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Psychometric Methods in Political Science

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Introduction

In political science, psychometric methods have been integrated with the spatial (geometric) voting model to measure latent quantities (e.g., ideology) from political choice and judgment behavior. The spatial voting model posits that individuals' preferences can be represented in abstract, geometric (usually Euclidian) space and that individuals will choose the alternative or stimulus closest to them (Downs, 1957; Enelow & Hinich, 1984). Psychometric methods can be used to recover the locations of the individuals and/or stimuli in the latent space using **preferential** or **perceptual** choice data. The two types of data may be indicators of the same construct even though they originate from different data-generating processes (Coombs, 1964). For instance, the ideological positions of a set of candidates may be measured with survey respondents' placements of the candidates on a left-right scale (perceptual data) or candidates' voting records on a series of legislative proposals (preferential data).[1] In this chapter, we review several different methods that have been developed for the analysis of each type of data in political science.

Psychometrics has contributed to the field of political science by showing that the key theoretical assumptions of the spatial voting model – that political preferences can be represented in geometric space and that political actors accurately perceive the distance between themselves and rival stimuli and choose accordingly – perform well under empirical scrutiny. An impressive regularity from psychometric analyses of political preferential and perceptual data is that the recovered choice spaces are low-dimensional, rarely consisting of more than two dimensions and virtually never more than three (Poole, 2005). That is, only one or two fundamental dimensions are usually sufficient to model legislative voting across hundreds of roll call votes (Poole & Rosenthal, 1997) or citizens' policy attitudes (Hare & Poole, 2012; Treier & Hillygus, 2009) and feeling thermometer rankings of candidates and parties (Bakker & Poole, 2013; Jacoby & Armstrong, 2014; Weisberg & Rusk, 1970). Moreover, citizens are also adept in

[1] In the United States Congress, recorded votes are referred to as "roll call" votes. We use the term "roll call voting" to refer to legislative voting in general throughout this chapter.

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perceiving the latent ideological positions of public officials, a finding we demonstrate in this chapter.

These latent dimensions are understood as **ideological** dimensions because they bundle or **constrain** a complex array of political preferences together as a belief system (Converse, 1964; Hinich & Munger, 1994). Advocacy for social welfare programs is bundled with opposition to military action in left-wing ideologies, while aversion to tax increases is bundled with support for abortion restrictions in right-wing ideologies. Converse (1964) emphasized that these ideological configurations need not be strictly logical, they can also arise from psychological or social sources. However, ideologies are not incoherent assemblages of policy positions: adherents must perceive that they encompass a fundamental vision of the "good society" (Hinich & Munger, 1994).

The application of psychometrics to political science has been so successful because of the ideological structure of political actors' perceptions and preferences. This ideological structure manifests itself in political choice and judgment behavior, and hence spatial "maps" of the latent space can be recovered and analyzed using psychometric techniques. First, however, the regularity of low-dimensional political choice spaces deserves some theoretical explanation: on such a dizzying array of issues, why are only a few dimensions necessary to explain individuals' political attitudes and choices? To address this question, we consider the primary sources of ideological constraint within the framework of the Basic Space theory developed by Hinich, Ordeshook, and their colleagues. We then proceed to an exposition of the scaling methods that have been developed and utilized in political science for the analysis of preferential and perceptual choice data.[2]

The Basic Space Theory

> One of the curious things about political opinions is how often the same people line up on opposite sides of different issues. These issues may have no intrinsic connection with each other. They may range from military spending to drug laws to monetary policy to education. Yet the same familiar faces can be found glaring at each other from opposite sides of the political fence, again and again. It happens too often to be coincidence and is too uncontrolled to be a plot. (Sowell, 2007, p. 3)

The two-space or Basic Space theory of ideology was developed by Melvin J. Hinich, Peter C. Ordeshook, and their colleagues (Cahoon, Hinich, & Ordeshook, 1976; Enelow and Hinich, 1984; Hinich and Munger, 1994, 1997; Hinich & Pollard, 1981; Ordeshook, 1976). It is of interest to us here because it provides a theoretical explanation for the results obtained from empirical scaling methods with a geometric interpretation of Converse's (1964) notion of ideological constraint.

The first work on the theory came with Cahoon, Hinich, and Ordeshook's (1976) use of a metric multidimensional scaling (MDS) procedure based on Torgerson

[2] Many of these scaling procedures are available as functions in the popular open-source program **R**. Our book *Analyzing Spatial Models of Choice and Judgment with R* (with David A. Armstrong, II., Ryan Bakker, Royce Carroll, and Howard Rosenthal) provides detailed instruction on how to use these procedures in **R**.

(1958) and Schönemann (1970) to scale citizens' feeling thermometer rankings of 1968 presidential candidates and sociopolitical groups (e.g., the "military," "Vietnam war protestors," and "liberals"). What they found was that the diverse set of thermometer rankings overlaid with each other on one of two latent dimensions (left-right ideology and partisanship), echoing earlier results from Weisberg and Rusk (1970) and Rusk and Weisberg (1972). Voters did choose candidates closest to them in the choice space, as predicted by the spatial model, but the structure of the recovered space was different than what they expected. Namely, the space consisted not of a comprehensive set of orthogonal, ordered issue dimensions, but rather of a greatly reduced set of abstract dimensions.

This result led Cahoon et al. (1976) to reconsider the standard spatial voting model in which the issues are confined to separate dimensions and each individual is assumed to have an ideal point (i.e., a most preferred location) on, and single-peaked preferences over, each issue dimension (e.g., Davis & Hinich, 1966). The Basic Space theory states that this is but one of **two** spaces: the complex issue or **action** space, and the low-dimensional **basic** space that is recovered by scaling procedures. The presence of constraint – the bundling of issues into a compact platform or program (Converse, 1964) – allows for the linear mapping of one space to the other. If individuals have highly structured (constrained) belief systems, then the action space reduces to the basic space. Hence, the Basic Space theory is a geometric model of Converse's notion of ideological constraint.

For instance, suppose that one group of voters or legislators favors an increase in defense spending, tighter immigration restrictions, and harsher penalties for illegal drug use, and another group takes the opposite position on all three issues. In this case, only a single (**basic**) dimension is needed to explain attitudinal variation between the two groups. The basic dimensions are often referred to as **ideological** dimensions because they organize a diverse set of issue positions under an ideological rubric: "an internally consistent set of propositions that makes both proscriptive and prescriptive demands on human behavior" (Hinich & Munger, 1994, p. 11).

Technically stated, let n represent the number of individuals (voters or legislators), let m represent the number of issue dimensions, and s the number of basic or ideological dimensions. According to the Basic Space theory, the relationship between the action and basic spaces can be summarized with the simple algebraic expression:

$$X = \Upsilon W \tag{28.1}$$

where X is the n by m matrix of individuals' positions on the issue dimensions, Υ is the n by s matrix of individual positions in the basic space, and W is an s by m matrix of linear mappings. That is, W maps the basic or ideological space onto the action space.

The Basic Space theory posits that political competition takes place in the latent, low-dimensional ideological space because this is the space that structures individuals' choice and judgment behavior. The understanding that voters and legislators operate in ideological space is consistent with results from psychology on how individuals make similarities judgments. Specifically, the Shepard–Nosofsky–Ennis model of stimulus comparison states that individuals compare two stored **exemplars** (representative models) in abstract space and, when asked to rate the similarity of the two objects, report the distance between them (Ennis, 1988; Nosofsky, 1986, 1992; Shepard, 1986, 1987). Their findings persuasively demonstrate that simple geometric models structure

individuals' similarities and preferential choice judgments. Gärdenfors (2000) has also presented a compelling case that spatial conceptualization is a natural way for humans to process and organize many different types of information. Why else would diagrams be so useful in such a variety of situations (Larkin & Simon, 1987), and, specifically to our point, spatial metaphors ("left," "right," and "center") be so prevalent in politics?

