McCall 2013; Jordan-Zachery 2007). This chapter acknowledges other methodologies as invaluable in understanding multiple constituted oppressive forces, and seeks to highlight the quantitative possibilities as just one area within the scope of methodological pluralism that scholars of intersectionality can pursue.

In one of the first paper's tackling how to apply intersectional theory to quantitative methods, McCall explains how one can operationalize categories empirically, as well as pushing conversations on how different methodologies lead to different kinds of substantive knowledge production (McCall 2005). Every methodological choice shapes the ultimate academic contribution; therefore, future directions on intersectional quantitative methods must interrogate how our modeling choices shape our intellectual products. The high stakes of research on those who are politically and institutionally underserved demands that these choices are interrogated thoroughly. Weldon furthers this by looking at multiple statistical models for understanding identity as well as bringing conversations of intersectionality into the subfield of Comparative Politics (Weldon 2006). She interrogates the utility of additive versus multiplicative conceptions of race and gender, and promotes a multiplicative approach which often operationalizes as interaction terms and an additional variable which captures a unique intersectional effect separate of the race and gender variables.

Arguably, some of the most important contributions to operationalizing intersectionality quantitatively come from Hancock who coins it as a research paradigm and as a way of conducting empirical science (Hancock 2007a). Hancock's transition of intersectionality into a research paradigm allows researchers to get away from the trap of looking at intersectionality as a testable research hypothesis posing certain expected outcomes. Intersectionality rather should frame the research design process and theory building and leave the relationship between identity categories as an open questions. Additionally, she takes this work on intersectionality as a research paradigm to frame discussions of quantitative methods for intersectionality and how to incorporate interpretive contextual priorities into quantitative work (Hancock 2007b, 2019). This work poses the utility of fuzzy set logic, and concretely demonstrates the limitation of many of our conventional regression methods (indicator variables and sub-group regressions).

Additionally, some scholars take the approach of not looking at the issues of the models, but proposing frameworks for fixing the data generating process. Scholars such as Barreto et al. (2018) build new datasets that allow for substantive researchers to have large enough sample sizes for conventional regression tactics, or some like Spry (2018) or Bowleg (2008) innovate new survey question tools to better capture the multidimensionality of identity. In this growth of empirical intersectionality, scholars have warned about the dangers of research without grounding in intersectional traditions. Dhamoon clarifies how intersectionality's empirical growth in Social Sciences also should be accompanied with a theoretical framework to ensure the application holds true to the roots if intersectional work, which is the freedom of Black women from oppressive structures (Dhamoon 2011).

In spite of the many advances made by these authors, Mügge et al. highlight the impacts of intersectionality's growth by bringing it into conversation with epistemological questions about knowledge production within the discipline of Political Science (Mügge et al. 2018). Intersectionality is rarely found in the top three journals in Political Science, with the majority of work being found in specialized outlets. Women of color scholars are well represented in authorship on intersectionality, but again outside of the top three journals. Further, these women of color scholars are more likely to center race than their White counterparts and are located predominantly in the U.S. The authors also show that within Political Science the majority of scholars consider intersectionality to be both a political project and research paradigm, and recognize the focus of research should be on marginalized groups. Mügge et al. (2018)'s work highlights that while intersectionality has made inroads into Political Science the most powerful journals in the discipline have yet to recognize its revolutionary potential.

Methodological Tensions

This growth of intersectionality within substantive researchers, methodological minded researchers, *and* across the Social Sciences at large frames questions for future directions of a field of intersectional quantitative methods. This area of intellectual opportunity should ask questions such as: What research practices are we applying to intersectionality where it may not fit? What statistical paradigms are most applicable? What modeling tactics are most applicable?

Scholars using quantitative methods in Political Science usually prioritize validity, reliability, and reproducibility by creating distance between the researchers and the researched, and leveraging the concept of objectivity (Schwartz-Shea and Yanow 2011). While this framework (positivism) presents certain advantages, intersectionality's roots in Black feminist theory and interpretivism make the transition from interpretive methods to quantitative methods often unsatisfactory Jordan-Zachery (2007). There are scholars who attempt to blur some of these boundaries, such as Hancock's proposals of fuzzy set logic or calls for qualitative nuance in variable operationalizations (Hancock 2007b; Weldon 2006). Despite these few advances in blending positivist and interpretive methods, the majority of empirical intersectional work has remained within positivism.

Intersectionality has long been used outside of positivist realm because these methods provide richer context (Jordan-Zachery 2007; Alexander-Floyd 2012). Intersectionality research outside of the quantitative realm is, "... a vibrant, complex body of knowledge" (Alexander-Floyd 2012). Interpretive methods can be characterized as prioritizing subjects' meaning-making in their context, the researcher as situated (acknowledging the researcher as a part of the research process), and sees the research process as flexible (takes different interpretations as inevitable) (Schwartz-Shea and Yanow 2011). The nuance and context needed for detailed description of intersections of oppression was often more suited to designs outside of quantitative methods McCall (2005). These shortcomings of solely positivist frameworks demonstrate the need for political methodologists to adopt methodological pluralism to blend interpretive priorities to answer questions of differential power and structural oppression.

Further, the statistics and positivist research communities both in Social Sciences and beyond place a premium on methods that increase predictive accuracy or explanatory power by the largest margin. This focus can lead to a misconception that an intersectional approach should always lead to large gains in methodological precision or accuracy. Hancock's "intersectionality-as-testable-explanation" shows this conflation, as an intersectional method is not a test of intersectionality's existence or performance (Hancock 2019). Rather, intersectionality is better explained as an "analytic sensibility" which provides a framework to structure the research question and methodological approach (Cho, Crenshaw, and McCall 2013). The research design does not assume homogeneity, rather allows for open empirical questions as to the relationship between identities. This means that there will be instances where the research employs an intersectional method, but does not see large gains beyond conventional main effects tactics, and instances where there are large gains. In both cases, intersectionality's existence is not in question, but is the foundational paradigm used to frame questions and methods. This leaves an opportunity for intersectional quantitative scholars to push back on predictive accuracy premiums, and shift conversations of intersectionality's effects to that of how a research paradigm shapes knowledge production.

In order to weave the current shortcomings of positivism with the strides made by empirical intersectionality scholars, I turn to D'Ignazio and Klein (2020)'s *Data Feminism*, which provides a set of best practices for how to incorporate feminist interpretive priorities into our modeling tactics and statistical framework choices. I will also outline how some of these tasks are undertaken in the discipline currently, and pose areas for new growth. *Data Feminism* addresses seven key considerations which allow for interpretive feminist priorities to be applied to the data science community broadly (D'Ignazio and Klein 2020). These will serve as foundational considerations for furthering the study of intersectional quantitative methods within Political Science also utilizing Hancock's intersectional research paradigm. The first component is to examine power within the world, specifically, who has it and who doesn't. Intersectional work in the discipline addresses power differentials in politics so this tenant is addressed by existing research (Mügge et al. 2018). The second is to challenge unequally distributed power and work towards justice with our research questions and methodological choices. Intersectional scholars who believe in the "world-making" possibilities for intersectionality particularly as a means to liberate those institutionally underserved are inherently challenging these power dynamics in both their substantive questions and usually with their methods (Nash 2018). Third is to broaden our conception of knowledge production by elevating emotion and embodiment, which comes from people being living and feeling bodies in the world. This can be accomplished by blending interpretive method priorities, which include this sort of situated knowledge from lived experience, into quantitative methodologies (Schwartz-Shea and Yanow 2011). The fourth component is rethinking binaries and hierarchies with respect categorizations and counting that perpetuate systems of oppression. Scholars who contribute work on rethinking data collection and survey methods practices have a direct hand in reshaping these categorizations in quantitative methods (Barreto et al. 2018; Bowleg 2008; Spry 2018). The fifth is to embrace pluralism in knowledge production and our methodological choices. While intersectional research was always pluralist in nature, there are boundless opportunities for diverse approaches to modeling tactics and research design to incorporate forms of knowledge previously excluded within Political Methodology in particular. The sixth is to incorporate context of both the researcher and the researched to be candid about bias and positionality. Bias and positionality have long been a discussion in circles that study race, gender, and class specifically, but they have yet to be widely accounted for in quantitative methods because of positivist research practices. They present a new area for development for intersectional quantitative methods. The last is to make labor visible between the researcher and subjects.

Within the context of this chapter, I pose that within Political Methodology, researchers can tackle facets of examining power, challenging power in our knowledge production, broadening our conception of knowledge production, embracing pluralism, and incorporating the situated nature of research by interrogating the functional form and statistical paradigm used to study intersectionality.

Statistical Learning and Functional Forms

Intersectional scholars and the outlined components of *Data Feminism* have laid the foundation for Political Methodology as a subfield to apply their tools to an intersectional research paradigm. Consider, for example, the framing for statistical learning contributed by James et al. (2013) which poses that all statistical learning can be characterized as learning from data about the world around us by looking at the relationship between our inputs ($X's$) and our outputs ($Y's$) (James et al. 2013). We define that relationship as $Y = \widehat{f}(x) + \epsilon$. Statistical researchers then have the autonomy to choose their $\widehat{f}$, which is the functional form of the relationship between *X* and *Y*, or in other words, the systematic information Xprovides about Y. I will argue that intersectional quantitative methodology as an emerging field should focus on how to properly specify the functional form of intersectionality with respect to Political Science questions using interpretive priorities. Interrogation of the functional form is particularly important in the face of the data constraints that intersectional scholars face. Under sampling of racial and ethnic groups, and then lacking the proper sample size to split again by gender, was a constraint faced even in Crenshaw's earliest work (Crenshaw 1989). Some have combatted this by purposefully oversampling by race and ethnicity, and building survey techniques that prioritize marginalized communities (Barreto et al. 2018).