These findings are relevant to the spatial voting model because the notion of **preference** used in economics and political science can be reduced to psychologists' notion of **similarity**. For example, suppose a voter has an ideal standard (or ideal **point** in political science) labeled X. To decide between Candidate A and Candidate B, the voter compares the similarity between X and A to the similarity between X and B. The voter will prefer Candidate A if the similarity between X and A is greater than X and B, and Candidate B if the reverse is true. Hence, spatial voting can be thought of as a form of similarities judgment.

The use of simple geometric models to make similarities judgments also stems from limits on human cognitive processing and storage abilities (Miller, 1956; Simon, 1985). In political science, ideologies and ideological labels are understood in the Basic Space theory as economical devices that reduce the complexity of the political world so that parties and candidates can communicate their broad policy agendas to voters and voters can hold them accountable. The idea that ideology could serve as a means to reduce information costs was originally posed by Downs (1957) in his seminal work *An Economic Theory of Democracy*. This view has also been articulated by Conover and Feldman (1989) and Popkin (1994), who demonstrate that voters can overcome low information to infer candidates' policy positions by connecting bits of information – cues, signals, and symbols – to recognized patterns from past experiences. For instance, voters may use only a few known (likely salient) policy positions of the candidates to locate their position in ideological space (e.g., a voter who knows only that Senator Edward Kennedy favors a national health insurance plan can safely place him on the left end of the ideological spectrum) (Hinich & Pollard, 1981, p. 328).

These types of heuristics are not foolproof (Tversky & Kahneman, 1974), but they are generally considered to be effective ways for citizens to grapple with a complex political world (Lupia & McCubbins, 1998). In addition, this process is aided by a polarized political environment where the parties are tightly and visibly constrained to their respective policy agendas (Levendusky, 2010). Campaigns also seem to play an important role in influencing the mapping functions between the two spaces; that is, how voters infer specific policy stances from ideological labels (Enelow & Hinich, 1984) and which issues are salient (Vavreck, 2009). Finally, the use of ideological labels is no doubt aided by their durability, since party platforms and elected officials themselves occupy remarkably stable ideological positions over time (Gerring, 1998; Poole, 2007).

From a psychological perspective, then, the direct use of the complex action space – with a separate dimension for each issue – for political decision-making tasks seems quite implausible. A reduced political choice space consisting of a small number of ideological dimensions is at least desirable, if not necessary, given the nature of human cognition: its practical limits and its propensity for geometric organization and pattern recognition. This goes a long way in explaining the success of the spatial model of choice in its empirical applications and the consistent recovery of only a few latent ideological dimensions from political choice data.

However, what are the specific mechanisms of ideological constraint? That is, how do issues become bundled into ideological "packages"? As Jost, Federico, and Napier (2009) discuss, political scientists and psychologists have tended to differ in their emphasis of top-down and bottom-up processes, respectively, in addressing this question. Political scientists have most frequently emphasized the role of political elites – parties, interest groups, and elected officials – in assembling ideological programs and providing competing "menus" of policy positions to the mass public (Converse, 1964; Sniderman & Bullock, 2004). In this view, citizens learn about the content of ideologies ("what goes with what," in Converse's words) based on elite behavior. According to Carmines and Stimson's (1989) influential theory of issue evolution, parties – especially losing or challenger parties – have powerful incentives to adopt and promote positions on new or latent issues in order to attract support (see also De Vries and Hobolt, 2012). Over time, it makes more and more sense that this issue position goes with other elements of a party's ideological platform. Indeed, the fact that the left or right position on a given issue can change (sometimes dramatically, as in the case of abortion in the 1970s (Stimson, 2004, pp. 58–60) illustrates the important role of elite political actors in the mapping process between the action and basic spaces.

Nonetheless, it seems unlikely that the regular folding of both economic and social/cultural issues into the left-right spectrum in a variety of political systems (Benoit & Laver, 2006; Poole & Rosenthal, 2007) could be entirely an artifact of elite manipulation. It is not immediately clear why support for traditional moral values and opposition to large social welfare programs should go together, but the fact that they so frequently do suggests there may be an underlying connection. Accordingly, psychologists (although also a growing number of political scientists) tend to view ideological constraint as stemming from manifold psychological sources: value orientations, personality traits, and motivational needs (Gerber et al., 2010; Goren, 2013; Jost et al., 2009). For example, it has been shown that openness to change promotes a left-wing political orientation, while heightened needs for order and certainty exert a rightward effect (Gerber et al., 2010; Jost, Glaser, Kruglanski, & Sulloway, 2003). The influence of some value orientations is mostly limited to attitudes in relevant policy contexts; for instance, religious orthodoxy has important effects on social/cultural issue attitudes but only weak effects for economic issues (Layman & Green, 2006). But theoretical (Sowell, 2007) and empirical (Barker & Tinnick, 2006; Hare, 2013) work has concluded that some values serve to promote consistent attitudes across the economic, social, and/or foreign policy domains.

The Basic Space theory and the phenomenon of ideological constraint provide important insight into the relevance of scaling results in political science. Namely, the data itself (for instance, a matrix of roll call votes in which legislators vote on multiple issues) can be understood as the complex action space. The recovered basic spaces are best understood as providing spatial maps of political competition: how individuals collectively perceive the choice space and make decisions between competing alternatives (which candidate to support, how to vote on a bill, etc.). It is important to emphasize that these spatial maps aren't just interesting or visually appealing, but are accurate representations of how legislators and voters think and make decisions. In other words, they are simplified models of the political process that nonetheless possess considerable explanatory power. Scaling or ideal point estimation procedures, then, are intimately connected to the field of psychometrics since both assume that latent dimensions of individual attributes (intelligence or ideology, for example) can be recovered through revealed measures of these attribute (test items or roll call votes).

Basic Space scaling

The Basic Space scaling procedure was developed by Poole (1998) and can be used to analyze both preferential and perceptual data organized as rectangular matrices. The model is built directly upon the Basic Space theory. Recall from Equation 28.1 that the Basic Space theory states that the observed n by m issue (action) space is a product of the n by s matrix of individual ideal points in the s-dimensional basic space and an s by m matrix of linear mappings. That is, if ideological constraint is present and individuals have structured belief systems (Converse, 1964), individual ideal points lie on a low-dimensional hyperplane through the complex action space. This low-dimensional hyperplane represents the ideological (basic) space that is recovered with the Basic Space procedure.

In the Basic Space scaling model, let x_{ij} be the ith individual's $(i = 1, \ldots, n)$ reported position on the jth issue $(j = 1, \ldots, m)$ and let X_0 be the n by m matrix of observed data where the 0 subscript indicates that elements are missing from the matrix – not all individuals report their positions on all issues. Let Ψ_{ik} be the ith individual's position on the kth $(k = 1, \ldots, s)$ basic dimension. The model estimated is:

$$X_0 = [\Psi W' + J_n c']_0 + E_0 \tag{28.2}$$

where Ψ is the n by s matrix of coordinates of the individuals on the basic dimensions, W is an m by s matrix of weights, c is a vector of constants of length m, J_n is an n length vector of ones, and E_0 if a n by m matrix of error terms. W and c map the individuals from the basic space onto the issue dimensions.

Our primary quantities of interest from Basic Space scaling are Ψ and W. Ψ provides the estimated positions of the individuals in the recovered s-dimensional space. W is analogous to a set of factor loadings from factor analysis in that they both provide information about how strongly each of the m items is related to the s latent dimension(s). However, the Basic Space scaling method differs from factor analysis in that the rectangular matrix of observed data X_0 is analyzed directly, rather than through a transformed correlation or covariance matrix as is the case with factor analytic methods. This approach is more consistent with the spatial (geometric) model of choice, since individual preferences and perceptions across a range of alternatives are modelled directly. Some information in the choice data (specifically, the means and variances of the variables) is also lost when collapsed to a correlation matrix (Jackman, 2001, p. 230).

The Basic Space scaling procedure has been implemented in two functions – **blackbox()** and **blackbox_transpose()** – available in the **R** package **basicspace** (Poole et al., 2013). The **blackbox()** function is used to analyze rectangular matrices of preferential choice data (e.g., survey respondents' policy preferences) in which the individuals are on the rows and the issues are on the columns. The **blackbox_transpose()** function is used to transpose and analyze rectangular matrices of preferential or perceptual choice data (e.g., feeling thermometers or left-right placements of political parties) so that the stimuli are on the rows and the individuals are on the columns. In both cases, fit statistics (R^2) can be used to assess how well a latent basic dimension explains variation in attitudes toward a particular issue or stimulus. In addition, the W_k terms are analogous to factor loadings in factor analysis in that they indicate how strongly a particular issue loads onto the kth basic dimension.