This chapter provides alternatives when this sort of survey data is unavailable due to data embargo or financial constraints. Therefore, investigating the functional form of intersectionality is particularly helpful when a researcher has underpowered samples (e.g., data from the American National Election Study (ANES)). Researchers must investigate different modeling tactics for $\widehat{f}$'s to find the correct best fit given data constraints and the intersectional paradigm. I also outline how the choice of shifting from the frequentist statistical paradigm to the Bayesian for operationalizing the functional form of intersectionality will bolster a researcher's ability to account for intersectionality in a situated and nuanced way in the next section.

There are three contemporary approaches to the functional form of intersectionality within quantitative methods as shown in Table 1. I will outline each in detail and explain their benefits and drawbacks. In the following section, I will pose why multilevel modeling balances the issues from the current methods.

Table 1 Functional Form Comparisons

Method	Functional Form	Benefits	Drawbacks
Indicator Variables	$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i + \epsilon_i$	- Accessibility to the academic community - Race and gender are included in the model rather than obfuscated completely	- Promotes additive understanding of identity - Masks intersectional effects by ignoring differences within race and gender groups - Lacks contextual richness
Interaction Terms	$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i + \epsilon_i$	- Allow for multiplicative/dependent relationship - Accessibility to the academic community	- Noisy (uncertain) estimate with small sample sizes (that are common in intersectional research) - Despite interaction, still relies on the understanding that the underlying constructs of race and gender variables are separate - Lack contextual richness
No Pooling Sub-Group Regressions	Black Women: $Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i + \epsilon_i$ Latinas: $Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i + \epsilon_i$ White Women: $Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i + \epsilon_i$	- Rectify the separation of raced and gendered lived experience - Clearly show subgroup differences in effects both for direction and magnitude	- Difficult to interpret - Does not allow for direct comparisons between groups - False discovery rate risks
Multilevel Modeling	Level 1: $Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + \epsilon_{ij}$ Level 2 Intercept: $\beta_{0j} = \gamma_{00} + \gamma_{01}\left(X_{ij}\right) + u_{oj}$ Level 2 Slope: $\beta_{1j} = \gamma_{10} + \gamma_{11}\left(X_{ij}\right) + u_{oj}$	- Proactively accounts for intersectional group-based heterogeneity - Reduces noisy small sample size estimates - Reduces risk of overfitting - New ways to explain group-based variation against total variation	- Less accessible to the broader Social Science community - Minimal gains in data-rich environment

Indicator variables are one of the most common tools used to try and capture the effect or race or gender in regression methods. It is understood among intersectional scholars that this is not the preferred approach; however, is the most common approach among quantitative social scientists using conventional regression tactics (Junn 2007). This *additive* approach methodologically isolates the individual effect of race and gender on an outcome (holding the other constant), and is not able to derive any shared effects of race and gender as it would with an interaction term (Weldon 2006). This is the first quantitative shortcoming. Within the methodology community, this method is considered a completely pooled model. "Pooling" refers to how a researcher handles group-based heterogeneity. A researcher can either pool the heterogeneity (combine all the groups into one larger group), not pool the groups (run all regressions separate for each group), or partially pool the groups (hedge the estimates from complete and no pooling approaches). Complete pooling methods will systematically understate group-based heterogeneity, making them ill-suited for intersectional research (Gelman and Hill 2006).

Theoretically, indicator variables also face issues in that "... [intersectionality] encompasses perspectives that maintain that such identity categories as gender, age, race, ethnicity, class, and sexuality are mutually constituted and cannot be added together" (Simien 2007). In other words, women of color are constantly influenced by the structural effects of race and gender identities, and consequently don't form opinions or decide to act based their gender or racial identity alone (Junn 2007; Hancock 2007b). By continuing to use indicator variables for race and gender, scholars can perpetuate artificial understandings of identity that privilege a single axis of identity (Brown 2014).

Interaction terms are also often used in order to understand intersectionality using a multiplicative relationship (Weldon 2006, Block, Golder, and Golder 2023). It allows for the estimation of a baseline and effect value for each intersectional or multidimensional race/gender group. Additionally, it estimates additive independent effects of race and gender along with the multiplicative relationship between race and gender. However, the interaction term assumes these variables are separate uncorrelated pieces, which goes against intersectional theory (Simien 2007). Additionally, without further injunctions, the interaction terms do not fully capture the qualitative nuance of the effects of race and gender combinations as they pose unique outcomes not a function of race and gender independently (Weldon 2006). These interaction terms also face further limitations in situations with small sample sizes, as the effect may be noisier (more uncertain) than in data rich situations (Gelman and Hill 2006). Data limitations within intersectional research have long been documented as data on racial minorities has previously been sparse, and separating those datasets by gender leaves sample sizes that ultimately lack statistical power (Barreto et al. 2018; Frasure-Yokley 2018). The multiplicative understanding of identity in practice falls short methodologically and theoretically as it still lacks context and has poor small sample size performance.[1]

Subgroup regressions (or a separate regression for each race-ethnic and gender intersection), are another method used by intersectional scholars (Frasure-Yokley 2018 ; Hancock 2019). This tactic lacks modeling parsimony as it requires as many regressions as subgroups and different dependent variables or sets of independent variables of interest, but accounts for the grouped nature of race and gender.[2] This method comes closer to incorporating intersectional theory. This is a version of not pooling groups. This can lead to overfitting issues with small sample sizes, and it is problematic for groups with small amounts of data in each group, as the researcher is likely to get more extreme estimates (Gelman and Hill 2006). In other words, no pooling methods will systematically overstate group-based heterogeneity (Gelman and Hill 2006).

These issues of subgroup regression are exacerbated by most datasets not having large sample sizes for robust statistical analysis by intersectional groups. This was outlined in the original discussions of intersectionality within Crenshaw's analysis of defendant experiences with the legal system. The defendants in "Demarginalizing the Intersections" had trouble proving their point as data on Black women was few and far between (Crenshaw 1989). Secondly, researchers can't directly compare coefficients across multiple models, so direct comparisons of effects across race and gender subgroups are lost. Lastly, interpretation is difficult for multiple dependent variables of interest and multiple subgroups, as this requires a multitude of regressions have to be run for each subgroup and effect being measured.

To be sure, innovations in modeling tactics will not solve all of the issues facing intersectional research, as data limitations for historically marginalized groups remain rampant. Innovations such as the Collaborative Multiracial Post Election survey, as previously mention, look circumvent these issues by changing the data generating process (Barreto et al. 2018). However, the question remains with regards to how to deal with existing data with small intersectional sample sizes. The American National Election Study, General Social Survey, and many experimental pieces contain interesting substantive data and data over long periods of time, but lack proper sample sizes of women of color. By combining new modeling tactics and statistical paradigms that inherently perform better with small samples sizes, intersectional research will not be beholden to only certain datasets. It is also vital to understand that there will never be a model that is a “silver bullet” as Hancock (2007b) points out that will fully capture all qualitative and interpretive nuance. However, the subfield of Political Methodology does have the opportunity to improve the current tactics.

Modeling Choices—Multilevel Models

As previously stated, completely pooled models (those using indicator variables or not looking and race/gender at all) are going to systematically understate group-based heterogeneity. The models that aren’t pooled at all (no pooling) are going to systematically overstate group-based heterogeneity (or overfit intersectional groups) because of the estimates not being taken into account with respect to other similar groups. Partial pooling serves as the happy medium, and can be achieved by fitting a multilevel model, which estimates an individual and group-level effect simultaneously. Partial pooling weights the individual level completely pooled estimate with the unpooled sub-group regression estimate.

Multilevel models (MLMs) are used properly articulate group-based heterogeneity (Gelman and Hill 2006). It has been shown in sociology and epidemiology, that multilevel models can have utility in intersectional contexts; however, they have yet to be brought to Political Science (Evans et al. 2018). The classic example of the utility of multilevel models is shown by Peugh (2010) where a study is conducted that analyzes students’ academic lives, but does not account for the effect of a given classroom. Without accounting for the effect a classroom (or group) has, a unique trend that holds across students in that classroom is missed. The same concept applies for intersectionality, where the classrooms are the combinations of race and gender identities. These identities are rooted in sociopolitical power structures that create unique lived experiences, or unique group-level effects, for those situated at the different combinations of race and gender. Consequently, the grouping variable should be specified to pool the substantively interwoven identities together, that is to say specify an additional level that combines racial and gender groups together. In specifying a multilevel model, the researcher estimates individual level effects which are analogous to the traditional main effects of a regression model as well as group-level effects which are sometimes referred to as random or mixed effects. These vary across individuals in the sample according to their race and gender group. These group-level effects thus capture the unique group-level effects articulated by intersectionality. Below is the individual-level effects formula. Here, *i* represents a given individual, and *j* represents the group.

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \epsilon_{ij}$$

$\beta_{0j}$and the coefficients β_{1j}represents group level effects that are estimated through partial pooling where the researcher weights the group-level estimates by the individual-level estimates. Partial pooling uses the grand mean for the individual level to inform each group-level coefficient (Gelman and Hill 2006). u_{oj}represents the residual error terms at the group level. The formulas for estimating group-level coefficients are shown below.

The grouping variable is represented by (j), and the coefficients of interest are $\beta$where the slope is $\beta_{0j}$and the coefficient is β_{1j}. Researchers estimate the group effect by adding the grand meanγ_{00}, the deviation from the grand mean in the second levelγ_{10}, and group specific means γ_{01}, γ_{11}. The group-level estimate for the intercept is $\beta_{0j}$and the group-level estimate slope is β_{1j}.

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\left(X_{ij}\right) + u_{oj}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}\left(X_{ij}\right) + u_{oj}$$

For the context of intersectional research, these MLMs are a fruitful frontier of expanding discussions of the functional form of intersectionality and their ability to provide effect estimates in small-sample size environments (such as in American National Election Survey, General Social Survey, or with experimental data). With small sample sizes, complete and no pooling estimates will systematically understate and overstate group-based heterogeneity, respectively. Even in the contexts of larger datasets which have larger subsamples of intersectional groups their presences is still so scarce in the overall data relative to majority groups that MLMs still out-perform conventional tactics.