Preferential Data

Procedures for the analysis of preferential choice data in political science are built on either Clyde Coombs' (1950, 1952, 1958, 1964) unfolding model or the cumulative scaling model. The unfolding model assumes the existence of two scales. The I scale represents an individual's preference ordering of alternatives and can be **unfolded** around the individual's ideal point to produce the J scale. The recovered J scale represents the locations of both the individuals and stimuli as points on a common evaluative dimension. For example, Figure 28.1 illustrates how the I scale for an individual with preference order ABC (that is, who prefers choice A to choice B, and choice B to choice C) is unfolded onto a common J scale. The intersection of the J and I scales marks this particular individual's ideal point, which is closest to choice A and furthest from choice C. As will be discussed, various criteria are used to unfold the I scales (the individual preference orderings) to recover the latent J scales; for instance, to maximize the likelihood of the observed choices (NOMINATE) or minimize the number of classification errors (Optimal Classification).

The unfolding model is easiest to conceptualize in unidimensional terms, but can easily be extended to cases in which multiple dimensions or J scales are needed to represent the preference orderings. Unfolding in s dimensions is accomplished by constructing a series of s-1 dimensional hyperplanes dividing each pair of stimuli alternatives (Coombs, 1964, Ch. 7). For example, unfolding three stimuli (A, B, and C) in two dimensions requires three hyperplanes (lines) in the latent space that divide A and B, A and C, and B and C. This produces a "Coombs mesh" with 3! (6) regions for each of the possible preference orderings (ABC, ACB, BAC, etc.). Finally, the unfolding model is consistent with the assumption of the standard spatial voting model that individuals possess single-peaked and symmetric utility functions over common latent dimensions (Coombs, 1964, pp. 193–195). Whether or not a specific functional form is specified for the utility function and the error term depends on whether the unfolding procedure is parametric or nonparametric.

Methods of cumulative scaling model the probability of a given response (e.g., the correct answer on a test item or a Yea vote on a bill) as a monotonically increasing or decreasing function over values of the latent attribute. Above some threshold individuals are predicted to answer correctly/vote Yea and below some threshold they are

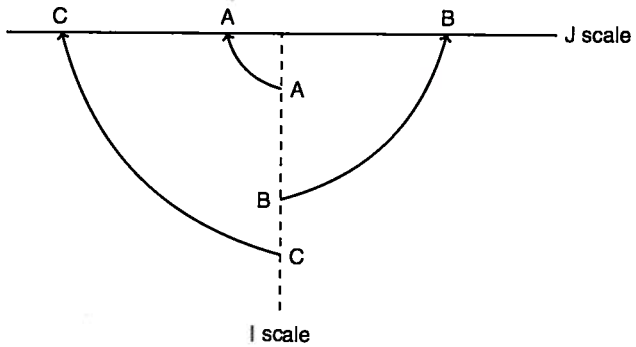

Figure 28.1 Unfolding in a single dimension.

predicted to answer incorrectly/vote Nay. Cumulative scaling methods, particularly Item Response Theory (IRT) models, have been especially prominent in social sciences in general and psychometrics in particular. Scalogram analysis or Guttman scaling (Guttman 1944, 1950) is simply a nonparametric form of the IRT model.

Interestingly, these two very different models are observationally equivalent in the context of political choice data (Poole, 2005; Weisberg, 1968). In the unfolding model, there are multiple outcomes for each policy alternative, and individuals choose the option closest to their ideal point. In one dimension, this forms a perfect scalogram (Weisberg, 1968). Hence, Guttman scaling methods and their IRT descendants can be and have been (e.g., Clinton, Jackman, & Rivers, 2004; Treier & Hillygus, 2009) used to analyze choice data (e.g., legislative roll call voting or public opinion survey responses) in political science.

The fields of political science and psychometrics have been the most intertwined in the development of scaling methods designed for the analysis of binary choice data (in which individuals vote Yea or Nay) like the kind routinely encountered in legislative and judicial settings. These types of procedures measure latent quantities (i.e., the position of legislators and policy alternatives in latent ideological space) based on the assumption that roll call votes are the product of the distance between legislators' ideal points and competing policy proposals. We next cover three of the most influential ideal point estimation methods in political science: Poole and Rosenthal's (1997) NOMINATE procedure, methods based on the IRT model (Clinton et al., 2004), and Poole's (2000) Optimal Classification algorithm.

Poole and Rosenthal's NOMINATE method

NOMINATE (an acronym for **Nominal Three-Step Estimation**) is a parametric unfolding method that is the product of a decades-long collaboration between political scientists Keith T. Poole and Howard Rosenthal (Poole & Rosenthal, 1985, 1991, 1997, 2007). NOMINATE recovers the locations of legislator ideal points and policy alternatives in latent ideological space from binary roll call data using alternating estimation methods developed in psychometrics (Chang & Carroll, 1969; Carroll & Chang, 1970; Takane, Young, & de Leeuw, 1977; Young, de Leeuw, & Takane, 1976). The application of the NOMINATE method to substantive questions has revealed numerous insights about American politics; for instance, that congressional roll call voting has been highly structured by no more than two underlying dimensions (one representing left-right conflict and the other representing regional or cross-cutting cleavages such as civil rights) and that the parties in Congress have moved apart from one another over recent decades. NOMINATE has also been used outside of the U.S. to study voting in the European Parliament (Hix, Noury, & Roland, 2006) and the United Nations (Voeten, 2000).

In the NOMINATE model, each legislator's utility function over the policy alternatives is treated as having a **deterministic** and a **stochastic** component. The deterministic component is based directly upon the spatial theory of choice: legislators and the roll call alternatives are treated as occupying positions in a common latent space and a legislator's roll call vote is a function of the relative distance between her ideal point and the two outcomes. An illustration of deterministic utility in a single dimension is provided in Figure 28.2. In this example, a legislator with an ideal point at 0 on an abstract policy

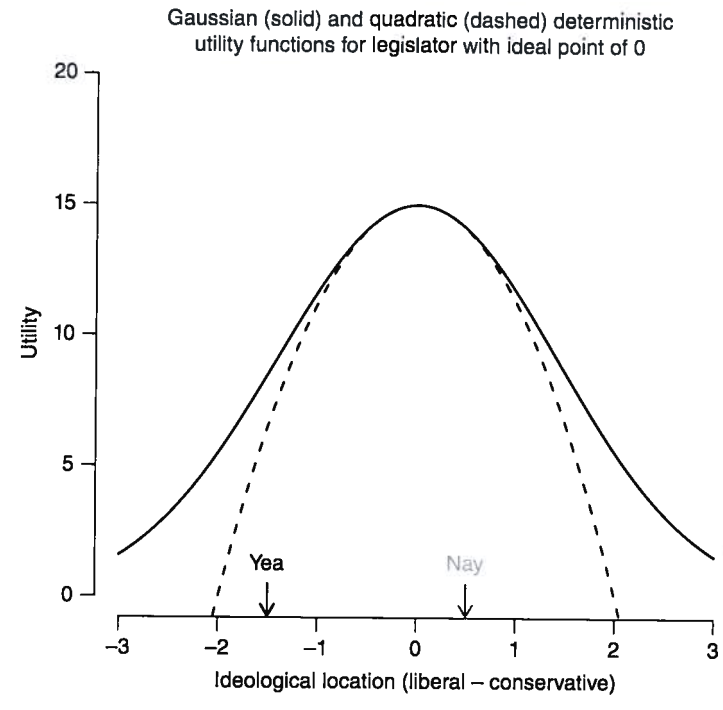

Figure 28.2 Deterministic utility over a single policy dimension.

dimension is faced with two alternatives on a roll call vote: Yea (with a corresponding location of −1.5) and Nay (located at 0.5).