To demonstrate the performance of the MLMs in comparison to conventional tactics I provide an example using models of intersectional subgroups using 2016 Cooperative Election Study (CES, formerly CCES) data (Figure 1). The models predict presidential approval based on party identification and race/gender intersections. Approval for Trump is measured from one to four with one being the most approving and four being the least; and party identification is measured on a scale from one to seven with one being strong Democrat, and seven being strong Republican. Each panel represents intersections of race and gender, and contains three separate models. The light grey dashed-only line represents the completely pooled model where all the group-based heterogeneity is combined and differences are ignored, which is shown by that line being the same across all panels. The grey dash and dot line represents the "no pooling" model which is a separate regression for each race and gender intersection. Lastly, the multilevel model is featured in the black solid line.

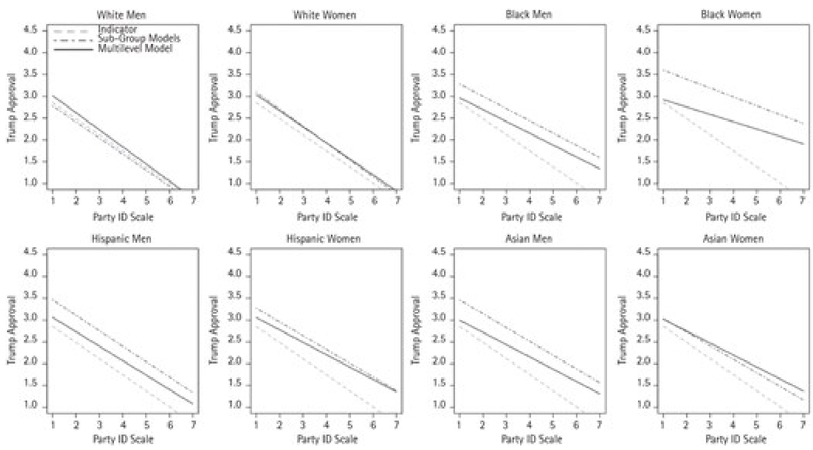

Figure 1 Methods Comparisons

In instances where the models perform very similar to each other, the lines will cluster on top of each other. This pattern is shown clearly by the majority groups in the data, White men and women. Their panels, the top two in the left-hand corner, show that the complete pooling, no pooling, and partially pooled estimates are virtually identical. This shows that our conventional modeling tactics are performing well for the group which has previously been the epistemological source of many of our unsatisfactory modeling tactics when they are translated to racial and ethnic minorities.

When there is a large enough sample size, the no pooling estimate will perform the same as the partially pooled estimate (Gelman and Hill 2006). The multilevel model shines in instances where the sample size is not large enough for the no pooled estimate, and where the completely pooled estimate is masking an intersectional effect. This is demonstrated best by the models for Black men and women in the top right-hand corner. These panels show a more extreme estimate for the no pooled model (the grey dot and dash line), a completely pooled model understating the group-based heterogeneity (light grey dash), and a partially pooled model providing an estimate that splits the difference between the two. Knowing that the model performance for the no pooling method is overstating, and the completely pooled is understating, the partially pooled model demonstrates an elegant way to prioritize methodologically underserved groups.*

Focusing on the experience of Black women in this instance, the three forms of pooling are then compared to an interaction model. These models are shown in Figure 2. The interaction model, shown in grey dashes, demonstrates a similar performance to the complete pooling method which we know from the literature understates group differences (Gelman and Hill 2006).

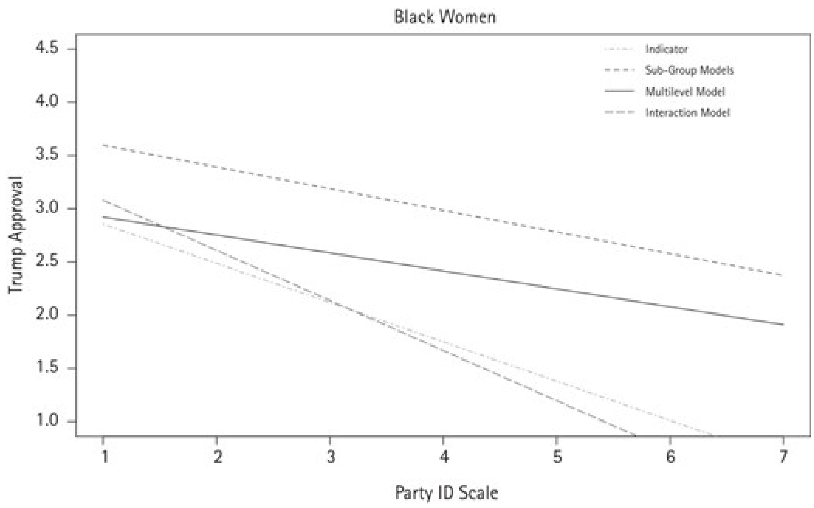

Figure 2 Methods Comparisons for Black Women

This example thus shows that the multilevel optimizes performance across all conventional methods and shows promise as a new way to operationalize the functional form of intersectionality within quantitative methods. The superior multilevel model performance findings are confirmed with cross-validation algorithm findings.