The functional form of the deterministic utility functions specifies how utility decreases as the policy moves away from the legislator's ideal point. Two standard utility functions are shown in Figure 28.2: The normal (Gaussian) function (the solid line) and the quadratic function (the dashed line). The major difference between the two preference functions lies in how they treat policy alternatives that are distant from a legislator's ideal point. The normal function posits that a legislator will become increasingly indifferent between two alternatives as they move away from her ideal point, while the quadratic function indicates just the reverse: that the drop-off in utility accelerates as the alternatives become more distant.[3] In the NOMINATE model, the deterministic utility function is normal, while the IRT model uses the quadratic function to model the deterministic component of legislators' utility. In both cases, a legislator with an ideal point of 0 in Figure 28.2 would most prefer a policy at her ideal point, but will accrue more utility by voting Nay than Yea.

[3] Use of the normal (Gaussian) distribution is consistent with findings from psychology that individuals use an exponential response function when judging the level of similarity between stimuli (Shepard, 1987). According to these results, perceived similarities are an exponential function of the actual similarity between two objects. That is, as two stimuli become more (objectively) dissimilar, the perceived dissimilarity between the two objects increases exponentially. When perceptual error is added, the expected value of the response function approximates the Gaussian form (Ennis, 1988; Nosofsky, 1986).

Accordingly, the deterministic component would predict a Nay vote in this case. However, the second component of utility – the stochastic component – is based on the random utility model developed in economics (McFadden, 1976) and introduces random shocks to the utility function. NOMINATE (specifically, the DW-NOMINATE procedure) uses the normal distribution to model the stochastic component or error term (ε_{ij}). The normal distribution is preferable because it guarantees that the ε_{ij} are a random sample from a known distribution (i.e., they are independent and identically distributed (iid) errors) and that their distributions are symmetric and unimodal (Poole, 2005, p. 98). Spatial voting errors (i.e., casting a vote inconsistent with the deterministic utility component) become less likely as the relative distances between a legislator's ideal point and the Yea and Nay alternatives increase. For example, in Figure 28.2, an error is more likely if the Yea and Nay alternatives are at −1.5 and 0.5, respectively, than at −3 and 0.5.

In the NOMINATE model, let U_{ijy} be the utility accrued from a Yea vote by the ith legislator $(i = 1, \ldots, n)$ on the jth roll call vote $(j = 1, \ldots, q)$. U_{ijy} is the sum of a deterministic and stochastic component, that is:

$$U_{ijy} = u_{ijy} + \varepsilon_{ijy} \tag{28.3}$$

where u_{ijy} is the deterministic component and ε_{ijy} is the stochastic (random) component or error term. To allow for the estimation of multiple dimensions, let k represent the number of dimensions $(k = 1, \ldots, s)$. The squared distance of the ith legislator (X_{ik}) to the Yea outcome for roll call j on the kth dimension (O_{jky}) is:

$$d^2_{ijky} = \left(X_{ik} - O_{jky}\right)^2 \tag{28.4}$$

When using the normal (Gaussian) function to model the deterministic component of utility, legislator i's utility from Equation 28.4 is:

$$U_{ijy} = u_{ijy} + \varepsilon_{ijy} = \beta e^{\left(-\frac{1}{2}\sum_{k=1}^{s} w_k d^2_{ijky}\right)} + \varepsilon_{ijy} \tag{28.5}$$

The deterministic component of Equation 28.5 (d^2_{ijky}, which is equal to $\left(X_{ik} - O_{jky}\right)^2$) means that legislator utility declines as the distance between the legislator's ideal point and the policy alternative increases. But, when multiple dimensions are estimated, it may not be realistic to assume that legislators are equally sensitive to deviations from their ideal points across different dimensions. The w_k term in Equation 28.5 represents salience weights ($w_k > 0$) that allow dimensions to vary in importance and the indifference curves of the utility function to be ellipses rather than circles.

In Equation 28.5, β is a constant term of little substantive interest. Because there is no natural metric, β adjusts for the overall noise level and is proportional to the variance of the error distribution. If the stochastic portion of the utility function is normally distributed with common variance, β is proportional to $\frac{1}{\sigma^2}$, where

$$\varepsilon \sim N(0, \sigma^2) \tag{28.6}$$

Hence the probability that legislator i votes Yea on the jth roll call is:

$$\begin{aligned} P_{ijy} &= P\left(U_{ijy} > U_{ijn}\right) \\ &= P(\varepsilon_{ijn} - \varepsilon_{ijy} < u_{ijy} - u_{ijn}) \\ &= \Phi\left(u_{ijy} - u_{ijn}\right) \\ &= \Phi\left[\beta\left(e^{\left(-\frac{1}{2}\sum_{k=1}^{s} w_k d^2_{ijky}\right)} - e^{\left(-\frac{1}{2}\sum_{k=1}^{s} w_k d^2_{ijkn}\right)}\right)\right] \end{aligned} \tag{28.7}$$

where Φ is the standard normal cumulative density function, restricting probabilities to be between 0 and 1. The greater the difference in utility between the roll call outcomes, the higher the probability of choosing the closer policy alternative.

Let Υ be the $p \times q$ matrix of observed roll call choices (y_{ij}). Given Υ, NOMINATE estimates the combination of parameters for legislator ideal points and roll call outcomes that maximizes the joint probability of the observed data (choices). The likelihood function is computed over the legislators and roll calls:

$$L\left(u_{ijy} - u_{ijn} | \Upsilon\right) = \prod_{i=1}^{n}\prod_{j=1}^{q}\prod_{\tau=1}^{2} P_{ij\tau}^{C_{ij\tau}} \tag{28.8}$$

which is the product of individual vote probabilities over the n legislators, q roll call votes, and 2 (Yea and Nay) choices. where τ is the index for Yea and Nay, $P_{ij\tau}$ is the probability of voting for choice τ as given by Equation 28.7, and $C_{ij\tau} = 1$ if the legislator's actual choice is τ, and 0 otherwise.

The likelihood function to be optimized is a continuous distribution over the $ps + 2qs + s$ hyperplane, where s is the number of estimated dimensions. ps is the number of legislator ideal points (X_{ik}), $2qs$ is the number of roll call parameters (the locations of the Yea and Nay alternatives O_{jky} and O_{jkn}), and s is the number of the β and $w_2, \ldots, w_s$ terms. For a hypothetical legislative session with 100 legislators and 500 roll calls estimated in two dimensions, this amounts to finding the maximum of a 2,202-dimensional hyperplane. This is a nontrivial optimization problem that NOMINATE solves using high-quality starting values for the legislator parameters and an alternating maximum likelihood procedure. Starting values for the legislator ideal points are calculated from the agreement score matrix (which is like a correlation matrix but shows the proportion of roll call votes that legislators vote in agreement with each other) and provisional values for the scaling constants β and w are assigned.

With these starting values, the three-step iterative estimation algorithm begins. First, holding the legislator ideal points and the β and w terms fixed, NOMINATE finds the values for the roll call parameters that maximize the likelihood function (the BHHH hill-climbing procedure (Berndt, Hall, Hall, & Hausman, 1974) is used in all three steps to optimize the objective function). Then, the likelihood function is maximized over the β and w terms while holding fixed the legislator ideal points and roll call parameters. Finally, the roll call parameters and the β and w terms are held fixed while searching for the values of the legislator ideal points that maximize the likelihood function. The process is repeated until convergence.

To illustrate the DW-NOMINATE procedure, we plot the 98th (1983–1985) U.S. Senate's vote to table a U.S.-Soviet nuclear freeze amendment from Senator Ted Kennedy (D-MA) in Figure 28.3. The first (x-axis) latent dimension represents liberal-conservative ideology, and the second (y-axis) dimension taps into regional differences within the parties (particularly between the Southern and Northern wings of the Democratic Party). The solid line running through the middle of the space is the cutting line. The cutting line (or plane in more than two dimensions) is equidistant from the Yea and Nay alternatives, and hence it divides the predicted Yea votes from the predicted Nay votes. Voting errors that are close to the cutting line are considered less serious since a legislator whose ideal point is directly on the cutting line will accrue the same deterministic utility from the Yea and Nay alternatives and will be indifferent between the two choices.