Paradigm Shift—Bayesinianism

Beyond the model chosen, a researcher can incorporate intersectional priorities within the statistical framework choice. Many quantitative scholars who apply intersectionality use frequentist regression tactics, which are the dominant statistical paradigm. This means that the researchers are operating in a statistical paradigm which bases statistical knowledge on frequencies of events in the long run, or gaining knowledge based on repeated events over time (Johnson, Ott, and Dogucu 2022). Frequentist statistics do not account for prior knowledge of the event, and base claims of certainty on only the data at hand. A Bayesian, however, balances prior data with the data at hand to make claims of relative plausibility of an event (Johnson, Ott, and Dogucu 2022).

Bayesian theorem is as follows:

$$posterior \propto prior * data$$

$$updated\ belief = prior * current\ evidence$$

The posterior, or our ultimate estimate of an event, is directly proportional our prior knowledge (belief) and the data we have at hand. The data we have at hand is also called the likelihood (Clark 2018). In other words, our updated beliefs are based on both the prior and our current evidence. The degree to which the prior updates our beliefs is based on the researcher's relative certainty about the event. *Informative priors* reflect a high degree of certainty and low variability about the event (Johnson, Ott, and Dogucu 2022). *Uninformative or diffuse priors* reflect little certainty or specific information about an event (Johnson, Ott, and Dogucu 2022). Priors can also be *flat* which denotes equal plausibility to all events (Johnson, Ott, and Dogucu 2022).

Each portion of the Bayesian equation is posed in the context of distributions of values, which is a critical component of Bayesian theory as opposed to frequentist theory. Bayesian methods garner more context than traditional regression (frequentism) (Western and Jackman 1994; Humphreys and Jacobs 2015). Bayesian methods estimate "Truth" as a distribution of values, rather than a single point estimate. This provides a more nuanced understanding of the "True" relationship being explored because one can look at a density plot of the posterior and get a clear picture of how plausible other outcomes are based on the center, spread, and skewness of the distribution (Gelman et al. 2013). Additionally, these methods of deriving certainty allow the researcher to move away from using p-values, which are often misconstrued as measures of truth and existence of effects (Wasserstein and Lazar 2016). Rather than misusing the p-value to determine whether a concept is "found" or not in dichotomous terms, Bayesian methods present the relative uncertainty around a given estimate through the posterior distribution for the researcher and the reader to decide for themselves if the evidence is compelling. Therefore, they are a more ethical way to present research findings in comparison to p-values. Using Bayesian methods allow the researchers focusing on intersectionality to also be in conversation with the crux of work in quantitative methods that are focusing on reducing reliance on p-values.

Another benefit of Bayesian methods is their similar position on subjectivity as interpretive methods. Positionality, subjectivity, and situated knowledge are actively accounted for in many interpretive and qualitative methods as the goal is to discover contextual meaning-making practices (Schwartz-Shea and Yanow 2011). Oftentimes, in positivist methodologies, researchers prioritize objectivity, or the ability to separate one's bias from the research. Interpretivists and Bayesians alike critique this process (albeit using different languages), arguing that bias will always be present, and it is a better research practice to proactively account for positionality and subjectivity in research design. By incorporating Bayesian stances on positionality into intersectional research, scholars tackle charges from *Data Feminism* with research designs that are pluralist, open-minded in the sources of knowledge production, and candid about research subjectivity (D'Ignazio and Klein 2020).

We can also incorporate our previous understandings of "Truth" through our prior distribution, which balances results based on theoretical or empirical context. Informative priors, those which convey certainty and less variability about an event, can be set based on previous quantitative research on the topic, or more importantly, based on previous interpretive or qualitative work. Intersectionality's long intellectual lineage outside of quantitative methods can be built directly into modeling practices. This provides context to the data at hand, and creates new knowledge that is based on intersectional thinkers previously excluded by frequentist methods, thus directly incorporating *Data Feminism's* points of more inclusive knowledge production and pluralism. Additionally, this practice can lead to new intellectual lineages as these posteriors are garnered by adding intersectional literatures which can be used as future priors, thus creating more situated knowledge and context in future results.

Take for example, a scenario where an intersectional researcher is trying to predict if a group they care about (say Black women) are going to vote in an upcoming election given constraints from voter identification laws, Alvarez, Bailey, and Katz (2008); Gillespie (2015). This example utilizes synthetic data on whether an individual voted 1) or did not vote 0), and calculates a posterior estimate of their behavior using the Bayesian theorem. The probability of voting is shown on the x-axis. The y-axis reflects the densities of the distributions, or the most likely probability of the outcome.