The cutting line in Figure 28.3 is nearly vertical, meaning that this vote primarily divides Senators along the liberal-conservative dimension. Most Republican Senators vote Yea and most Democratic Senators vote Nay, but the spatial (geometric) model of choice offers an improvement on simple party-line model by capturing ideological differences within the parties: classifying liberal Republicans as Nay votes and conservative Democrats as Yea votes. Accordingly, DW-NOMINATE produces only three classification errors (isolated in the right panel of Figure 28.3), all of which are very close to the cutting line. Indeed, the PRE (proportional reduction in error) statistic – which measures the improvement in classification beyond the baseline of predicting that all cases are in the modal category – is a very high 0.92. Figure 28.3 illustrates why spatial "maps" are so useful in understanding and conveying the latent structure underlying political competition.

One of the species of NOMINATE procedures – W-NOMINATE – has been implemented in the **wnominate** package in **R** (Poole, Lewis, Lo, & Carroll, 2011). W-NOMINATE uses the deterministic utility function provided in Equation 28.5 that allows different salience weights on the estimated dimensions. The errors in the W-NOMINATE are assumed to follow a logit distribution. Finally, W-NOMINATE constrains the legislators and roll call midpoints to lie within an s-dimensional hypersphere of radius one (in other words, between −1 and 1 in the one-dimensional model and within the unit circle in the two-dimensional model). W-NOMINATE is a static procedure that is meant to be applied to one or possibly a few legislative sessions, but it is very computationally efficient and its results are highly correlated with those from other NOMINATE procedures.

Item Response Theory (IRT) models

Scholars in the field of psychometrics are no doubt already familiar with the IRT model and the subject has been covered extensively throughout this volume. In this section, we focus on the extension of the two-parameter Bayesian IRT model to the analysis of binary and ordinal choice data in political science. This effort has been spearheaded in a series of works by Simon Jackman (Clinton et al., 2004; Jackman 2000, 2001; Treier & Jackman, 2008) and Andrew Martin and Kevin Quinn (Martin & Quinn, 2002; Quinn 2004) and use of the Bayesian IRT model in political science has been facilitated by the development of the **R** packages **pscl** (Jackman, 2011) and **MCMCpack** (Martin, Quinn, & Park, 2011).

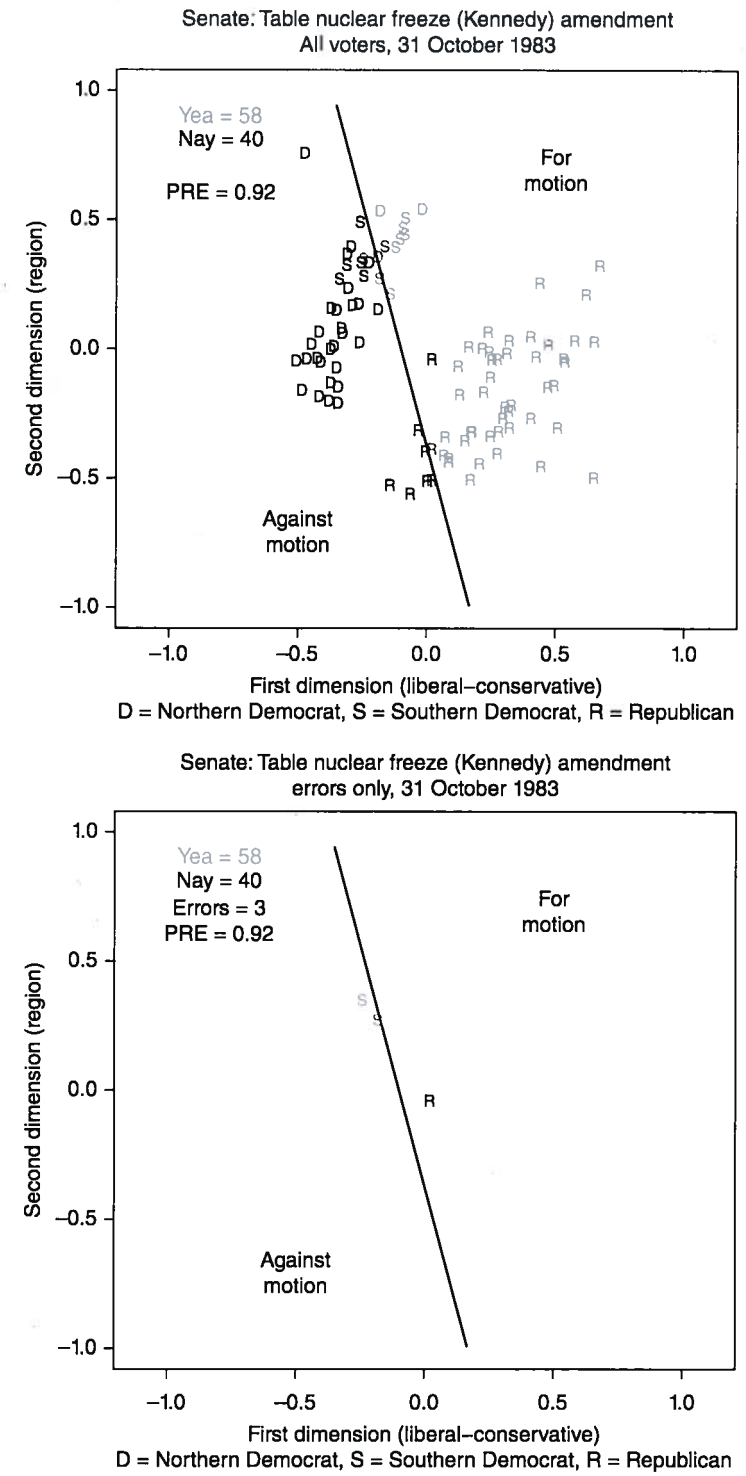

Figure 28.3 DW-NOMINATE scaling of U.S. Senate roll call vote.

The IRT model was developed to measure a latent individual attribute such as mental ability from observed indicators such as test items. This model has been extended to political science by substituting latent ability with political ideology, test subjects with legislators, and test items with roll call votes. The discrimination parameter indicates how well a roll call vote classifies individuals based on ideology, and can thus be interpreted in the same manner as the factor loading of an item in factor analysis. In political science, the quantity of interest is usually the individual parameters (the legislator ideal points) rather than the item parameters as in psychometric testing (Clinton et al., 2004, p. 356).

Since IRT models involve the estimation of the ability, difficulty, and (in the two-parameter model) discrimination parameters, Bayesian methods are attractive because they allow for the simultaneous estimation of the parameters. More specifically, the Gibbs sampler offers an efficient means of analyzing high-dimensional posterior densities, like those regularly produced from legislative roll call data. The Gibbs sampler breaks down the high-dimensional posterior density into a series of more tractable components and samples from the conditional densities for each component, improving the approximation to the posterior density at each iteration (Jackman, 2009, pp. 214–221).

In the Clinton–Jackman–Rivers (CJR) model, x_i is the legislator ideology score (ideal point), α_j is the roll call difficulty parameter and β_j is the roll call discrimination parameter. As before, let i index legislators, $(i = 1, \ldots, n)$ and j index roll calls $(j = 1, \ldots, q)$. The CJR model uses the quadratic function to model legislators' utility function. Hence, in a single dimension, legislator i's utility for the Yea outcome on the jth roll call is:

$$U_{ijy} = u_{ijy} + \varepsilon_{ijy} = -\left(x_i - O_{jy}\right)^2 + \varepsilon_{ijy} \tag{28.9}$$

As with NOMINATE, the CJR model assumes that errors are normally distributed. Assuming quadratic utility and normally distributed errors, the probability that legislator i votes Yea on the jth roll call is:

$$\begin{aligned} P_{ijy} &= P\left(U_{ijy} > U_{ijn}\right) \\ &= P(\varepsilon_{ijn} - \varepsilon_{ijy} < u_{ijy} - u_{ijn}) \\ &= P(\varepsilon_{ijn} - \varepsilon_{ijy} < \| x_i - O_{jn}\|^2 - \|x_i - O_j\|^2 \\ &= P(\varepsilon_{ijn} - \varepsilon_{ijy} < 2\left(O_{jy} - O_{jn}\right)' x_i + O'_{jn} O_{jn} - O'_{jy} O_{jy} \\ &= \Phi\left(\beta'_j x_i - \alpha_j\right) \end{aligned} \tag{28.10}$$

The midpoint on the jth roll call is equal to $\frac{\alpha_j}{\beta_j}$, which represents the point at which legislators are equally distant from and hence indifferent between the two outcomes.

Equation 28.10 yields the likelihood function:

$$L(\boldsymbol{B}, \boldsymbol{\alpha}, \boldsymbol{X} | \boldsymbol{\Upsilon}) = \prod_{i=1}^{n} \prod_{j=1}^{q} \left(P_{ijy}\right)^{y_{ij}} \left(1 - P_{ijy}\right)^{1 - y_{ij}} \tag{28.11}$$

which, as in Equation 28.8, is the product of individual vote probabilities over the n legislators and q roll call votes. In Equation 28.12, $\boldsymbol{B}$ is a $q \times s$ matrix of β_j values, $\boldsymbol{\alpha}$ is a q length vector of α_j values, and $\boldsymbol{X}$ is a $n \times s$ (Clinton et al., 2004; Jackman, 2001). Priors (usually vague normal) are assigned for the unknown parameters $\boldsymbol{B}$, $\boldsymbol{\alpha}$, and $\boldsymbol{X}$. This yields the posterior distribution:

$$\pi(\boldsymbol{B}, \boldsymbol{\alpha}, \boldsymbol{X} | \boldsymbol{\Upsilon}) \propto p(\boldsymbol{B}, \boldsymbol{\alpha}, \boldsymbol{X}) \times L(\boldsymbol{B}, \boldsymbol{\alpha}, \boldsymbol{X} | \boldsymbol{\Upsilon}) \tag{28.12}$$

which is then analyzed with MCMC simulation methods to produce estimates of the quantities of interest. One advantage of the Bayesian approach is that uncertainty estimates can be easily obtained by summarizing the posterior distributions of the parameters (although the parametric bootstrap can be used to estimate standard errors for estimates from "frequentist" methods like NOMINATE: Lewis & Poole, 2004).

Despite its relatively recent introduction to political science, the Bayesian IRT model has produced a surge of interest in the field. The method has been used to study legislative voting (Clinton & Meirowitz, 2001, 2003), judicial behavior (Martin & Quinn, 2002), the measurement of democracy across nations (Treier & Jackman, 2008), ideology in the mass public (Treier & Hillygus, 2009), spatial voting in the American electorate (Jessee, 2009), and legislative representation of constituent preferences (Bafumi & Herron, 2010).

As the IRT model continues to expand in political science, two issues concerning its application in multidimensional cases will need to be addressed. First, when a single item difficulty parameter (α_j) is estimated for each roll call in a multidimensional IRT model, then this is implicitly a **compensatory** (as opposed to a **noncompensatory**) model (Bolt & Lall, 2003). That is, scores on each of the dimensions are interchangeable in influencing the probability of observing a given response (e.g., a Yea vote) rather than independent as in the noncompensatory model (Reckase, 1985, 2010). For example, if separate dimensions are estimated for economic and social policy preferences, a high (conservative) score on the economic dimension can offset or compensate a low (liberal) score on the social dimension. This may or may not be the appropriate model given the nature of the application, and more attention to the distinction between compensatory and noncompensatory models is needed in political science.

The second challenge concerns identification in the general multidimensional IRT model, and in this case, it may be political scientists (see Bakker and Poole, 2013; Rivers, 2003) who are able to contribute to psychometrics. A solution remains unidentified so long as multiple configurations of the parameters are equally valid. In a single dimension, identification can be easily achieved with a normalization constraint: requiring that the estimated ideal points have mean 0 and variance 1 (Clinton et al., 2004). In multiple dimensions, identification requires constraints on some of the subject and/or item parameters; for example, setting some legislator ideal points to fixed locations or restricting some roll calls to discriminate only on a single dimension. However, **over-identification** arises when two or more points are fixed and the distances between them are no longer elastic (that is, the distances are constrained to equal some fixed amount) (Bakker & Poole, 2013). Hence, the uncertainty about the true distances between the fixed points propagates to other inter-point distances in the solution.

The Bakker–Poole (2013) solution to identification (in the context of Bayesian metric MDS) is to "freeze" the posterior distributions of the legislators in certain quadrants. In two dimensions, this is achieved by setting one point at the origin and the first or second dimension coordinate of another point at 0. At the end of each iteration of the MCMC procedure (in this case, slice sampling), the sign of the draws from the

legislators' posterior densities are compared to the target configuration and rotated if they do not match. This method produces a **minimally** restricted, identified solution.

Optimal Classification

Optimal Classification (OC) is a nonparametric unfolding method developed by Poole (2000) and available in the **R** package **oc** (Poole, Lewis, Lo, & Carroll, 2012). OC is nonparametric in that it does not make parametric assumptions about the functional form of the error process or legislators' utility functions other than that they are single-peaked and symmetric. As an unfolding procedure, OC uses binary choice data to recover the locations of both legislators and policy alternatives in latent space. The algorithm has been applied in psychometric contexts outside of political science; for instance, linguistic studies (Croft & Poole, 2008).

Unlike the parametric methods discussed previously, OC is not designed to estimate the parameters that maximize the joint likelihood of the observed legislative choice data. The goal of OC is to estimate the configuration of legislator ideal points and roll call cutting planes (which divide predicted Yea votes from predicted Nay votes) that maximizes the correct classification of the choices themselves. Equivalently stated, OC seeks to **minimize** the number of classification errors, meaning that no error is treated as more or less severe than others.

The OC procedure is executed in three steps. First, a starting configuration of the legislator coordinates is generated through an eigenvalue/eigenvector decomposition of the double-centered agreement score matrix.[4] Second, from this configuration, the cutting plane procedure uses an iterative process to position cutting planes on each roll call vote in such a manner that the number of classification errors is minimized. The configuration of all cutting planes is also known as a **Coombs mesh** (Coombs, 1964). An example of a Coombs mesh is shown in Figure 28.4, which was generated by plotting the cutting lines from 100 random roll call votes from the 98th U.S. Senate.

As can be seen in Figure 28.4, the cutting lines intersect to form a large number of **polytopes**: bounded regions in the latent space that correspond to patterns of Yea/Nay choices. For example, a triangular polytope formed by the intersection of three cutting planes may be on the Yea side of the first roll call vote and the Nay side of the second and third votes. A legislator who voted *YNN* could be placed in this polytope with no classification errors. Indeed, in the final step of the OC routine, the legislator procedure then locates the polytope for each legislator which maximizes correct classification. For example, the *R* token near the middle of Figure 28.4 denotes the polytope in which OC places Senator Alfonse D'Amato (R-NY). This polytope minimizes Senator D'Amato's total number of voting errors.

The difference between parametric (NOMINATE and IRT) and nonparametric (OC) methods for the analysis of preferential choice data can be understood as a trade-off between making strong parametric assumptions about the data and precise estimation of the parameters. In a single dimension, the OC result is identified only up to a rank order and in two dimensions legislators are identified only to a polytope, although this is sufficient for the recovery of metric-level information (Peress, 2012).

[4] A matrix is double-centered by subtracting the row and column means from, adding the grand mean to, and multiplying by −0.5 each entry of the matrix.