I will demonstrate how the posterior is influenced by choosing different priors. The first prior will be centered at 0.5 which indicates that the researcher thinks that a Black woman is just as likely to vote as not vote. The second demonstrates an informed prior, which is recommended in this chapter, that is centered at 0.875. For this prior, the researcher has reason to believe that Black women are more likely to turn out than not in a given context they're studying, for example a state or area that has very lenient voter restriction and identification laws (Alvarez, Bailey, and Katz 2008; Gillespie 2015).[3] Lastly, I will demonstrate how diffuse (almost flat) priors effect the posterior, in a situation where the researcher thinks both outcomes (to vote or not vote) are equally likely. Each prior is using a Beta distribution as the outcome is binomial (Clark 2018).[4]

In Figure 3 I show how to calculate whether an individual votes or not by balancing the prior (theta) in $\theta_{prior} = \beta\,(10,\ 10)$and the likelihood (data). This is our prior with a center at 0.5. In the context of this fictional example means that our best guess based on our prior knowledge of Black women's political behavior is that there is a 50% chance that a Black woman will turn out to vote.[5] This example is informative for the visual, but less substantively informative in the example research.

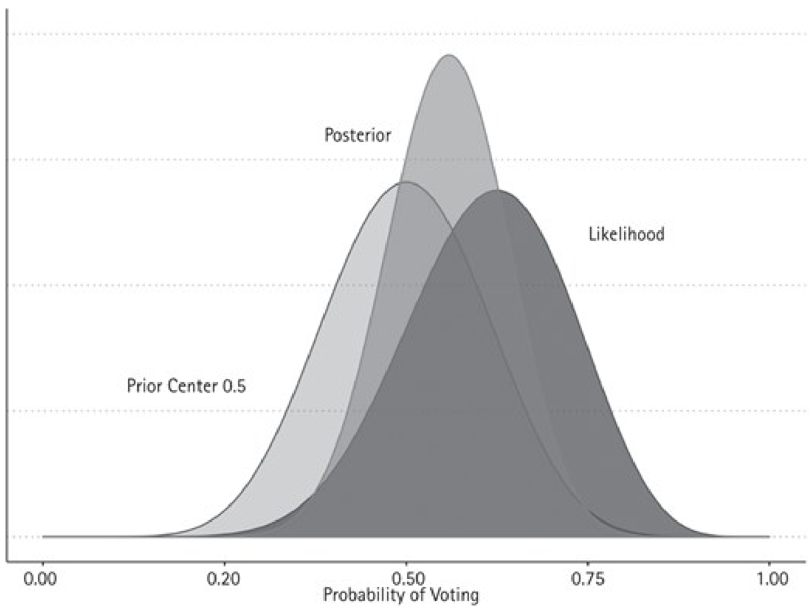

Figure 3 Balancing the Prior and the Likelihood Informative Prior

The prior is shown in light grey, the likelihood (current data) in dark grey, and the posterior in grey. In this instance, the current data is centered at 0.625 (a 62.5% chance of voting). Therefore, the posterior will balance the prior of 0.5 and the data at 0.625 with an estimate of 0.575. In another scenario the researcher may have a wealth of prior knowledge about Black women's political behavior (including from interpretive and qualitative research) in the context of certain geographic areas, with certain kinds of candidates on the ballot, and the kind of election (presidential, midterm, or local). This contextual information could lead to a prior belief that Black women are very likely to turn out to vote, say an 80% chance. We can then set a prior at$\theta_{prior} = \beta\,(8,\ 2)$, which has a center at 0.875.