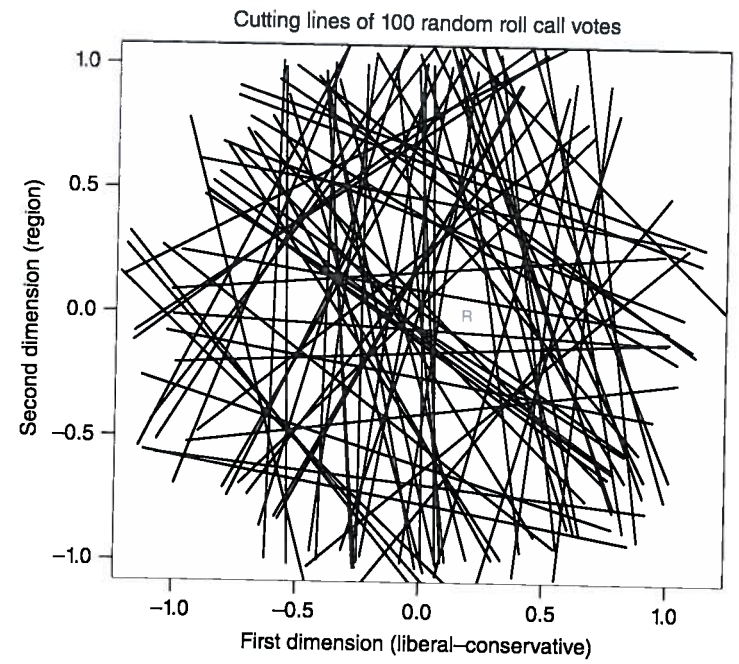

Figure 28.4 Coombs mesh from optimal classification scaling of the 98th U.S. Senate.

This means that in Figure 28.4, Senator D'Amato could be anywhere inside the specified polytope, but by default OC places him in the center. However, parametric assumptions (e.g., the assumption that errors are iid) can be quite costly, and in these cases OC provides a more accurate picture of preferential choice behavior (Rosenthal and Voeten, 2004). However, in many cases the results from parametric and nonparametric methods are virtually identical (Poole & Rosenthal, 2001).

Perceptual Data

Perceptual data is collected by asking individuals (usually public opinion survey respondents or experts) to evaluate the positions of stimuli on abstract policy dimensions. For example, the Chapel Hill Expert Survey (CHES) asks political experts to place European national parties on an eleven-point left-right ideological scale (Bakker et al., 2012). This type of data is of great interest to political scientists because they allow us to test the basic tenets of spatial voting theory and to assess democratic accountability. For instance, do citizens accurately perceive the policy positions of their elected representatives, and if so, do they hold them accountable for drifting from their own preferences?

However, the greatest challenge in interpreting perceptual data is that of interpersonal incomparability or differential item functioning (DIF). In political science, DIF and DIF-correction mechanisms have been detailed by Henry Brady (Brady, 1985, 1990) and more recently by Gary King and colleagues (King, Murray, Salomon, & Tandon, 2004). DIF arises when individuals interpret the meaning of the response categories on a scale differently. Personal biases are a frequent source of DIF. For

instance, a radical leftist may place a left-of-center party near the middle of an ideological scale, while a very right-wing respondent may place the same party on the extreme leftward end of the scale.

Various procedures have been developed to correct for DIF and recover the true locations of individuals and stimuli from perceptual data. In this section, we focus our attention on the Aldrich–McKelvey scaling method (Aldrich & McKelvey, 1977), which has been the workhorse DIF-correction procedure in political science since its development in the late 1970s.[5] The fundamental insight of Aldrich and McKelvey (1977) is that respondents distort their reported placements in estimable ways based on differences in their ratings of common stimuli. Suppose that the true positions of Party A and Party B are 2 and 5, respectively, on a seven-point scale. If Respondent 1 places Party A at 1 and Party B at 4, then it is clear that we should shift all of Respondent 1's placements (including her own self-placement) to the right one unit. The stimuli are often real parties or candidates, but may be fictional vignettes (especially if there is are no stimuli that are familiar to all of the respondents) (Bakker, Jolly, Polk, & Poole, 2014).

We next provide an exposition of the original Aldrich–McKelvey scaling model and a Bayesian means of estimating the model developed by Armstrong et al. (2014).

Aldrich–McKelvey scaling

The Aldrich–McKelvey (A-M) scaling model proceeds as follows. Let z_{ij} be the perceived location of stimulus j $(j = 1, \ldots, q)$ by individual i $(i = 1, \ldots, n)$. The A–M model assumes that the individual reports a noisy linear transformation of the true location of stimulus $j(z_j)$; that is

$$\alpha_i + \beta_i z_j = z_{ij} + u_j \tag{28.13}$$

where u_{ij} satisfies the usual Gauss–Markov assumptions of zero mean, homoscedasticity, and independence (Aldrich & McKelvey, 1977, p. 113). To illustrate the intuition behind Equation 28.13, assume that the true position of Party L on a ten-point, left-right or liberal-conservative is 3 (making it a left-wing party). Let Party R, a right-wing party, occupy the position of 7 on the scale. According to Equation 28.13, individuals' placements of these parties can be distorted in one (or both) of two ways: they can shift the placements too far to the left or right (for example, a very left-wing individual may view party L as insufficiently left-wing and party R as extremely right-wing, and her placements of the two parties might be 5 and 9, respectively) or they can stretch or flip the true positions of the stimuli. The first type of distortion is captured by the α_i term and the second type is captured by the b_i term. When individuals flip the space (for example, placing party L to the right of party R), b_i will be negative. Hence, the sign on the b_i values is a useful way to screen respondents by level of political information (i.e., whether they correctly perceive the ordering of stimuli along an issue scale) (Palfrey & Poole, 1987).

[5] Alternative methods to diagnose and treat DIF using "anchoring vignettes" have been developed by King et al. (2004) and Wand (2013) and are available in the **R** package **anchors** (Wand et al., 2011). Note that the *B*-scale detailed in Wand (2013) is equivalent to a nonparametric form of Aldrich–McKelvey scaling.

Let $\hat{z}_j$ be the estimated location of stimulus j and let $\hat{\alpha}_i$ and $\hat{\beta}_i$ be the estimates of α_i and β_i; define

$$\hat{\alpha}_i + \hat{\beta}_i \hat{z}_j - z_{ij} = e_{ij} \tag{28.14}$$

Hence, by estimating the perceptual distortion parameters α_i (the intercept or shift term) and β_i (the weight or stretch term) for each individual, we can recover the z_j: the "true" (DIF-corrected) locations of the stimuli and individuals. Of course, there remains the practical issue of how the perceptual distortion parameters are to be estimated. The original A-M scaling procedure solved the problem with an elegant approach that worked around computing limitations in the 1970s by using Lagrangian multipliers to minimize the loss function (Aldrich & McKelvey, 1977, pp. 111–113). Hence, the original A–M procedure is a maximum likelihood estimation (MLE) method.

Advances in computing power have made Bayesian (Markov chain Monte Carlo (MCMC)-based) estimation of the A-M model tractable, and the Bayesian approach (BAM, for Bayesian Aldrich–McKelvey scaling) offers two major advantages (see Armstrong et al., 2014). First, it is straightforward to directly assess uncertainty in the BAM estimates because inferences are made directly from the marginal posterior densities of the parameters. Second, BAM allows for the inclusion of individuals with missing responses. The degree of "missingnesss" is simply transmitted as greater uncertainty for the individual distortion parameters.

The BAM scaling procedure is a variation of the Bayesian factor model (Jackman, 2009, pp. 438–444). In the standard factor model, the latent variable or factor is indexed by individual and the factor loadings are held constant across all observations. The BAM scaling model, however, reverses this indexing. That is, the factor loadings (α_i and b_i) are allowed to vary across individuals while the latent variable ($\hat{z}_j$) is held constant:

$$z_{ij} \sim N\left(\mu_{ij}, \tau_{ij}\right) \tag{28.15}$$

$$\mu_{ij} = \alpha_i + \beta_i z_j \tag{28.16}$$

$$\tau_{ij} = \tau_i \tau_j \tag{28.17}$$

BAM scaling can be executed with MCMC simulation programs such as WinBUGS (Lunn et al., 2000) or JAGS (Plummer, 2003).[6] Next, we use BAM scaling to analyze perceptual data from the 2010 Cooperative Congressional Election Study (CCES) (Ansolabehere, 2012), which surveyed 55,400 respondents. In one series of questions, respondents were asked to rate the ideological positions of their states' U.S. Senators and major party Senatorial candidates on a seven-point liberal-conservative scale. We combine these data with respondents' placements of themselves and four national (and hence, common) stimuli – President Barack Obama, the Democratic and Republican parties, and the Tea Party movement—on the same ideological scale. We run the

[6] Code available at: http://voteview.com/BAM.asp. The maximum likelihood Aldrich–McKelvey scaling method is available in the **aldmck()** function in the **basicspace** package in **R** (Poole et al., 2013).