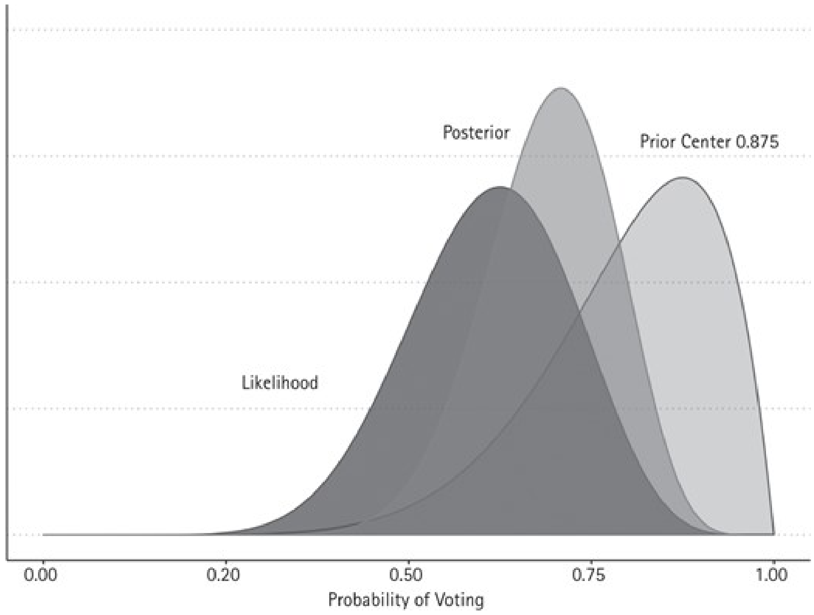

Figure 4 Balancing the Prior and the Likelihood Informative Prior

This prior of 0.875 seen in Figure 4 is balanced with the data that is still centered at 0.625, which leaves a posterior estimate of 0.7. This is an example of how Bayesian methods balance a more certain prior with the data at hand to garner an estimate that is informed by Black political behavior epistemologies. Lastly, Figure 5 demonstrates a diffuse prior or an instance where a researcher has little inclination of which value is most plausible, or instance where the researcher does not want to presuppose any particular outcome. The prior is centered 0.5, the data at 0.625, so the posterior estimate is 0.615. Since the researcher had weaker priors, the posterior result is largely driven by the data at hand and the posterior curve sits largely on top of the likelihood curve.

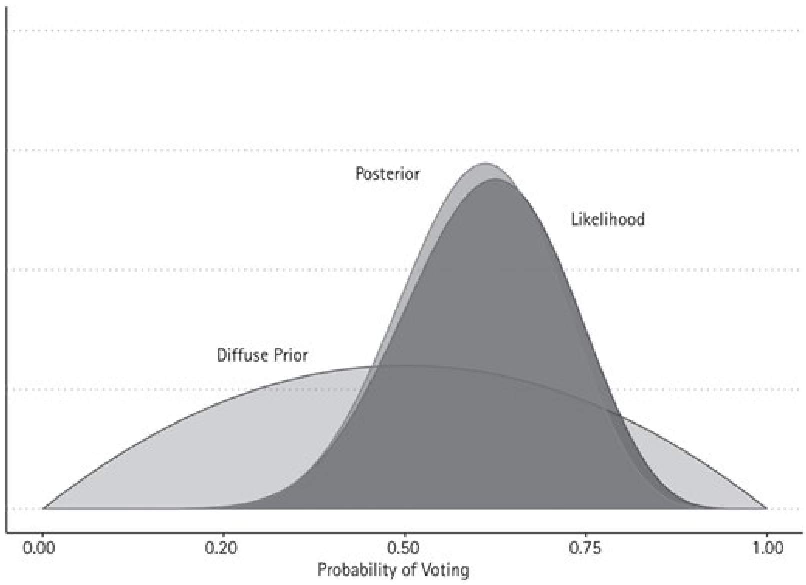

Figure 5 Balancing the Prior and the Likelihood Diffuse Prior

Putting Bayesian methods into conversation with lessons learned from *Data Feminism*, intersectional researchers can directly address broadening conceptions of knowledge production, embracing pluralism, and candid conversations about positionality through shifting their statistical paradigm. Bayesian methods first allow for interpretive forms of knowledge production (which incorporate embodiedness and emotions) be directly built into quantitative work. This incorporation of multiple forms of knowledge speaks directly to embracing methodological pluralism both in the conception of sources of truth and functional approaches. Further, the researcher can prioritize the situated nature of research and research practices from the outset.

Conclusion

From this review, scholars can see the new frontiers posed by intersectional quantitative methods, where pluralist-minded researchers can incorporate Political Methodology's tactics to questions of intersectional importance. This chapter outlined this promising field which has been born out of the labor of a diverse set of scholars set on creating more inclusive and open-minded research methodologies. These scholars have created paradigms and frameworks for operationalizing intersectionality empirically and set the stage for innovation in new modeling tactics and statistical paradigms.

While conventional methods of regression remain the dominant approach to studying intersectional methods quantitatively, this piece also poses the utility of taking a pluralist mentality. By expanding approaches to modeling intersectionality to the interrogation of the functional form, an intersectional researcher can choose the optimal method to capture intersectionality's complexity. Specifically, scholars can look to use multilevel modeling tactics to counteract some of the shortcomings of existing datasets for intersectional research. Lastly, this piece posed the utility of Bayesian statistical paradigms for intersectionality to accommodate previously excluded forms of knowledge production and try to capture the deeply contextual relationships of intersectional identities.

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Notes

1 The frequentist paradigm refers to traditional statistical approaches as opposed to using the Bayesian paradigm with priors. Both of these concepts will be explained in later sections.

2 Parsimony means simplicity, and models that are simple ease interpretability. It is a desired aspect of a statistical model.

3 The basis for the synthetic example was built using a modified version of (Clark 2018)’s pedagogical examples.

4 The 0.5 and flat priors are less likely to be specified in research but are helpful instructional tools for the purpose of this chapter.

5 See Clark (2018) for information on creating these visualizations and the simulation.

Notes

* There are some limitations with specifying group-level effects when there are still too small of sample sizes in each group in the frequentist paradigm. Partial pooling is an imperfect solution to a difficult problem with existing data. Estimating a Bayesian model rather than a frequentist can help address this, particularly if the scholar uses empirical priors.