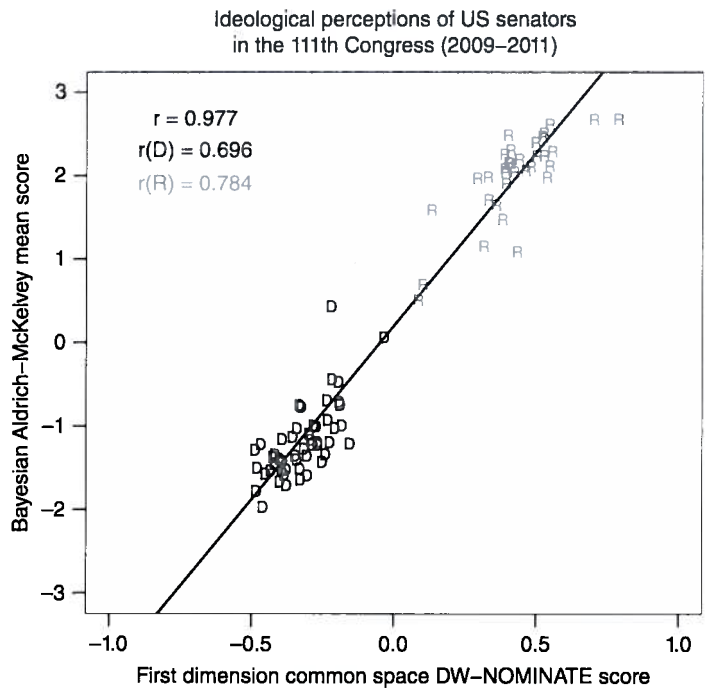

Figure 28.5 Citizens' perceptions of the ideological positions of U.S. Senators.

BAM scaling procedure using a burn-in period of 10,000 iterations and two chains of 2,500 iterations thinned by 5.

The means of the samples are used as the point estimates of z_j: the DIF-corrected estimate of citizens' ideological perceptions of the political stimuli. In Figure 28.5, we plot incumbent Senators' first (liberal-conservative) dimension Common Space DW-NOMINATE score with the BAM estimates. It is immediately clear that popular perceptions of Senators' locations on the liberal-conservative spectrum are strongly correlated with their ideological positions as measured by their roll call voting record (see also Jacobsmeier, 2013). The Pearson correlation between the two for Senators in the 111th Congress is 0.977, although this figure is biased upwards given the distinction between the two parties. A more demanding test involves whether citizens are able to ideologically differentiate between Senators of the same party. The intra-party correlations between the DW-NOMINATE and BAM scores suggest that they are, with Democrats correlated at 0.696 (Kendall's $\tau = 0.494$) and Republicans are correlated at 0.784 ($\tau = 0.582$). Indeed, in 21 of 26 states in which both Senators were of the same party and included in the CCES's ideological placement section, the BAM and DW-NOMINATE scores have the same ideological ordering.

Consistent with the Basic Space theory, these results suggest that citizens are capable of piecing together limited amounts of political information to develop accurate, spatially organized ideological profiles of elected officials (see also Jacoby & Armstrong, 2014). These bits of information used to infer ideological locations may include legislators' roll call votes or positions on salient issues (Ansolabehere & Jones, 2010; Nyhan et al., 2012), campaign rhetoric (Franklin, 1991), or other heuristic devices such as personal affect (Brady & Sniderman, 1985). Nyhan et al.'s (2012) results are especially important on this point: they find that voters' ideological perceptions of incumbent members of Congress mediate the effect of visible congressional roll call votes on incumbent vote shares. These finding mesh with the Basic Space theory's prediction that competition will occur in the basic (ideological) space. Indeed, the basic space (the liberal-conservative dimension) appears to structure the behavior of both elected officials in Congress and evaluations of them by their constituents.

Concluding Thoughts

We conclude by discussing some promising future directions for research at the intersection of psychometrics and political science. The first involves the accurate representation of political actors' preferences over the abstract policy space. Utility functions – quadratic or normal (Gaussian) – are usually simply assumed, with occasional theoretical debate about which functional form best approximates individual preferences across policy alternatives. Carroll et al. (2013), however, develop a method (α-NOMINATE) that addresses this question by estimating a parameter (α) that shapes the utility function to fit the observed choice data (see also Carroll et al. (2014) for the **anominate** package in **R**). They find that in a diverse set of legislative and judicial contexts, the value of the α parameter strongly points toward the Gaussian function. This result fits well with psychological findings concerning the exponential response function discussed earlier. We think this is a good illustration of just how rich political choice data can be. Consequently, these types of models need not be limited to producing ideal point estimates, but can also uncover ever-deeper insights into the nature of political actors' decision-making processes.

The second area in which further work is needed involves the mapping process between the basic and action spaces. For instance, how realistic is the assumption (implicit in Equation 28.1) that all individuals project their issue positions onto their ideal points on the basic dimensions in the same manner? That is, is the mapping process between the two spaces homogenous across individuals? This issue has been addressed in part in the field of legislative studies by examining the role of selective party pressure in legislators' roll call voting behavior (McCarty, Poole, & Rosenthal, 2001). However, public opinion offers another arena where these sorts of question abound. Here, we suspect that differences in political information levels could have a mediating influence on the mapping process. Because public opinion data contains such rich variation across individuals and across time (i.e., political contexts), it also offers an opportunity to parse out the relative influence of elite and individual-level (e.g., core values and beliefs) factors as sources of constraint.

Finally, the methods discussed in this chapter have most frequently been applied to legislative roll call data, but their utility is certainly not limited to this particular political arena. Other types of political choice data can be analyzed using the basic spatial model presented here. For example, Bonica (2014) treats campaign contributions as choices and uses this data to simultaneously estimate the ideological positions of hundreds of thousands of individual donors, political organizations, and candidates. Numerous insights into public opinion have also been revealed by analyzing survey data with these types of scaling methods (see, e.g., Hare and Poole, 2012; Jacoby, 1994, 1995; Treier &

Hillygus, 2009). There are also exciting opportunities to apply spatial models to "big data"; for example, measuring the ideological locations of social network users (Barberá, 2012). All of these and more are promising frontiers for expanding the use of psychometric-based techniques in political science.

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Code Appendix

Code 1 R code for chapter examples.

```
library(pscl)
library(wnominate)
library(oc)
#
#
#  Utility functions
#
norm.util <- function(x){ return(15*exp(-0.25*(0-x)^2))}
quad.util <- function(x){ return(15+15*(-0.25*(0-x)^2))}

plot(c(-3,3),c(0,20),type="n",bty="n",
     main="Gaussian (solid) and Quadratic (dashed)
     Deterministic\nUtility
     Functions for Legislator with Ideal Point of 0",
xlab="Ideological Location (Liberal - Conservative)",
ylab="Utility",cex.lab=1.2)
lines(seq(-3,3,0.01), norm.util(seq(-3,3,0.01)),lwd=2,
lty=1)
lines(seq(-3,3,0.01), quad.util(seq(-3,3,0.01)),lwd=2,
lty=2)
arrows(-1.5,0.5,-1.5,-0.75,length=0.1,lwd=2,
col="gray20")
text(-1.5,1.0,"Yea",font=2,col="gray20")
arrows(0.5,0.5,0.5,-0.75,length=0.1,lwd=2,col="gray60")
text(0.5,1.0,"Nay",font=2,col="gray60")
#
#
#  Optimal Classification
#
hr89 <- readKH("c:/Dropbox/Files/Research/
Psychometrics_PoliticalScience/sen98kh.ord",
        dtl=NULL,
        yea=c(1,2,3),
        nay=c(4,5,6),
        missing=c(7,8,9),
        notInLegis=0,
        desc="90th House Roll Call Data",
        debug=FALSE)
#
result <- oc(hr89, dims=2, minvotes=20, lop=0.005,
polarity=c(1,3))
#
```